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Nowcasting and short-term forecasting of Russian GDP with a dynamic factor model

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Contents

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Abstract

Real-time assessment of quarterly GDP growth rates is crucial for evaluation of economy's current perspectives given the fact that respective data is normally subject to substantial publication delays by national statistical agencies. Large information sets of real-time indicators which could be used to approximate GDP growth rates in the quarter of interest are in practice characterized by unbalanced data, mixed frequencies, systematic data revisions, as well as a more general curse of dimensionality problem. The latter issues could, however, be practically resolved by means of dynamic factor modeling that has recently been recognized as a helpful tool to evaluate current economic conditions by means of higher frequency indicators.

Our major results show that the performance of dynamic factor models in predicting Russian GDP dynamics appears to be superior as compared to other common alternative specifications. At the same time, we empirically show that the arrival of new data seems to consistently improve DFM's predictive accuracy throughout sequential nowcast vintages. We also introduce the analysis of nowcast evolution resulting from the gradual expansion of the dataset of explanatory variables, as well as the framework for estimating contributions of different blocks of predictors into now-casts of Russian GDP.

Keywords: GDP nowcast, dynamic factor models, principal components, Kalman filter, nowcast evolution
JEL: C53, C82, E17

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1 Introduction

Over the last decade Russia has experienced periods of both favorable and adverse conditions for economic growth which were caused simultaneously by internal and external factors. The increase in GDP throughout the steady trend in oil price growth starting in 2002 was followed by a dramatic downturn in the second half of 2008 and most of 2009, which came in the aftermath of a global economic and financial crisis. Further revival in economic growth was not persistent and still accompanied by some fluctuations in GDP dynamics. In the last couple of years the Russian economy has found itself in another slump, the nature and future prospects of which could perhaps be simultaneously described by a set of structural factors, deterioration of external economic conditions, as well as increased uncertainty given the consequences of the recent global political tensions and imposed sanctions.

Significant swings in the dynamics of macroeconomic variables and structural changes in the economy in general bring additional complications to the process of forecasting economic activity. The latter task is of great importance for conducting macroeconomic policy as a whole. With respect to the functions of the central bank, reliable real time assessments and forecasts of future GDP growth, as well as identification of the major forces driving the changes in growth, are essential for conducting monetary policy and analyzing its possible effects on the economy over various horizons.

The problem of nowcasting GDP is mainly due to the fact that actual data on economic growth for the current quarter are usually published by the main national statistical office with a delay of at least 45 calendar days. However, statistical models using more timely data on higher frequency indicators, the dynamics of which can perhaps provide signals as to economic activity in the current quarter, are often now accepted as a common tool for assessing GDP growth in real time. The latter dataset of timely predictors, however, may be characterized by mixed frequencies or may be subject to various publication lags and hence different observation lengths at each point in time (the *ragged end problem*).

This study aims to exploit the dynamic factor model (DFM) framework for the purpose of nowcasting and short-term forecasting of Russian GDP using a large information set of potential predictors and studying its major performance results as compared to other possible specifications. We employ the DFM methodology, advocated by *Doz, Giannone, Reichlin (2011)* and *Giannone, Reichlin, Small (2008)*, in nowcasting and short-term forecasting Russian GDP. The latter approach allows for estimating the DFM in the state space form by using the Kalman filter to cope with unbalanced datasets that are characterized particularly by ragged ends.

The results of our empirical study generally show that a large-scale DFM on the whole performs well in short-term forecasting and nowcasting of Russian GDP, generally outperforming most commonly known benchmark models in terms of predictive accuracy. We also show that new statistical releases of higher frequency explanatory indicators tend to consistently improve the accuracy of model-based nowcasts and backcasts of Russian GDP for the given quarter of interest. The latter conclusion does not, however, strictly hold for the cases of one- and two-quarter ahead forecasts of GDP, which is most likely attributable to the much greater forecasting uncertainty of longer horizons.

Another important finding is that DFM specifications based solely on hard data (which primarily include industrial production, investments, domestic retail trade turnover, foreign trade indicators and unemployment statistics) display similar accuracy of nowcasts of Russian GDP as compared to larger information sets that additionally encompass various survey data, as well as financial and external indicators. Larger datasets, nevertheless, bring a considerable value-added in terms of a more plausible DFM forecast performance over larger horizons of one and two quarters.

As for the explanatory factors for Russia's recent growth dynamics, one of our main conclusions is that leading and coinciding indicators in the form of survey data, hard data, and external and financial statistics were generally in line with each other in explaining the recent slowdown in Russian GDP growth. The results of the latest DFM-based forecasting and nowcasting vintages clearly show, however, that some variable groups pointed at quite different growth perspectives, as survey data and financial indicators have particularly proven to be the most clear indicators of current and future possible sharp slowdowns of the Russian economy.

Our paper is further structured as follows. *Section 2* presents the model setup and statistical data used in our study to perform model-based predictions of Russian GDP. *Section 3* describes our estimation process and analyses the accuracy of DFM's forecasts of Russian GDP over various horizons. *Section 4* is devoted to a brief comparison of DFM's predictive performance with that of alternative benchmark models. *Section 5* introduces some recent empirical implications of using the results of our DFM in explaining the major sources of real time model-based assessments of Russian GDP. The final section concludes.

2 Model setup and data

The main idea behind factor models, which are now receiving substantial attention in the context of econometric forecasting, consists in the fact that the dynamics of a large set of economic indicators are generally driven by a small number of common factors. Moreover, the overall idiosyncratic component in observed indicators seems to diminish with the inclusion of additional predictors in the factor model. The DFM proposed in our study for nowcasting and short-term forecasting of Russian GDP can be given the following state-space representation:

$$X_t = \Lambda F_t + \varepsilon_t \tag{1}$$

$$F_t = \Omega F_{t-1} + \zeta_t \tag{2}$$

$$y_t = Z F_t^Q + \Xi F_{t-1}^Q + \alpha y_{t-1} + \eta_t \tag{3}$$

X_t is the matrix of observed indicators at month t, F_t is the matrix of several identified latent factors (in our further baseline DFM specifications there are three of these), y_t is quarterly seasonally adjusted GDP growth (in constant 2008 prices) officially published by Russia's Federal State Statistics Service (Rosstat), Λ, Ω, Z, Ξ, α are matrices of estimated unknown parameters and $\varepsilon_t, \zeta_t, \eta_t$ are idiosyncratic error terms. Equations *(1)–(3)* are estimated via the quasi maximum likelihood approach which, as shown in *Doz, Giannone, Reichlin (2011),* provides reliable estimates over large datasets and yields robustness to model misspecifications. Further details on the estimation process will be discussed extensively in *Section 3*.

Our dataset includes 116 explanatory variables that are mostly observed on a monthly basis. We include in our model those variables that are reported by Rosstat and Bank of Russia, as well as indicators monitored and disclosed by reputable financial market participants and other institutions. The dataset is further broken down into three major categories (blocks):

Block 1: survey data

(50 variables: includes statistics on leading indicators based on surveys studying producers' sentiments and preconditions for industry growth: primarily, Markit PMI data and diffusion indices published by Russian Economic Barometer for various industries).

Block 2: hard data

(36 variables: industrial production, investments, domestic trade turnover, employment data, trade balance indicators and other relevant variables).

Block 3: external and financial data

(30 variables: indicators of economic growth in major trading partners, commodity prices, real sector and interbank interest rates, money and credit growth, stock market indices, capital flows).

Figure 1 Approximate timing of statistical releases of explanatory variables for Russian GDP included in the DFM

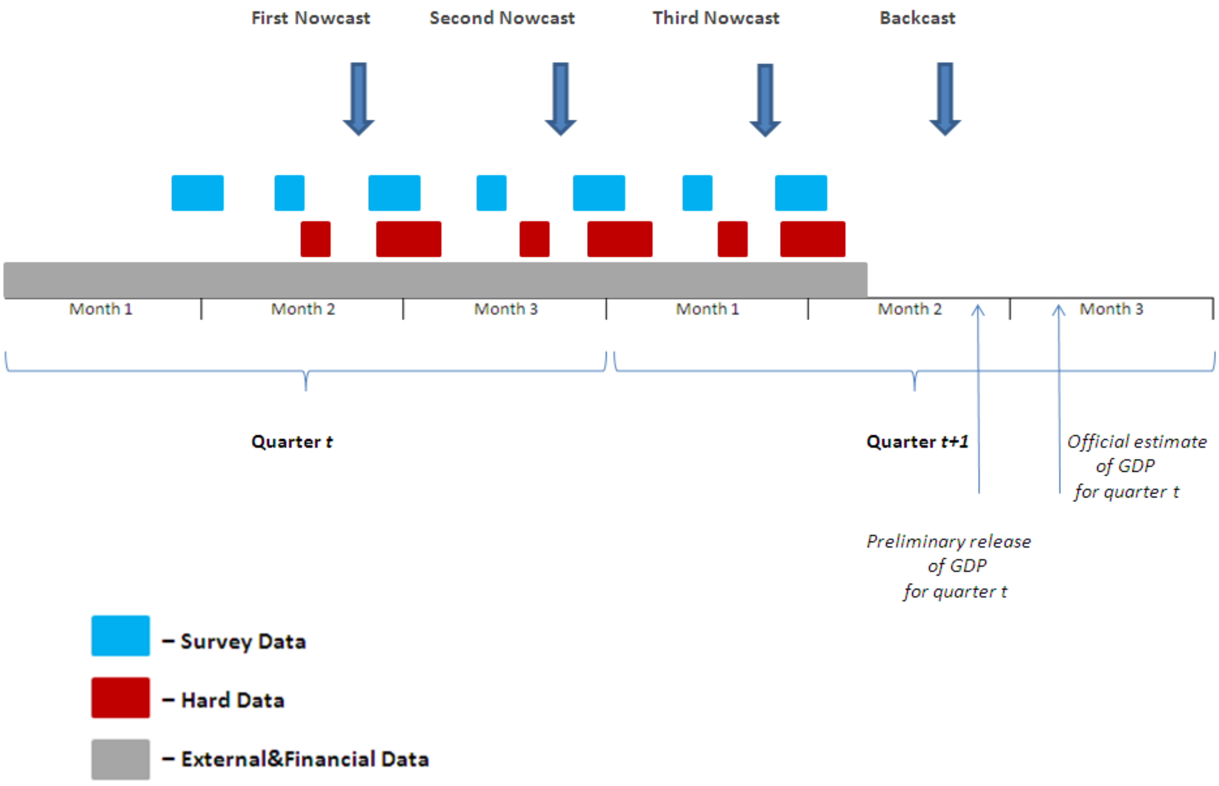


Figure 1 schematically shows the timing of statistical releases of explanatory variables used in our DFM specification. At this stage it is important to note that for some specific calendar months we perform model-based vintages of nowcasts, forecasts and backcasts of Russian GDP close to the 20th day of the next calendar month. For example, if the nowcast vintage for the fourth quarter of the calendar year is performed around November 20th, it employs the most recent data available up to October, which is the first calendar month of the quarter of interest, so the exercise is treated as the first vintage of nowcast for the current quarter, and so on.

We generally explain our choice of the above-mentioned period for performing DFM-based nowcast and forecast vintages for Russian GDP by the fact that in Russia this is the period for some crucial hard data releases for the previous months (primarily, industrial production, investments and retail trade). Our further analysis shows that this subset of statistical data is, in particular, a crucial contributor to the quality of GDP nowcasts for Russia. Consequently, when making projections of Russian GDP growth for the current quarter, it is of great importance to the forecaster that the following data are usually revealed prior to the upcoming vintage. In general, however, nowcast exercises throughout the quarter of interest can obviously be performed more frequently, as the question of optimal nowcast vintage periodicity is explicitly addressed in some recent studies (see, for example, *Bragoli et al. (2014)* for further details).

It is also worth mentioning that one particular property of external&financial variables consists in the fact that some of these are observed on a daily basis (in our particular dataset, these are commodity prices, interbank interest rates, stock market indices, ruble exchange rates). Hence, such information can be used to approximate most of the timely indicators for the current month when the GDP nowcast and forecast exercises are performed. We opt for incorporating into our DFM simulations the data for the previous month in the most recent daily statistics. This is done by converting such data into monthly frequency by taking the average of the respective values observed from the 21st day of the previous month to the 20th day of the current month (instead of just computing the monthly average for the previous calendar month and ignoring the most recent daily data). For the moment, the following procedure did not significantly improve our estimation results as compared to the case where values of the most timely predictors are averaged over the previous calendar month. We, nevertheless, claim that the possibility of performing such a monthly shift with respect to daily predictors of GDP used in the DFM could be essential for periods that include wide fluctuations. The latter phenomena have been recently observed for the Russian economy, given, for instance, the extremely volatile ruble exchange rate dynamics seen generally throughout the second half of 2014.

Prior to the estimation process, all the time series are transformed so as to insure stationarity and to link the partially observed monthly values of predictors that are published in the current quarter with their respective dynamics in the previous quarter. The latter aspect may prove crucial in the process of constructing unobservable common factors on a quarterly basis, which are then used as explanatory variables of quarterly GDP growth. In this respect, we follow mainly *Mariano, Murasawa (2003)* and *Giannone, Reichlin, Small (2008)* and introduce the following three types of transformations into our monthly dataset (X_{it} denotes levels of a given time series):

Three-month differences:

$$x_{it} = X_{it} - X_{it-3} \tag{4}$$

Three-month averages:

$$x_{it} = \frac{1}{3}(X_{it} + X_{it-1} + X_{it-2}) \tag{5}$$

Average “rolling quarter” growth rates:

$$x_{it} = \frac{1}{3}(\ln X_{it} - \ln X_{it-3}) + \frac{1}{3}(\ln X_{it-1} - \ln X_{it-4}) + \frac{1}{3}(\ln X_{it-2} - \ln X_{it-5}) \tag{6}$$

A list of explanatory variables and their transformation types outlined above is provided in *Appendix I*.

3 Estimation process and results of DFM's predictive accuracy

3.1 Baseline methodology

We now proceed with the detailed description of the estimation process of the DFM.

In the *first step*, unknown parameters from equations *(1)–(2)*, and unobserved future values of monthly predictors are estimated iteratively by principal components and a Kalman filter, as suggested in *Giannone, Reichlin, Small (2008)*. We further consider our latest GDP forecast vintage to be that performed in late January 2015, which in our framework corresponds to the third nowcast of 2014Q4 and forecasts up to 2015Q2. The estimation process was performed over the monthly sample *June 2002–December 2014* (*151 observations*). However, monthly and eventually quarterly unobservable factors are also extrapolated for two extra quarters ahead (up to the end of 2015Q2 as of now), since that period is the longest forecast horizon of interest here. We eventually identify three latent factors based on our preliminary tests of DFM’s predictive power as compared to similar specifications with fewer lags.

As our *second step*, the latter estimates are incorporated into equation *(3)* and latent factors are converted into quarterly frequency in order to proceed with standard OLS estimation of the regression of real GDP growth on its lagged values and values of unobserved factors. The sample picked for estimating equation *(3)* on the basis of identified quarterly unobserved components is *2003Q1 – 2014Q3*, which now includes *47* observations. The final specification of equation *(3)* includes real GDP growth in the previous quarter, contemporary values of three identified latent factors, as well as their previous quarter lags, and a constant term. This choice resulted from our prior statistical tests, which included *AIC* and *BIC* as conventional lag length criteria, and analysis of data fit and RMSEs for different specifications; the results are set out in the following sections.

One of the major caveats in the process of estimating equation *(3)* consists in the fact that it uses values of GDP growth for the preceding quarter, the actual data on which are not normally disclosed by Rosstat until late in the second month or early in the third month of current quarter. Moreover, forecasts for the next quarter rely on GDP growth in current quarter, which is also subject to nowcasting itself. Finally, forecasts for quarter *T+2* depend upon DFM-based GDP forecasts for quarter *T+1* as well.

Consequently, we proceed with the estimation as follows. We begin by running equation *(3)* for the first nowcast of the starting quarter 2003Q1 on the basis of the actually known value of GDP growth for the preceding quarter (2002Q4). This allows us to obtain the earliest unknown parameter estimates of the GDP equation and to use them to produce the nowcast for 2003Q1, calculated on the latest high frequency data as of January 2003. The Kalman filter is then used to construct future values of PCA-estimated unobserved latent factors for the maximum of eight months ahead: two more months in the current quarter to be nowcasted plus six months for the forecast of two quarters ahead (up to September 2003). The first nowcast for 2003Q1 produced by the model is simultaneously taken as a lagged value of GDP growth and plugged into equation *(3)* with its current parametrization in order to compute the forecast for 2003Q2. The latter figure could be used to obtain the first DFM forecast for 2003Q3. The following procedure is then performed over the whole sample period.

With respect to the estimation procedure outlined above, a specific approach to the seasonal adjustment of data must also be elaborated. Initially we use the conventional TRAMO-SEATS approach to extract the seasonal component from the dataset of explanatory variables. This approach, however, seems to be worth some further elaboration. In particular, *Orphanides &van Norden (2002)* and *Rusnak (2013)* argue that the use of seasonally adjusted data on the whole sample when parameterizing and evaluating the model's predictive accuracy for previous points in time may unfairly provide the model with valuable information about possible turning points in the dynamics of predictors that was not actually available in those past periods. Against this background, we adopt a fairer approach: sequentially performing a seasonal adjustment each time new information on predictors arrives during the sample period.

The issue of picking a specific training sample for bringing the model to the data and estimating DFM's predictive accuracy in pseudo real time is also worth some prior discussion.

On the one hand, we do not want this sample to be too short since model-based errors would then be subject to a lower level of statistical confidence and greater uncertainty. On the other hand, picking a longer sample for studying DFM's forecast and nowcast precision is subject to caveats related to statistical breaks in the data. Provided that in the process of simulating the model over the training sample period we aim at reestimating the DFM's parameters recursively together with the arrival of new relevant data each month and use the latest parametrization results for producing further nowcasts and backcasts, data for the most recent periods are generally of greater importance. In this respect, our *baseline training sample* runs from 2012Q1 up to 2014Q3 (most recent observation of Russian quarterly GDP as of late January 2015) and includes 11 historical observations. Under *alternative simulations*, we perform pseudo real time vintages of forecasts, nowcasts and backcasts for the subsample 2006Q1–2014Q3[1] (*35 historical observations*).

By using information on the monthly values of predictors within each quarter of the training sample, short-term forecasts, nowcasts and backcasts of real GDP growth for the quarter of interest can be produced for each point in time. We choose the root mean squared error (RMSE) of the forecasts, nowcasts and backcasts of GDP as a common tool for evaluating our DFM's predictive accuracy. RMSEs over each forecast horizon are computed as follows:

$$RMSE = \sqrt{\frac{\sum_{t=1}^{N}(y_t^Q - \hat{y}_t^Q)^2}{n}} \tag{7}$$

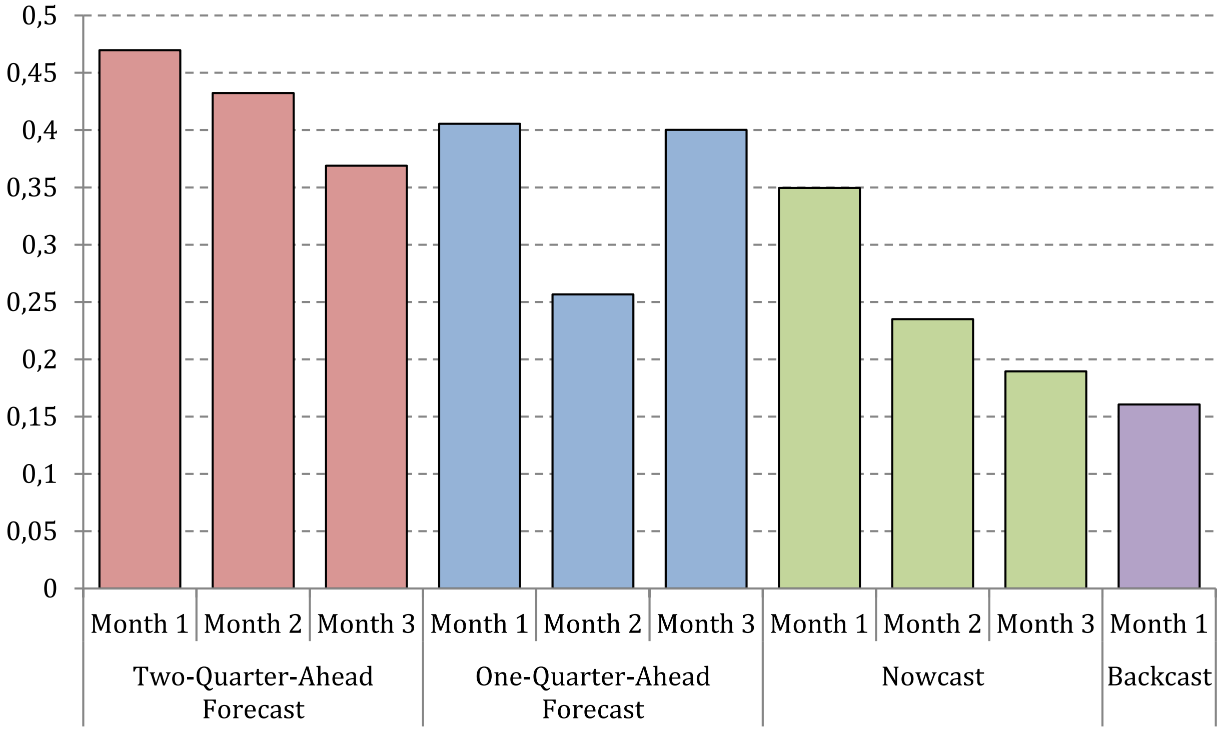
y_t^Q and $\hat{y}_t^Q$ denote actual and predicted values of quarterly real GDP growth for Russia, respectively, n is the number of observations within the training sample, and N is the last observation of the training sample as of now (2014Q3). Figure 2 depicts estimated average RMSEs of forecasts, nowcasts and backcasts over eleven quarters in pseudo real time for full sample estimates derived from baseline simulation.

We perform ten exercises in total: six vintages of one- and two-quarter-ahead forecasts for quarter T (from the first month of quarter T–2 up to the third month of quarter T–1), three vintages of nowcasts for quarter T (consecutively using data for the first, second and third months

[1] This excludes the time period between 2008Q3 and 2009Q2 which was characterized by a sharp and quite unforeseen slump of the Russian economy in the sharpest phase of the world economic and financial crisis.

of the current quarter), and one vintage of backcast in the first month of quarter *T+1* (further backcast vintages are not produced since Rosstat's first assessments of GDP growth for the preceding quarter are already published with about a 45–60 calendar day lag, i.e. at the end of second or at the beginning of third month of quarter *T+1*).

Figure 2 Average RMSEs



Note: The chart depicts average RMSEs of pseudo real time 2-quarter, 1-quarter-ahead forecasts, nowcasts and backcast of Russian GDP growth in 2012Q1–2014Q3 (DFM estimates).

According to DFM estimates within different blocks and block mixes, forecast accuracy generally seems to improve as we approach the period when actual GDP data for the quarter of interest are published. Before actual monthly predictors for the forecasted quarter are observed, these values are by construction extrapolated using the Kalman filter. Uncertainty about these values does not seem to monotonously decrease as we move through quarters *T–2* and *T–1*. For instance, average RMSEs for one- and two-quarter ahead forecasts exceed the respective average RMSEs of the two-quarter-ahead forecast in the third month of quarter *T–2*. However, starting from the second month of quarter *T–1*, average RMSE declines more clearly as new relevant data presumably start to arrive. The highest predictive accuracy eventually comes from the backcast in the first month of quarter *T+1*, which is broadly in line with prior intuition.

3.2 Other DFM specifications

We then proceed by comparing the results of our DFM-based RMSEs computed under baseline simulations (116 explanatory variables, three latent factors, training sample starting at 2012Q1) to the respective predictive accuracy of alternative DFM specifications and training samples. The latter include:

1. DFMs based on individual data blocks and block pairs.
2. DFMs based on fewer latent factors.
3. Restricted information set (reduced consecutively to 90 and 45 variables, as compared to 116 variables in baseline simulations).
4. Alternative pseudo real time running from 2006Q1, as opposed to 2012Q1 in baseline scenario.
5. Benchmark competitor models (introduced explicitly in Section 4).

3.2.1 Individual data blocks and block pairs

First we turn to a comparison of point estimates of our DFM-based RMSEs with respective simulations across particular data blocks and block pairs. Figures 3a and 3b display average RMSEs for baseline pseudo real time DFM simulations across specific data blocks, as well as across different pairs of data blocks. Detailed statistics for RMSE point estimates across different data subsamples and forecast horizons for baseline DFM simulations are presented in Table II.1 in *Appendix II*.

Figure 3a Average RMSEs: Individual Groups

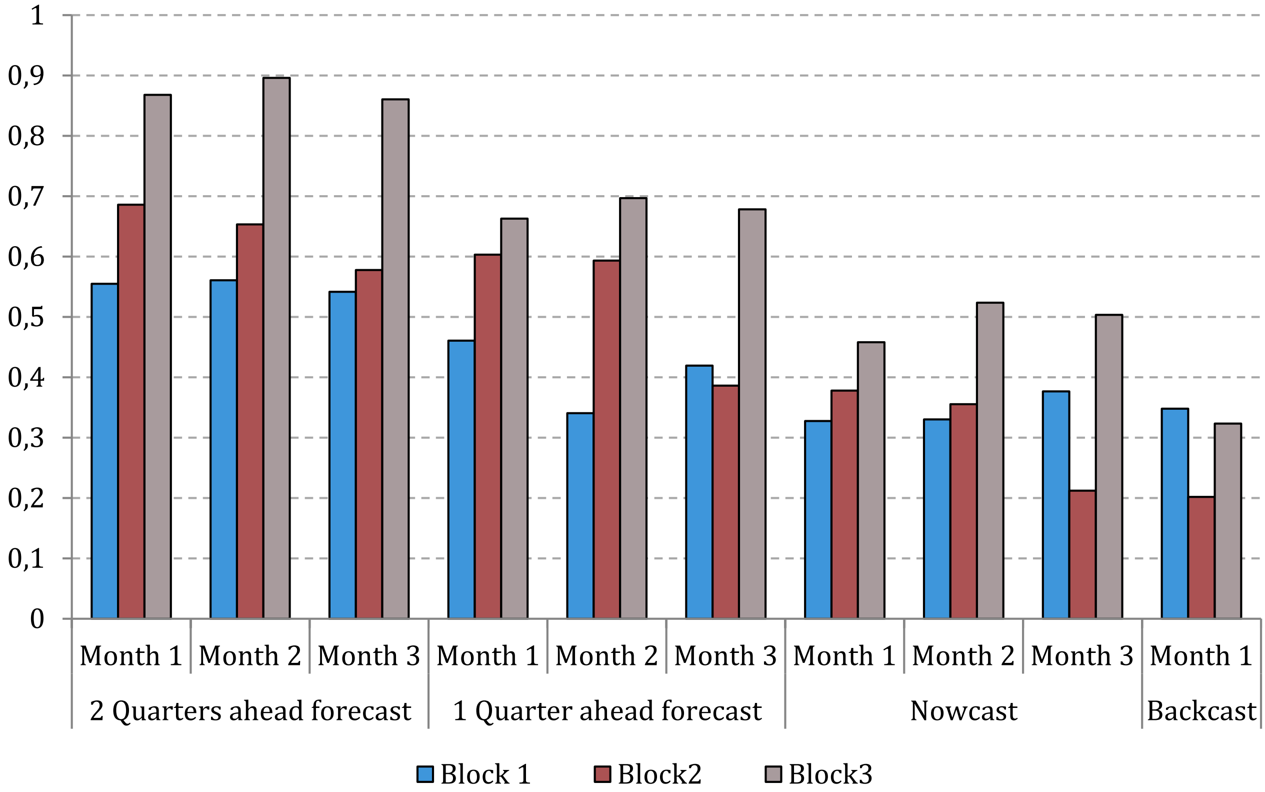
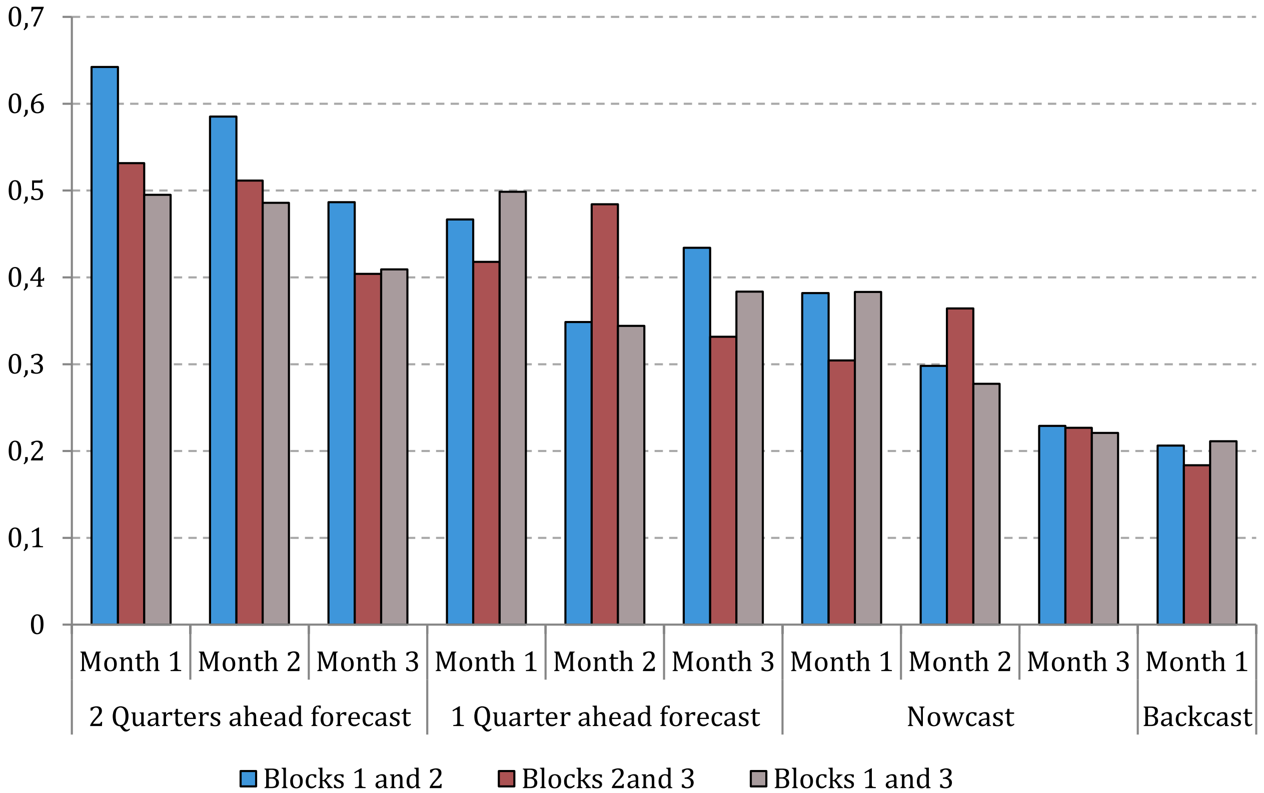


Figure 3b Average RMSEs: Group Pairs



A comparison of forecast performance on stand-alone blocks under baseline simulations suggests that the *survey data* block within our DFM framework outperforms the *hard data* and *external&financial* blocks in forecasting Russian GDP. One possible explanation for this is that leading indicators should by definition be more successful in forecasting future GDP, whereas hard data movements reflect the most current economic activity and are presumably more important for nowcasting and backcasting of GDP. Thus, RMSEs of late forecasts and nowcasts obtained over the hard data block start to fall below the respective RMSEs of the survey block.

External&financial block is apparently dominated by the *survey data* and *hard data* blocks. Our additional tests suggest that in many cases the former does not provide a statistically significant improvement in forecasting or nowcasting performance, although forecasting quality obviously does not deteriorate with the inclusion of the respective variables in the DFM. The latter result is generally in line with some other recent studies (see e.g. *Banbura et al. (2012)*). Nevertheless, as has been shown above, a combination of the three blocks improves point estimates of RMSEs over forecast horizons considered[2].

Our baseline results generally show that the RMSE is lower for full sample simulations as compared to the same exercise with only partial block inclusion. This is generally the case for one-quarter- and two-quarter-ahead forecast vintages. However, the nowcast and backcast accuracy of specifications that involve 36 identified hard data variables is quite close to the goodness of fit yielded by full sample models, regardless of the number of latent factors identified in the DFM (see Table II.1 in *Appendix II*).

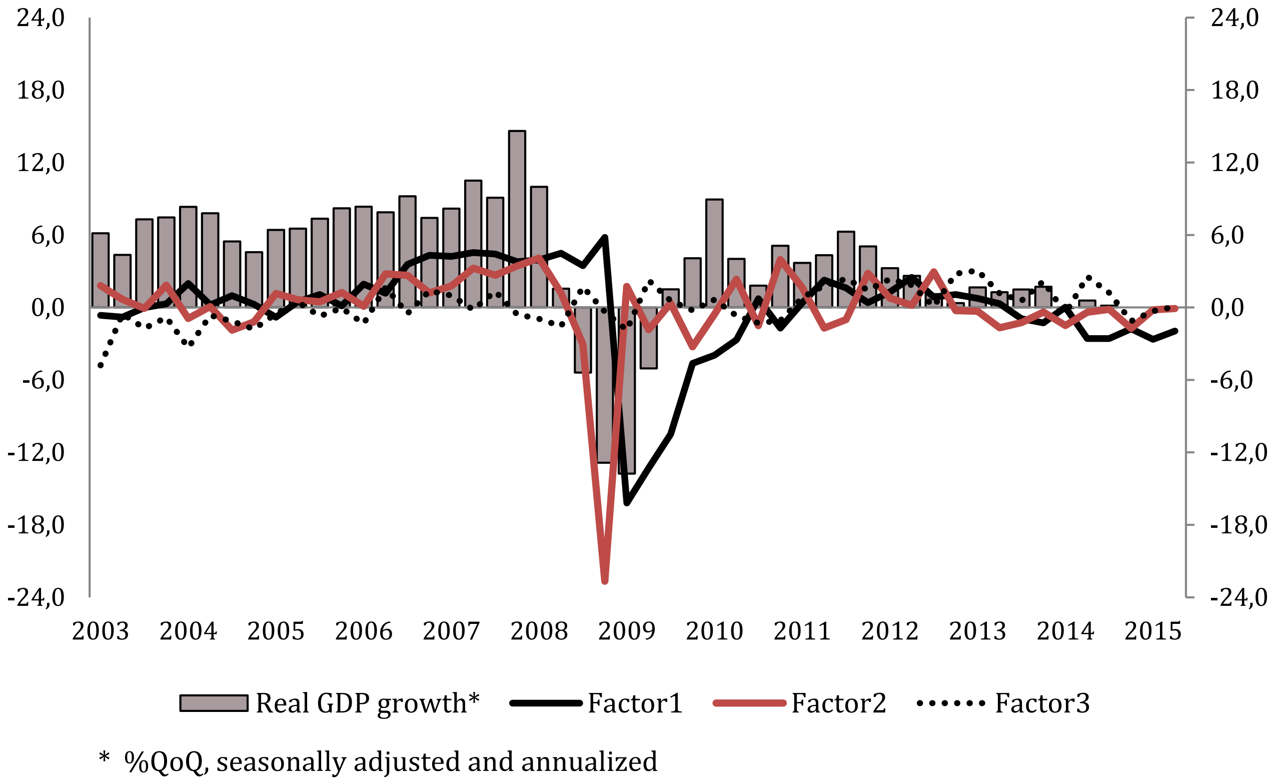
3.2.2 Fewer unobservable factors

DFM's forecast accuracy resulting from baseline pseudo real time simulations over two unobservable factors appears to be on average worse than that over three latent factors. The latter effect is expectedly tracked down in DFM simulations with larger portions of explanatory variables of different kinds, i.e. over the full dataset and block pairs rather than individual blocks (see Table II.2 in *Appendix II* for further details).

[2] The results provided above, however, are subject to further statistical tests. In order to check the statistical significance of the difference in forecasts between blocks we, as a rule, also employed the conventional *Diebold-Mariano test* of equal predictive accuracy. Its results clearly indicated a better performance with full sample and survey data specifications as compared to other possible block mixes.

Somewhat surprisingly, our results show that, whereas under three-factor framework full sample specifications outperform truncated ones (that is, separate blocks or combinations of different block pairs) at almost all forecast horizons, in models with two unobservable factors survey data seem to dominate all alternative block mixes (including full sample specification), especially for one- and two-quarter-ahead forecasts.

Figure 4 Unobserved common factors of real GDP growth identified by principal components and their two-quarter-ahead forecasts by Kalman filter (as of January 2015)



Sources: Rosstat, authors’ calculations.

On the one hand, the result outlined above could perhaps be explained by the fact that the survey data consist mainly of leading indicators that appear to be more relevant for predicting future movements in GDP as opposed to its estimates in real time, i.e. nowcasts. This is also true for some of the financial variables (mainly interest rates, money supply and credit developments) that have more pronounced lagged effects on GDP growth in contrast e.g. to hard data variables. On the other hand, inclusion of an extra latent factor in the DFM improves the relative quality of full sample forecasts (along with some other crucial statistical properties). The latter factor may lead to an important result that the third latent factor under the full sample framework captures additional valuable information on survey indicators, as the first two unobservable components are mainly dominated by other data blocks, primarily hard data. This is clearly shown in Figure 4 which depicts three quarterly latent factors obtained in full sample simulations and estimated by principal components.

The dynamics of the first unobserved factor somewhat resembles quarterly change in Russian economic growth and is highly correlated with hard data indicators that largely encompass industrial production, retail trade, investments and other relevant indicators. The dynamics of the remaining two latent factors appear to be more mixed, and relatively larger weights in these cases are assigned to survey indicators, as well as *external&financial data*, which seem to contribute to improvements in the forecasts and nowcasts of GDP.

3.2.3 Restricted information sets of 90 and 45 variables

Another important issue with respect to the choice of particular observable variables for forecasting with large factor models consists in choosing the appropriate dimension of the information set. To check for parsimony, we reduced our sample size from 116 explanatory monthly variables to 90 and 45 respectively, leaving equal numbers of variables within each block, so that neither type of data dominates (that is, 30 and 15 variables from each block respectively).

RMSEs of the latter simulations are also provided in Tables II.3a and II.3b in *Appendix II*. Restricted subsamples on the whole worsen the DFM's predictive accuracy at one- and two-quarter forecast horizons. However, truncated models yield clearly lower RMSEs for nowcasting and backcasting vintages. The DM test rejected the null hypothesis of equal predictive accuracy for most of the truncated specifications against models with the full data set, and rejected the null of equal predictive accuracy with full sample baseline specifications (116 variables) for nowcasts and backcasts.

Taken together with the fact that different data blocks seem to valuably contribute to DFM's forecasting quality and that full sample specifications exhibit lower RMSEs on average, the results stated above generally indicate that the initially chosen dataset of 116 explanatory variables is quite informative and that presumably there are no any specific groups of variables that systematically provide misleading noise with respect to the model's forecasts and nowcasts. The use of this large information set is, however, justified mainly for forecasts and perhaps for early nowcasts, as models with fewer but most important variables (constructed on some mixed blocks involving hard data block or hard data block only) produce similar prediction errors.

3.2.4 Alternative pseudo real time simulations

Despite the fact that estimation of DFM parameters was carried out over a rather short data sample, to allow for a somewhat more reliable testing of the model's predictive accuracy, we find the results outlined in the previous sections to be generally robust to particular specifications of the pseudo real time training sample. In particular, results of RMSE calculations in alternative pseudo real time given by the period 2006Q1–2014Q3 generally correspond to our baseline conclusion on the relative predictive accuracy of DFMs constructed over the whole information set, on the one hand, and individual blocks and group pairs, on the other hand (for further details see Table II.4 in *Appendix II*).

4 Comparison of DMS's predictive accuracy against benchmark models

In our study we eventually chose three alternative benchmark specifications for comparing forecast performance of DFM with benchmarks: naïve random walk (*RW*), bridge equations (*BRIDGE*) and dynamic factor model of RenCap–NES (*RenCap-NES*).

Random walk

First is the conventional naïve random walk which, however, is usually associated with a relatively poor forecasting performance in the case of developing economies, whereas a more substantial pattern in GDP dynamics is exhibited as compared to developed countries. However, in periods of less volatility in GDP dynamics, random walk forecasts still prove to be relatively plausible. RW forecasts are produced from a simple equation of the form

$$y_t = y_{t-k} + \varepsilon_t, \varepsilon_t \sim N(0, \sigma^2) \tag{8}$$

Bridge equations

We also estimate conventional bridge equations (see e.g. *Baffigi et al. (2004)*) as one of the benchmark competitor models. Forecasting with bridge equations is performed in two steps. First, we forecast monthly indicators to deal with ragged ends using an ARMA(2,2) model. Monthly predictors are then averaged to quarterly frequency and used to forecast GDP or its components via simple bivariate regressions of the following form:

$$y_t = \alpha + \sum_{i=1}^{T} \beta_i^k (L) x_{it}^k + \xi_t, \xi_t \sim N(0, \sigma^2) \quad (9)$$

The appropriate lag length is chosen by the standard Akaike, Schwartz and/or Hannan-Quinn criteria.

We estimate a single bridge equation for GDP (supply-side model), and bridge equations for each GDP component (demand-side model). Industrial production in core industries is used as a monthly indicator for the supply-side model. In the demand-side model, we use turnover of retail trade and services to forecast households' consumption, and monthly indicators of fixed capital investment, exports and imports to forecast the corresponding quarterly national accounts indicator.

Rencap–NES leading GDP indicator model

The RenCap-NES Leading GDP Indicator is a joint project of Renaissance Capital and the New Economics School in Moscow, aimed at producing forecasts and nowcasts of Russian GDP on the basis of a large dataset of explanatory variables. The econometric approach of RenCap-NES Leading GDP Indicator is also based on factor modeling[3].

Our results of forecasting comparison with benchmark models are presented in Table 1.

Table 1 Average RMSEs of DFM (baseline pseudo real time simulations): Comparison with benchmark specifications

Model and forecast horizon	Forecast quarter *T+2*			Forecast quarter *T+1*			Nowcast quarter *T*			Backcast
	Month 1	Month 2	Month 3	Month 1	Month 2	Month 3	Month 1	Month 2	Month 3	Month 1
DFM	**0.47**	**0.43**	**0.37**	**0.41**	**0.26**	**0.33**	**0.30**	**0.24**	**0.19**	**0.16**
RW[4]	0.58	0.47	0.47	0.47	0.39	0.39	0.39	0.30	0.30	0.30
BRIDGE	–	–	–	0.59	0.42	0.54	0.54	0.55	0.59	0.50
RenCap–NES	–	–	1.12	0.79	0.68	0.69	0.68	–	–	–

Sources: RenCap – NES, authors' calculations

[3] More information on the RenCap-NES Leading GDP Indicator for Russia can be obtained at https://research.rencap.com/eng/RenCap-NES_Leading_GDP_Indicator.asp

[4] The RMSEs of random walk are provided for the second and third month of the current quarter when at least preliminary releases on previous quarter's GDP become disclosed. For the first months, we use the two-quarter lag to predict GDP growth assuming that at that time the data for the previous quarter are then known.

Our above-reported estimates generally point at better performance in terms of accuracy of the DFM in comparison with the random walk, bridge equations and RenCap–NES models. Moreover, point estimates for RMSEs of almost all block combinations over both baseline and alternative training samples are lower than those yielded by bridge equations and the RenCap–NES factor model approach (see also *Appendix II* for more details).

Bridge equations seem to be outperformed not just by the DFM estimated in our paper, but by random walk forecasts of Russian GDP as well. This favors the use of a much larger information set for improving GDP's forecasting accuracy, which is precisely what is done in our study.

Surprisingly, RenCap–NES forecasts and early nowcast do not yield higher predictive accuracy in comparison with less sophisticated benchmarks, although the methodology used in this study is also associated with factor modeling. As far as the description of the methodology available on the RenCap-NES website is available, a possible explanation for such a result may be connected with the fact that this alternative approach does not strictly employ the preliminary transformations of variables suggested by equations (4)–(6), which turns out to be crucial in depicting quarterly changes in explanatory variables and consistency of their representation in GDP dynamics. We leave the latter issue for future research.

5 Analytical implications of DFM's results for studying recent GDP developments in Russia

5.1 Nowcast evolution exercise

In order to study the decomposition of the current nowcast's value into impacts of different variables, we use the DFM's parametrization at each point in time to perform the "nowcast evolution" exercise. Under the "nowcast evolution" exercise observable variables are incorporated into the model step-by-step in an arbitrary order. By convention, the first to be included are indicators that are observed most recently, i.e. for month *t–1* if the nowcast exercise is being performed at month *t* (December 2014 and January 2015 respectively in the most recent vintage presented in this paper). These are consecutively followed by data observed up to *t–2* and *t–3* (that is, respectively, November 2014 and October 2014 in the most recent vintage). Within each of these periods of latest data availability, the ordering is similar: *survey data*, *hard* *data*, *external&financial data*. Ordering of variables within each group is done randomly and corresponds to the sequence, in which variables in *Appendix I* are listed.

Figure 5 Evolution of DFM-based GDP nowcast for 2014Q4 (performed in January 2015) and comparison with results of previous nowcast vintages, % over previous quarter (annualized)

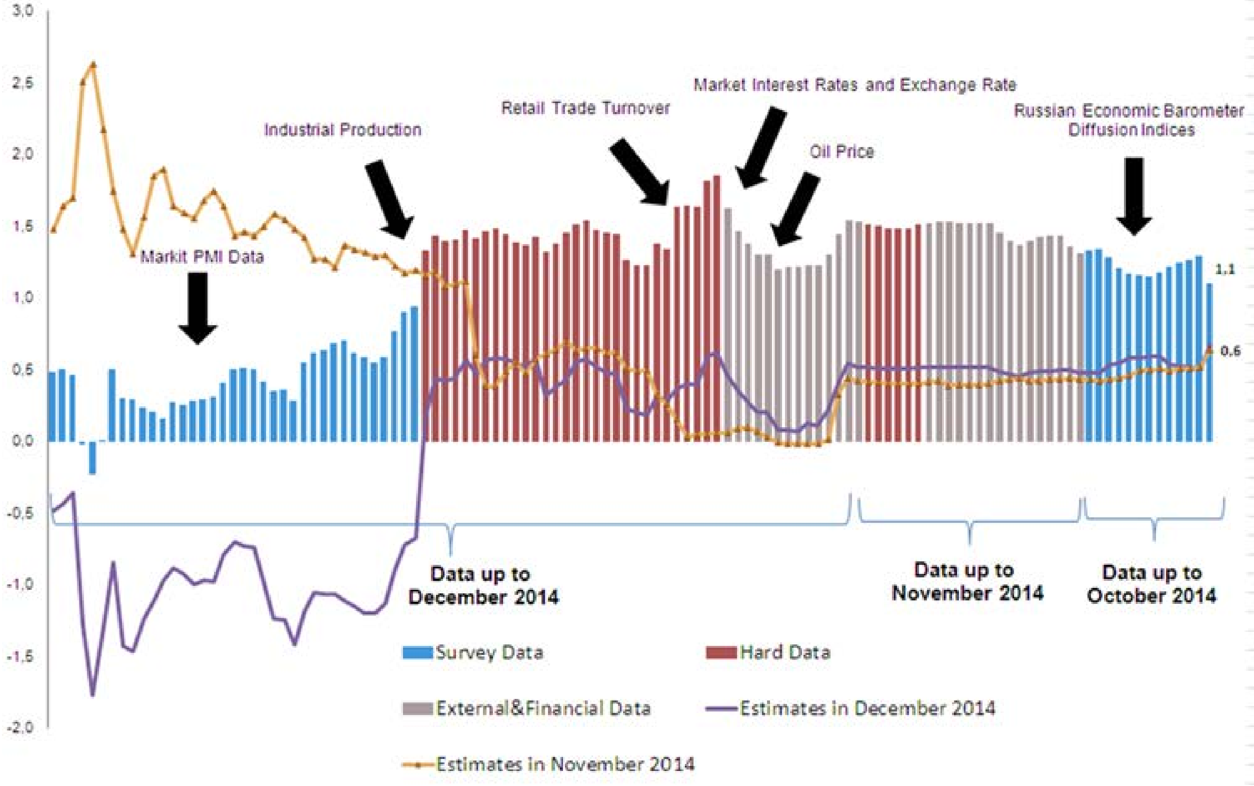


Figure 5 depicts the model-based evolution of the nowcast for 2014Q4, performed in late January 2015 using data on observable predictors for previous months. The latest survey data contain relatively modest signs of economic growth in 2014Q4 as compared to most of the other indicators used in our DFM. Among the major negative contributors are several Market PMI indices, although this result may be somewhat misleading given that at that stage too few variables had been introduced into the DFM. The latest release on Russian industrial production growth for December 2014, however, was generally quite positive and better than many economists' prior expectations; and it led to an upward-revised nowcast estimate based on recent survey data. This was followed by industrial production across different sectors, recent data on which either raises the GDP nowcast or is somewhat in line with the nowcast of GDP yielded by previous variables. The retail trade turnover variable, which comes closer to the middle of our sequence of variables used in the nowcast evolution exercise, seems to introduce a sizeable change into the nowcast provided by the DFM constructed on almost 60 survey and hard data variables which were added to the model prior to that. However, the nowcast based on the most recent survey and hard data was later substantially revised downwards on the basis of financial statistics, which were to a large extent reflected in increasing interest rates resulting from growing uncertainty and the Bank of Russia's highly hawkish policy towards the end of 2014, as well as by some external indicators, albeit the continuation of the oil price slump in December also played a crucial role.

It is also important to note that data which were released with longer delays did not seem to be highly significant for the change in the nowcast of Russian GDP for 2014Q4, after the most recent statistics had already been introduced into the DFM. This is not the usual case, however, when we look at the corresponding evolutions of nowcasts in some other periods.

In general, however, the results of the three nowcast vintages for 2014Q4 clearly demonstrate that most of the macroeconomic data for December 2014 appeared to be much more favorable in terms of signalling economic growth as compared to the earlier data, which were used in the two previous vintages conducted in December 2014 and November 2014 respectively. As a result, our final nowcast of quarterly annualized real GDP growth in Russia for 2014Q4 has reached the level of 1.1%, clearly above the estimate of 0.6% obtained one month prior.

5.2 Contributions of data blocks

Another crucial aspect of nowcasting models that use large datasets of explanatory variables consists in calculating the contributions of different series or groups of data to the nowcast.

In the previously described nowcast evolutions exercise we began by introducing variables into the estimation process one by one and reestimate the nowcast after each addition of a variable. In this way, we could observe how some particular changes in values of variables or variable groups affect our GDP nowcast as compared to the estimate produced by the preceding variables. However, we could not simply estimate the contributions of each variable to the nowcast, because the three blocks go in a specific order. Nowcast evolution as a result of adding to the estimation process all variables from hard data block does not reveal precisely the contribution of the hard data block to the nowcast, as it is merely a contribution to the nowcast conditional on previously included survey data. Thus, if a hard data block (with respect to our deliberate preferences) had come first, its evolution would probably have been different from the estimated evolution if it were included after survey and/or external&financial data. In a bid to overcome this issue, we perform the following simple procedure:

Step 1 At the initial time period the nowcast is run six times by mixing the three blocks in all possible ways (block 1, block 2, block 3; block 3, block 1, block 2, and so on…) Obviously, each time our model nowcast would be the same. But in that case each of the three blocks would stand in first, second and third place exactly two times.

Step 2 Calculate the sum of each block's evolution along all six simulated nowcasts. Clearly, the sum over six nowcasts along all three blocks will be equal to 6 times the value of nowcast.

Step 3 Divide the sum for each block by 6 times the value of nowcast to obtain the relative and absolute contributions of each block.

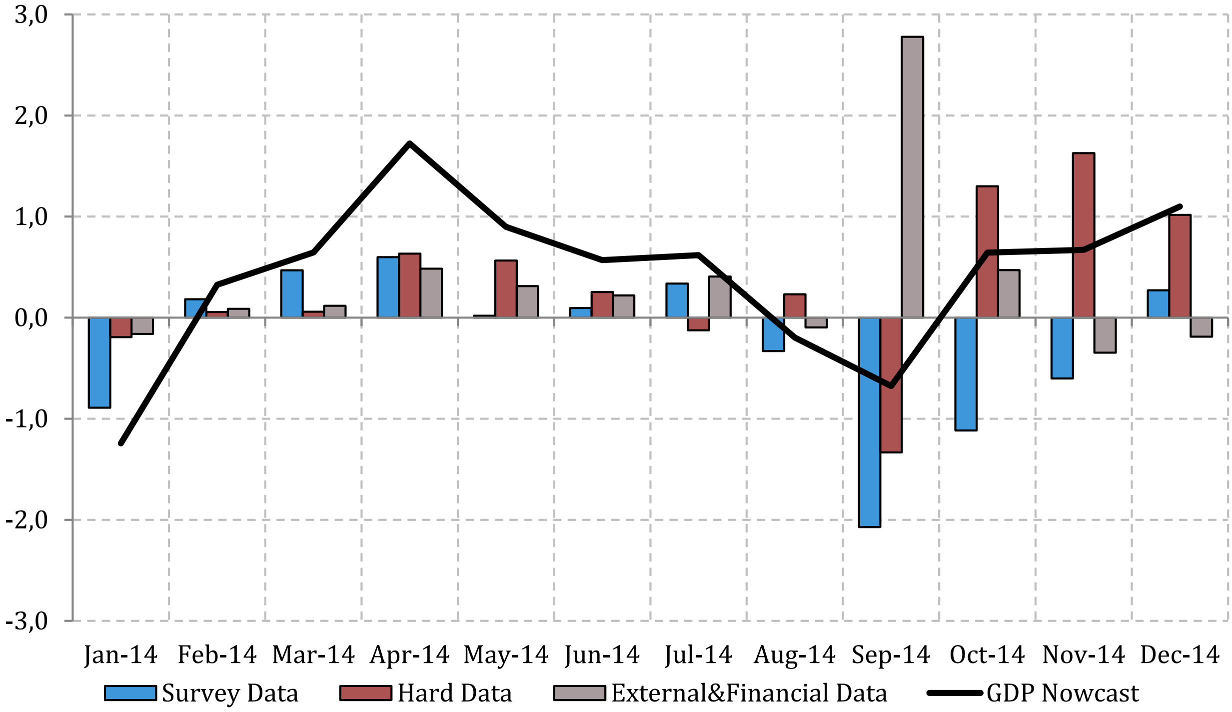
Step 4 Replicate this procedure for all nowcast iterations and/or quarters of interest.

Figure 6 shows the results of twelve monthly vintages of nowcasts performed for each of the quarters of 2014, as well as the estimated block contributions. Our estimates clearly show that the three identified blocks have recently been contributing to DFM's nowcasts both in similar and opposite directions. For instance, in the first half of 2014 all three blocks of indicators contributed to GDP nowcasts in line with each other. The explanation for the slowdown in the second half of the year is somewhat less unambiguous from the point of view of indicators which we use to capture GDP dynamics. That is, relatively unfavourable releases of hard data in July and September were followed by a sizeable rebound of this data block throughout 2014Q4.

Survey indicators, however, contributed positively to quarterly GDP growth estimates up to July 2014 but for the four following months have been producing progressively larger negative effects on model-based GDP nowcasts. This coincided with the period of rising economic uncertainty in Russia, which resulted mainly from recent geopolitical tensions and sanctions imposed on Russia by a group of countries. Nevertheless, as could be observed from the most recent model estimates over the latest data on explanatory variables, available up to December 2014, survey data releases for the respective months appeared to have become more promising in terms of current growth and do not yet point to the sharp slowdown in the Russian economy expected by most analysts.

External and financial indicators in turn have apparently contributed positively to GDP nowcasts throughout most of 2014. However, tighter lending conditions combined with growing financial uncertainty in the last several months of the year yielded a negative estimated contribution of this data block in the second and third monthly nowcast vintages for 2014Q4. A positive spike in the block's impact on the final nowcast for 2014Q3 (conducted in October 2014 on the latest monthly data available up to September 2014) could be perhaps attributed to some favourable growth statistics from the U.S. and to the fact that data within this block technically did not signal such a high probability for a quarterly slowdown in Russian economic growth as did other indicators.

Figure 6 Contributions of different blocks of data into nowcasts of Russian quarterly GDP growth in 2014, % over previous quarter (annualized)



Our analysis of this block's nowcasting and forecasting performance throughout the training sample generally suggests its relevance among other indicators and, as opposed to suggestions in some other recent publications, we still opt for keeping it in the model. However, in some particular periods the necessity of this block's inclusion in the model should perhaps be subject to further study, especially given that Russian economy's expected slump was largely driven by the effects of imposed sanctions.

5.3 Changes in model uncertainty of forecasts and nowcasts over time

We also use the actual RMSEs for each of the three vintages of one- and two-quarter-ahead forecasts, plus three vintages of nowcasts and one backcast vintage for Russian GDP obtained under pseudo real time simulations to bootstrap confidence intervals for the resulting DFM predictions.

Figure 7 Forecasts and nowcast of annualized quarterly real GDP growth rate for Russia in 2014Q4 and bootstrapped 70% confidence intervals

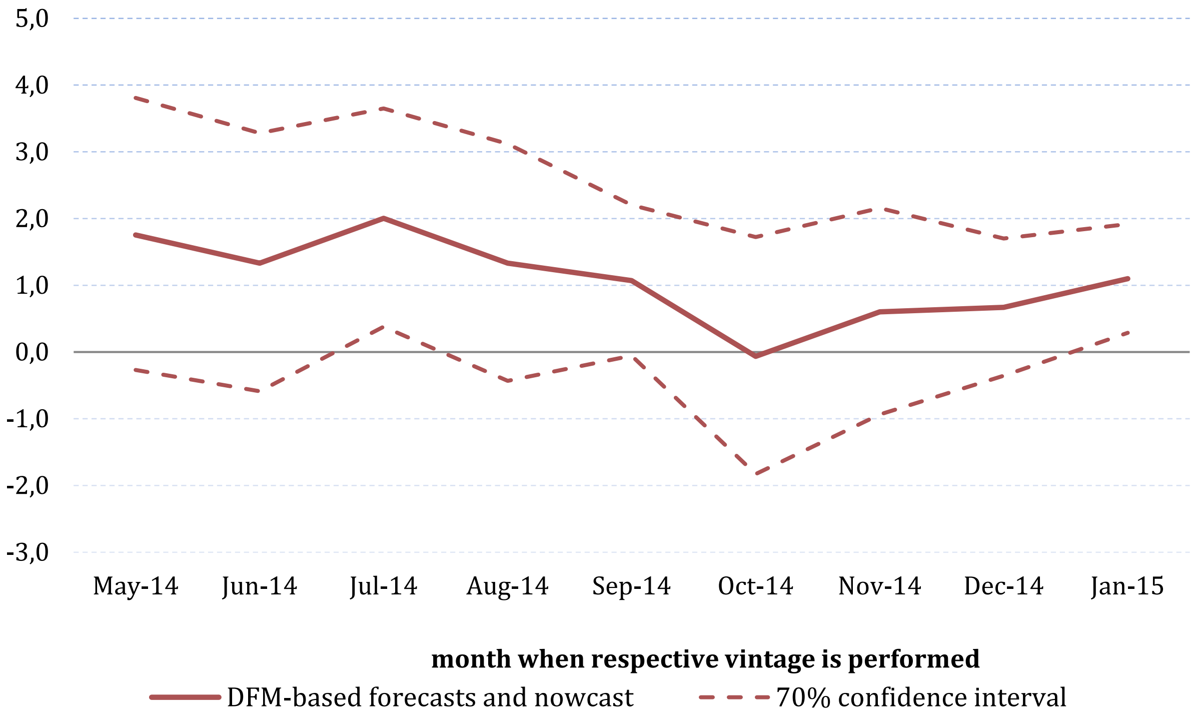


Figure 7 gives an illustrative example of the changes in the DFM-based prediction of annualized growth rate of real GDP for 2014Q4, as this quarter is approached. As of now, the chart depicts the results of nine out of ten DFM vintages: three two-quarter-ahead forecasts (the first one being produced in May 2014 on the latest monthly data available up to April 2014), three one-quarter-ahead forecasts and three nowcasts (the last one performed in January 2015 on the latest monthly data available up to December 2014). The backcast for 2014Q4 was also expected to be produced in late February 2015, along with the expected release of respective preliminary estimates by Rosstat (results are not included in this paper).

Relatively unfavorable data began to gradually reduce the value of the forecast starting from data as of August 2014 (that is, latest vintage of one-quarter-ahead forecast) and onwards. This is fairly close to the horizon over which we particularly observe the reduction in point estimates of RMSEs under our baseline simulations in pseudo real time (see also Figure 2). As for the uncertainty issue, one can clearly see that the width of confidence bands, which were bootstrapped on the basis of actually calculated values of RMSEs, decreases along with the shrinking of the forecast horizon. Eventually, most certainty is assigned to the final nowcast vintage for 2014Q4, performed in January 2015 on the latest monthly data as of December 2014.

5.4 GDP forecasts for the "Rolling year"

One further practical addition to our results for the GDP nowcast would be to analyze the combined performance of DFM's forecasts and nowcasts by comparing model-based figures for annual real GDP growth in Russia against actual data arriving later. For this purpose we bring our DFM-based forecasts not only to official quarterly seasonally adjusted GDP growth rates, but also to yearly growth rates (that is, the sum of non-seasonally adjusted real GDP figures for the four quarters of interest divided by the corresponding sum for the same four quarters of the previous year).

At each calendar month of the baseline training sample we calculate two DFM-based forecasts of the levels of real seasonally adjusted GDP for one and two quarters ahead respectively, as well as one latest nowcast in the current quarter. These three figures are later converted to non-seasonally adjusted GDP using ARIMA forecasts of Russian GDP's seasonal component from the TRAMO-SEATS. The resulting three figures are then added to the actual GDP for the previous quarter[5] to obtain the overall level of GDP for the current four quarters, which is eventually compared to the similar sum for the previous "rolling year". Our results are shown in reestimatde.

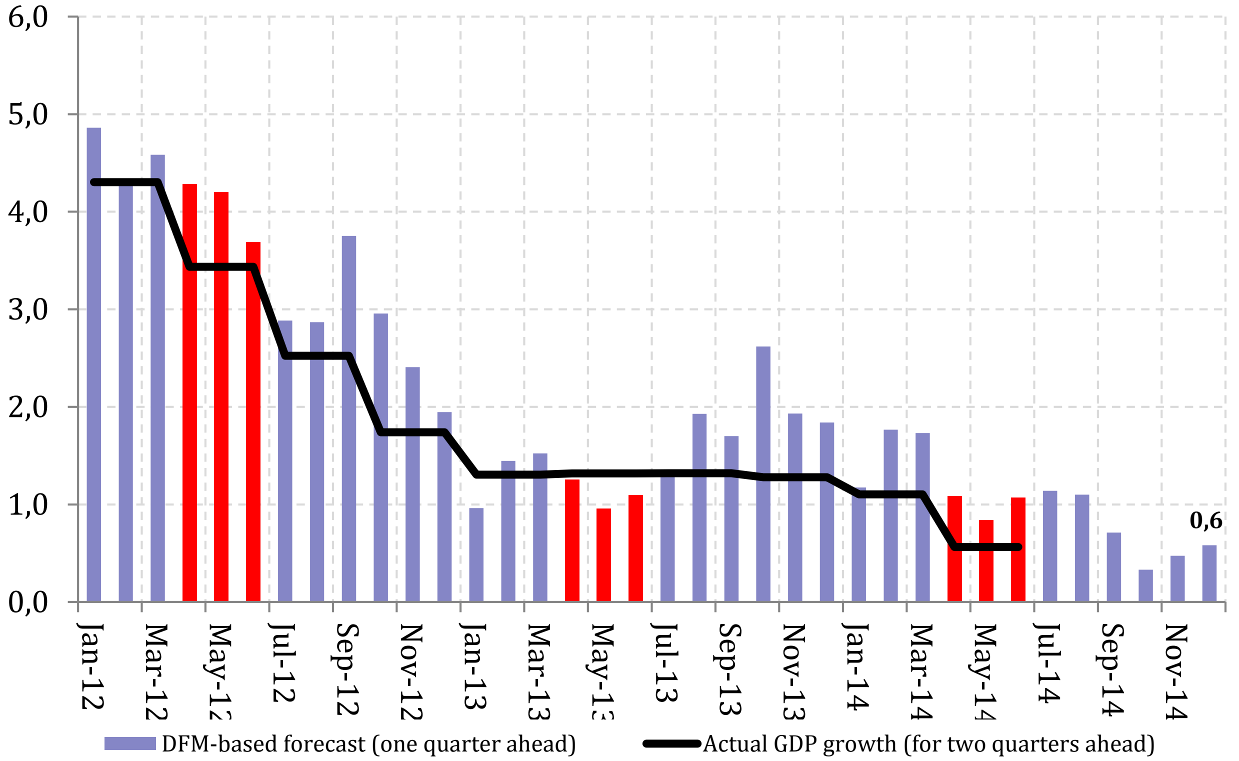
Actual data on real quarterly GDP growth are available at most for 2014Q3 as of the period for which our last exercise, prior to the publication of this paper, was conducted. However, given the fact that Rosstat published its first estimate of GDP in 2014 without a quarterly breakdown at the very start of February (annual growth of real GDP 0.6% as compared to 2013), the respective figure is treated as actual data on GDP growth as well[6]. Hence, the chart depicts the true one- and two-quarter-ahead forecasts of GDP growth for the "rolling year" up to the end

[5] Ideally, when such an exercise is performed on the latest statistical data available, at most on first months of each quarter, model-estimated backcasts of GDP instead of actually published data have to be introduced into the calculation. This is explained by the fact that when first vintages of nowcasts are made, data on GDP growth for the previous quarter may not yet be published. However, we evade the issue for several reasons. The first reason is that we produce first nowcasts for the current quarter somewhat in the middle of the second month using data for the preceeding month at most. At that point of time a preliminary, but fairly reliable estimate of the GDP growth rate may already be released either by officials from the Ministry of Economy or by Rosstat. The second reason is that even if the latter fact does not hold for some quarters, our model-based GDP backcasts are by far not the main source of our DFM's forecast errors, as our interest mainly focuses on nowcasting and forecasting performance.

[6] The first estimate of Russian GDP growth for 2014Q4 cannot be directly calculated from the published yearly value. Upon this latest statistical release, Rosstat officially claimed that the latter yearly figure is revised and now not fully in line with the previously published quarterly breakdown of Russian GDP (which we currently use in the model). The revised quarterly data is expected to be disclosed later in March 2015. Given that, we provide actual data on Russian "rolling year" GDP growth up to 2014Q4, whereas the pseudo real time of DFM's predictive accuracy runs only up to 2014 Q3.

of 2014Q2, that is, June 2014. At the same time, our current two-quarter ahead forecast for yearly real GDP growth in Russia for 2015Q2 is 0.6%. This figure, as has been also stated above, does not yet reflect economists' recent concerns about a probable serious slump of the Russian economy in 2015 (largely due to the effect of imposed sanctions), as the statistical data observed up to December 2014 do not signal a future deep recession. Nevertheless, given all the uncertainty associated with one- and two-quarter-ahead model forecasts, combined with signs of possible future structural breaks in the path of Russian economic growth, our recent estimate provided above will most likely be subject to further substantial model-based revisions with the arrival of new data in the upcoming quarters.

Figure 8 GDP nowcasts and forecasts for one and two quarters ahead, % over previous "Rolling year"



Sources: Federal State Statistics Service (Rosstat), authors' calculations

Note: DFM-based "rolling year" forecasts are calculated as Actual Data on Previous Quarter + Nowcast of Current Quarter + Forecast for Two Quarters Ahead, expressed as a percentage growth of total real GDP for previous four quarters. Red bars correspond to real GDP growth forecasts for the calendar year.

As for the data-fit issue in general, it should be noted that in several periods within our baseline training sample the "rolling-year" DFM-based forecasts of Russian GDP are relatively close to the *ex post* published data. In some periods obvious deviations of forecast from actual data are also observed. This could be explained, on the one hand, by higher forecast uncertainty of unobserved components and, naturally, GDP at longer horizons. Higher forecast errors for one- and two-quarter-ahead forecasts of Russian GDP (as compared to nowcasts) have been empirically obtained in our study. However, our analysis shows that in some periods individual nowcast errors also contributed substantially. On the other hand, since our forecasting equation for quarterly real GDP includes a one-quarter lag of GDP, nowcast errors are also by construction incorporated into forecasts for the next quarter, which in turn reduces the accuracy of the GDP forecast for two quarters ahead.

6 Conclusions

The focus of our research was on using the dynamic factor model (DFM) approach for nowcasting and forecasting of Russian GDP and elaborating some important practical implications that could be derived on the basis of DFM predictions.

One of our key results suggests that models based on a few latent factors and encompassing large sets of various relevant macroeconomic variables demonstrate quite plausible historical forecast performance for Russian GDP over different short-term horizons, and are generally quite successful in competing with possible alternative specifications (such as random walk forecasts and traditional bridge models). Empirical evidence shows that, along with further releases of new information on high frequency predictor variables, forecast RMSEs continuously decline as we gradually approach the time of official data release for real GDP growth rate in the previous quarter. This decrease can be characterized as being somewhat monotonous starting from latest one-quarter-ahead forecasts and moving towards the quarter of interest, as DFM-based predictions of Russian real GDP become less uncertain.

As for the problem of determining the optimal size of the dataset for dynamic factor models, our paper demonstrates some interesting but still not unambiguous findings. Unlike the results presented in some recent studies, which suggest that one should not include too many predictors in the factor model because of possible irrelevant noise contained in many time series, we find that the DFM specification encompassing over 100 variables contributes slightly to an increase in forecast accuracy, even while the size of the dataset is reduced by as much as two or three times. Although not true in every case, this increase in predictive accuracy with a larger information set is found to be statistically significant. In general, DFMs seem to perform clearly better than simplistic models that are not constructed in a factor framework.

Our analysis of DFM's predictive accuracy shows that models based either on hard data on about 30–40 variables or mixed data blocks of 40–60 variables in total seem to exhibit nowcast and backcast accuracy quite similar to that of models constructed over substantially larger datasets of over 100 variables. However, models with larger datasets, which additionally incorporate survey and financial indicators, bring a clear improvement in forecasting GDP over one- and two-quarter horizons. The latter conclusions argue for considering the possibility of using different blocks or block mixes of identified higher frequency explanatory variables for predicting Russian GDP, depending on the forecast horizons.

Further results of our study relate to the analysis of the contributions of different blocks of data identified above to historical nowcasts, examining nowcast evolution for different quarters of interest along with consecutive inclusion of new potential predictors in the model, identifying major sources of forecast updates and revisions in real time, carrying out the factor model's robustness checks, comparing with alternative widely-used methodologies, and performing some other practical exercises.

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Appendix I List of variables, respective publication lags and transformation types

№	Block	Variable name	Publication lag	Latest monthly observation[7]	Transformation type
1	Block1 (Survey)	Rosstat's Business Confidence Index: Manufacturing Sector	1–2 calendar days	Month *t–1*	3
2	Block1 (Survey)	Rosstat's Business Confidence Index: Extracting Sector	1–2 calendar days	Month *t–1*	3
3	Block1 (Survey)	Rosstat's Business Confidence Index: Utilities Sector	1–2 calendar days	Month *t–1*	3
4	Block1 (Survey)	PMI: COMPOSITE – OUTPUT	5 calendar days	Month *t–1*	1
5	Block1 (Survey)	PMI: COMPOSITE – NEW ORDERS	5 calendar days	Month *t–1*	1
6	Block1 (Survey)	PMI: COMPOSITE – INPUT PRICES	5 calendar days	Month *t–1*	1
7	Block1 (Survey)	PMI: COMPOSITE – OUTPUT PRICES	5 calendar days	Month *t–1*	1
8	Block1 (Survey)	PMI: COMPOSITE –EMPLOYMENT	5 calendar days	Month *t–1*	1
9	Block1 (Survey)	PMI: COMPOSITE – WORK BACKLOG	5 calendar days	Month *t–1*	1
10	Block1 (Survey)	PMI: MANUFACTURING (total)	1–2 calendar days	Month *t–1*	1
11	Block1 (Survey)	PMI: MANUFACTURING – OUTPUT	1–2 calendar days	Month *t–1*	1
12	Block1 (Survey)	PMI: MANUFACTURING – NEW ORDERS	1–2 calendar days	Month *t–1*	1
13	Block1 (Survey)	PMI: MANUFACTURING – NEW EXPORT ORDERS	1–2 calendar days	Month *t–1*	1
14	Block1 (Survey)	PMI: MANUFACTURING – FINISHED GOODS	1–2 calendar days	Month *t–1*	1
15	Block1 (Survey)	PMI: MANUFACTURING – EMPLOYMENT	1–2 calendar days	Month *t–1*	1
16	Block1 (Survey)	PMI: MANUFACTURING – STOCKS OF PURCHASE	1–2 calendar days	Month *t–1*	1
17	Block1 (Survey)	PMI: MANUFACTURING –QUANTITY OF PURCHASE	1–2 calendar days	Month *t–1*	1
18	Block1 (Survey)	PMI: MANUFACTURING – INPUT PRICES	1–2 calendar days	Month *t–1*	1
19	Block1 (Survey)	PMI: MANUFACTURING – OUTPUT PRICES	1–2 calendar days	Month *t–1*	1
20	Block1 (Survey)	PMI: MANUFACTURING – DELIVERY TIMES	1–2 calendar days	Month *t–1*	1
21	Block1 (Survey)	PMI: MANUFACTURING – WORK BACKLOGS	1–2 calendar days	Month *t–1*	1
22	Block1 (Survey)	PMI: SERVICES – BUSINESS ACTIVITY	1–2 calendar days	Month *t–1*	1
23	Block1 (Survey)	PMI: SERVICES – NEW BUSINESS	1–2 calendar days	Month *t–1*	1
24	Block1 (Survey)	PMI: SERVICES – OUTSTANDING BUSINESS	1–2 calendar days	Month *t–1*	1
25	Block1 (Survey)	PMI: SERVICES – EMPLOYMENT	1–2 calendar days	Month *t–1*	1
26	Block1 (Survey)	PMI: SERVICES – PRICES CHARGED	1–2 calendar days	Month *t–1*	1
27	Block1 (Survey)	PMI: SERVICES – INPUT PRICES	1–2 calendar days	Month *t–1*	1

[7] Particular monthly lag of the variable that is eventually used in our DFM is determined upon the availability of data by approximately 20th calendar day of each month.

№	Block	Variable name	Publication lag	Latest monthly observation[7]	Transformation type
28	Block1 (Survey)	PMI: SERVICES – BUSINESS EXPECTATIONS	1–2 calendar days	Month *t–1*	1
29	Block1 (Survey)	*Russian Economic Barometer:* Expectation Diffusion Index: Sales Prices: Enterprises with Rising Indicator Next 3 Months	15 calendar days	Month *t–1*	2
30	Block1 (Survey)	*Russian Economic Barometer:* Expectation Diffusion Index: Purchasing Prices: Enterprises with Rising Indicator Next 3 Months	15 calendar days	Month *t–1*	2
31	Block1 (Survey)	*Russian Economic Barometer:* Expectation Diffusion Index: Wages: Enterprises with Rising Indicator Next 3 Months	15 calendar days	Month *t–1*	2
32	Block1 (Survey)	*Russian Economic Barometer:* Expectation Diffusion Index: Employment: Enterprises with Rising Indicator Next 3 Months	15 calendar days	Month *t–1*	2
33	Block1 (Survey)	*Russian Economic Barometer:* Expectation Diffusion Index: Production: Enterprises with Rising Indicator Next 3 Months	15 calendar days	Month *t–1*	2
34	Block1 (Survey)	*Russian Economic Barometer:* Expectation Diffusion Index: Equipment Purchase: Enterprises with Rising Indicator Next 3 Months	15 calendar days	Month *t–1*	2
35	Block1 (Survey)	*Russian Economic Barometer:* Expectation Diffusion Index: Financial Situation: Enterprises with Improving Situation Next 3 Months	15 calendar days	Month *t–1*	2
36	Block1 (Survey)	Russian Economic Barometer: Expectation Diffusion Index: Orders: Enterprises with Rising Indicator Next 3 Months	15 calendar days	Month *t–1*	2
37	Block1 (Survey)	Russian Economic Barometer: Expectation Diffusion Index: Debt to Banks: Enterprises with Rising Indicator Next 3 Months	15 calendar days	Month *t–1*	2
38	Block2 (Hard)	Russia: Industrial Production, Total (Monthly % Change)	15 calendar days	Month *t–1*	3
39	Block2 (Hard)	Russia: Industrial Production: Mining and Quarrying (Monthly % Change)	20 calendar days	Month *t–1*	3
40	Block2 (Hard)	Russia: Industrial Production: Manufacturing (Monthly % Change)	20 calendar days	Month *t–1*	3
41	Block2 (Hard)	Russia: Industrial Production: Electricity, Gas & Water Supply (Monthly % Change)	20 calendar days	Month *t–1*	3
42	Block2 (Hard)	Russia: IP: Metallurgical Production & Finished Metalware (Monthly % Change)	20 calendar days	Month *t–1*	3
43	Block2 (Hard)	Russia: IP: Pulp, Paper, Publishing & Printing (Monthly % Change)	20 calendar days	Month *t–1*	3
44	Block2 (Hard)	Russia: IP: Chemicals (Monthly % Change)	20 calendar days	Month *t–1*	3
45	Block2 (Hard)	Russia: IP: Coke and Petroleum Products (Monthly % Change)	20 calendar days	Month *t–1*	3
46	Block2 (Hard)	Russia: IP: Electrical and Optical Equipment (Monthly % Change)	20 calendar days	Month *t–1*	3
47	Block2 (Hard)	Russia: IP: Food, Beverages, and Tobacco (Monthly % Change)	20 calendar days	Month *t–1*	3
48	Block2 (Hard)	Russia: IP: Leather and Leather Products (Monthly % Change)	20 calendar days	Month *t–1*	3
49	Block2 (Hard)	Russia: IP: Other Nonmetallic Mineral Products (Monthly % Change)	20 calendar days	Month *t–1*	3
50	Block2 (Hard)	Russia: IP: Manufacture of Textiles (Monthly % Change)	20 calendar days	Month *t–1*	3
51	Block2 (Hard)	Russia: IP: Rubber and Plastic Products (Monthly % Change)	20 calendar days	Month *t–1*	3
52	Block2 (Hard)	Russia: IP: Transport Equipment (Monthly % Change)	20 calendar days	Month *t–1*	3
53	Block2 (Hard)	Russia: IP: Wood and Wood Products (Monthly % Change)	20 calendar days	Month *t–1*	3

№	Block	Variable name	Publication lag	Latest monthly observation[7]	Transformation type
54	Block2 (Hard)	Russia: IP: Machinery and Equipment (Monthly % Change)	20 calendar days	Month *t–1*	3
55	Block2 (Hard)	Russia: Output: Agriculture (Monthly % Change)	20 calendar days	Month *t–1*	3
56	Block2 (Hard)	Volume of Orders in Construction (Monthly % Change)	20 calendar days	Month *t–1*	3
57	Block2 (Hard)	Housing Developments (Monthly % Change)	20 calendar days	Month *t–1*	3
58	Block2 (Hard)	Russia: Investment in Fixed Capital (Monthly % Change)	20 calendar days	Month *t–1*	3
59	Block2 (Hard)	Retail sales turnover (Monthly % Change)	20 calendar days	Month *t–1*	3
60	Block2 (Hard)	Retail sales turnover: food, beverages and tobacco (Monthly % Change)	20 calendar days	Month *t–1*	3
61	Block2 (Hard)	Retail sales turnover: non–food items (Monthly % Change)	20 calendar days	Month *t–1*	3
62	Block3 (External&Financial)	Moscow interbank overnight effective rate (MIACR)	No lag	Month *t–1*	2
63	Block3 (External&Financial)	Nominal effective exchange rate (Monthly % Change)	One calendar week	Month *t–1*	3
64	Block3 (External&Financial)	Real effective exchange rate (Monthly % Change)	One calendar week (subject to further revision in 30 days)	Month *t–1*	3
65	Block3 (External&Financial)	Foreign currency reserves (Monthly % Change)	No lag	Month *t–1*	3
66	Block3 (External&Financial)	Moscow stock exchange index MICEX (Monthly % Change)	No lag	Month *t–1*	3
67	Block3 (External&Financial)	Oil prices (Monthly % Change)	No lag	Month *t–1*	3
68	Block3 (External&Financial)	Wheat prices (Monthly % Change)	No lag	Month *t–1*	3
69	Block3 (External&Financial)	Gas prices (Monthly % Change)	No lag	Month *t–1*	3
70	Block3 (External&Financial)	Aluminum prices (Monthly % Change)	No lag	Month *t–1*	3
71	Block3 (External&Financial)	Nickel prices (Monthly % Change)	No lag	Month *t–1*	3
72	Block3 (External&Financial)	US Industrial Production (Monthly % Change)	One calendar month	Month *t–1*	3
73	Block3 (External&Financial)	European Commission Manufacturing Confidence EU 27 Industrial Confidence	20 calendar days	Month *t–1*	2
74	Block3 (External&Financial)	US ISM Manufacturing PMI SA	20 calendar days	Month *t–1*	2
75	Block3 (External&Financial)	Investment deflator (Monthly % Change)	20 calendar days	Month *t–1*	3
76	Block2 (Hard)	Exports of goods and services (Monthly % Change)	30–35 calendar days	Month *t–2*	3
77	Block2 (Hard)	Exports of goods and services to non-CIS countries (Monthly % Change)	30–35 calendar days	Month *t–2*	3
78	Block2 (Hard)	Exports of goods and services to CIS countries (Monthly % Change)	30–35 calendar days	Month *t–2*	3
79	Block2 (Hard)	Real Unit Labor Costs (Monthly % Change)	30–35 calendar days	Month *t–2*	3
80	Block2 (Hard)	Real Disposable Income (Monthly % Change)	30–35 calendar days	Month *t–2*	3
81	Block2 (Hard)	Real Pensions (Monthly % Change)	30–35 calendar days	Month *t–2*	3
82	Block2 (Hard)	Services Paid (Monthly % Change)	30–35 calendar days	Month *t–2*	3

№	Block	Variable name	Publication lag	Latest monthly observation[7]	Transformation type
83	Block2 (Hard)	Railway Cargo Turnover (Monthly % Change)	30–35 calendar days	Month *t–2*	3
84	Block2 (Hard)	Railway Freight Volumes (Monthly % Change)	30–35 calendar days	Month *t–2*	3
85	Block2 (Hard)	Russia: Total Output [5 Basic Indicators] (Monthly %Change)	45 calendar days	Month *t–2*	3
86	Block2 (Hard)	Unemployment, %	45 calendar days	Month *t–2*	2
87	Block2 (Hard)	Employed (Monthly % Change)	45 calendar days	Month *t–2*	3
88	Block3 (External&Financial)	Short–term loans to non-financial institutions (Monthly %Change)	45 calendar days	Month *t–2*	3
89	Block3 (External&Financial)	Long-term loans to non-financial institutions (Monthly %Change)	45 calendar days	Month *t–2*	3
90	Block3 (External&Financial)	Short-term loans to population (Monthly %Change)	45 calendar days	Month *t–2*	3
91	Block3 (External&Financial)	Long-term loans to population (Monthly %Change)	45 calendar days	Month *t–2*	3
92	Block3 (External&Financial)	M2 monetary aggregate (Monthly %Change)	45 calendar days	Month *t–2*	3
93	Block3 (External&Financial)	M0 monetary aggregate (Monthly %Change)	45 calendar days	Month *t–2*	3
94	Block3 (External&Financial)	Interest rate on short-term deposits for population	45 calendar days	Month *t–2*	2
95	Block3 (External&Financial)	Interest rate on short-term deposits of non-financial institutions	45 calendar days	Month *t–2*	2
96	Block3 (External&Financial)	Interest rate on long-term deposits for population	45 calendar days	Month *t–2*	2
97	Block3 (External&Financial)	Interest rate on long-term deposits of non-financial institutions	45 calendar days	Month *t–2*	2
98	Block3 (External&Financial)	Eurostat Industrial Production EU Industry Ex Construction (Monthly %Change)	45 calendar days	Month *t–2*	3
99	Block3 (External&Financial)	Industrial Production, Eurozone (total)	45 calendar days	Month *t–2*	3
100	Block3 (External&Financial)	Interest rate on short-term loans to population	45 calendar days	Month *t–2*	2
101	Block3 (External&Financial)	Interest rate on short-term loans to non-financial institutions	45 calendar days	Month *t–2*	2
102	Block3 (External&Financial)	Interest rate on long-term loans to population	45 calendar days	Month *t–2*	2
103	Block3 (External&Financial)	Interest rate on long-term loans to non-financial institutions	45 calendar days	Month *t–2*	2
104	Block1 (Survey)	*Russian Economic Barometer:* Expectation Diffusion Index: Sales Prices: Enterprises with Rising Indicator Next 1 Month	60 calendar days	Month *t–3*	2
105	Block1 (Survey)	*Russian Economic Barometer:* Expectation Diffusion Index: Purchasing Prices: Enterprises with Rising Indicator Next 1 Month	60 calendar days	Month *t–3*	2
106	Block1 (Survey)	*Russian Economic Barometer:* Expectation Diffusion Index: Wages: Enterprises with Rising Indicator Next 1 Month	60 calendar days	Month *t–3*	2
107	Block1 (Survey)	*Russian Economic Barometer:* Expectation Diffusion Index: Employment: Enterprises with Rising Indicator Next 1 Month	60 calendar days	Month *t–3*	2
108	Block1 (Survey)	*Russian Economic Barometer:* Expectation Diffusion Index: Production: Enterprises with Rising Indicator Next 1 Month	60 calendar days	Month *t–3*	2

№	Block	Variable name	Publication lag	Latest monthly observation[7]	Transformation type
109	Block1 (Survey)	*Russian Economic Barometer:* Expectation Diffusion Index: Equipment Purchase: Enterprises with Rising Indicator Next 1 Month	60 calendar days	Month *t–3*	2
110	Block1 (Survey)	*Russian Economic Barometer:* Expectation Diffusion Index: Financial Situation: Enterprises with Improving Situation Next 1 Month	60 calendar days	Month *t–3*	2
111	Block1 (Survey)	*Russian Economic Barometer:* Expectation Diffusion Index: Orders: Enterprises with Rising Indicator Next 1 Month	60 calendar days	Month *t–3*	2
112	Block1 (Survey)	*Russian Economic Barometer:* Expectation Diffusion Index: Debt to Banks: Enterprises with Rising Indicator Next 1 Month	60 calendar days	Month *t–3*	2
113	Block1 (Survey)	*Russian Economic Barometer:* Capacity Utilisation Rate: Actual: Normal Monthly Level=100	60 calendar days	Month *t–3*	2
114	Block1 (Survey)	*Russian Economic Barometer:* Labour Utilisation Rate: Actual: Normal Monthly Level=100	60 calendar days	Month *t–3*	2
115	Block1 (Survey)	*Russian Economic Barometer:* Stocks: Actual: Normal Monthly Level=100	60 calendar days	Month *t–3*	2
116	Block1 (Survey)	*Russian Economic Barometer:* Orders: Actual: Normal Monthly Level=100	60 calendar days	Month *t–3*	2

Appendix II Comparative analysis of RMSEs across different DFM specifications

Table II.1 Baseline simulation: Summary of average RMSEs of DFM forecasts, nowcasts and backcast (pseudo real time 2012Q1–2014Q3, 116 explanatory variables)

Model and forecast horizon	Forecast quarter T+2			Forecast quarter T+1			Nowcast			Backcast
	Month 1	Month 2	Month 3	Month 1	Month 2	Month 3	Month 1	Month 2	Month 3	Month 1
Full sample	**0.47**	**0.43**	**0.37**	**0.41**	**0.26**	0.40	0.35	**0.24**	**0.19**	**0.16**
Block1 (survey data)	0.55	0.56	0.54	0.46	0.34	0.42	0.33	0.33	0.38	0.35
Block2 (hard data)	0.69	0.65	0.58	0.60	0.59	0.39	0.38	0.36	0.21	0.20
Block 3 (external &financial data)	0.87	0.90	0.86	0.66	0.70	0.68	0.46	0.52	0.50	0.32
Blocks 1&2	0.64	0.59	0.49	0.47	0.35	0.43	0.38	0.30	0.23	0.21
Blocks 2&3	0.53	0.51	0.40	0.42	0.48	**0.33**	**0.30**	0.36	0.23	0.18
Blocks 1&3	0.50	0.49	0.41	0.50	0.34	0.38	0.38	0.28	0.22	0.21
Best DFM	**0.47**	**0.43**	**0.37**	**0.41**	**0.26**	**0.33**	**0.30**	**0.24**	**0.19**	**0.16**

Table II.2 RMSEs for baseline pseudo real time simulations (2012Q1–2014Q3): DFM with two unobservable factors

Model and forecast horizon	Forecast quarter T+2			Forecast quarter T+1			Nowcast T			Backcast T-1
	Month 1	Month 2	Month 3	Month 1	Month 2	Month 3	Month 1	Month 2	Month 3	Month 1
Full sample	0.76	0.72	0.67	0.66	0.48	0.53	0.43	0.30	0.24	0.24
Block1 (survey data)	**0.62**	**0.58**	**0.54**	**0.48**	**0.36**	0.42	**0.34**	0.28	0.29	0.30
Block2 (hard data)	0.69	0.65	0.56	0.59	0.59	**0.39**	0.39	0.38	**0.20**	**0.19**
Block 3 (external &financial data)	0.88	0.83	0.74	0.60	0.53	0.45	0.37	0.34	0.26	0.21
Blocks 1&2	0.69	0.64	0.60	0.56	0.40	0.45	0.38	0.30	0.26	0.24
Blocks 2&3	0.87	0.84	0.74	0.70	0.69	0.53	0.41	0.42	0.28	0.23
Blocks 1&3	0.69	0.64	0.57	0.57	0.39	0.42	0.39	**0.27**	0.23	0.25
Best DFM	**0.62**	**0.58**	**0.54**	**0.48**	**0.36**	**0.39**	**0.34**	**0.27**	**0.20**	**0.19**

Table II.3a RMSEs for baseline pseudo real time simulations (2012Q1–2014Q3): 45 explanatory variables

Model and forecast horizon	Forecast quarter T+2			Forecast quarter T+1			Nowcast T			Backcast T–1
	Month 1	Month 2	Month 3	Month 1	Month 2	Month 3	Month 1	Month 2	Month 3	Month 1
Full sample	0.71	0.62	**0.47**	**0.44**	**0.38**	0.50	0.48	0.25	0.25	0.20
Block1 (survey data)	**0.55**	**0.56**	0.55	0.46	**0.38**	0.56	**0.29**	0.36	0.32	0.37
Block2 (hard data)	0.66	0.60	0.52	0.51	0.49	**0.36**	0.33	0.30	0.22	0.21
Block 3 (external &financial data)	0.75	0.69	0.58	0.55	0.41	0.41	0.35	0.27	0.24	0.18
Blocks 1&2	0.73	0.66	0.61	0.66	0.51	0.60	0.41	**0.23**	**0.19**	**0.16**
Blocks 2&3	0.88	0.85	0.74	0.71	0.74	0.58	0.43	0.38	0.26	0.20
Blocks 1&3	0.62	0.57	0.55	0.50	0.39	0.41	0.45	0.37	0.28	0.24
Best DFM	**0.55**	**0.56**	**0.47**	**0.44**	**0.38**	**0.36**	**0.29**	**0.23**	**0.19**	**0.16**

Table II.3b RMSEs for baseline pseudo real time simulations (2012Q1–2014Q3): 90 explanatory variables

Model and forecast horizon	Forecast quarter T+2			Forecast quarter T+1			Nowcast T			Backcast T–1
	Month 1	Month 2	Month 3	Month 1	Month 2	Month 3	Month 1	Month 2	Month 3	Month 1
Full sample	**0.53**	**0.53**	0.50	0.50	**0.33**	0.49	0.39	**0.21**	**0.18**	**0.16**
Block1 (survey data)	0.71	0.73	0.65	0.58	0.50	0.55	0.41	0.56	0.42	0.44
Block2 (hard data)	0.67	0.63	0.55	0.56	0.59	**0.42**	0.36	0.32	0.20	**0.16**
Block 3 (external &financial data)	0.88	0.89	0.86	0.68	0.70	0.68	0.47	0.49	0.48	0.30
Blocks 1&2	0.82	0.77	0.73	0.68	0.54	0.57	0.39	0.32	0.27	0.22
Blocks 2&3	0.62	0.55	**0.45**	**0.42**	0.51	0.43	**0.33**	0.34	0.23	0.18
Blocks 1&3	0.67	0.61	0.56	0.56	0.38	0.46	0.38	0.29	0.25	0.22
Best DFM	**0.53**	**0.53**	**0.45**	**0.42**	**0.33**	**0.42**	**0.33**	**0.21**	**0.18**	**0.16**

Table II.4 RMSEs for alternative pseudo real time simulations (2006Q1–2014Q3): 116 explanatory variables

Model and forecast horizon	Forecast quarter T+2			Forecast quarter T+1			Nowcast T			Backcast T–1
	Month 1	Month 2	Month 3	Month 1	Month 2	Month 3	Month 1	Month 2	Month 3	Month 1
Full sample	**0.65**	**0.63**	**0.60**	0.77	**0.76**	**0.70**	0.54	0.44	0.35	0.27
Block1 (survey data)	1.98	2.04	1.80	1.29	1.31	1.22	0.69	0.75	0.70	0.50
Block2 (hard data)	0.77	0.96	1.07	0.73	0.95	0.95	0.49	0.58	0.54	0.30
Block 3 (external &financial data)	0.97	0.80	0.74	1.04	0.77	0.70	0.67	0.57	0.62	0.41
Blocks 1&2	1.01	0.92	0.81	0.90	0.87	0.75	0.58	**0.43**	**0.32**	**0.25**
Blocks 2&3	0.70	0.81	0.92	**0.62**	0.78	0.78	**0.48**	0.50	0.48	0.31
Blocks 1&3	0.69	0.63	0.62	0.73	0.77	0.73	0.57	0.55	0.48	0.35
Best DFM	**0.65**	**0.63**	**0.60**	**0.62**	**0.76**	**0.70**	**0.48**	**0.43**	**0.32**	**0.25**

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