Bank of Russia

Nowcasting Russian GDP in a mixed-frequency DSGE model with a panel of non-modelled variables

Working Paper Series

No. 145 / February 2025

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The author would like to thank colleagues for their discussions on the results of this work during internal seminars held at the Bank of Russia in May and August 2024. Special gratitude is extended to the anonymous reviewers and the employees of the Volga-Vyatka Main Branch of the Bank of Russia for their valuable comments, which significantly enhanced the quality of this study.

Bank of Russia Working Paper Series is anonymously refereed by members of the Bank of Russia Research Advisory Board and external reviewers.

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Abstract

This study focuses on improving the accuracy of nowcasting in DSGE models. We extend one of the general equilibrium models of the Russian economy by incorporating mixed-frequency data. Specifically, we introduce an equation that links a panel of non-modelled high-frequency indicators to observable variables, whose dynamics are determined directly by the model. The out-of-sample pseudo-real-time forecasting procedure demonstrates that incorporating these additional variables enhances the accuracy of Russian GDP nowcasting using the DSGE model. This improvement makes the model's forecasts comparable in accuracy to state-of-the-art econometric models and superior to univariate models. We also investigate the extent to which fluctuations in high-frequency indicators are associated with macroeconomic factors, as well as the economic shocks driving the explained portion of these fluctuations. While the structural interpretation of non-modelled variables is a potential strength of the model, caution is warranted due to the econometric methodology employed.

Keywords: nowcasting, GDP, DSGE model, mixed frequency data, pseudo real-time forecasting

JEL- classification: C53, C82, E32, E37

1. Introduction

Business cycles, also known as *short-term fluctuations in economic activity*, are not periodic (*Burns and Mitchell, 1946*). There are inherent lags in macroeconomic policy aimed at stabilizing the economy around a long-term growth path, both in terms of decision-making and the resulting economic effects. This underscores the importance of accurately projecting macroeconomic fundamentals in the short term for effective economic policy formulation[1]. Consequently, this study focuses on macroeconomic forecasting, specifically addressing the challenge of forecasting output — a key variable for analyzing both business cycles and economic growth theory.

The most widely accepted measure of a country's economic activity is gross domestic product[2] (GDP). In most countries, statistical agencies calculate this macroeconomic aggregate on a quarterly basis, and the data are released with significant time lags[3]. This delay complicates the timely assessment of current economic activity, and the process is further complicated by the fact that GDP data are often revised after publication, with the magnitude of these revisions[4] sometimes being substantial. As a result, estimating GDP growth for the current quarter has become an independent area of forecasting. Since the work of *Nunes (2005)*, this type of forecasting has been commonly referred to as *nowcasting*[5], and it is the focus of our research.

While empirical models have been extensively used for nowcasting, structural and semi-structural models have been widely employed for medium-term forecasting since the work of *Smets and Wouters (2003, 2007)*. These models take into account the Lucas critique and can therefore be used to assess the effects of macroeconomic policy and provide recommendations for its implementation.

However, the estimation and application of this class of models typically rely on a limited number of observable quarterly variables. This aggregation to quarterly values can introduce potential bias in the parameter estimates[6] and hampers the ability to nowcast key macroeconomic variables. In practice, the latter challenge leads to using nowcasts from

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[1] It is important to note that, from a macroeconomic perspective, *short-term* periods can denote different time horizons, as their duration depends on the degree of nominal rigidities in prices and wages within the economy. In the New Keynesian model, on which this paper is based, stabilization policy affects the real economy due to these rigidities. For more details, see *Galí (2008)*.

[2] Nevertheless, the observable GDP variable may not fully correspond to the unobservable output variable in a specific macroeconomic model, which supports the case for using multiple indicators to measure economic activity. However, this study focuses on GDP forecasting, and issues related to the uncertainty of measuring output fall outside its scope. *Boivin and Giannoni (2006)* present a framework for a *data-rich* DSGE model that treats underlying theoretical concepts as unobserved common factors, with the observed data series serving as imperfect indicators of these factors. *Iiboshi et al. (2015)* and *Gelfer (2019, 2021)* apply this approach in empirical analyses, and *Kryshko (2011a)* introduces several improvements to data-rich DSGE models, including faster computation of the posterior likelihood function and parameter estimation.

[3] According to *Stundziene et al. (2024)*, in major global economies (United States, European Union and BRICS countries), first GDP estimates for the previous quarter are typically released four to six weeks after the end of the reporting period. Rosstat, Russia's statistical agency, publishes a preliminary GDP estimate on the 30th business day following the end of the quarter (*Rosstat, 2018*).

[4] Although revisions can be accounted for during GDP forecasting, we set this issue aside and perform all our calculations in pseudo-real time. The works of *Astafyeva and Turuntseva (2021)* and *Gornostaev et al. (2022)* focus on the extent of revisions made to Russian GDP. *Gornostaev et al. (2021)* compare the size of these revisions with those in historical GDP data for OECD countries. *Anesti et al. (2022)* present an approach that incorporates the uncertainty of early GDP estimates into short-term forecasting using a dynamic factor model. *Sharafutdinov (2023)* applies a similar method to assess the uncertainty of Russian GDP.

[5] Hereinafter, the terms *nowcast(ing)* and *forecast(ing)* are used interchangeably to refer to GDP forecasting for the current quarter. In other words, in this paper, *forecasting* is synonymous with *nowcasting*.

[6] For more details, see the works of *Kim (2012)* and *Foroni and Marcellino (2014b)*.

empirical models[7]. While this strategy may seem like a reasonable solution, as it ultimately enhances the accuracy of nowcasts, forecasts generated by empirical models do not always align with the underlying macroeconomic model in terms of specifications[8].

With these considerations in mind, this study aims to improve the accuracy of nowcasts in DSGE models. We focus on forecasting Russian GDP growth using the model of a small open export-oriented economy developed by *Kreptsev and Seleznev (2017)*. This model is included in the Bank of Russia's macroeconomic toolkit (*Mogilat et al., 2021*), which underscores the relevance of our research. To enhance nowcast accuracy, we apply the methodology of *Giannone et al. (2016)*, which allows us to adapt the original DSGE model (estimated on quarterly data) for use with mixed-frequency data, and incorporating a panel of non-modelled monthly indicators[9]. Our research demonstrates that these indicators play a key role in improving the accuracy of Russian GDP growth nowcasts by providing timely flash estimates of the economy's current state.

In a study by *Červená and Schneider (2014)*, this methodology improved the accuracy of nowcasts for Austrian GDP, while *Meyer-Gohde and Shabalina (2022)* used it to forecast US GDP. However, to the best of our knowledge, this approach has never been applied to the Russian economy, and our research aims to fill this gap. We compare the accuracy of out-of-sample forecasts of Russian GDP growth in the DSGE-m model with several empirical approaches, such as factor-augmented mixed-frequency regressions (FA-MIDAS) and dynamic factor models (DFM), as well as a set of benchmark models, including univariate time series models (AR, AR-X, RW).

To evaluate the forecasting performance, we employ pseudo-real-time calculations that determine nowcast accuracy based on the information available at a specific moment. Thus, we do not use historical data vintages that account for revisions in various Russian economic indicators (*Gornostaev et al., 2022*). As a result, our analysis emphasizes the estimates of the relative forecasting power of the models rather than their absolute accuracy, which may be biased due to the use of pseudo-real-time dataset (*Mamedli and Shibitov, 2021*). Similar to the findings of *Červená and Schneider (2014)*, we demonstrate that incorporating information from a panel of non-modelled monthly indicators enhances the accuracy of GDP growth projections within a DSGE model.

Our empirical analysis, conducted on a test sample spanning from 2017 Q1 to 2023 Q2, shows that this approach improves out-of-sample GDP growth forecast accuracy by 41%; the nowcast error is, on average, 1 percentage point lower when non-modelled variables are included in the mixed-frequency DSGE model. Moreover, we find that the forecasting accuracy of the proposed model is comparable to several econometric methods used for GDP nowcasting, such as FA-MIDAS and DFM. Notably, it proves significantly more accurate than univariate benchmarks like AR-X, AR, and RW models. Specifically, the relative accuracy increase in this case is 50%, with the nowcast error for Russian GDP growth using the DSGE-m model being, on average, 1.6 percentage points lower than that of the univariate benchmarks.

The empirical results we obtained demonstrate that the improvement in nowcast accuracy within the mixed-frequency DSGE model arises from the inclusion of an additional set of macroeconomic series. This suggests that data from non-modelled high-frequency

[7] *Mogilat et al. (2021)* describe the process of the short-term forecasting for macroeconomic indicators at the Bank of Russia, noting that it relies on a wide range of information and serves as input for medium-term forecasting models. According to the authors, the latter include the quarterly projection model (QPM) described by *Orlov (2021)* as well as a number of DSGE models, including the one presented by *Kreptsev and Seleznev (2017)* which this study relies on.
[8] For more details, see the work of *Kryshko (2011b)*.
[9] From this point forward, this model will be referred to as *DSGE-m model*.

indicators may influence the dynamics of variables in the DSGE model while also reflecting the impact of common macroeconomic factors. At the same time, various studies have shown that the variables comprising such panels of high-frequency indicators often exhibit a significant degree of idiosyncratic fluctuations[10]. Accordingly, to better understand how our panel of non-modelled monthly variables is linked to the dynamics of the core model, we estimate the fluctuations associated with structural and idiosyncratic shocks. Over the period under study (2003 Q1–2023 Q2), an average of 45% of the variance in the monthly indicators can be attributed to economically meaningful factors, while the remaining 55% represents noise and does not provide insights into the dynamics of the model. This estimate remains unchanged even when the 2020–2023 period is excluded from the sample. The most informative indicators, in terms of macroeconomic signal, are those related to the real economy (*hard data*); 68% of the variance in these indicators is explained by the DSGE model. Notably, the fluctuations in these variables have become increasingly aligned with the structural shocks in recent years (2020–2023).

Unlike empirical models, the DSGE-m model used for nowcasting Russian GDP growth allows us to analyze which macroeconomic shocks are associated with the explained portion of fluctuations in the non-modelled monthly variables. However, compared to other studies that rely on the methodology of *Giannone et al. (2016)*, we note certain econometric limitations in this approach, which hinder a structural interpretation of these indicators. Nonetheless, we argue that the ability to construct such a historical decomposition is an advantage of the DSGE-m model over empirical models, as it provides economic context to the fluctuations in the auxiliary variables used for nowcasting.

Related literature. This study contributes to the empirical research on short-term forecasting of Russian GDP (*Styrin and Potapova, 2009; Porshakov et al., 2016; Achkasov, 2016; Dahlhaus et al., 2017; Ponomarev and Pleskachev, 2018; Mikosch and Solanko, 2019; Stankevich, 2020; Zhemkov, 2021; Zubarev and Rybak, 2021; Gareev and Polbin, 2022; Zubarev et al., 2022; Krupkina et al., 2022; Makeeva and Stankevich, 2022; Stankevich, 2023; Fisherman, 2023; Fokin, 2023; Makeeva et al., 2024; Lyakhnova and Kolenko, 2024; Mogilat et al., 2024*). Like several other authors (*Červená and Schneider, 2014; Giannone et al., 2016; Yau and Hueng, 2019; Meyer-Gohde and Shabalina, 2022*), we focus on improving the accuracy of GDP nowcasts in a DSGE model. Unlike the studies of *Yau and Hueng (2019)* and *Meyer-Gohde and Shabalina (2022)*, we do not use mixed-frequency data to estimate the structural parameters of the DSGE model. Instead, we apply the approach of *Giannone et al. (2016)*, which modifies a DSGE model previously estimated on quarterly data.

Contribution to the literature. To the best of our knowledge, this is the first effort employing macroeconomic (structural) models to nowcast Russian GDP. The predictive performance of the model is compared with the empirical forecasting methods commonly used in both research and practice. Unlike other studies focused on nowcasting Russian GDP, we conduct an econometric analysis of non-modelled monthly variables, allowing us

[10] According to the findings of *Andreini et al. (2023)*, who nowcast Germany's GDP using a Dynamic Factor Model, common factors explain 46% of the variance in observable variables over the 1991–2018 sample period, while the remaining 54% of fluctuations are driven by idiosyncratic factors. In the work of *Camacho and Lopez-Buenache (2023)*, estimates based on the FRED-QD database indicate that 50–60% of fluctuations in variables describing the U.S. economy are not attributable to common factors. Previously, *Stock and Watson (2002)* used a similar dataset and showed that common factors accounted for 39–53% of the variance in the observable series. *Giannone et al. (2002, 2004)* and *Boivin and Ng (2006)* present somewhat differing assessments based on the panels of U.S. macroeconomic variables they analyzed. In the former case, idiosyncratic fluctuations were estimated to account for 30–40% of the variance, while in the latter, the range was higher, at 56–69%, depending on the number of common factors included in the model.

to assess the extent to which the dynamics of these indicators convey meaningful signals about macroeconomic dynamics.

This paper is organized as follows. *Section 2* reviews previous studies on GDP nowcasting. *Section 3* provides a short description of the quarterly DSGE model and the methodology used for its transformation into a mixed-frequency model, incorporating a panel of non-modelled variables that improve the accuracy of GDP nowcasts. *Section 4* details the dataset used in the empirical calculations. *Section 5* presents the econometric estimates of the model. In *Section 6*, we compare the accuracy of Russian GDP growth projections generated by the DSGE-m model with those from several empirical models. *Section 7* concludes the research. Throughout the paper, references are made to *Appendices A–D*, which provide supplementary information.

2. Overview of the common GDP nowcasting methods

2.1. Regression models

Empirical strategies[11] for nowcasting GDP rely on additional information from flash indicators (monthly, weekly, or even daily) that may capture the current state of the economy. Earlier studies have often used the multiple regression model, also known as the *bridge equation*, for this purpose. In this model, quarterly GDP growth is forecast using a balanced panel of monthly variables, which are aggregated into quarterly values. While this approach is easy to implement, it comes with certain limitations. First, nowcasting using this model is only feasible when all monthly observations for the entire quarter are available. In practice, when data for some explanatory variables are missing, the missing values are typically projected using univariate time series models (*Trehan, 1989, 1992; Parigi and Schlitzer, 1995; Ingenito and Trehan, 1996; Rünstler and Sédillot, 2003; Baffigi et al., 2004; Golinelli and Parigi, 2007*). Second, bridge equations are unsuitable for nowcasting if the explanatory variables have different publication lags. As *Wallis (1986)* points out, this creates *the ragged edge problem*, which leaves the panel unbalanced. These issues ultimately shorten the forecast horizon and limit the ability to produce the most timely GDP estimates. Moreover, the quarterly aggregation of monthly variables risks losing valuable information that could otherwise improve forecast accuracy.

The latter consideration explains the choice of the *mixed data sampling (MIDAS) regression* formulated by *Ghysels et al. (2004, 2007)*. This model allows for a parsimonious method for the parameterization of high-frequency indicators based on distributed lag functions that aggregate the values of the explanatory variables into the lower frequency of the predictor variable[12]. Beginning with the work of *Clements and Galvão (2008, 2009)*, MIDAS regressions have been extensively[13] used in nowcasting and demonstrate acceptable accuracy relative to other models. *Kuzin et al. (2011)* show that projections for the Euro area in a MIDAS model with a lag of the dependent variable (AR-MIDAS) are more

[11] A detailed review of the most common nowcasting models is presented in *Bańbura et al. (2013)*, *Foroni and Marcellino (2013)*, and *Cascaldi-Garcia et al. (2023)*. In this work, we briefly discuss the variety of approaches and substantiate our choice of models.

[12] It is also possible to use a MIDAS regression that excludes the weighting function — unrestricted MIDAS (U-MIDAS). *Foroni et al. (2015)* conduct simulation experiments and show that in the event of a slight discrepancy in frequency between the dependent and independent variables (e.g., quarterly GDP nowcasts based on monthly data), U-MIDAS proves to be preferable to MIDAS with the exponential Almon lag. In the empirical part of the study, the authors draw on the example of GDP nowcasting in the US and the Euro area to conclude that U-MIDAS is not inferior to conventional MIDAS regressions in accuracy.

[13] According to a meta-analysis conducted by *Stundziene et al. (2024)*, MIDAS is used in 22.8% of published works dedicated to nowcasting, more often than bridge equations (10.4%), vector autoregression models (17.6%), and machine learning algorithms (5.2%). However, it lags behind factor models, which are utilized in 42.5% of the studies.

accurate than those produced univariate autoregression (AR) and mixed-frequency vector autoregression (MF-VAR) models. *Bai et al. (2013)* compare MIDAS regressions with state-space models in simulation experiments and empirical exercises in US GDP forecasting, concluding that the two approaches are comparable in accuracy. *Foroni and Macellino (2014a)* explore a disaggregation approach to nowcasting the Euro area's GDP (by both production side and expenditure side) and find that the MIDAS regressions (AR-MIDAS and MIDAS with factors) outperform AR models, bridge equations, and MF-VAR in terms of accuracy. *Schumacher (2016)* builds an out-of-sample forecast for the Euro area's GDP based on a post-recession sample (2010 Q1–2014 Q4) and shows that MIDAS outperforms bridge equations in forecasting power. In certain cases, MIDAS even surpasses more advanced nowcasting models; the works of *Kuck and Schweikert (2021)* and *Zhang et al. (2023)* use GDP forecasting for Baden-Württemberg (a German state) and China, respectively, concluding that MIDAS regressions perform favorably compared to dynamic factor models (DFM).

MIDAS model also demonstrates high predictive capabilities when applied to the Russian economy. According to *Mikosch and Solanko (2019)*, nowcasts of Russian GDP growth based on U-MIDAS and MIDAS-R-nealmon (a model featuring a non-exponential Almon polynomial) are more accurate than bridge equations, particularly during periods of high volatility. This finding is particularly relevant for our study, as the test sample in the empirical section includes the crises of 2020 and 2022. As *Makeeva and Stankevich (2022)* show, nowcasts of Russian GDP growth made using U-MIDAS and MIDAS-R-nealmon are consistently more accurate than forecasts generated by DFM, AR(1), and, in certain cases, MF-BVAR. Additionally, Markov switching MIDAS models, as studied by *Stankevich (2023)*, exhibit the highest predictive accuracy compared to conventional MIDAS and MF-BVAR models.

In the empirical part of this study, we also utilize MIDAS as one of the competing models for nowcasting Russian GDP growth. Importantly, to ensure a parsimonious parameterization, conventional MIDAS models are estimated with a small number of regressors, while we handle a relatively large number of observable variables[14]. Therefore, we employ the factor-augmented MIDAS (FA-MIDAS) regression proposed by *Marcellino and Schumacher (2010)*. The explanatory variables in this model consist of static factors derived from a DFM, which is estimated using a two-step method based on the approaches of *Giannone et al. (2008)* and *Doz et al. (2011)*.

2.2. Multivariate time series (State Space) models

In addition to regression approaches[15], GDP nowcasting can also be based on multivariate time series models, including state-space models. These models, when coupled

[14] See Table B1 in Appendix B.

[15] For reasons of brevity, we omit parametric and non-parametric machine learning methods, despite their growing prevalence in GDP nowcasting during the high volatility of the 2020 pandemic. *Huber et al. (2023)* estimate a mixed-frequency vector autoregression (MF-VAR), the functional form of which is determined non-parametrically using the Bayesian additive regression trees algorithm. For 2020, this model demonstrates a significant increase in the accuracy of out-of-sample GDP projections for the euro area compared to a linear MF-VAR. In a test sample for the US economy covering 2000–2018, *Soybilgen and Yazgan (2021)* show that decision-tree algorithms (including bagged decision trees, random forest, and stochastic gradient tree boosting) outperform dynamic factor models (DFM) in the accuracy of quarterly GDP nowcasts. According to *Richardson et al. (2021)*, various machine learning algorithms (such as LSBoost, SVM, neural networks, and regularized regressions) yield more accurate nowcasts of New Zealand's GDP (2009–2019) than DFM and autoregressive models (AR). Similar conclusions are reached regarding China's GDP (*Zhang et al., 2023*). In the context of the Russian economy, *Gareev and Polbin (2022)* find that the accuracy of GDP projections from regularization models (ridge, LASSO, and elastic net) is higher than those from other algorithms (including bagging, k-nearest neighbors, random forest, support vector machines, and XGBoost) and univariate benchmarks (AR and AR with an exogenous variable). *Lyakhnova and Kolenko (2024)* utilize regularization

with the Kalman filtering and smoothing, allow for the use of mixed-frequency data and unbalanced panels, enabling the real-time nowcasting of GDP despite the non-synchronous publication of data for various indicators. By forecasting all regressors included in the model, these approaches enhance the interpretability of short-term forecasts by identifying observable variables associated with changes in GDP projections. For that reason, *Bańbura and Modugno (2010)* introduce the concept of *news*, which measures the contribution of new information from each observable variable to the revision of the GDP forecast. *Hayashi and Tachi (2021)* later propose an improved method for estimating the effects of updates to historical data on forecast revisions. In terms of empirical results, *Modugno et al. (2016)* find that real sector variables are the most informative for fine-tuning GDP nowcasts, using Turkey as an example. Regarding the Russian economy, *Dahlhaus et al. (2017)* demonstrate that re-estimating the model parameters results in a much greater change in projected GDP growth for Russia compared to other emerging economies, such as Brazil, China, India, and Mexico. This finding reflects the relatively volatile nature of Russian data, according to the authors.

Of the multivariate time series models, two approaches are most commonly used for GDP nowcasting: mixed-frequency vector autoregression (MF-VAR) and dynamic factor models (DFM)[16]. The MF-VAR model simulates the joint dynamics of quarterly GDP and monthly indicators. The Bayesian estimation method proposed by *Schorfheide and Song (2015)* helps mitigate the *curse of dimensionality*, allowing for the estimation of VAR models that include a large number of observable variables. Overall, MF-(B)VAR has demonstrated relatively strong predictive accuracy. *McCracken et al. (2021)* find that a MF-BVAR nowcast of US GDP performs similarly to the Survey of Professional Forecasters in terms of accuracy, though it falls short when compared to the Blue Chip Economic Indicators (BCEI) survey in a test sample from 1985 to 2017. However, *Brave et al. (2019)* do not find a significant difference between MF-BVAR nowcasts and BCEI projections based on a 2004–2016 sample. Similarly, *Cimadomo et al. (2022)* conclude that MF-BVAR nowcasts of US GDP are comparable in accuracy to the DFM-based forecasts produced by the Federal Reserve Bank of New York[17], as described by *Bok et al. (2018)* and later enhanced by *Almuzara et al. (2023)*. VAR models also perform well in empirical studies focused on nowcasting Russia's GDP. *Stankevich (2020)* compares MIDAS and MF-BVAR nowcasts over different test samples (2014–2018 and 2016–2018) and finds that vector autoregressions yield the highest accuracy. According to *Makeeva and Stankevich (2022)*, MF-BVAR-based GDP forecasts are more accurate than those derived from DFM, MIDAS, and AR(1) models. *Fokin (2023)* further demonstrates that MF-BVAR nowcasts significantly improve accuracy compared to quarterly BVAR, autoregressive integrated moving average (ARIMA) models, and naive forecasts.

The dynamic factor model (DFM), developed by *Geweke (1977)* and *Sargent and Sims (1977)*, is grounded in the stylized fact that most economic variables move together in the same direction (up to a sign), thereby forming business cycles in the economy. This empirical observation was first noted by *Burns (1946)*, who analyzed hundreds of US macroeconomic series. *Stock and Watson (1989)* formalized this conclusion, isolating several latent factors in their model of unobservable components. These latent factors capture the fluctuations of key macroeconomic variables, creating coincident and leading indicators of economic activity.

models to nowcast the GDP gap (the difference between observable actual output and unobservable potential output) based on data from the Bank of Russia's monthly survey of non-financial companies. According to the authors' calculations, from January to October 2023, the Root Mean Squared Error (RMSE) of this model was slightly lower than that of ARIMA.

[16] *Stock and Watson (2016)* and *Barhoumi et al. (2017)* provide detailed reviews of dynamic factor models.

[17] https://www.newyorkfed.org/research/policy/nowcast

The use of dynamic factor models (DFMs) in GDP nowcasting, including for Russia, began with the work of *Evans (2005)* and *Giannone et al. (2008)*. *Styrin and Potapova (2009)* implemented a DFM that proved more accurate than random walk models, univariate autoregressions, forecasts from the Russian Ministry of Economic Development, and estimates based on the HSE University indices. *Porshakov et al. (2016)* further developed a DFM for the Bank of Russia, used to estimate and nowcast GDP, demonstrating higher accuracy compared to bridge equations, random walk models, and the earlier DFM by *Styrin and Potapova (2009)*. *Achkasov (2016)* refined the model of *Porshakov et al. (2016)* by separately estimating unobservable factors for different groups of high-frequency macroeconomic indicators. The accuracy of the model's nowcasts improved as more monthly data became available. *Dahlhaus et al. (2017)* also highlighted the relative accuracy of DFM-based GDP nowcasts for Russia, outperforming univariate time series models. *Ponomarev and Pleskachev (2018)* compared DFM-based growth forecasts with estimates from various institutions (HSE University, the Center for Macroeconomic Analysis and Short-term Forecasting, and the Russian Ministry of Economic Development) for 2014–2016, emphasizing the use of high-frequency data. *Zhemkov (2021)* focused on forecast combination approach and found DFM to be superior to other singular models like MIDAS, naive forecasting, dynamic model averaging/switching (DMA/DMS), and factor-augmented vector autoregression (FAVAR). *Zubarev and Rybak (2021)* produced a DFM forecast that was significantly more accurate than the real-time GDP estimates from the Russian Ministry of Economic Development. Later, *Zubarev (2022)* and *Krupkina et al. (2022)* showed that DFM outperformed mixed-frequency Bayesian VAR (MF-BVAR) models in terms of forecasting power. *Rybak (2023)* noted that using real-time data for OECD economies improved the accuracy of Russia’s GDP nowcasts for 2016–2019 but did not significantly enhance forecasts during the 2020–2021 crisis. Most recently, *Mogilat et al. (2024)* applied input-output tables to develop a disaggregated GDP forecast based on sectoral value added. Their approach outperformed univariate benchmarks such as ARIMA and random walk (RW) models, as well as VAR models and direct DFM GDP forecasts.

Our study also employs a pool of DFM specifications as competing models for forecasting Russia’s GDP.

3. Methodology

3.1. Quarterly DSGE model

The approach to GDP nowcasting in this paper is based on the enhanced DSGE model of the Russian economy proposed by *Kreptsev and Seleznev (2017)*.

We choose this model for two key reasons. First, it forms part of the model toolkit used by the Bank of Russia for developing monetary policy recommendations (*Mogilat et al., 2021*), making it highly relevant for practical macroeconomic analysis and forecasting. Second, it incorporates a stochastic trend for technological advances, enabling the use of initial GDP growth rates as an observable variable. This captures both the cyclical component and a shifting underlying growth component[18].

The model's equations are provided in Appendix A. It simulates the dynamics of a small, open, export-oriented economy characterized by nominal rigidities in domestic, import, and export prices, domestic wages, loan and deposit rates, and capital adjustment

[18] According to *Polbin and Skrobotov (2016)*, *Polbin (2020)*, and *Malikova and Fokin (2022)*, the underlying component of Russia’s GDP growth has undergone significant changes in recent decades. This underscores the importance of using models that endogenously estimate the long-term growth rates of Russia’s GDP, as these models are better suited to capturing the evolving economic dynamics and structural shifts within the Russian economy.

costs. It also incorporates financial frictions and household consumption habits. The stochastic element of the model is driven by the impact of 22 shocks.

Importantly, we do not independently estimate the model's parameters; instead, we calibrate them based on the average posterior characteristics derived from 22 observable variables for the 2006 to 2016 period.

3.2. Transition to the mixed-frequency DSGE model

The solution of the log-linearised quarterly DSGE model can be presented in state-space[19] form as follows[20]:

$$s_{t_q} = \mathcal{T}_\theta s_{t_q-1} + \mathcal{B}_\theta \varepsilon_{t_q} \quad (1)$$

$$Y_{t_q} = \mathcal{M}_{0,\theta} s_{t_q} + \mathcal{M}_{1,\theta} s_{t_q-1}, \quad (2)$$

where s_{t_q} represents the vector of unobservable state variables at time t_q (in quarters); ε_{t_q} represents structural shocks at time t_q; $Y_{t_q} = \left(y_{1,t_q}, \dots, y_{k,t_q}\right)'$ is the vector of stationary observable variables at time t_q; $\mathcal{T}_\theta$, $\mathcal{B}_\theta$, $\mathcal{M}_{0,\theta}$ and $\mathcal{M}_{1,\theta}$ are matrices determined by θ, the vector of estimated deep parameters of the DSGE-q model.

Equation (1) captures the dynamics of the unobservable state variables s_{t_q}, adjusted for structural shocks ε_{t_q}. Equation (2) connects stationary observable series Y_{t_q} with unobservable state variables s_{t_q}. The second term in equation (2), $\mathcal{M}_{1,\theta} s_{t_q-1}$, accounts for the fact that some observable variables are expressed in first differences[21].

For nowcasting purposes, the model is extended to include additional monthly indicators, following the methodology of *Giannone et al. (2016)*. This enables the integration of mixed-frequency data while maintaining consistency with the quarterly DSGE model. Here's how the key components fit together:

1. **Monthly observable variables**. To integrate monthly data into the model, we introduce a new time index, denoted as t_m, where m represents the month. The vector $Y_{t_m} = \left(y_{1,t_m}, \dots, y_{k,t_m}\right)'$ is defined as the set of monthly observable variables corresponding to the quarterly observable series.

To ensure that the monthly data aligns with the quarterly series, the value of each variable in Y_{t_m} at the last month of each quarter must coincide with the observable quarterly values. This means the values for months 1 and 2 of a given quarter are interpolated or estimated, while the value for month 3 (the last month of the quarter) corresponds exactly to the quarterly observed data[22]. This alignment between the unobservable monthly values and the observed quarterly values ensures that the model can incorporate monthly dynamics into the framework without losing consistency with the quarterly data.

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[19] The model in this form is obtained through stochastic simulation of the calibrated model using Dynare (*Adjemian et al., 2011*). Unlike the original study by *Kreptsev and Seleznev (2017)*, we exclude the possibility of measurement errors in the dynamics of the observable variables. This adjustment simplifies the framework while still maintaining the essential dynamics of the Russian economy for nowcasting purposes.

[20] Hereinafter, our notation system follows the conventions established by *Giannone et al. (2016)*. This ensures consistency and clarity in the presentation of the model and its results throughout the study.

[21] In the case of DSGE-q, this applies to domestic and global GDP, household and government consumption, investments, exports, and real wages, as well as to GDP deflators, investments, imports, exports, and the growth of real oil prices.

[22] For more details, see Section 4 as well as the works of *Mariano and Murazawa (2003)* and *Giannone et al. (2008)*. For example, monthly price growth in this case must be converted into quarterly terms (to reflect growth over a moving quarter). The values of several monthly variables (e.g. the interest rates and unemployment) should be the average for the last three months.

2. **Monthly state variables and dynamics**. The unobservable monthly state variables s_{t_m} are defined such that their values in the last month of each quarter coincide with the unobservable quarterly state variables s_{t_q} from the quarterly DSGE model. The dynamics of these monthly state variables are described by:

$$s_{t_m} = \mathcal{T}_\theta s_{t_m-3} + \mathcal{B}_\theta \varepsilon_{t_m} \tag{3}$$

This equation is equivalent to the original quarterly equation (1) when t_m corresponds to the last month of the quarter. For the monthly changes, a new equation (4) is introduced:

$$s_{t_m} = \mathcal{T}_m s_{t_m-1} + \mathcal{B}_m \varepsilon_{m,t_m}, \tag{4}$$

where $\mathcal{T}_m$ is a stable matrix consisting of real numbers and ε_{m,t_m} represents independent normally distributed shocks. This recursively defines the monthly dynamics and accounts for monthly shocks ε_{m,t_m}.

3. **Recursive expression**. To match equation (4) with equation (3), the monthly dynamics are recursively rewritten[23] as:

$$s_{t_m} = \mathcal{T}_m^3 s_{t_m-3} + \left[\mathcal{B}_m \varepsilon_{m,t_m} + \mathcal{T}_m \mathcal{B}_m \varepsilon_{m,t_m-1} + \mathcal{T}_m^2 \mathcal{B}_m \varepsilon_{m,t_m-2}\right] \tag{5}$$

4. **Monthly matrices**. To ensure consistency with the quarterly DSGE model, the following key transformations are applied:

$$\mathcal{T}_m = \mathcal{T}_\theta^{1/3} \tag{6}$$

$$vec(\mathcal{B}_m \mathcal{B}_m') = (I + \mathcal{T}_m \otimes \mathcal{T}_m + \mathcal{T}_m^2 \otimes \mathcal{T}_m^2)^{-1} vec(\mathcal{B}_\theta \mathcal{B}_\theta') \tag{7}$$

To calculate the cube root of the matrix $\mathcal{T}_\theta$, we reduce its dimensionality and, to avoid rank deficiency, find a minimal state-space representation. This allows us to find the canonical (spectral) decomposition[24] of the matrix $\mathcal{T}_\theta$:

$$\mathcal{T}_\theta = \mathcal{V}\mathcal{D}\mathcal{V}^{-1}, \tag{8}$$

where $\mathcal{V}$ is a matrix composed of the coordinates of the eigenvectors and $\mathcal{D}$ is a diagonal matrix with the corresponding eigenvalues. Finally, based on decomposition (8), we find the cube root of matrix $\mathcal{T}_\theta$ as

$$\mathcal{T}_m = \mathcal{T}_\theta^{1/3} = \mathcal{V}\mathcal{D}^{1/3}\mathcal{V}^{-1},$$

where $\mathcal{D}^{1/3}$ is the diagonal matrix containing the cube roots of the eigenvalues[25] of $\mathcal{T}_\theta$.

5. **Shock Structure**. A simplifying assumption is made that the three monthly shocks coincide with the quarterly shock:

$$\varepsilon_{m,t_m} = \varepsilon_{m,t_m-1} = \varepsilon_{m,t_m-2} = \varepsilon_{t_q}$$

This allows for the determination of $\mathcal{B}_m$ from the equation (7):

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[23] *Giannone et al. (2016)* note that if the state variables include *stock* variables, formula (4) does not involve approximation. If vector s_{t_m} consists of *flow* variables, the definition of the monthly variables as quarterly averages implies an irreversible MA process. Therefore, simulating this monthly process as if it is autoregressive leads to a specification error. *Doz et al. (2012)* show that the negative effect of this specification error is small.

[24] In a more general case, when matrix $\mathcal{T}_\theta$ cannot be diagonalised, it can be reduced to the Jordan form or the Schur decomposition can be used.

[25] Note that matrix $\mathcal{D}$ may include both real and complex conjugate eigenvalues. The real eigenvalues have one valid cube root and two complex conjugate roots. For each of the complex conjugate eigenvalues, there are three different complex cube roots. Similar to Giannone et al. (2016), in the case of real eigenvalues, we choose their real cube roots. In the case of a complex conjugate eigenvalue, we choose the cube root characterised by the smallest argument of the complex number.

$$\mathcal{B}_m + \mathcal{T}_m\mathcal{B}_m + \mathcal{T}_m^2\mathcal{B}_m = \mathcal{B}_\theta \quad (9)$$

6. **New Observation Equation**. A new observation equation is written for the monthly model in place of the observation equation (2) from the quarterly DSGE model. For series Y_{t_m} observed only at quarterly intervals, the observation equation is:

$$Y_{t_m} = \mathcal{M}_m s_{t_m}, \quad (10)$$

where $\mathcal{M}_m = \left(\mathcal{M}_{0,\theta} + 0\cdot L + 0\cdot L^2 + \mathcal{M}_{1,\theta}L^3\right)$ and L is the lag operator.

As a result, equations (4) and (10) describe the monthly dynamics of the DSGE model. In our case, several of the variables that make up Y_{t_m} are observed on a monthly basis,[26] while others are observed on a quarterly basis. Since real-time forecasting involves the non-synchronous[27] release of new data on various observable variables (due to the *ragged edge* problem), measurement errors $V_{t_m}(v_{1,t_m},\dots,v_{k,t_m})'$ are added to equation (10), and unobservable components of Y_{t_m} are estimated using the Kalman filter:

$$Y_{t_m} = \mathcal{M}_m s_{t_m} + V_{t_m}, \quad (11)$$

where $var(v_{i,t_m}) = 0$ if y_{i,t_m} is observed, and $var(v_{i,t_m}) = \infty$ otherwise.

This methodology allows for a refined mixed-frequency model that incorporates higher-frequency information, enhancing the precision of nowcasts by using both monthly and quarterly data in the same consistent framework.

3.3. Inclusion of non-modelled variables

Let us denote $X_{t_m} = (x_{1,t},\dots,x_{n,t})'$ as a vector of the non-modelled monthly variables, which have previously been reduced to stationary form[28]. Like Y_{t_m}, these variables must be transformed so that the values in the last month of each quarter correspond to the quarterly change.

To account for changes in X_{t_m}, a model consisting of equations (4) and (11), following *Giannone et al. (2016),* is complemented with a ratio that links X_{t_m} with the observable DSGE variables:

$$X_{t_m} = \mu + \Lambda Y_{t_m} + e_{t_m}, \quad (12)$$

where $e_{t_m} = (e_{1,t_m},\dots,e_{k,t_m})'$ is the vector of idiosyncratic shocks of the non-modeled series, which is assumed to be orthogonal to Y_{t_m}. The parameters $\mu_{n\times 1}$, $\Lambda_{n\times k}$, and the covariance matrix of the shocks $E(e_{t_m}e_{t_m}') = R_{n\times n}$ are estimated using the OLS based on a balanced panel of variables[29].

X_{t_m} is included in the model to enhance the accuracy of nowcasting the observable variables in the DSGE model. For this reason, X_{t_m} in equation (12) depends on Y_{t_m}, and not on s_{t_m}, ensuring that it does not influence the historical dynamics of the model variables or structural shocks.

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[26] Such variables include the interest rate of the domestic and global money markets, the domestic and global consumer price indices, real wages and oil prices. The simulated variables are described in Table B1 in Appendix B.
[27] See the Publication Lag column in Table B1 in Appendix B.
[28] The method for transforming the observable variables is described in Section 3 and in the "Transformation Type" column of Table B1 in Appendix B.
[29] In our case, not all of the variables included in the vector Y_{t_m} are observed on a monthly basis. Therefore, following *Giannone et al. (2016)*, we estimate the parameters of equation (11) based on the quarterly series.

When equation (12) is used for real-time forecasting, the variables included in X_{t_m} are also affected by the ragged edge problem. Therefore, the variance of the idiosyncratic component is $var(e_{i,t_m}) = [R]_{i,i}$ if x_{i,t_m} is observed and is $var(v_{i,t_m}) = \infty$ otherwise.

Therefore, our mixed-frequency DSGE model for nowcasting (*DSGE-m model*) consists of equations (4), (11) and (12) respectively:

$$s_{t_m} = \mathcal{T}_m s_{t_m-1} + \mathcal{B}_m \varepsilon_{m,t_m}$$

$$Y_{t_m} = \mathcal{M}_m s_{t_m} + V_{t_m}$$

$$X_{t_m} = \mu + \Lambda Y_{t_m} + e_{t_m}$$

In the section that follows, we discuss which data we use as non-modeled monthly variables (X_{t_m}) and as observable variables in the DSGE model (Y_{t_m}) to make further empirical estimates.

4. Data

For the DSGE-m calculations, we use a large dataset of time series spanning from 2003 Q1 to 2023 Q2. The list of variables is presented in Table B1 in Appendix B. The model uses two types of observable variables: *modeled* and *non-modeled*.

The modelled variables are those whose dynamics are determined by the quarterly DSGE model[30]. Of the 22 observable variables used by *Kreptsev and Seleznev (2017)* to estimate the model parameters, 12 are included in DSGE-m. This is due to several reasons. First, some variables are not available over the entire time span under review, particularly the four observable variables related to the banking sector. Second, DSGE-m may struggle to determine unobservable state variables for a part of observable variables. For instance, the variables for exchange rate growth and reserve changes are static and are excluded from the model as we transform it to the mixed-frequency representation. Lastly, we do not include the GDP deflator and its components during the work with the mixed-frequency model, as we consider them less relevant for nowcasting Russia's real GDP growth. Whenever DSGE-m allows for the use of monthly observations, we prefer to use monthly rather than quarterly variables when possible, including domestic and global money market rates, consumer price indices, real wages, and oil prices.

The non-modeled variables include observable variables linked to the model's core variables through equation (12) to improve nowcast accuracy. The selection of indicators is based on several considerations.

First, we draw upon previous research in nowcasting Russia's GDP. Most studies use similar sets of variables[31], including indicators from Rosstat's real-time monthly bulletins on the Russian economy, closely tied to GDP (*hard variables*); surveys from real sector firms reflecting business sentiment and short-term plans (*soft variables*); and domestic financial market indicators signaling emerging macroeconomic trends (*financial variables*).

Second, we focus on monthly indicators whose statistics are released quickly within a quarter, thus improving the accuracy of GDP nowcasts.

[30] Using the notation from Section 3, the modelled variables are included in the vector Y_{t_m}.

[31] It's important to note that we rely on variables calculated by third parties and do not use our own proprietary indicators. Among these, a significant category is information environment indicators, which are calculated by evaluating the sentiment of news items. *Yakovleva (2018)* was the first to construct and apply such indices for macroeconomic forecasting in the context of the Russian economy. However, *Makeeva et al. (2024)* observed that their calculated news index did not improve the accuracy of Russia's GDP nowcasts when using common econometric models, such as MIDAS, MF-VAR, and DFM.

Third, we use variables with long historical data, as the estimation method for the parameters of bridge equation (12) requires a balanced data panel.

We also address several additional aspects of the data used.

Before calculations, we seasonally adjust[32] the observable variables. In most cases[33], we independently remove the seasonal component using the X-13 ARIMA-SEATS method. Importantly, when assessing the accuracy of pseudo-real-time nowcasts for Russia's GDP, we re-estimate the seasonal component each time new data arrives, rather than removing it in advance using the full dataset[34]. This approach prevents seasonal adjustment algorithms from “looking ahead” when working with a limited data set, better simulating real-time forecasting.

However, like most other studies, our calculations do not use historical data vintages. Instead, all historical data is as of early September 2023. As a result, we overlook the fact that statistical agencies frequently revise the retrospective dynamics of real sector indicators, such as national accounts and real wages. While *Mamedli and Shibitov (2021)* highlight the potential upward bias in pseudo-real-time forecasts when applied to the Russian economy, we focus not on the absolute forecasting error of DSGE-m but on its relative performance compared to competing and benchmark models under the same conditions. From this perspective, ignoring vintage data does not distort our key findings.

Unlike *Kreptsev and Seleznev (2017)*, who used the US GDP deflator to estimate parameters of the quarterly DSGE model, we use the consumer price index, as it is available on a monthly basis. For the external economy, total external output is represented by household consumption.

Following *Giannone et al. (2016)*, we transform the non-modeled variables to ensure stationarity. The simulated variables are transformed to match the unobservable state variables s_{t_m} associated with them. We use three types of transformation (with $z_{i,t}$ as the initial value of the observable variable):

1. No transformation: $z_{i,t}$, applicable to money market interest rates in Russia and abroad.

2. Log percentage growth: $z^*_{i,t} = 100 \cdot [ln(z_{i,t}) - ln(z_{i,t-1})]$. For simulated variables, this transformation is applied to consumer price indices, real wages, system of national accounts indicators, and oil prices. For non-modeled series, this applies to hard variables, stock indices, and foreign currency reserves.

3. Absolute change: $z'_{i,t} = z_{i,t} - z_{i,t-1}$. This transformation is applied to soft variables (survey data).

In line with *Giannone et al. (2016)*, we also apply quarterly transformations[35] to observable variables to capture dynamics over a moving quarter, following the rules outlined by *Mariano and Murazawa (2003)* and *Giannone et al. (2008)*:

[32] See the *Seasonality Test and Removal* column in Table B1 in Appendix B.
[33] For the main variables, we do not perform our own seasonality adjustment for the Russian consumer price index (CPI). Instead, we rely on the estimates provided by the Bank of Russia (https://cbr.ru/statistics/ddkp/aipd/). Similarly, for US GDP and inflation, we use the seasonally adjusted values from the respective US statistical agencies. As for the non-modelled variables, we do not remove seasonality from the Bank of Russia’s business survey data. Instead, we use the seasonally adjusted values provided by the pollster. This approach ensures consistency and comparability with the external datasets, without introducing our own adjustments.
[34] This procedure is applied to all variables, with the exception of those listed in Footnote 41.
[35] For details, see Section 3.2.

1. Variables without transformation are measured as a moving quarterly average: $\frac{1}{3}\left(z_{i,t}+z_{i,t-1}+z_{i,t-2}\right)$.

2. Variables measured as log percentage growth are converted to moving quarterly growth rates: $\frac{1}{3}\left(z^*_{i,t}+2z^*_{i,t-1}+3z^*_{i,t-2}+2z^*_{i,t-3}+z^*_{i,t-4}\right)$.

3. Variables measured as absolute changes are transformed into the absolute change over the moving quarter: $\frac{1}{3}\left(z'_{i,t}+2z'_{i,t-1}+3z'_{i,t-2}+2z'_{i,t-3}+z'_{i,t-4}\right)$.

The non-modeled variables are then normalized, so that each indicator has a sample mean of zero and a sample variance of one.

Finally, regarding publication lags, most of our time series provide relatively up-to-date information on the economy's current state. Specifically, the information on all non-modeled variables lags no more than two months behind the present, with about half of the indicators no more than one month behind.

In the next section, we estimate the DSGE-m parameters using the described dataset.

5. Estimation

In DSGE-m, we use the system of equations including the state equation (4), observation equation (11), and equation (12), which describes the relationship between the dynamics of modelled and non-modelled variables:

$$s_{t_m}=\mathcal{T}_m s_{t_m-1}+\mathcal{B}_m\varepsilon_{m,t_m}$$

$$Y_{t_m}=\mathcal{M}_m s_{t_m}+V_{t_m}$$

$$X_{t_m}=\Lambda Y_{t_m}+e_{t_m}$$

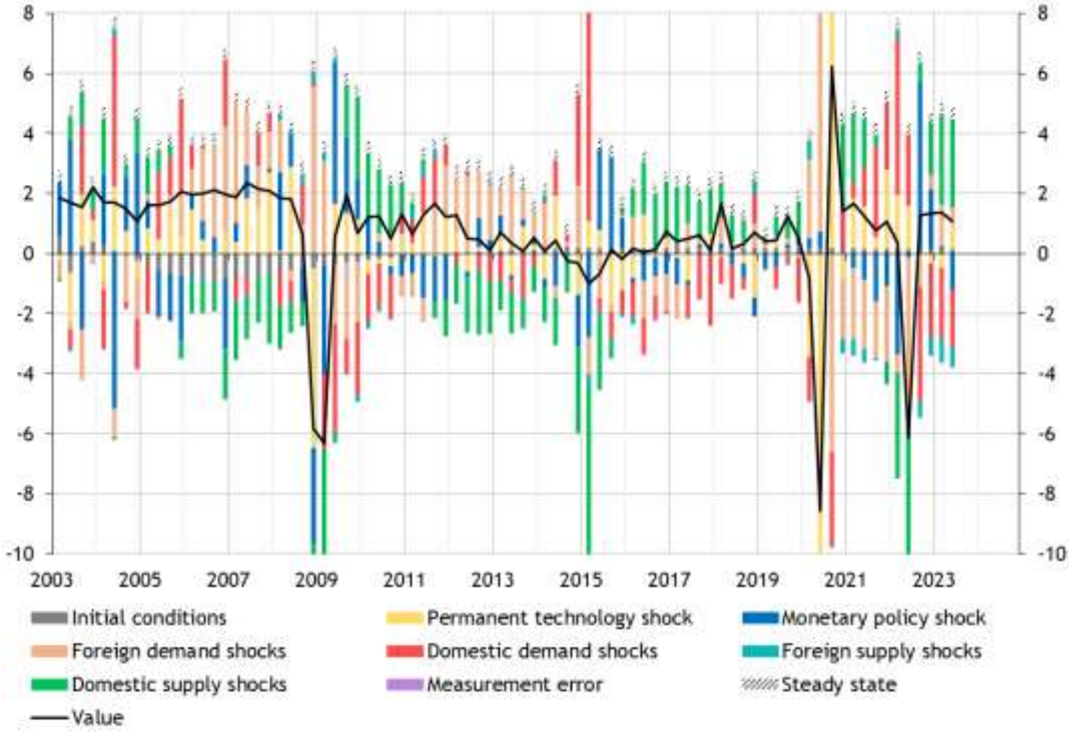
The parameters of equation (12) are estimated using the OLS on a balanced panel of macroindicators covering 2003 Q1–2023 Q2[36]. Using known matrices $\mathcal{T}_m$, $\mathcal{B}_m$ and $\mathcal{M}_m$, the model is specified in a state-space form (see Diagram C1, Appendix C) and estimated via the Kalman filter and smoother to obtain estimates of unobservable variables (s_{t_m}), measurement errors (V_{t_m}), idiosyncratic components (e_{t_m}), and structural shocks (ε_{m,t_m}).

The estimates of the structural shock are presented in Figure C1, Appendix C. The results show that crisis episodes during 2008–2009, 2014–2015, 2020–2021, and 2022–2023 are marked by significant fluctuations in long-term supply, negative external oil price shocks, and risk premiums, along with domestic demand surges from households[37] and the government[38]. These fluctuations, along with short-term supply declines, explain the tightening[39] and subsequent easing of monetary policy during these periods. The estimated structural shocks help explain the dynamics of the modelled variables (Figure C2, Appendix C)[40], such as GDP, inflation, interest rates, and oil prices. Fluctuations in Russian exports are mainly driven by external shocks, while GDP (Figure 1), domestic demand components (consumption, investment, government spending) and real wages reflect the impact of long-

[36] The elements of these matrices are determined by the DSGE structural parameters, which we calibrate using the Bayesian estimates of the quarterly DSGE model estimated by *Kreptsev and Seleznev (2017)*.
[37] The exceptions are the early phase of the 2020 pandemic crisis and the second half of 2022.
[38] The only exception is the 2014–2015 crisis, which is marked by budget consolidation.
[39] The exception is the 2020–2021 crisis, when monetary policy was broadly consistent with the model recommendations based on the Taylor rule.
[40] Hereinafter, for ease of understanding, we group structural shocks according to the classifications established in Table C2 in Appendix C.

term technology shocks[41]. Periods of rapid inflation before inflation targeting are associated with loose monetary policy, and inflation spikes in 2014–2015 and 2022 were triggered by temporary supply contractions amid elevated domestic demand[42]. The sustainably high growth of consumer prices before inflation targeting is to a large degree explained by the loose monetary policy. In line with the assumptions introduced[43], the fluctuations in the modelled variables are overall fully explained within the scope of the model (Table C1, Appendix C), since each of these variables is associated with a corresponding unobservable variable in the model.

Figure 1. Decomposition of Russia's GDP growth (% QoQ change, seasonally adjusted) into structural shocks



Note. Structural shocks are grouped according to the classification presented in Table C2, Appendix C.

Source: author's calculations.

While DSGE-m explains the dynamics of modelled variables well, non-modelled variables – introduced to enhance nowcasting accuracy – are only partially explained by the model (see Table 1, Table C1 in Appendix C). About 55% of the variance in these auxiliary variables comes from idiosyncratic shocks, which are independent of macroeconomic signals. Hard variables, reflecting the real economy, are more informative, with 68% of their variance explained, especially in sectors like consumer goods and industrial production. The

[41] Similar to the *Kreptsev and Seleznev (2017)* model, the equilibrium steady-state growth rate for both the domestic and global economies is calibrated at 1.5% per year. The remaining parameters – such as the equilibrium rate, target inflation rate, and equilibrium growth rate of oil prices – are also aligned with the authors' assumptions.

[42] The positive demand shocks and their offsetting contribution to the GDP decline between late 2014 and early 2015 are supported by estimates from *Lomonosov et al. (2020)*, which are based on a BVAR structural model without distinguishing between internal and external shocks. Additionally, *Novak and Shulgin (2020)* identify the positive contribution of intertemporal consumer preference shocks to inflation and the GDP gap in Q1 2015 using a New Keynesian model of a small open export-oriented economy with incomplete financial markets. This finding is further corroborated by the DSGE model with three groups of households presented by *Vikharev et al. (2023)*.

[43] See equation (11) in Section 3.2.

explanatory power of these variables has increased post-2020. Survey-based soft variables explain less variance, with roughly 70% of their volatility due to noise. However, business sentiment surveys, particularly those from the Bank of Russia, offer useful insights with a 54–59% variance explained. Financial market indicators display noise levels comparable to other non-modelled variables, with foreign currency reserves having the least noise, partially due to their inclusion in the quarterly DSGE model.

Table 1. The share of variance in non-modelled variables explained within the model

	Hard	**Soft**	**Financial**	**All non-modelled variables (in average)**
Full sample (2003 Q1 – 2023 Q2)	0.68	0.29	0.39	**0.45**
Short sample (2003 Q1 – 2019 Q4)	0.45	0.31	0.43	**0.40**

Notes: Hard represents indicators included in monthly statistical reports on the state of the Russian real sector; *Soft* denotes real sector survey data; *Financial* stands for domestic financial market indicators (for more details, see Table B1, Appendix B). The share of explained variance is calculated as the coefficient of determination (R^2) in a pairwise linear regression of the actual variables on their in-sample projections using DSGE-m.

Source: author's calculations.

The historical decomposition of these non-modelled variables using DSGE-m offers insights into the macroeconomic shocks that affect monthly indicators (Figures C3–C5, Appendix C). However, due to the reduced-form nature of their modeling, a structural interpretation of their fluctuations is limited. For example, monetary policy shocks sometimes appear contractionary due to potential misestimated coefficients, such as the case with stock indices in 2022–2023. This limitation underscores the challenges in fully explaining high-frequency data within DSGE-m. Despite this, historical decompositions provide valuable insights into the relationship between monthly indicators and macroeconomic shocks, which is critical for real-time GDP nowcasting.

In the next section, we will compare the accuracy of DSGE-m nowcasts with alternative forecasting methods.

6. Assessment of forecasting performance

6.1. Outline of the procedure

We generate a series of out-of-sample forecasts for Russia's GDP growth for the current[44] quarter across all models under consideration. The training sample consists of a balanced panel of macroindicators, encompassing data from Q1 2003 to Q4 2016. The changes in the variables from Q1 2017 to Q2 2023 are utilized as the test sample[45]. Each

[44] We focus exclusively on forecasting the current quarter because, as outlined in the methodology of *Giannone et al. (2016)*, the inclusion of high-frequency indicators in DSGE-m does not significantly influence the changes in unobservable variables or shocks beyond the current quarter. *Červená and Schneider (2014)* demonstrate that the accuracy of GDP forecasts for one quarter ahead, under these assumptions, is comparable to that of the quarterly DSGE model.
[45] The lower bound of the test sample is determined by the fact that the parameters of equations (1) and (2) were estimated by *Kreptsev and Seleznev (2017)* using data through 2016. Consequently, this model has already been trained on the dataset available up to 2017.

quarter, we re-estimate the parameters[46] of the models following the release of flash data for Russia's GDP, adhering to the publication lag detailed in Table B1 of Appendix B.

To align with practical conditions for GDP nowcasting, we perform pseudo-real-time forecasts across all models under study. This approach accounts for the lag in data publication across various variables (reflecting the order of statistical releases) but does not utilize vintage data (the values of the variables at the initial point in time before statistical agencies update them)[47].

Each time we nowcast GDP for a specific quarter, we conduct four forecast iterations at the following points in time (see Table B2, Appendix B):

1. **End of the first month of the current quarter (1M Q0)**. Due to data publication lags, only non-modelled domestic financial market indicators, oil prices, and interbank rates are available for the current quarter.

2. **End of the second month of the current quarter (2M Q0)**. This month provides the most information on hard variables for the first month of the current quarter, as well as data on Russia's GDP for the previous quarter.

3. **End of the third month of the current quarter (3M Q0)**. At this point, full current quarter data on monthly domestic financial market indicators, oil prices, and interbank market rates have been released. We also gain access to newly released data on changes in the components of GDP for the previous quarter.

4. **End of the first month of the next quarter (1M Q1)**. Since data on Russia's GDP for the forecast quarter is still unavailable, we conduct not only nowcasting but also backcasting, which involves forecasting GDP for the previous quarter. This is when we receive complete quarterly information on changes in real sector indicators (hard variables), certain survey data (soft variables) for the last month of the forecast quarter, and US GDP data for the past quarter.

In each iteration, all competing models utilize the same information set available at that specific time, allowing us to compare the accuracy of the nowcast estimates.

6.2. Forecast accuracy metrics

We use the root mean square forecast error (RMSFE) to measure the accuracy of the quarterly GDP growth forecasts:

$$RMSFE = \sqrt{\frac{1}{T-\tau+1}\sum_{t=\tau}^{T} e_t^2} = \sqrt{\frac{1}{T-\tau+1}\sum_{t=\tau}^{T}\left(GDP_t - \widehat{GDP_t}\right)^2}, \tag{13}$$

where GDP_t is the actual GDP growth for the quarter; $\widehat{GDP_t}$ is the out-of-sample forecast; T is the sample length (82 quarters in our case, from 2003 Q1 to 2023 Q2), and τ is the initial period of the test sample (2017 Q1).

In addition to obtaining point estimates of the RMSFE, we test for significant differences in forecast accuracy between the models using the *Diebold and Mariano (1995)* test. The test's decision statistics are adjusted for small sample sizes (*Harvey et al., 1997*). The null hypothesis is that there are no differences in forecast error between the two models being compared, while the alternative hypothesis varies depending on the type of test:

$H_0: E[{e_1}^2 - {e_2}^2] = 0$

$H_a: E[{e_1}^2 - {e_2}^2] \neq 0$ (in the case of a two-sided test)

[46] The re-estimation does not pertain to the deep DSGE parameters, which we calibrate based on the estimates provided by *Kreptsev and Seleznev (2017)*.

[47] We disregard vintage data for the reasons outlined in Section 4.

$H_a: E[{e_1}^2 - {e_2}^2] > 0$ (in the case of a one-sided test)

where e_1, e_2 represent the forecast errors in models 1 and 2, respectively.

Similar to *Itkonen and Juvonen (2017)* and *Kuck and Schweikert (2021)*, we also analyze, in addition to accuracy, the mean forecast error (MFE), calculated as follows:

$$MFE = \frac{1}{T-\tau+1}\sum_{t=\tau}^{T} e_t = \frac{1}{T-\tau+1}\sum_{t=\tau}^{T}\left(GDP_t - \widehat{GDP}_t\right), \quad (14)$$

The proximity of this indicator to zero suggests that the forecast is not systematically biased (i.e., there is no upward or downward bias) relative to the actual GDP growth. To draw statistical conclusions for each of our models, we test the hypothesis that the average forecast error is equal to zero using a two-sided t-test:

$H_0: E(e_t) = 0$

$H_a: E(e_t) \neq 0$

6.3. Competing models

We compare the accuracy of DSGE-m GDP forecasts with alternative econometric strategies that researchers consider reliable candidates for potential nowcasting tools: dynamic factor models (DFM) and mixed-frequency factor regression (FA-MIDAS). We also use several benchmark models, including a univariate autoregression (AR), a univariate autoregression with an exogenous variable (AR-X), and a random walk (RW) model.

6.3.1. DSGE model without the panel of non-modelled variables (DSGE-mnp)

In addition to the models discussed above, we use a mixed-data-frequency DSGE model that does not include a panel of non-modeled variables X_{t_m}. As shown in Section 2.2, the model in this case consists of equations (4) and (11):

$$s_{t_m} = \mathcal{T}_m s_{t_m-1} + \mathcal{B}_m \varepsilon_{m,t_m}$$

$$Y_{t_m} = \mathcal{M}_m s_{t_m} + V_{t_m}$$

without equation (12):

$$X_{t_m} = \Lambda Y_{t_m} + e_{t_m}$$

Hereinafter, we compare the accuracy of nowcasts of Russian GDP based on this model with the baseline model (DSGE-m) to assess the role of non-modeled variables in improving forecast accuracy.

6.3.2. Dynamic factor model (DFM)

We use a static factor model, which takes the following state-space form:

$$Y_t = \Lambda F_t + \xi_t, \quad \xi_t \sim i.i.d.N(0, \Sigma) \quad (15)$$

$$F_t = A_1 F_{t-1} + \cdots + A_p F_{t-p} + u_t, \quad u_t \sim i.i.d.N(0, Q) \quad (16)$$

where Y_t is an $N \times 1$ vector of the pre-normalized observable variables, F_t is an $r \times 1$ vector of the unobservable components (factors), ξ_t is an $N \times 1$ vector of the normally distributed, uncorrelated idiosyncratic shocks with a diagonal covariance matrix Σ, u_t is a $q \times 1$ vector of normally distributed reduced shocks with covariance matrix Q, Λ is an $N \times r$ matrix of factor loadings, and $A_1 \ldots A_r$ are $r \times r$ matrices of the coefficients of the autoregressive dynamics of the unobservable factors.

We estimate the unobservable factors and parameters of this model using the two-stage method described by *Giannone et al. (2008)* and *Doz et al. (2011)*.

In the first stage, we compute the values of the static factors $\widehat{F}_t$ using principal component analysis applied to the balanced panel $\overline{Y}_t$. We then use the least squares method to estimate the parameters of equations (15) and (16), and calculate estimates for the idiosyncratic components $\widehat{\xi_t} = Y_t - \widehat{\Lambda}\widehat{F_t}$ and the shocks $\widehat{u_t} = \widehat{F_t} - \widehat{A_1}\widehat{F_{t-1}} - \cdots - \widehat{A_p}\widehat{F_{t-p}}$.

In the second stage, the estimates of parameters and factors obtained in the first stage are used to produce the final estimates and forecast values of the unobservable components based on the complete (unbalanced) panel Y_t using the Kalman smoother.

It is important to note that, before parameterizing the model, we apply quarterly transformations to all the observable variables[48]. GDP growth ($\hat{y}_{t+h}$) is estimated using the bridge equation, a regression on predicted factor values $\widehat{F_{t+h}}$ (bridging with factors):

$$\hat{y}_{t+h} = \widehat{\beta_0} + \hat{\beta}\widehat{F_{t+h}}, \tag{17}$$

where the parameters $\widehat{\beta_0}$ and $\hat{\beta}$ are estimated by least squares regression.

The model parameters in equations (15) – (17) are re-estimated each quarter following the release of new GDP data. We choose the number of static unobservable factors r, the number of shocks q, and the lag length p based on the information criterion of *Bai and Ng (2002)* for r and q, and the Bayesian information criterion (BIC) for p. During the robustness check, we estimate the accuracy of GDP nowcasts based on models with different values of r, q and p (see Table D2, Appendix D), testing 36 specifications.

6.3.3. Mixed-frequency factor regression (FA-MIDAS)

Similar to DFM, this model enables the forecasting of a low-frequency variable (GDP growth, in our case) using information from higher-frequency indicators. To achieve this, we apply the FA-MIDAS regression proposed by *Marcellino and Schumacher (2010)*. This model employs static factors ($\hat{f}_{t_m}$) as regressors, which are estimated and projected based on the DFM. In our case, the model takes the form:

$$y_{t_q+h_q} = y_{t_m+h_m} = \beta_0 + \beta_1 b\left(L_m, \vec{\theta}\right)\hat{f}_{t_m}^{(3)} + \varepsilon_{t_m+h_m}, \tag{18}$$

where $b\left(L_m, \vec{\theta}\right) = \sum_{k=0}^{K} c\left(k, \vec{\theta}\right) L_m^k$, and L_m is the lag operator ($L_m f_{t_m} = f_{t_m-1}$).

As in several studies on forecasting Russia's GDP *(Mikosch and Solanko, 2019; Zhemkov, 2021; Makeeva and Stankevich, 2022)*, we use two types of weighting functions:

1) Exponential Almon:

$$c\left(k, \vec{\theta}\right) = \frac{\exp(\theta_1 k + \cdots + \theta_Q k^Q)}{\sum_{k=0}^{K} \exp(\theta_1 k + \cdots + \theta_Q k^Q)},$$

2) Non-exponential Almon:

$$c\left(k, \vec{\theta}\right) = \sum_{k=0}^{K} (\theta_1 k + \cdots + \theta_Q k^Q).$$

Following the approaches of *Clemens and Galvão (2008, 2009)*, *Kuzin et al. (2011)*, and *Schumacher (2016)*, we use weighting functions with two parameters (θ_1 and θ_2). To ensure comparability with other studies focused on forecasting Russia's GDP (e.g., *Zhemkov, 2021*), the regressor in all MIDAS specifications is the first unobservable factor estimated via the DFM, which explains the largest share of variance in the observable variables.

We do not use lags of the predictor variable in any FA-MIDAS specification for several reasons. First, studies have shown that including a GDP growth lag can reduce forecast accuracy (*Stankevich, 2020; Zhemkov, 2021*), partly because early GDP estimates in real-time forecasting are preliminary and are later revised by statistical agencies (e.g., due to gradual revisions of seasonally adjusted growth estimates over time). Second, in pseudo-

[48] To nowcast Russian GDP using the DFM and FA-MIDAS models, we employ the same set of variables as in the DSGE-m model (see Table B1, Appendix B).

real-time GDP nowcasting, lags cannot be applied to projections for the first month of the current quarter[49] because GDP data for the previous quarter is unavailable at that time.

The procedure for out-of-sample GDP forecasting using FA-MIDAS is as follows:

1) *Data preparation*: Create a dataset of the information available at a specific time.
2) *Factor estimation*: Use DFM (with r factors and p autoregressive lags), to estimate unobservable factors ($\hat{f}_{t_m}$).
3) *FA-MIDAS regression*: Estimate a pool of FA-MIDAS regressions using the non-linear least squares method. Models include up to 12 lags of the monthly factor values and one of the two weight functions, resulting in 24 specifications.
4) *Model selection*: Choose the specification with the lowest Bayesian Information Criterion (BIC).
5) *GDP projection*: Estimate current-quarter GDP growth based on the selected specification.

This process results in 36 FA-MIDAS specifications, depending on the DFM used in the first step. For each specification, we assess the accuracy of the quarterly GDP projections (see Table D3 in Appendix D). As the main model, we present the results of the regression where unobservable factors are estimated using a DFM with two unobservable factors and six autoregressive lags in the state equation (16).

6.4. Benchmark models

In addition to the competing models, we employ several benchmark models. Unlike the advanced models discussed earlier, these benchmarks project GDP with minimal assumptions and limited reliance on high-frequency data. They serve as a straightforward reference point, offering clear evidence of the relative performance of advanced econometric nowcasting strategies. A detailed description of these benchmark models is provided below.

6.4.1. Univariate autoregression (AR)

Using GDP data, we estimate the parameters of the following model:

$$y_t = \mu + \sum_{p=1}^{P} a_p y_{t-p} + \varepsilon_t, \tag{19}$$

where μ and $a_1, \dots a_p$ are the parameters to be estimated.

The parameters of the AR process are re-estimated each quarter as new GDP data becomes available. To evaluate forecasting accuracy, we consider models with up to six lags (see Table D6, Appendix D) and use the AR(1) forecast estimates as the primary model.

6.4.2. Univariate Autoregression with Exogenous Variables (AR-X)

Unlike the AR(p) model, this specification incorporates an independent variable, x_t:

$$y_t = \mu + \sum_{p=1}^{P} a_p y_{t-p} + \beta x_t + \varepsilon_t \tag{20}$$

Following *Gareev and Polbin (2022)*, we include Urals oil prices as the exogenous variable x_t and use the growth of this indicator over the moving quarter. When new oil price data becomes available, we extrapolate the most recent value to the end of the quarter and update our GDP forecast accordingly.

As in the AR model, to evaluate forecast accuracy, we consider specifications with up to six lagged values of quarterly GDP growth (see Table D6, Appendix D). The one-lag specification is used as the primary model for forecasting.

[49] In our tables and figures, this period is labelled as “1M Q0”.

6.4.3. Random walk model (RW)

This model assumes that GDP growth in the next quarter equals the growth in the previous quarter, subject to forecast error:

$$y_t = y_{t-1} + \varepsilon_t \tag{21}$$

The forecast from this model serves as the simplest benchmark for evaluating the quality of competing models. It is also used, in particular, to calculate the relative RMSFE (see *Section 6.5* below).

6.5. Results

The accuracy estimates for the key model specifications are presented in Table 2 and Figure D1 (Appendix D). To ensure the robustness of the key results, we conduct a similar accuracy assessment using alternative specifications of the competing and benchmark models (Tables D2, D3, and D6, Appendix D).

Since forecasting is performed in pseudo-real time, we focus on analyzing the relative, rather than absolute, nowcast errors of the models. For each calculation of the relative RMSFE, the divisor is the RMSFE estimate from the random walk (RW) model:

$$RMSFE_{relative,i} = \frac{RMSFE_i}{RMSFE_{RW}} \tag{22}$$

A relative RMSFE value of less than one indicates that model i performs better than the RW model, while a value greater than one indicates worse performance.

To draw statistical conclusions about the point estimates of the RMSFE, we test the equality of the models' predictive abilities using the Diebold–Mariano test (*Diebold and Mariano, 1995*). The results of the pairwise tests of the models' predictive abilities are summarized in Table D1 (Appendix D). If the null hypothesis is not rejected for both two-sided and one-sided tests, we conclude that the forecasting power of the compared models is equal.

We also analyze the mean forecast error (MFE) of the models under study (see Table 3 and Figure D2, Appendix D). A positive (negative) MFE value indicates that the model, on average over the test sample, underestimates (overestimates) GDP growth in the forecast quarter. As with the RMSFE, we statistically test the resulting MFE estimates using a two-sided t-test for zero mean forecast error, as described in Section 5.2. This test is conducted not only for the main models, but also for the alternative model specifications (Tables D4, D5, and D7, Appendix D).

The results lead to several important conclusions:

1. Inclusion of non-modeled variables in DSGE models improves GDP nowcast accuracy.

Statistical tests reveal that by the end of the second month of the current quarter — when most monthly data for the first month of the forecast quarter are available — GDP projections from the DSGE-m model are more accurate than those from DSGE-mnp. This finding corroborates previous studies on GDP nowcasting using DSGE models incorporating high-frequency variables (*Červená and Schneider, 2014; Giannone et al., 2016; Meyer-Gohde and Shabalina, 2022*).

As more monthly data become available, the GDP forecast error in DSGE-m steadily decreases, whereas in DSGE-mnp, it remains relatively constant throughout the quarter, improving only after the forecast quarter ends when data for key variables are updated[50].

[50] Our additional calculations (including Figure D3, Appendix D) indicate that nearly the entire reduction in the RMSFE for the DSGE-mnp model can be attributed to the earlier release of US GDP data compared to Russia's

On average, forecasts from DSGE-m are 41% more accurate than those from DSGE-mnp, which corresponds to a 1 percentage point (pp) reduction in GDP nowcast error when additional variables are included in the DSGE model.

While the MFE in DSGE-m deviates more significantly from zero compared to DSGE-mnp, t-tests indicate that neither model exhibits statistically significant expected forecast errors.

2. The accuracy of GDP nowcasts in DSGE-m is comparable to DFM and FA-MIDAS, but DSGE-m does not show any systematic forecast error.

Although point estimates of RMSFE are higher for DSGE-m during the first two months of the quarter, the Diebold-Mariano test does not reject the hypothesis that DSGE-m nowcasting accuracy is comparable to that of DFM and FA-MIDAS. Moreover, DSGE-m demonstrates significantly higher accuracy in backcasting compared to these models.

The robustness of this conclusion is supported by the fact that the RMSFE estimates for the main DFM and FA-MIDAS models are lower than those for alternative specifications under consideration. Despite upward biases in GDP growth estimates observed in FA-MIDAS and DFM, DSGE-m emerges as the preferred model for GDP nowcasting.

Beyond accuracy, DSGE-m enables real-time analysis of macroeconomic shocks and their relationships with GDP fluctuations and other variables, providing an additional advantage.

3. Models utilizing high-frequency variables (DSGE-m, DFM, FA-MIDAS) outperform benchmark models in GDP nowcasting accuracy.

This finding aligns with most studies[51] that leverage real-time indicator panels to enhance nowcast accuracy. Statistically, DSGE-m, DFM, and FA-MIDAS all outperform the random walk (RW) model starting at the end of the first month of the forecast quarter. FA-MIDAS, in particular, demonstrates significantly better accuracy than AR-X and AR models.

By the end of the second month, DSGE-m significantly outperforms the AR model, while DFM surpasses AR-X. At the end of the third month, DSGE-m consistently demonstrates superior forecasting power compared to all benchmark models.

On average, GDP growth forecasts from DSGE-m are 1.5 times more accurate than those from benchmark models, with a 1.6 pp lower nowcast error. Notably, FA-MIDAS occasionally outperforms DFM, likely due to the informational advantage of regression models based on mixed-frequency data.

GDP during the acute phase of the 2020 crisis. At that time, most economies, including Russia, experienced a contraction in Q2 2020 followed by a rapid recovery in Q3 2020.

[51] See the Introduction for details.

Table 2. Relative Root Mean Squared Forecast Error (RMSFE) of Russia's Quarterly GDP Growth (2017 Q1 – 2023 Q2)

Model	Nowcast			Backcast
	1M (Q0)	2M (Q0)	3M (Q0)	1M (Q1)
DSGE-m	0.67	0.44	0.24	0.21
DSGE-mnp	0.76	0.70*	0.71**	0.41*
DFM	0.56	0.25	0.32	0.31*
FA-MIDAS	0.38	0.24	0.25	0.24*
AR-X	0.64	0.59	0.62**	0.62**
AR	0.74	0.81**	0.81**	0.81*
RW	1.00*	1.00**	1.00**	1.00**

Notes: Q0 represents the current quarter, while Q1 refers to the next quarter.
1M, 2M, and 3M indicate the end of the first, second, and third months, respectively.
Results for each model are shown relative to the RMSFE of the RW model. A value less (more) than one indicates that the model performs better (worse) than the RW model.
*(**) indicates that the RMSFE of the model in the row exceeds the RMSFE of DSGE-m at the 10% (5%) significance level.
Detailed results of statistical tests comparing the RMSFE of the models are provided in Table D1, Appendix D.

Source: author's calculations.

Table 3. Mean Forecast Error (MFE) of Russia's Quarterly GDP Growth (2017 Q1 – 2023 Q2)

Model	Nowcast			Backcast
	1M (Q0)	2M (Q0)	3M (Q0)	1M (Q1)
DSGE-m	0.38	0.33	0.12	-0.15
DSGE-mnp	0.05	0.06	0.08	0.04
DFM	-0.03	-0.15	-0.39	-0.48**
FA-MIDAS	-0.44	-0.40**	-0.34*	-0.38**
AR-X	-0.27	-0.20	-0.20	-0.20
AR	-0.15	-0.06	-0.06	-0.06
RW	0.06	0.01	0.01	0.01

Notes: Q0 denotes the current quarter, while Q1 refers to the next quarter.
1M, 2M, and 3M indicate the end of the first, second, and third months, respectively.
*(**) signifies a deviation of the MFE from zero based on a two-sided t-test for zero mean forecast error at the 10% (5%) significance level.

Source: author's calculations.

7. Conclusion

This study aims to enhance the accuracy of DSGE models in forecasting Russian GDP. The analysis is based on the small open export-oriented economy model developed by *Kreptsev and Seleznev (2017)*, part of the Bank of Russia's macroeconomic forecasting toolkit. Following the methodology proposed by *Giannone et al. (2016)*, we adapt the original model — constructed using quarterly data — for applications with mixed-frequency data. Additionally, the model is augmented with a panel of non-modelled monthly indicators that reflect the current state of the Russian economy. This enhanced model, referred to as DSGE-m, is employed for real-time nowcasting of Russian GDP growth within the current quarter. Using an out-of-sample pseudo-real-time forecasting procedure, we evaluate the predictive performance of DSGE-m against a range of widely adopted empirical nowcasting methods. This comparison highlights DSGE-m's utility as a nowcasting tool within the broader context of macroeconomic forecasting.

Consistent with findings in prior research, this study demonstrates that incorporating high-frequency data into a DSGE model significantly enhances the accuracy of Russia's GDP projections. This improvement is evident even when comparing DSGE-m to benchmark models such as AR-X, AR, and RW, where DSGE-m consistently outperforms in terms of forecast accuracy. Furthermore, DSGE-m's forecasting power is shown to be on par with advanced nowcasting methods like FA-MIDAS and DFM. This result underscores the model's effectiveness in leveraging high-frequency information to provide robust and reliable GDP nowcasts.

Furthermore, we rely on DSGE-m to conduct an econometric analysis of the panel of non-modeled variables to improve the accuracy of Russia's GDP nowcasts.

First, we examine the extent to which fluctuations in these indicators are driven by macroeconomic shocks. During the period under study (2003 Q1–2023 Q2), an average of 45% of the variance in the monthly indicators is attributable to economically meaningful causes, while the remaining fluctuations (noise) carry no information about changes in the key macrovariables. The robustness of this estimate is confirmed through a short sample excluding the crises of 2020 and 2022. The most informative indicators, in terms of broad macroeconomic trends, are those related to the real sector (68% of the explained variance), which most directly reflect ongoing trends in various sectors.

Second, we demonstrate that the explained portion of the fluctuations in the non-modelled variables can be aligned with structural shocks, which is a notable advantage of DSGE-m compared to the empirical models in their current form. Several limitations of our approach are outlined by *Giannone et al. (2016)*, which prevent a comprehensive structural analysis of the dynamics of the non-modelled variables.

It should be noted that the results of this study have certain limitations concerning short-term GDP forecasts, including those based on DSGE models.

First, a more thorough and accurate study of forecast accuracy would necessarily involve the use of data vintages, that is, the historical values of all the variables used, accounting for their gradual revisions. For this reason, this study focuses on a comparative analysis of the forecasting power of models and excludes the examination of absolute nowcast errors.

Second, we do not explore the applicability of the approach proposed by Giannone et al. (2016) as part of semi-structural models, which are used by central banks alongside DSGE models[52] for simulation, counterfactual analysis, medium-term scenario forecasting,

[52] See, in particular, the work of *Orlov (2021)*, which describes the Bank of Russia's Quarterly Projection Model.

and the formulation of stabilization policy recommendations. Nonetheless, we see no obstacles to applying our approach to this class of macroeconomic models.

Finally, the use of DSGE-m not only in GDP nowcasting but also in forecasting all major macroeconomic variables over longer-term horizons is outside the scope of this study, as is the analysis of macroeconomic policy effects. It is important to note that the approach of *Giannone et al. (2016)* that we employ is designed to ensure that the dynamics of DSGE-m fully align with those of the original DSGE-q model. *Červená and Schneider (2014)* rightly observe that coinciding dynamics are possible if the model does not include a stochastic trend. In our model, the stochastic trend is embedded in factor-wide productivity, which assumes permanent shocks and long-term changes in output and its components. This enables us to directly analyze observable GDP growth, the forecasting of which is the primary goal of this study. Given this limitation, we do not recommend using DSGE-m as the primary DSGE model for simulation analysis or medium-term scenario forecasting, but instead view it as a potential GDP nowcasting model that offers, in addition to acceptable forecast accuracy, a macroeconomic interpretation of the non-modelled auxiliary variables.

Ultimately, to further enhance the accuracy of short-term forecasts using DSGE models, the approach outlined in this paper can be applied to other models that incorporate these characteristics. Taking into account the noted limitations regarding the structural analysis of non-modeled indicators, this approach can be modified in future work. This leaves an ample room for further research.

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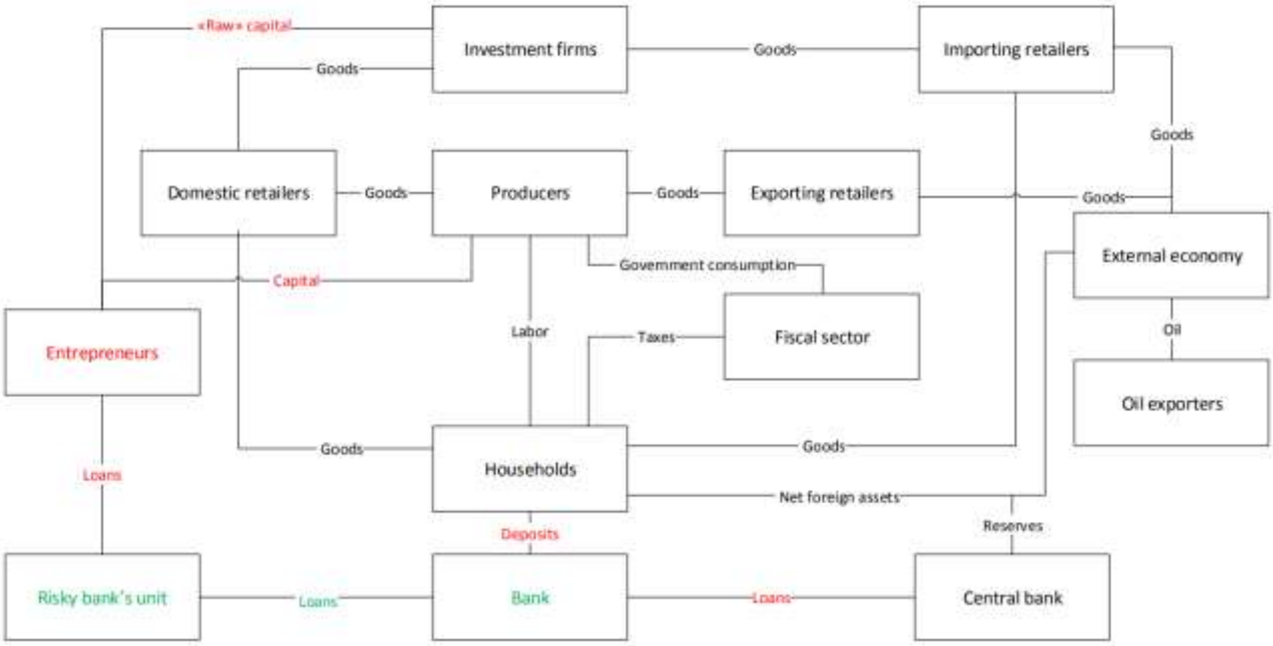
Appendix A

Figure A1. Structural scheme of the original DSGE model (DSGE-q)



Notes. The economic agents and connections added when the banking sector is included in the model are highlighted in color.

Source: *Kreptsev and Seleznev (2017)*.

Description of the model

It is assumed that various types of economic agents interact within a small open export-oriented economy, collectively driving changes in macroeconomic variables.

1. Households

The continuum of domestic households[53] maximizes expected discounted utility, which depends on two variables: consumption (C_t) and the number of working hours (l_t). Utility is also influenced by past consumption (hC_{t-1}), allowing the model to capture habits that drive a more persistent response of consumption to economic shocks. In maximizing utility, households encounter two types of shocks (see Table A1) that temporarily alter their preferences for labor (ζ_t^L) and consumption (ζ_t^C). The utility function of a representative domestic household is expressed as:

$$U_{j,t} = \mathbb{E}_t \sum_{i=0}^{\infty} \beta^i \left(\zeta_t^C \ln\left(C_{j,t+i} - hC_{t+i-1}\right) - \zeta_t^L \frac{l_{j,t+i}^{1+\phi}}{1+\phi} \right), \tag{A.1}$$

where β is the household's subjective discount factor; h is the parameter reflecting consumption habits; ϕ is the inverse of the Frisch elasticity of labor supply; $\frac{\zeta_t^C}{\zeta_{ss}^C} = \left(\frac{\zeta_{t-1}^C}{\zeta_{ss}^C}\right)^{\rho_{\zeta_C}} \exp\left(e_t^{\zeta_c}\right)$, $e_t^{\zeta_c}$ is the shock of domestic preferences; $\frac{\zeta_t^L}{\zeta_{ss}^L} = \left(\frac{\zeta_{t-1}^L}{\zeta_{ss}^L}\right)^{\rho_{\zeta_l}} \exp\left(e_t^{\zeta_l}\right)$, $e_t^{\zeta_l}$ is a labor supply shock.

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[53] In listing the variables, we omit indices for economic agents where they are not essential.

Households operate under a budget constraint that reflects the sources and uses of their income. Their income comprises: labor income ($W_t l_t$), interest income from domestic ($R_{t-1}B_{t-1}$) and foreign assets ($R_{t-1}^{NFA}\varepsilon_t B_{t-1}^*$), non-recurrent payments (Π_t) such as net tax and profits from the ownership of firms. The household allocates this income to consumption ($P_t C_t$) and savings ($B_t + \varepsilon_t B_t^*$). Households have monopolistic power in the labor market, enabling them to set wages. However, adjusting wages incurs menu costs, introducing nominal wage rigidity following the framework of *Rotemberg (1982)*. This rigidity is modeled by a quadratic cost function of wage adjustments. The budget constraint is therefore:

$$P_t C_{j,t} + B_{j,t} + \varepsilon_t B_{j,t}^* = W_{j,t} l_{j,t} + R_{t-1} B_{j,t-1} + R_{t-1}^{NFA}\varepsilon_t B_{j,t-1}^* + \Pi_{j,t} - \frac{k_w}{2}\left(\frac{W_{j,t}}{W_{j,t-1}e^{g_{w,ss_t}}} - (\pi_{t-1})^{\iota_w}(\pi_*)^{1-\iota_w}\right)^2 W_t l_t, \tag{A.2}$$

where P_t is the price level (price of one unit of consumption); ε_t is the nominal exchange rate; W_t is the hourly wage; k_w is the wage rigidity parameter; ι_w is the weight assigned to the backward-looking component in wage adjustments; π_* is the target inflation rate; and g_{w,ss_t} is the equilibrium wage growth.

2. Producers

Domestic producers create intermediate goods using labor (l_t) and production capital (K_t), which are leased from domestic households and entrepreneurs, respectively. he output of these producers is influenced by constant (A_t) and temporary (A_t^c) technological advances, adjusted for fixed costs:

$$Y_{j,t} = A_t A_t^c l_{j,t}^{\alpha} K_{j,t}^{1-\alpha} - \Phi(A_t)^{\frac{1}{\alpha}}, \tag{A.3}$$

where $A_t = A_0 \exp(g_{A_t})$, $\frac{g_{A_t}}{g_{A,ss}} = \left(\frac{g_{A_{t-1}}}{g_{A,ss}}\right)^{\rho_{g_A}} \exp(e_t^{g_A})$, $e_t^{g_A}$ is a permanent technology shock, $\frac{A_t^c}{A_{ss}^c} = \left(\frac{A_{t-1}^c}{A_{ss}^c}\right)^{\rho_{A_c}} \exp(e_t^{A_c})$, $e_t^{A_c}$ is a temporary technology shock, and α is output elasticity with respect to labor, indicating the share of labor in production.

Producers operate under perfect competition and maximize current profit, taking into account factor costs:

$$\Pi_{j,t}^Y = P_t^Y Y_{j,t} - W_t l_{j,t} - Z_t K_{j,t}, \tag{A.4}$$

where P_t^Y is the unit price of an intermediate good and Z_t is the rental cost of production capital.

The intermediate goods produced by these firms are consumed by the government sector (G_t), used by domestic retailers supplying consumer goods ($C_{H,t}$) and investment goods ($I_{H,t}$) to the domestic market ($Y_t^H = I_{H,t} + C_{H,t}$), and by exporting retailers selling non-commodity goods (Y_t^{*H}) abroad:

$$Y_t = G_t + Y_t^H + Y_t^{*H} + \frac{k_H}{2}\left(\frac{P_{t+i}^H}{P_{t+i-1}^H} - (\pi_{t-1}^H)^{\iota_H}(\pi_*)^{1-\iota_H}\right)^2 Y_t^H \frac{P_t^H}{P_t^Y} + \frac{k_{*H}}{2}\left(\frac{P_t^{*H}}{P_{t-1}^{*H}} - (\pi_{t-1}^{*H})^{\iota_{*H}}(\pi^*)^{1-\iota_{*H}}\right)^2 Y_t^{*H} \frac{\varepsilon_t P_t^{*H}}{P_t^Y}, \tag{A.5}$$

3. Domestic retailers

Domestic retailers buy intermediate goods from local producers and sell them to firms packaging consumer and investment goods under monopolistic competition. In doing so, these retailers maximize expected discounted real profit, taking into account demand for their own products (with constant elasticity), the cost of buying intermediate goods ($P_t^Y Y_t^H$), and the presence of menu costs. This allows for the introduction of nominal price rigidity in the model according to Rotemberg (1982). Firms also face mark-up shocks related to their own products, which affect the demand elasticity with respect to prices ($\varepsilon_{h,t}$):

$$\Pi_j^H = \mathbb{E}_t \sum_{i=0}^{\infty} \beta^i \left(\frac{P_{k,t+i}^H Y_{k,t+i}^H}{P_{t+i}} - \frac{P_{t+i}^Y Y_{k,t+i}^H}{P_{t+i}} - \frac{k_H}{2} \left(\frac{P_{k,t+i}^H}{P_{k,t+i-1}^H} - (\pi_{t-1}^H)^{\iota_H} (\pi_*)^{1-\iota_H} \right)^2 Y_{t+i}^H \frac{P_{t+i}^H}{P_{t+i}} \right), \quad (A.6)$$

where $Y_{k,t}^H = \left(\frac{P_{k,t}^H}{P_t^H}\right)^{-\varepsilon_{h,t}} Y_t^H$ is the demand for products, $\frac{\varepsilon_{h,t}}{\varepsilon_{h,ss}} = \left(\frac{\varepsilon_{h,t-1}}{\varepsilon_{h,ss}}\right)^{\rho^{\varepsilon_h}} \exp\left(e_t^{\varepsilon_h}\right)$, and $e_t^{\varepsilon_h}$ is the markup shock related to domestic retailers' products; $\pi_t^H = \frac{P_t^H}{P_{t-1}^H} \pi_t$ represents the growth in prices for domestic retailers, k_H is the price rigidity parameter of domestic retailers, and ι_H is the weight of the backward-looking component of changes in domestic retailers' prices.

4. Importing retailers

Importing retailers also maximize expected discounted real profit under monopolistic competition. They purchase foreign goods (Im_t) at price P_t^{F*} and then sell them to domestic firms and households at price P_t^F, dealing with constant-elasticity demand ($\varepsilon_{f,t}$):

$$\Pi_j^F = \mathbb{E}_t \sum_{i=0}^{\infty} \beta^i \left(\frac{P_{k,t+i}^F Im_{k,t}}{P_{t+i}} - \frac{\varepsilon_{t+i} P_{t+i}^{F*} Im_{k,t+i}}{P_{t+i}} - \frac{k_F}{2} \left(\frac{P_{k,t+i}^F}{P_{k,t+i-1}^F} - (\pi_{t-1}^F)^{\iota_F} (\pi_*)^{1-\iota_F} \right)^2 Im_{t+i} \frac{P_{t+i}^F}{P_{t+i}} \right), \quad (A.7)$$

where $Im_{k,t} = \left(\frac{P_{k,t}^F}{P_t^F}\right)^{-\varepsilon_{f,t}} Im_t^H$ is the demand for imports, $\frac{\varepsilon_{f,t}}{\varepsilon_{f,ss}} = \left(\frac{\varepsilon_{f,t-1}}{\varepsilon_{f,ss}}\right)^{\rho^{\varepsilon_f}} \exp\left(e_t^{\varepsilon_f}\right)$, and $e_t^{\varepsilon_f}$ is the markup shock related to the products of importing retailers; P_t^{F*} is the unit price of the retailer-purchased import product in foreign currency $\pi_t^F = \frac{P_t^F}{P_{t-1}^F} \pi_t$ is the growth of prices for the products of importing retailers, k_F is the price rigidity parameter for importing retailers, and ι_F is the weight of the backward-looking component of changes in the prices of importing retailers.

5. Exporting retailers

Similar to other retailers, exporting retailers sell domestic goods to a foreign economy at price P_t^{*H}, thereby generating non-commodity exports in the domestic economy (Y_t^{*H}):

$$\Pi_j^{*H} = \mathbb{E}_t \sum_{i=0}^{\infty} \beta^i \left(\frac{P_{k,t+i}^{*H} Y_{k,t+i}^{*H}}{\varepsilon_{t+i} P_{t+i}} - \frac{P_{t+i}^Y Y_{k,t+i}^H}{P_{t+i}} - \frac{k_{*H}}{2} \left(\frac{P_{k,t+i}^{*H}}{P_{k,t+i-1}^{*H}} - (\pi_{t-1}^{*H})^{\iota_{*H}} (\pi^*)^{1-\iota_{*H}} \right)^2 Y_{t+i}^{*H} \frac{P_{t+i}^{*H}}{\varepsilon_{t+i} P_{t+i}} \right), \quad (A.8)$$

where $Y_{k,t}^{*H} = \left(\frac{P_{k,t}^{*H}}{P_t^{*H}}\right)^{-\varepsilon_{*h,t}} Y_t^H$ is the demand for non-commodity exports, $\frac{\varepsilon_{*h,t}}{\varepsilon_{*h,ss}} = \left(\frac{\varepsilon_{*h,t-1}}{\varepsilon_{*h,ss}}\right)^{\rho^{\varepsilon_{*h}}} \exp\left(e_t^{\varepsilon_{*h}}\right)$, and $e_t^{\varepsilon_{*h}}$ the is markup shock related to exporting retailers' products, $\pi_t^{*H} = \frac{P_t^{*H}}{P_{t-1}^{*H}} \pi_t^*$ represents the growth of prices for exporting retailers' products, k_{*H} is the price rigidity parameter for exporting retailers, ι_{*H} is the weight of the backward-looking component of changes in exporting retailers' prices, and π^* is the target inflation rate in the foreign economy.

6. Packaging firms

Packaging firms create final consumer and investment goods, with constant elasticity of substitution for domestic ($Y_t^H = I_{H,t} + C_{H,t}$) and foreign ($Im_t = C_{F,t} + I_{F,t}$) products:

$$C_{j,t}^p = \left(\gamma_C^{\frac{1}{\eta_C}} C_{j,H,t}^{1-\frac{1}{\eta_C}} + (1-\gamma_C)^{\frac{1}{\eta_C}} C_{j,F,t}^{1-\frac{1}{\eta_C}} \right)^{\frac{\eta_C}{\eta_C - 1}} \quad (A.9)$$

$$I_{j,t} + a(u_t)\bar{K}'_{j,t} = U_t\left(\gamma_I^{\frac{1}{\eta_I}} I_{j,H,t}^{1-\frac{1}{\eta_I}} + (1-\gamma_I)^{\frac{1}{\eta_I}} I_{j,F,t}^{1-\frac{1}{\eta_I}}\right)^{\frac{\eta_I}{\eta_I-1}}, \tag{A.10}$$

where η_C is the elasticity of substitution of domestic and imported consumer goods, γ_C is the share of domestic products in consumption, $I_{j,t}$ are investment goods net of the costs[54] of capital consumption $a(u_t)\bar{K}'_{j,t}$, $\bar{K}'_{j,t}$ is capital, $\frac{U_t}{U_{ss}} = \left(\frac{U_{t-1}}{U_{ss}}\right)^{\rho_U}\exp(e_t^U)$, e_t^U is the shock to the production of investment goods, u_t is capital utilisation, η_I is the elasticity of substitution of domestic and imported investment goods, and γ_I is the share of domestically produced investment goods.

The producers of final consumer goods lack monopolistic power and maximize current profits from the goods and services sold to households and the costs of buying domestic and imported consumer goods from retailers:

$$\Pi_{j,t}^C = P_t C_{j,t}^p - P_t^H C_{j,H,t} - P_t^F C_{j,F,t}, \tag{A.11}$$

where P_t is the unit price of the final consumer good.

The producers of final investment goods operate in the same market conditions and also maximize current profits:

$$\Pi_{j,t}^I = P_t^I\left(I_{j,t} + a(u_t)\bar{K}'_{j,t}\right) - P_t^H I_{j,H,t} - P_t^F I_{j,F,t}, \tag{A.12}$$

where P_t^I is the unit price of the final investment good.

7. Investment firms

Investment firms build capital in the economy ($\bar{K}_t$) using investment goods (I_t). They generate revenue from the sale of capital to entrepreneurs at price Q_t. The costs of the investment firms include the costs of buying investment goods ($P_t^I I_t$) and buying from entrepreneurs the capital that remains at the end of the production cycle, adjusted for depreciation: $\bar{K}'_t = (1-\delta)\bar{K}_{t-1}$. Maximising expected discounted real return, investment firms deal with capital adjustment costs (see *Christiano et al., 2005*):

$$\Pi_j^{\bar{K}} = \mathbb{E}_t \sum_{i=0}^{\infty} \beta^i \left(\frac{Q_{t+i}\bar{K}_{j,t+i} - P_{t+i}^I I_{j,t+i} - Q_{t+i}\bar{K}'_{j,t+i}}{P_{t+i}}\right), \tag{A.13}$$

where $\bar{K}_{j,t} = \bar{K}'_{j,t} + \left(1 - \frac{k_I}{2}\left(\frac{I_{j,t}}{I_{j,t-1}e^{g_{I,ss_t}}} - 1\right)^2\right) I_{j,t}$ is the dynamics of capital, and k_I is the parameter defining the cost of a deviation in the growth of investment from equilibrium.

8. Entrepreneurs

To buy capital from investment firms, entrepreneurs use credit (B_t) and equity (N_t): $Q_t\bar{K}_t = B_t + N_t$. Credit is provided by financial intermediaries at interest rate R_t^{en}. From one unit of acquired capital, entrepreneurs can subsequently use a random amount of capital: $\bar{K}_t = \omega_t \bar{K}_{t-1}$. Having determined capital utilisation (u_t), entrepreneurs lease it to intermediate goods manufacturers at price Z_t, and sell the remaining capital (adjusted for depreciation) $(1-\delta)Q_t\bar{K}_t$ back to investment firms. As a result, in period t, entrepreneurs' profit from capital utilization is formed as follows:

$$\Pi_t^{en} = \omega_t R_t^k Q_{t-1}\bar{K}_{t-1} - R_t^{en} B_{t-1}, \tag{A.14}$$

where $R_t^k = \frac{(u_t Z_t - a(u_t)P_t^I) + (1-\delta)Q_t}{Q_{t-1}}$ is the return per unit of capital.

[54] For further details on the functional form of $a(u_t)$, see the work of *Kreptsev and Seleznev (2017)*.

If entrepreneurs' costs (loan payments) exceed their revenue (income from the sale of capital), they become bankrupt. Based on (A.14), $\bar{\omega}_t$ defines the bankruptcy threshold[55]: in the event that shock ω_t exceeds the bankruptcy threshold, the entrepreneur is considered a survivor. Survivor entrepreneurs maximize the expected (adjusted for distribution ω) equity of the following period:

$$\mathbb{E}_t N_{t+1} = \mathbb{E}_t \gamma_t \left[\left(\int_{\bar{\omega}_t}^{\infty} \omega_t p_{t-1}(\omega) d\omega\right) R_{t+1}^k Q_t \bar{K}_t - \left(\int_{\bar{\omega}_t}^{\infty} p_{t-1}(\omega) d\omega\right) R_{t+1}^{en} B_t\right], \tag{A.15}$$

where $\frac{\gamma_t}{\gamma_{ss}} = \left(\frac{\gamma_{t-1}}{\gamma_{ss}}\right)^{\rho^\gamma} \exp\left(e_t^\gamma\right)$, and e_t^γ is the shock to the proportion of survivor entrepreneurs.

9. Banks

Banks lend to risky units (B_t), conduct operations with the central bank and other banks (IB_t), and accept household deposits (D_t). Each bank also has its own capital (J_t). The asset and liability sides of their balance sheets take the form:

$$B_{jt} + IB_{jt} = D_{jt} + J_{jt} \tag{A.16}$$

The banks' revenues include interest on outstanding loans $\left(R_{t-1}^b - 1\right) B_{t-1}$ and interest payments on interbank and central bank transactions: $(R_{t-1} - 1) IB_{t-1}$. The banks' costs include the interest costs of deposits $(R_{t-1}^D - 1) D_{t-1}$, production costs ($\delta_b J_{t-1}$), and non-recurrent transfers to households (TR_t^b). It is assumed that banks, due to their monopolistic power in the credit and deposit markets, deal with menu costs when setting rates. This allows the introduction of nominal rigidity of interest rates into the model. Furthermore, it is assumed that the costs of equity adjustment are quadratic: $\frac{k^K}{2}\left(\frac{J_t}{B_t} - \omega^J\right)^2 J_t$. The banks maximize the expected discounted amount of real payments to households, which are proportional to the banks' profits:

$$E_t \sum_{i=0}^{\infty} \beta^i \frac{(1-o_{t+i})}{P_{t+i}} \Pi_{j,t+i}^b \tag{A.17}$$

$$\Pi_{j,t+i}^b = \left(R_{j,t+i-1}^b - 1\right) B_{j,t+i-1} + (R_{t+i-1} - 1) IB_{j,t+i-1} - \left(R_{j,t+i-1}^D - 1\right) D_{j,t+i-1} - \frac{k^K}{2}\left(\frac{J_{j,t+i}}{B_{j,t+i}} - \omega^J\right)^2 J_{t+i} - \frac{k^b}{2}\left(\frac{R_{j,t+i}^b}{\left(R_{j,t+i-1}^b\right)^{\iota_b} \left(R_{ss}^b\right)^{1-\iota_b}} - 1\right)^2 B_{t+i} - \frac{k^D}{2}\left(\frac{R_{j,t+i}^D}{\left(R_{j,t+i-1}^D\right)^{\iota_d} \left(R_{ss}^D\right)^{1-\iota_d}} - 1\right)^2 D_{t+i} - \delta_b J_{j,t+i-1} - TR_{t+i}^b, \tag{A.18}$$

where $J_{j,t} = \frac{J_{j,t-1}}{\varepsilon_t^{cap}} + o_t \Pi_{j,t}^b$ is the dynamics of equity, $\frac{\varepsilon_t^{cap}}{\varepsilon_{ss}^{cap}} = \left(\frac{\varepsilon_{t-1}^{cap}}{\varepsilon_{ss}^{cap}}\right)^{\rho^{cap}} \exp\left(e_t^{\varepsilon_{cap}}\right)$, and $e_t^{\varepsilon_{cap}}$ is the shock to changes in bank equity; $B_{j,t} = \left(\frac{R_{j,t}^b}{R_t^b}\right)^{-\varepsilon^b} B_t$ is the demand for credit, with ε^b being the interest rate elasticity of loans; $D_{j,t} = \left(\frac{R_{j,t}^D}{R_t^D}\right)^{\varepsilon_t^D} D_t$ is the supply of deposits, and ε_t^D is the interest rate elasticity of deposits; $\frac{\varepsilon_t^D}{\varepsilon_{ss}^D} = \left(\frac{\varepsilon_{t-1}^D}{\varepsilon_{ss}^D}\right)^{\rho^{\varepsilon_D}} \exp\left(e_t^{\varepsilon_D}\right)$, and $e_t^{\varepsilon_D}$ represents the shock to markup on deposit rates; $(1 - o_t)$ is the proportion of allocations to households, k^K is the parameter defining the costs of a deviation in the growth of equity from equilibrium ω^J; k^b is the interest rate rigidity parameter, ι_b is the weight of the backward-looking component

[55] The bankruptcy threshold is random and follows a log-normal distribution, with variance $\sigma_{\omega,t}$. The variance evolves as follows: $\frac{\sigma_{\omega,t}}{\sigma_{\omega,ss}} = \left(\frac{\sigma_{\omega,t-1}}{\sigma_{\omega,ss}}\right)^{\rho^{\sigma_\omega}} \exp\left(e_t^{\sigma_\omega}\right)$, where $e_t^{\sigma_\omega}$ is the risk shock.

of interest rate-setting, k^D is the parameter for the rigidity of deposit rates, and ι_d is the weight of the backward-looking component of deposit rate-setting.

10. Risky banks' units

The risky units focus on corporate lending. If the shock affecting entrepreneurs (ω_t) exceed the bankruptcy threshold ($\overline{\omega}_t$), the revenue of high-risk units is the debt of entrepreneurs and the interest on it ($R_t^{en}B_{t-1}$). In the event of the bankruptcy of entrepreneurs, the revenue of the risk unit is the fixed part of the income from the sale of capital: $(1-\mu)\omega R_t^k Q_{t-1}\overline{K}_{t-1}$. The costs of the risky banks' units are determined by the interest costs of debt to the bank's principal division: $R_{t-1}^b B_{t-1}$. The risky units' profit is assumed to be zero for each period , which leads to the following equation:

$$\left(1-\int_0^{\overline{\omega}_t} p_{t-1}(\omega)\,d\omega\right)R_t^{en}B_{j,t-1}+(1-\mu)\omega R_t^k Q_{t-1}\overline{K}_{j,t-1}\int_0^{\overline{\omega}_t} p_{t-1}(\omega)\,d\omega = R_{t-1}^b B_{j,t-1} \quad \text{(A.19)}$$

11. Commodity exporters

Commodity exporters[56] are considered a separate economic agent. They incur zero costs for commodity extraction (a cornucopia is assumed) and sell the total volume abroad at a price set by the global market. The prices of the commodity (P_t^{oil}) and their exports (S_t^{oil}) change in an inertial manner under the influence of temporary shocks ($e^{e_t^{oil}}$, $e_t^{S_{oil}}$):

$$\frac{P_t^{oil}}{P_*^{oil}}=\left(\frac{P_{t-1}^{oil}}{P_*^{oil}}\right)^{\rho_{P^{oil}}}\exp\left(e_t^{oil}\right) \quad \text{(A.20)}$$

$$\frac{S_t^{oil}}{S_*^{oil}}=\left(\frac{S_{t-1}^{oil}}{S_*^{oil}}\right)^{\rho_{S^{oil}}}\exp\left(e_t^{S_{oil}}\right) \quad \text{(A.21)}$$

12. Central bank

The central bank implements its monetary policy under a strict inflation targeting regime. It sets the nominal interest rate (R_t) based on the current period's inflation (π_t), taking into account the inertia of the rule (ϕ_R) and possible temporary deviation from it (e_t^R):

$$\frac{R_t}{R_*}=\left(\frac{R_{t-1}}{R_*}\right)^{\phi_R}\left(\frac{\pi_t}{\pi_*}\right)^{(1-\phi_R)\phi_\pi}\exp(e_t^R) \quad \text{(A.22)}$$

It is also assumed that the central bank is able to conduct non-recurrent interventions in the foreign exchange market (e_t^{res}) using foreign currency reserves ($dRes_t$):

$$\frac{dRes_t}{(A_t)^{\frac{1}{\alpha}}P_t^*}=e_t^{res}, \quad \text{(A.23)}$$

where P_t^* is the unit price of a good in the foreign (external) economy.

13. Fiscal sector

The government follows a balanced budget policy in each period: public consumption is financed through lump-sum taxes. Changes in public consumption, in turn, are determined by a first-order autoregressive process, adjusted for temporary shocks (e_t^G):

$$\frac{G_t}{G_*}=\left(\frac{G_{t-1}}{G_*}\right)^{\rho_G}\exp(e_t^G) \quad \text{(A.24)}$$

14. External economy

The external world, unaffected by domestic shocks, generates demand for the non-commodity exports of the domestic economy:

$$Y_t^{*H}=\gamma_{export}(p_t^{*H})^{-\eta_{export}}Y_t^*, \quad \text{(A.25)}$$

[56] Oil is assumed to be the only export commodity in the model.

where η_{export} is the price elasticity of non-commodity exports and Y_t^* is the output of the foreign economy.

Foreign households' consumption is characterized by habits (h^*). They maximise expected discounted utility by choosing the optimal consumption path (C^*) and the number of working hours (l_t^*) in a perfectly competitive labor market:

$$U_{j,t}^* = E_t \sum_{i=0}^{\infty} (\beta^*)^i \left(\zeta_t^{*C} \ln\left(C_{j,t+i}^* - h^* C_{t+i-1}^*\right) - \zeta_t^{*L} \frac{\left(l_{j,t+i}^*\right)^{1+\phi^*}}{1+\phi^*} \right), \tag{A.26}$$

where $\frac{\zeta_t^{*C}}{\zeta_{ss}^{*C}} = \left(\frac{\zeta_{t-1}^{*C}}{\zeta_{ss}^{*C}}\right)^{\rho_{\zeta_{C*}}} \exp\left(e_t^{\zeta_{c*}}\right)$, with $e_t^{\zeta_{c*}}$ being the shock to foreign household preferences.

Firms act as price-takers, using labor to produce final goods (Y_t^*) and maximize profits:

$$Y_{j,t}^* = A_t^* A_t^{\frac{1}{\alpha}} l_{j,t}^* \tag{A.27}$$

$$\Pi_{j,t}^{Y*} = P_t^* Y_{j,t}^* - W_t^* l_{j,t}^*, \tag{A.28}$$

where $\frac{A_t^*}{A_{ss}^*} = \left(\frac{A_{t-1}^*}{A_{ss}^*}\right)^{\rho_{A*}} \exp\left(e_t^{A_*}\right)$, and $e_t^{A_*}$ represents the temporary technology shock of the foreign economy.

Only households generate demand for goods in the foreign economy, meaning all output is allocated to consumption:

$$Y_t^* = C_t^* \tag{A.29}$$

The central bank pursues its monetary policy according to a modified *Taylor (1993)* rule:

$$\frac{R_t^*}{R^*} = \left(\frac{R_{t-1}^*}{R^*}\right)^{\phi_R^*} \left(\frac{\pi_t^*}{\pi^*}\right)^{(1-\phi_R^*)\phi_\pi^*} \exp\left(e_t^{*R}\right), \tag{A.30}$$

where e_t^{*R} is the foreign monetary policy shock.

15. Remaining equations

Additionally, we define the balance of payments equation (A.31), the dynamics of imports adjusted for importing retailers' costs (A.32), the rate on net foreign assets (A.33), the dynamics of the risk premium (A.34), the real exchange rate (A.35), and relative prices for imports (A.36):

$$P_t^{oil} S_t^{oil} + P_t^{*H} Y_t^{*H} + IP_t - P_t^{F*} IM_t = B_t^* - R_{t-1}^{NFA} B_{t-1}^* + dRes_t \tag{A.31}$$

$$IM_t = Im_t + \frac{k_F}{2} \left(\frac{P_t^F}{P_{t-1}^F} - (\pi_{t-1}^F)^{\iota_F} (\pi_*)^{1-\iota_F} \right)^2 Im_t \frac{P_t^F}{\varepsilon_t P_t^{F*}} \tag{A.32}$$

$$R_t^{NFA} = R_t^* \exp\left(\varphi_{NFA}(rer_t d_t^* - rer_{ss} d_{ss}^*) - \varphi_{oil}\left(p_t^{oil} - p_{ss}^{oil}\right) \right) z_t^{RP} \tag{A.33}$$

$$\frac{z_t^{RP}}{Z_*^{RP}} = \left(\frac{z_{t-1}^{RP}}{Z_*^{RP}}\right)^{\rho^{z_{RP}}} \exp\left(e_t^{z_{RP}}\right) \tag{A.34}$$

$$rer_t = rer_{t-1} g_t^{\varepsilon} \frac{\pi_t^*}{\pi_t} \tag{A.35}$$

$$\frac{P_t^{F*}}{P_*^{F*}} = \left(\frac{P_{t-1}^{F*}}{P_*^{F*}}\right)^{\rho^{P_{F*}}} \exp\left(e_t^{p_{F*}}\right), \tag{A.36}$$

where $B_t^* = -D_t^*$ represents net foreign assets, IP_t is cross-border transfers, g_t^ε is the growth in the (nominal) exchange rate, $e_t^{z_{RP}}$ is the risk premium shock, and $e_t^{p_{F*}}$ is the shock of relative prices of imported goods.

Table A1. Structural shocks of the quarterly DSGE model (DSGE-q)

$e_t^{\zeta_c}$	A preference shock
$e_t^{\zeta_l}$	A labor supply shock
$e_t^{A_c}$	A temporary technology shock
$e_t^{g_A}$	A permanent technology shock
$e_t^{\varepsilon_h}$	A markup shock for domestic retailers
$e_t^{\varepsilon_f}$	A markup shock for importing retailers
$e_t^{\varepsilon_{*h}}$	A markup shock for exporting retailers
e_t^{U}	An investment technology shock
$e_t^{\sigma_\omega}$	A risk shock
e_t^{γ}	A financial wealth shock (γ_t)
$e_t^{\varepsilon_D}$	A markup shock for deposit rates
$e_t^{\varepsilon_{cap}}$	A capital dynamics shock
$e_t^{S_{oil}}$	A shock of oil exports
e_t^{oil}	A real oil price shock
e_t^{R}	A monetary policy shock
e_t^{res}	A reserves shock
e_t^{G}	A government consumption shock
$e_t^{\zeta_{c*}}$	A foreign preferences shock
$e_t^{A_*}$	A foreign temporary technology shock
e_t^{*R}	A foreign monetary policy shock
$e_t^{p_{F*}}$	A shock of relative prices of imported goods
$e_t^{z_{RP}}$	A risk premium shock

Source: *Kreptsev and Seleznev (2017)*.

Appendix B

Table B1. Data description

№	Observable Variable	Category	Source	Freq.	Seasonal Adjustment	Transformation Type	Publication lag (in calendar days, approximately)
			Modelled variables				
1	MIACR Interest Rate: 1 Day	-	BoR	M	No	1	0
2	Consumer Price Index	-	FSSS	M	No	2	8
3	Real Wages	-	FSSS	M	Yes	2	55
4	Real Gross Domestic Product	-	FSSS	Q	Yes	2	45
5	Real Household Consumption Expenditures	-	FSSS	Q	Yes	2	90
6	Real Investments	-	FSSS	Q	Yes	2	90
7	Urals Oil Price	-	MF	M	No	2	0
8	Real Exports	-	FSSS	Q	Yes	2	90
9	US Real Gross Domestic Product	-	BEA	Q	No	2	30
10	US Federal Funds Effective Rate	-	FRED	M	No	1	0
11	US Consumer Price Index	-	BLS	M	No	2	10
12	Real Government Consumption Expenditures	-	FSSS	Q	Yes	2	90
			Non-modelled variables				
1	Agricultural Production Index	Hard	FSSS	M	Yes	2	25
2	Construction Works Value Index	Hard	FSSS	M	Yes	2	25
3	Freight Turnover Index	Hard	FSSS	M	Yes	2	25
4	Industrial Production Index	Hard	FSSS	M	Yes	2	25
5	Labour Force Demand	Hard	FSSS	M	Yes	2	25
6	Labour Force Unempoyed	Hard	FSSS	M	Yes	2	25
7	Paid Services Rendered to Population Index	Hard	FSSS	M	Yes	2	25
8	Passenger Turnover Index	Hard	FSSS	M	Yes	2	25
9	Public Catering Turnover Index	Hard	FSSS	M	Yes	2	25
10	Retail Trade Turnover Index	Hard	FSSS	M	Yes	2	25
11	Wholesale Trade Turnover Index	Hard	FSSS	M	Yes	2	25
12	Actual Diffusion Index: Employment	Soft	REB	M	Yes	3	45
13	Actual Diffusion Index: Equipment Purchase	Soft	REB	M	Yes	3	45
14	Actual Diffusion Index: Orders	Soft	REB	M	Yes	3	45
15	Actual Diffusion Index: Production	Soft	REB	M	Yes	3	45
16	Actual Diffusion Index: Purchasing Prices	Soft	REB	M	Yes	3	45
17	Actual Diffusion Index: Sales Prices	Soft	REB	M	Yes	3	45
18	Actual Diffusion Index: Sales/Purchasing Prices Ratio	Soft	REB	M	Yes	3	45
19	Actual Diffusion Index: Stocks	Soft	REB	M	Yes	3	45

20	Actual Diffusion Index: Wages	Soft	REB	M	Yes	3	45
21	Capacity Utilisation Rate: Actual (Normal Monthly Level = 100)	Soft	REB	M	Yes	3	60
22	Enterprises Debt to Banks (Normal Monthly Level = 100)	Soft	REB	M	Yes	3	60
23	Enterprises in Good or Normal Financial Situation	Soft	REB	M	Yes	3	60
24	Enterprises not Buying Equipment for 2 Months and More	Soft	REB	M	Yes	3	60
25	Expectation Diffusion Index: Debt to Banks	Soft	REB	M	Yes	3	45
26	Expectation Diffusion Index: Employment	Soft	REB	M	Yes	3	45
27	Expectation Diffusion Index: Equipment Purchase	Soft	REB	M	Yes	3	45
28	Expectation Diffusion Index: Financial Situation	Soft	REB	M	Yes	3	45
29	Expectation Diffusion Index: Orders	Soft	REB	M	Yes	3	45
30	Expectation Diffusion Index: Production	Soft	REB	M	Yes	3	45
31	Expectation Diffusion Index: Purchasing Prices	Soft	REB	M	Yes	3	45
32	Expectation Diffusion Index: Sales Prices	Soft	REB	M	Yes	3	45
33	Expectation Diffusion Index: Wages	Soft	REB	M	Yes	3	45
34	Labour Utilisation Rate: Actual (Normal Monthly Level = 100)	Soft	REB	M	Yes	3	60
35	Production Costs: Current Estimates	Soft	MoB	M	No	3	20
36	Demand for businesses' products (services): Current Estimates	Soft	MoB	M	No	3	20
37	Prices for businesses' products (services): Current Estimates	Soft	MoB	M	No	3	20
38	Production output, Scope of Contracted Works, Turnover and Services: Current Estimates	Soft	MoB	M	No	3	20
39	Demand for Businesses' Products (Services): Expectations for 3 Months Ahead	Soft	MoB	M	No	3	20
40	Prices for businesses' products (services): Expectations for 3 Months Ahead	Soft	MoB	M	No	3	20
41	Production output, Scope of Contracted Works, Turnover and Services: Expectations for 3 Months Ahead	Soft	MoB	M	No	3	20
42	Orders: Actual (Normal Monthly Level = 100)	Soft	REB	M	Yes	3	60
43	Stocks: Actual (Normal Monthly Level = 100)	Soft	REB	M	Yes	3	60
44	Government Bonds Zero Coupon Yield: Redemption Term 1 Year	Financial	MOEX	M	No	3	0
45	Government Bonds Zero Coupon Yield: Redemption Term 3 Years	Financial	MOEX	M	No	3	0
46	Government Bonds Zero Coupon Yield: Redemption Term 10 Years	Financial	MOEX	M	No	3	0

47	MOEX Russia Index	Financial	MOEX	M	No	2	0
48	Official Reserve Assets	Financial	BoR	M	No	2	7
49	RTS Index	Financial	MOEX	M	No	2	0

Notes. 1 – without transformation; 2 – log growth, $100 \cdot \left[\ln\left(x_{i,t}\right) - \ln\left(x_{i,t-1}\right)\right]$; 3 – absolute growth, $x_{i,t} - x_{i,t-1}$. FSSS – Federal State Statistics Service (eng.rosstat.gov.ru); BoR – Bank of Russia (cbr.ru/eng); MF – The Ministry of Finance of the Russian Federation (minfin.gov.ru/en), BEA – Bureau of Economic Analysis (bea.gov), FRED – Federal Reserve Economic Data (fred.stlouisfed.org), BLS – Bureau of Labor Statistics (bls.gov), РЭБ – Russian Economic Barometer (new.imemo.ru/en/rebstat), MoB – Bank of Russia's Monitoring of Businesses (cbr.ru/dkp/mp), MOEX – Moscow Exchange (moex.com/en)

Source: Author's calculations.

Table B2. Stylized calendar of new data releases of nowcasting Russian GDP growth for the current quarter (Q0)

Month	Quarter	Observable Variable	Calendar Day	Period of release
1M	Q0	Official Reserve Assets	7	3M Q(-1)
1M	Q0	Consumer Price Index	8	3M Q(-1)
1M	Q0	US Consumer Price Index	10	3M Q(-1)
1M	Q0	Actual Diffusion Index: Employment	15	2M Q(-1)
1M	Q0	Actual Diffusion Index: Equipment Purchase	15	2M Q(-1)
1M	Q0	Actual Diffusion Index: Orders	15	2M Q(-1)
1M	Q0	Actual Diffusion Index: Production	15	2M Q(-1)
1M	Q0	Actual Diffusion Index: Purchasing Prices	15	2M Q(-1)
1M	Q0	Expectation Diffusion Index: Sales Prices	15	2M Q(-1)
1M	Q0	Actual Diffusion Index: Sales/Purchasing Prices Ratio	15	2M Q(-1)
1M	Q0	Actual Diffusion Index: Orders	15	2M Q(-1)
1M	Q0	Actual Diffusion Index: Wages	15	2M Q(-1)
1M	Q0	Expectation Diffusion Index: Debt to Banks	15	2M Q(-1)
1M	Q0	Expectation Diffusion Index: Employment	15	2M Q(-1)
1M	Q0	Expectation Diffusion Index: Equipment Purchase	15	2M Q(-1)
1M	Q0	Expectation Diffusion Index: Financial Situation	15	2M Q(-1)
1M	Q0	Expectation Diffusion Index: Orders	15	2M Q(-1)
1M	Q0	Expectation Diffusion Index: Production	15	2M Q(-1)
1M	Q0	Expectation Diffusion Index: Purchasing Prices	15	2M Q(-1)
1M	Q0	Expectation Diffusion Index: Sales Prices	15	2M Q(-1)
1M	Q0	Expectation Diffusion Index: Wages	15	2M Q(-1)
1M	Q0	Production Costs: Current Estimates	20	3M Q(-1)
1M	Q0	Demand for businesses' products (services): Current Estimates	20	3M Q(-1)
1M	Q0	Prices for businesses' products (services): Current Estimates	20	3M Q(-1)
1M	Q0	Production output, Scope of Contracted Works, Turnover and Services: Current Estimates	20	3M Q(-1)
1M	Q0	Demand for Businesses' Products (Services): Expectations for 3 Months Ahead	20	3M Q(-1)
1M	Q0	Prices for businesses' products (services): Expectations for 3 Months Ahead	20	3M Q(-1)
1M	Q0	Production output, Scope of Contracted Works, etc.: Expectations for 3 Months Ahead	20	3M Q(-1)
1M	Q0	Real Wages	25	2M Q(-1)
1M	Q0	Agricultural Production Index	25	3M Q(-1)
1M	Q0	Construction Works Value Index	25	3M Q(-1)
1M	Q0	Freight Turnover Index	25	3M Q(-1)
1M	Q0	Industrial Production Index	25	3M Q(-1)
1M	Q0	Labour Force Demand	25	3M Q(-1)
1M	Q0	Labour Force Unempoyed	25	3M Q(-1)
1M	Q0	Paid Services Rendered to Population Index	25	3M Q(-1)
1M	Q0	Passenger Turnover Index	25	3M Q(-1)

1M	Q0	Public Catering Turnover Index	25	3M Q(-1)
1M	Q0	Retail Trade Turnover Index	25	3M Q(-1)
1M	Q0	Wholesale Trade Turnover Index	25	3M Q(-1)
1M	Q0	Capacity Utilisation Rate: Actual (Normal Monthly Level = 100)	30	2M Q(-1)
1M	Q0	Enterprises Debt to Banks (Normal Monthly Level = 100)	30	2M Q(-1)
1M	Q0	Enterprises in Good or Normal Financial Situation	30	2M Q(-1)
1M	Q0	Enterprises not Buying Equipment for 2 Months and More	30	2M Q(-1)
1M	Q0	Labour Utilisation Rate: Actual (Normal Monthly Level = 100)	30	2M Q(-1)
1M	Q0	Orders: Actual (Normal Monthly Level = 100)	30	2M Q(-1)
1M	Q0	Stocks: Actual (Normal Monthly Level = 100)	30	2M Q(-1)
1M	Q0	MIACR Interest Rate: 1 Day	30	1M Q0
1M	Q0	Urals Oil Price	30	1M Q0
1M	Q0	US Federal Funds Effective Rate	30	1M Q0
1M	Q0	Government Bonds Zero Coupon Yield: Redemption Term 1 Year	30	1M Q0
1M	Q0	Government Bonds Zero Coupon Yield: Redemption Term 3 Years	30	1M Q0
1M	Q0	Government Bonds Zero Coupon Yield: Redemption Term 10 Years	30	1M Q0
1M	Q0	MOEX Russia Index	30	1M Q0
1M	Q0	RTS Index	30	1M Q0
1M	Q0	US Real Gross Domestic Product	30	Q(-1)
2M	Q0	Official Reserve Assets	7	1M Q0
2M	Q0	Consumer Price Index	8	1M Q0
2M	Q0	US Consumer Price Index	10	1M Q0
2M	Q0	Real Gross Domestic Product	15	Q(-1)
2M	Q0	Actual Diffusion Index: Employment	15	3M Q(-1)
2M	Q0	Actual Diffusion Index: Equipment Purchase	15	3M Q(-1)
2M	Q0	Actual Diffusion Index: Orders	15	3M Q(-1)
2M	Q0	Actual Diffusion Index: Production	15	3M Q(-1)
2M	Q0	Actual Diffusion Index: Purchasing Prices	15	3M Q(-1)
2M	Q0	Expectation Diffusion Index: Sales Prices	15	3M Q(-1)
2M	Q0	Actual Diffusion Index: Sales/Purchasing Prices Ratio	15	3M Q(-1)
2M	Q0	Actual Diffusion Index: Orders	15	3M Q(-1)
2M	Q0	Actual Diffusion Index: Wages	15	3M Q(-1)
2M	Q0	Expectation Diffusion Index: Debt to Banks	15	3M Q(-1)
2M	Q0	Expectation Diffusion Index: Employment	15	3M Q(-1)
2M	Q0	Expectation Diffusion Index: Equipment Purchase	15	3M Q(-1)
2M	Q0	Expectation Diffusion Index: Financial Situation	15	3M Q(-1)
2M	Q0	Expectation Diffusion Index: Orders	15	3M Q(-1)
2M	Q0	Expectation Diffusion Index: Production	15	3M Q(-1)
2M	Q0	Expectation Diffusion Index: Purchasing Prices	15	3M Q(-1)
2M	Q0	Expectation Diffusion Index: Sales Prices	15	3M Q(-1)
2M	Q0	Expectation Diffusion Index: Wages	15	3M Q(-1)
2M	Q0	Production Costs: Current Estimates	20	1M Q0
2M	Q0	Demand for businesses' products (services): Current Estimates	20	1M Q0
2M	Q0	Prices for businesses' products (services): Current Estimates	20	1M Q0
2M	Q0	Production output, Scope of Contracted Works, Turnover and Services: Current Estimates	20	1M Q0
2M	Q0	Demand for Businesses' Products (Services): Expectations for 3 Months Ahead	20	1M Q0
2M	Q0	Prices for businesses' products (services): Expectations for 3 Months Ahead	20	1M Q0
2M	Q0	Production output, Scope of Contracted Works, etc.: Expectations for 3 Months Ahead	20	1M Q0
2M	Q0	Real Wages	25	3M Q(-1)
2M	Q0	Agricultural Production Index	25	1M Q0
2M	Q0	Construction Works Value Index	25	1M Q0
2M	Q0	Freight Turnover Index	25	1M Q0
2M	Q0	Industrial Production Index	25	1M Q0
2M	Q0	Labour Force Demand	25	1M Q0
2M	Q0	Labour Force Unempoyed	25	1M Q0

2M	Q0	Paid Services Rendered to Population Index	25	1M Q0
2M	Q0	Passenger Turnover Index	25	1M Q0
2M	Q0	Public Catering Turnover Index	25	1M Q0
2M	Q0	Retail Trade Turnover Index	25	1M Q0
2M	Q0	Wholesale Trade Turnover Index	25	1M Q0
2M	Q0	Capacity Utilisation Rate: Actual (Normal Monthly Level = 100)	30	3M Q(-1)
2M	Q0	Enterprises Debt to Banks (Normal Monthly Level = 100)	30	3M Q(-1)
2M	Q0	Enterprises in Good or Normal Financial Situation	30	3M Q(-1)
2M	Q0	Enterprises not Buying Equipment for 2 Months and More	30	3M Q(-1)
2M	Q0	Labour Utilisation Rate: Actual (Normal Monthly Level = 100)	30	3M Q(-1)
2M	Q0	Orders: Actual (Normal Monthly Level = 100)	30	3M Q(-1)
2M	Q0	Stocks: Actual (Normal Monthly Level = 100)	30	3M Q(-1)
2M	Q0	MIACR Interest Rate: 1 Day	30	2M Q0
2M	Q0	Urals Oil Price	30	2M Q0
2M	Q0	US Federal Funds Effective Rate	30	2M Q0
2M	Q0	Government Bonds Zero Coupon Yield: Redemption Term 1 Year	30	2M Q0
2M	Q0	Government Bonds Zero Coupon Yield: Redemption Term 3 Years	30	2M Q0
2M	Q0	Government Bonds Zero Coupon Yield: Redemption Term 10 Years	30	2M Q0
2M	Q0	MOEX Russia Index	30	2M Q0
2M	Q0	RTS Index	30	2M Q0
3M	Q0	Official Reserve Assets	7	2M Q0
3M	Q0	Consumer Price Index	8	2M Q0
3M	Q0	US Consumer Price Index	10	2M Q0
3M	Q0	Actual Diffusion Index: Employment	15	1M Q0
3M	Q0	Actual Diffusion Index: Equipment Purchase	15	1M Q0
3M	Q0	Actual Diffusion Index: Orders	15	1M Q0
3M	Q0	Actual Diffusion Index: Production	15	1M Q0
3M	Q0	Actual Diffusion Index: Purchasing Prices	15	1M Q0
3M	Q0	Expectation Diffusion Index: Sales Prices	15	1M Q0
3M	Q0	Actual Diffusion Index: Sales/Purchasing Prices Ratio	15	1M Q0
3M	Q0	Actual Diffusion Index: Orders	15	1M Q0
3M	Q0	Actual Diffusion Index: Wages	15	1M Q0
3M	Q0	Expectation Diffusion Index: Debt to Banks	15	1M Q0
3M	Q0	Expectation Diffusion Index: Employment	15	1M Q0
3M	Q0	Expectation Diffusion Index: Equipment Purchase	15	1M Q0
3M	Q0	Expectation Diffusion Index: Financial Situation	15	1M Q0
3M	Q0	Expectation Diffusion Index: Orders	15	1M Q0
3M	Q0	Expectation Diffusion Index: Production	15	1M Q0
3M	Q0	Expectation Diffusion Index: Purchasing Prices	15	1M Q0
3M	Q0	Expectation Diffusion Index: Sales Prices	15	1M Q0
3M	Q0	Expectation Diffusion Index: Wages	15	1M Q0
3M	Q0	Production Costs: Current Estimates	20	2M Q0
3M	Q0	Demand for businesses’ products (services): Current Estimates	20	2M Q0
3M	Q0	Prices for businesses’ products (services): Current Estimates	20	2M Q0
3M	Q0	Production output, Scope of Contracted Works, Turnover and Services: Current Estimates	20	2M Q0
3M	Q0	Demand for Businesses’ Products (Services): Expectations for 3 Months Ahead	20	2M Q0
3M	Q0	Prices for businesses’ products (services): Expectations for 3 Months Ahead	20	2M Q0
3M	Q0	Production output, Scope of Contracted Works, etc.: Expectations for 3 Months Ahead	20	2M Q0
3M	Q0	Real Wages	25	1M Q0
3M	Q0	Agricultural Production Index	25	2M Q0
3M	Q0	Construction Works Value Index	25	2M Q0
3M	Q0	Freight Turnover Index	25	2M Q0
3M	Q0	Industrial Production Index	25	2M Q0
3M	Q0	Labour Force Demand	25	2M Q0
3M	Q0	Labour Force Unempoyed	25	2M Q0

3M	Q0	Paid Services Rendered to Population Index	25	2M Q0
3M	Q0	Passenger Turnover Index	25	2M Q0
3M	Q0	Public Catering Turnover Index	25	2M Q0
3M	Q0	Retail Trade Turnover Index	25	2M Q0
3M	Q0	Wholesale Trade Turnover Index	25	2M Q0
3M	Q0	Capacity Utilisation Rate: Actual (Normal Monthly Level = 100)	30	1M Q0
3M	Q0	Enterprises Debt to Banks (Normal Monthly Level = 100)	30	1M Q0
3M	Q0	Enterprises in Good or Normal Financial Situation	30	1M Q0
3M	Q0	Enterprises not Buying Equipment for 2 Months and More	30	1M Q0
3M	Q0	Labour Utilisation Rate: Actual (Normal Monthly Level = 100)	30	1M Q0
3M	Q0	Orders: Actual (Normal Monthly Level = 100)	30	1M Q0
3M	Q0	Stocks: Actual (Normal Monthly Level = 100)	30	1M Q0
3M	Q0	MIACR Interest Rate: 1 Day	30	3M Q0
3M	Q0	Urals Oil Price	30	3M Q0
3M	Q0	US Federal Funds Effective Rate	30	3M Q0
3M	Q0	Government Bonds Zero Coupon Yield: Redemption Term 1 Year	30	3M Q0
3M	Q0	Government Bonds Zero Coupon Yield: Redemption Term 3 Years	30	3M Q0
3M	Q0	Government Bonds Zero Coupon Yield: Redemption Term 10 Years	30	3M Q0
3M	Q0	MOEX Russia Index	30	3M Q0
3M	Q0	RTS Index	30	3M Q0
3M	Q0	Real Household Consumption Expenditures	30	Q(-1)
3M	Q0	Real Investments	30	Q(-1)
3M	Q0	Real Exports	30	Q(-1)
3M	Q0	Real Government Consumption Expenditures	30	Q(-1)
1M	Q1	Official Reserve Assets	7	3M Q0
1M	Q1	Consumer Price Index	8	3M Q0
1M	Q1	US Consumer Price Index	10	3M Q0
1M	Q1	Actual Diffusion Index: Employment	15	2M Q0
1M	Q1	Actual Diffusion Index: Equipment Purchase	15	2M Q0
1M	Q1	Actual Diffusion Index: Orders	15	2M Q0
1M	Q1	Actual Diffusion Index: Production	15	2M Q0
1M	Q1	Actual Diffusion Index: Purchasing Prices	15	2M Q0
1M	Q1	Expectation Diffusion Index: Sales Prices	15	2M Q0
1M	Q1	Actual Diffusion Index: Sales/Purchasing Prices Ratio	15	2M Q0
1M	Q1	Actual Diffusion Index: Orders	15	2M Q0
1M	Q1	Actual Diffusion Index: Wages	15	2M Q0
1M	Q1	Expectation Diffusion Index: Debt to Banks	15	2M Q0
1M	Q1	Expectation Diffusion Index: Employment	15	2M Q0
1M	Q1	Expectation Diffusion Index: Equipment Purchase	15	2M Q0
1M	Q1	Expectation Diffusion Index: Financial Situation	15	2M Q0
1M	Q1	Expectation Diffusion Index: Orders	15	2M Q0
1M	Q1	Expectation Diffusion Index: Production	15	2M Q0
1M	Q1	Expectation Diffusion Index: Purchasing Prices	15	2M Q0
1M	Q1	Expectation Diffusion Index: Sales Prices	15	2M Q0
1M	Q1	Expectation Diffusion Index: Wages	15	2M Q0
1M	Q1	Production Costs: Current Estimates	20	3M Q0
1M	Q1	Demand for businesses’ products (services): Current Estimates	20	3M Q0
1M	Q1	Prices for businesses’ products (services): Current Estimates	20	3M Q0
1M	Q1	Production output, Scope of Contracted Works, Turnover and Services: Current Estimates	20	3M Q0
1M	Q1	Demand for Businesses’ Products (Services): Expectations for 3 Months Ahead	20	3M Q0
1M	Q1	Prices for businesses’ products (services): Expectations for 3 Months Ahead	20	3M Q0
1M	Q1	Production output, Scope of Contracted Works, etc.: Expectations for 3 Months Ahead	20	3M Q0
1M	Q1	Real Wages	25	2M Q0
1M	Q1	Agricultural Production Index	25	3M Q0
1M	Q1	Construction Works Value Index	25	3M Q0

1M	Q1	Freight Turnover Index	25	3M Q0
1M	Q1	Industrial Production Index	25	3M Q0
1M	Q1	Labour Force Demand	25	3M Q0
1M	Q1	Labour Force Unempoyed	25	3M Q0
1M	Q1	Paid Services Rendered to Population Index	25	3M Q0
1M	Q1	Passenger Turnover Index	25	3M Q0
1M	Q1	Public Catering Turnover Index	25	3M Q0
1M	Q1	Retail Trade Turnover Index	25	3M Q0
1M	Q1	Wholesale Trade Turnover Index	25	3M Q0
1M	Q1	Capacity Utilisation Rate: Actual (Normal Monthly Level = 100)	30	2M Q0
1M	Q1	Enterprises Debt to Banks (Normal Monthly Level = 100)	30	2M Q0
1M	Q1	Enterprises in Good or Normal Financial Situation	30	2M Q0
1M	Q1	Enterprises not Buying Equipment for 2 Months and More	30	2M Q0
1M	Q1	Labour Utilisation Rate: Actual (Normal Monthly Level = 100)	30	2M Q0
1M	Q1	Orders: Actual (Normal Monthly Level = 100)	30	2M Q0
1M	Q1	Stocks: Actual (Normal Monthly Level = 100)	30	2M Q0
1M	Q1	MIACR Interest Rate: 1 Day	30	1M Q1
1M	Q1	Urals Oil Price	30	1M Q1
1M	Q1	US Federal Funds Effective Rate	30	1M Q1
1M	Q1	Government Bonds Zero Coupon Yield: Redemption Term 1 Year	30	1M Q1
1M	Q1	Government Bonds Zero Coupon Yield: Redemption Term 3 Years	30	1M Q1
1M	Q1	Government Bonds Zero Coupon Yield: Redemption Term 10 Years	30	1M Q1
1M	Q1	MOEX Russia Index	30	1M Q1
1M	Q1	RTS Index	30	1M Q1
1M	Q1	US Real Gross Domestic Product	30	Q0
2M	Q1	Official Reserve Assets	7	1M Q1
2M	Q1	Consumer Price Index	8	1M Q1
2M	Q1	US Consumer Price Index	10	1M Q1
2M	Q1	Real Gross Domestic Product	15	Q0

Notes. Q(-1) – previous quarter; Q0 – current quarter; Q1 – next quarter
1M – first month of the quarter; 2M – second month of the quarter; 3M – third month of the quarter

Source: author’s calculations.

Appendix C

Scheme C1. State Space representation of the DSGE-m model

$$\begin{bmatrix} Y_{t_m}^{Quarterly} \\ Y_{t_m}^{Monthly,growth} \\ Y_{t_m}^{Monthly,level} \\ X_{t_m} \end{bmatrix} = \begin{bmatrix} \mathcal{M}_{m,Q} & 0 & 0 & -\mathcal{M}_{m,Q} \\ \mathcal{M}_{m,M} & 0 & 0 & -\mathcal{M}_{m,M} \\ \mathcal{M}_{m}{}^{M} & 0 & 0 & 0 \\ \Lambda & 0 & 0 & -\Lambda \end{bmatrix} \begin{bmatrix} s_{t_m} \\ s_{t_m-1} \\ s_{t_m-2} \\ s_{t_m-3} \end{bmatrix} + \begin{bmatrix} v_{t_m} \\ 0 \\ 0 \\ e_{t_m} \end{bmatrix}$$

$$\begin{bmatrix} s_{t_m} \\ s_{t_m-1} \\ s_{t_m-2} \\ s_{t_m-3} \end{bmatrix} = \begin{bmatrix} \mathcal{T}_m & 0 & 0 & 0 \\ I_N & 0 & 0 & 0 \\ 0 & I_N & 0 & 0 \\ 0 & 0 & I_N & 0 \end{bmatrix} \begin{bmatrix} s_{t_m-1} \\ s_{t_m-2} \\ s_{t_m-3} \\ s_{t_m-4} \end{bmatrix} + \mathcal{B}_m \begin{bmatrix} \varepsilon_{m,t_m} \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

Notes. $Y_{t_m}^{Quarterly}$ is a vector of modelled variables, which are observed in a quarterly frequency (“Real Gross Domestic Product”, “Real Household Consumption Expenditures”, “Real Investments”, “Real Exports”, “US Real Gross Domestic Product”, “Real Government Consumption Expenditures”)

$Y_{t_m}^{Monthly,growth}$ is a vector of modelled variables (in growth rates), which are observed monthly (“Consumer Price Index”, “Real Wages”, “Urals Oil Price”, “US Consumer Price Index”)

$Y_{t_m}^{Monthly,level}$ is a vector of modelled variables (in growth rates), which are observed monthly (“MIACR Interest Rate: 1 Day”, “US Federal Funds Effective Rate”)

X_{t_m} is a vector of non-modelled observable variables

$\mathcal{M}_{m,Q}, \mathcal{M}_{m,M}, \mathcal{M}_{m,M}, \mathcal{M}_{m}{}^{M}$ are selection matrices for matching observed and unobserved (state) variables Y_{t_m}

$-\mathcal{M}_{m,Q}$ и $-\mathcal{M}_{m,M}$ are selection matrices for variables measured in growth rates

Λ is a matrix of factor loadings which connects non-modelled variables X_{t_m} with modelled observable variables

v_{t_m} is a vector of measurement errors for a subset of modelled variables $Y_{t_m}^{Quarterly}$

e_{t_m} is a vector of idiosyncratic shocks for non-modelled variables X_{t_m}

ε_{m,t_m} is a vector of structural shocks (see Table C2)

Source: author’s calculation.

Tables C1. The proportion of variance in observable variables explained by the model

Observable Variable	Category	Full Sample (2003 Q1-2023 Q2)	Short Sample (2003 Q1-2019 Q4)
Modelled variables			
MIACR Interest Rate: 1 Day	-	1.00	1.00
Consumer Price Index	-	1.00	1.00
Real Wages	-	1.00	1.00
Real Gross Domestic Product	-	1.00	1.00
Real Household Consumption Expenditures	-	1.00	1.00
Real Investments	-	1.00	1.00
Urals Oil Price	-	1.00	1.00
Real Exports	-	1.00	1.00
US Real Gross Domestic Product	-	1.00	1.00
US Federal Funds Effective Rate	-	1.00	1.00
US Consumer Price Index	-	1.00	1.00
Real Government Consumption Expenditures	-	1.00	1.00
Non-modelled variables			
Agricultural Production Index	Hard	0.22	0.26
Construction Works Value Index	Hard	0.51	0.51
Freight Turnover Index	Hard	0.56	0.59
Industrial Production Index	Hard	0.75	0.77
Labour Force Demand	Hard	0.66	0.61
Labour Force Unempoyed	Hard	0.37	0.14
Paid Services Rendered to Population Index	Hard	0.96	0.42
Passenger Turnover Index	Hard	0.90	0.03
Public Catering Turnover Index	Hard	0.93	0.49
Retail Trade Turnover Index	Hard	0.88	0.81
Wholesale Trade Turnover Index	Hard	0.76	0.34
Actual Diffusion Index: Employment	Soft	0.20	0.24
Actual Diffusion Index: Equipment Purchase	Soft	0.26	0.24
Actual Diffusion Index: Orders	Soft	0.32	0.30
Actual Diffusion Index: Production	Soft	0.23	0.22
Actual Diffusion Index: Purchasing Prices	Soft	0.18	0.17
Actual Diffusion Index: Sales Prices	Soft	0.21	0.24
Actual Diffusion Index: Sales/Purchasing Prices Ratio	Soft	0.02	0.03
Actual Diffusion Index: Stocks	Soft	0.09	0.17
Actual Diffusion Index: Wages	Soft	0.33	0.36
Capacity Utilisation Rate: Actual (Normal Monthly Level = 100)	Soft	0.42	0.47
Enterprises Debt to Banks (Normal Monthly Level = 100)	Soft	0.12	0.09
Enterprises in Good or Normal Financial Situation	Soft	0.35	0.28
Enterprises not Buying Equipment for 2 Months and More	Soft	0.17	0.22
Expectation Diffusion Index: Debt to Banks	Soft	0.23	0.15
Expectation Diffusion Index: Employment	Soft	0.32	0.33
Expectation Diffusion Index: Equipment Purchase	Soft	0.29	0.31
Expectation Diffusion Index: Financial Situation	Soft	0.31	0.26
Expectation Diffusion Index: Orders	Soft	0.24	0.23
Expectation Diffusion Index: Production	Soft	0.38	0.44
Expectation Diffusion Index: Purchasing Prices	Soft	0.34	0.39
Expectation Diffusion Index: Sales Prices	Soft	0.30	0.35
Expectation Diffusion Index: Wages	Soft	0.43	0.48
Labour Utilisation Rate: Actual (Normal Monthly Level = 100)	Soft	0.35	0.44
Production Costs: Current Estimates	Soft	0.19	0.20
Demand for businesses’ products (services): Current Estimates	Soft	0.70	0.69
Prices for businesses’ products (services): Current Estimates	Soft	0.29	0.27
Production output, Scope of Contracted Works, Turnover and Services: Current Estimates	Soft	0.61	0.57
Demand for Businesses’ Products (Services): Expectations for 3 Months Ahead	Soft	0.41	0.54
Prices for businesses’ products (services): Expectations for 3 Months Ahead	Soft	0.20	0.08
Production output, Scope of Contracted Works, etc.: Expectations for 3 Months Ahead	Soft	0.42	0.55
Orders: Actual (Normal Monthly Level = 100)	Soft	0.37	0.42
Stocks: Actual (Normal Monthly Level = 100)	Soft	0.06	0.07
Government Bonds Zero Coupon Yield: Redemption Term 1 Year	Financial	0.24	0.28
Government Bonds Zero Coupon Yield: Redemption Term 3 Years	Financial	0.27	0.33
Government Bonds Zero Coupon Yield: Redemption Term 10 Years	Financial	0.27	0.32
MOEX Russia Index	Financial	0.63	0.41
Official Reserve Assets	Financial	0.63	0.68
RTS Index	Financial	0.50	0.55

Source: author’s calculations.

Table C2. Structural shocks and its classification

Notation	Shock	Group
$e_t^{\zeta_c}$	A preference shock	Domestic demand
$e_t^{\zeta_l}$	A labor supply shock	Domestic supply
$e_t^{A_c}$	A temporary technology shock	Domestic supply
$e_t^{g_A}$	A permanent technology shock	–
$e_t^{\varepsilon_h}$	A markup shock for domestic retailers	Domestic supply
$e_t^{\varepsilon_f}$	A markup shock for importing retailers	Domestic supply
$e_t^{\varepsilon_{*h}}$	A markup shock for exporting retailers	Foreign demand
e_t^{U}	An investment technology shock	Domestic supply
$e_t^{\sigma_\omega}$	A risk shock	Domestic demand
e_t^{γ}	A financial wealth shock	Domestic demand
$e_t^{\varepsilon_D}$	A markup shock for deposit rates	Domestic demand
$e_t^{\varepsilon_{cap}}$	A capital dynamics shock	Domestic demand
$e_t^{S_{oil}}$	A shock of oil exports	Foreign demand
e_t^{oil}	A real oil price shock	Foreign demand
e_t^{R}	A monetary policy shock	–
e_t^{res}	A reserves shock	Domestic demand
e_t^{G}	A government consumption shock	Domestic demand
$e_t^{\zeta_{c*}}$	A foreign preferences shock	Foreign demand
$e_t^{A_*}$	A foreign temporary technology shock	Foreign supply
e_t^{*R}	A foreign monetary policy shock	Foreign demand
$e_t^{p_{F*}}$	A shock of relative prices of imported goods	Domestic supply
$e_t^{z_{RP}}$	A risk premium shock	Foreign demand

Source: *Kreptsev and Seleznev (2017)*, author’s calculations.

Figure C1. Estimates of structural shocks

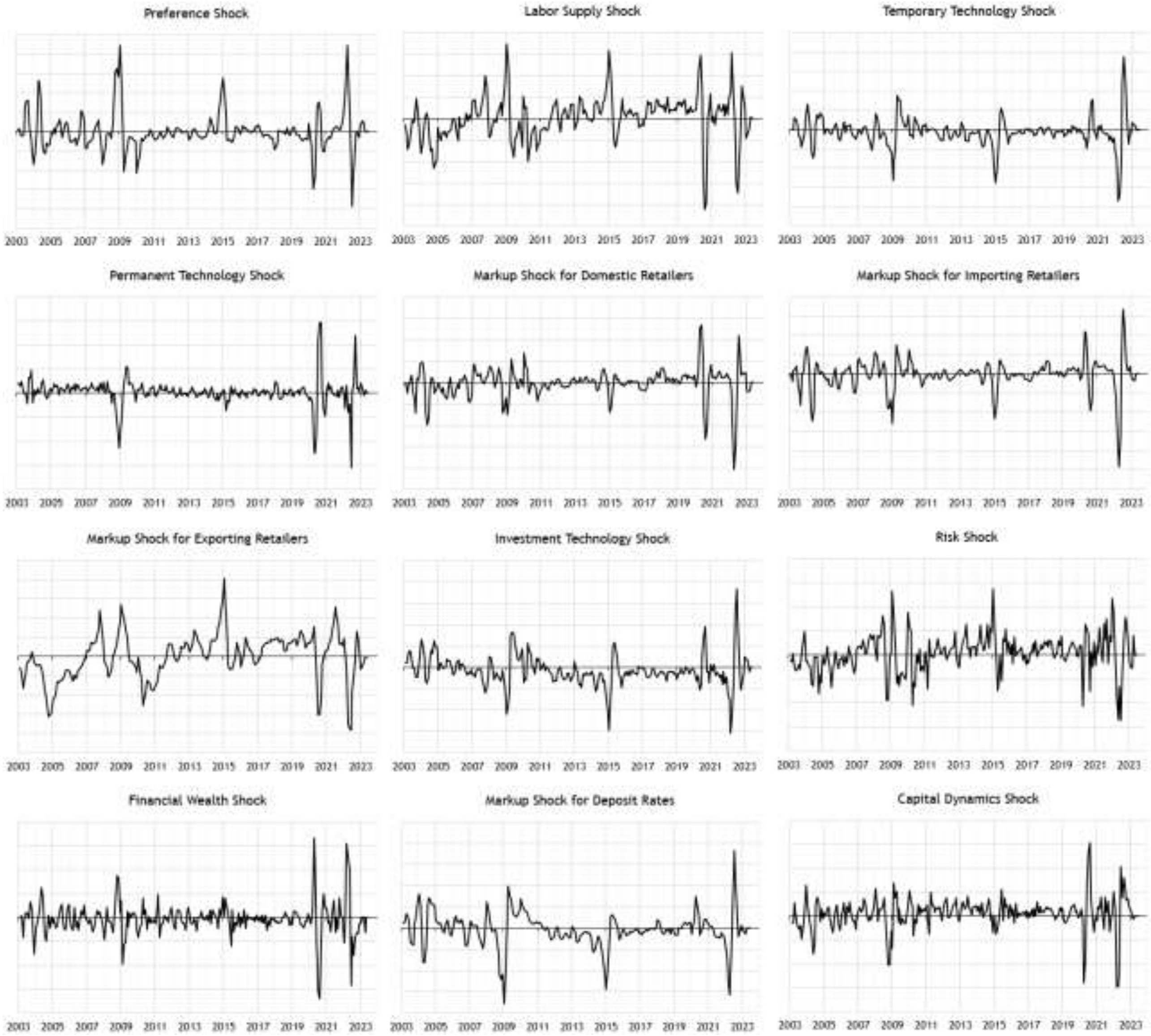
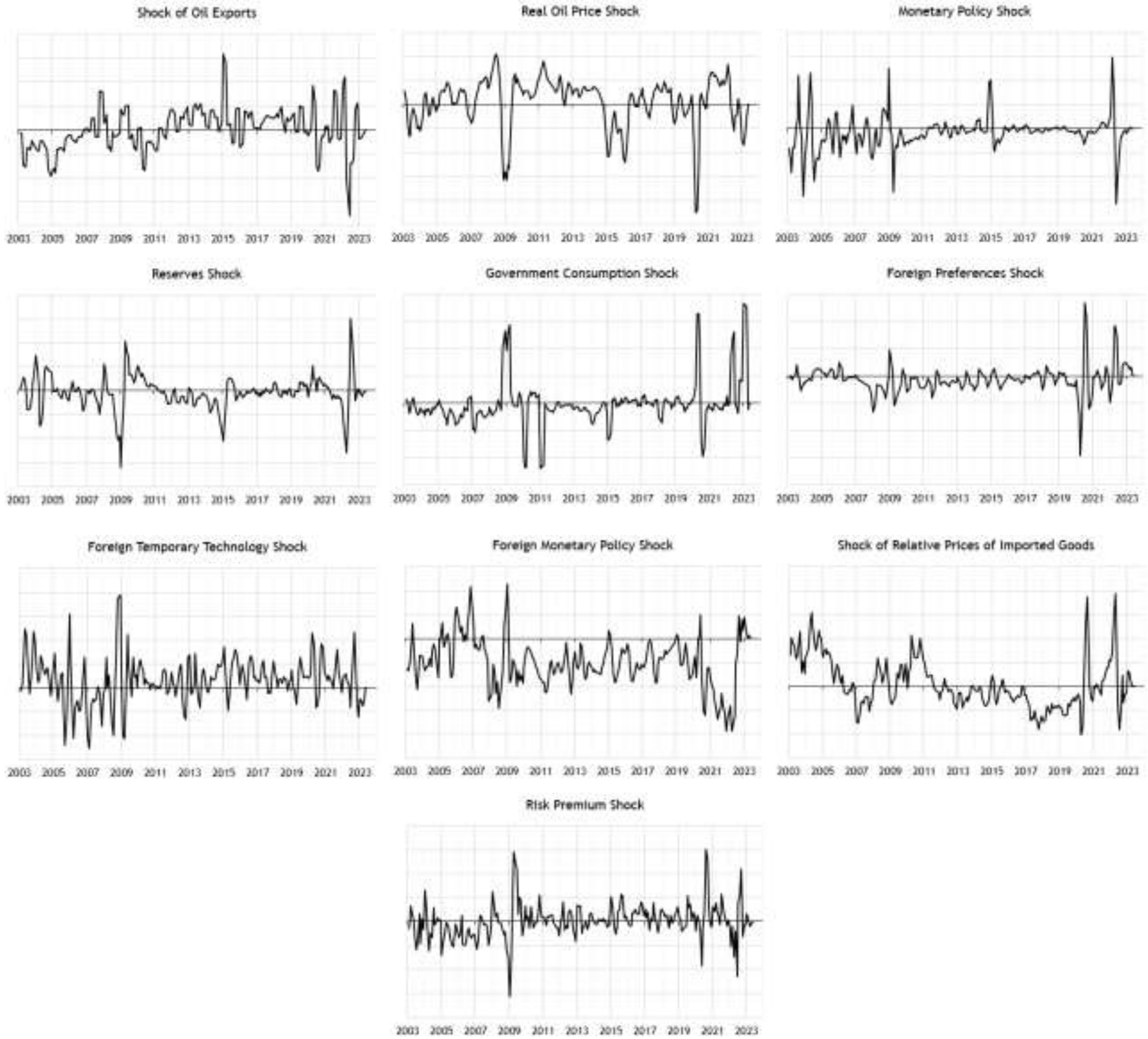
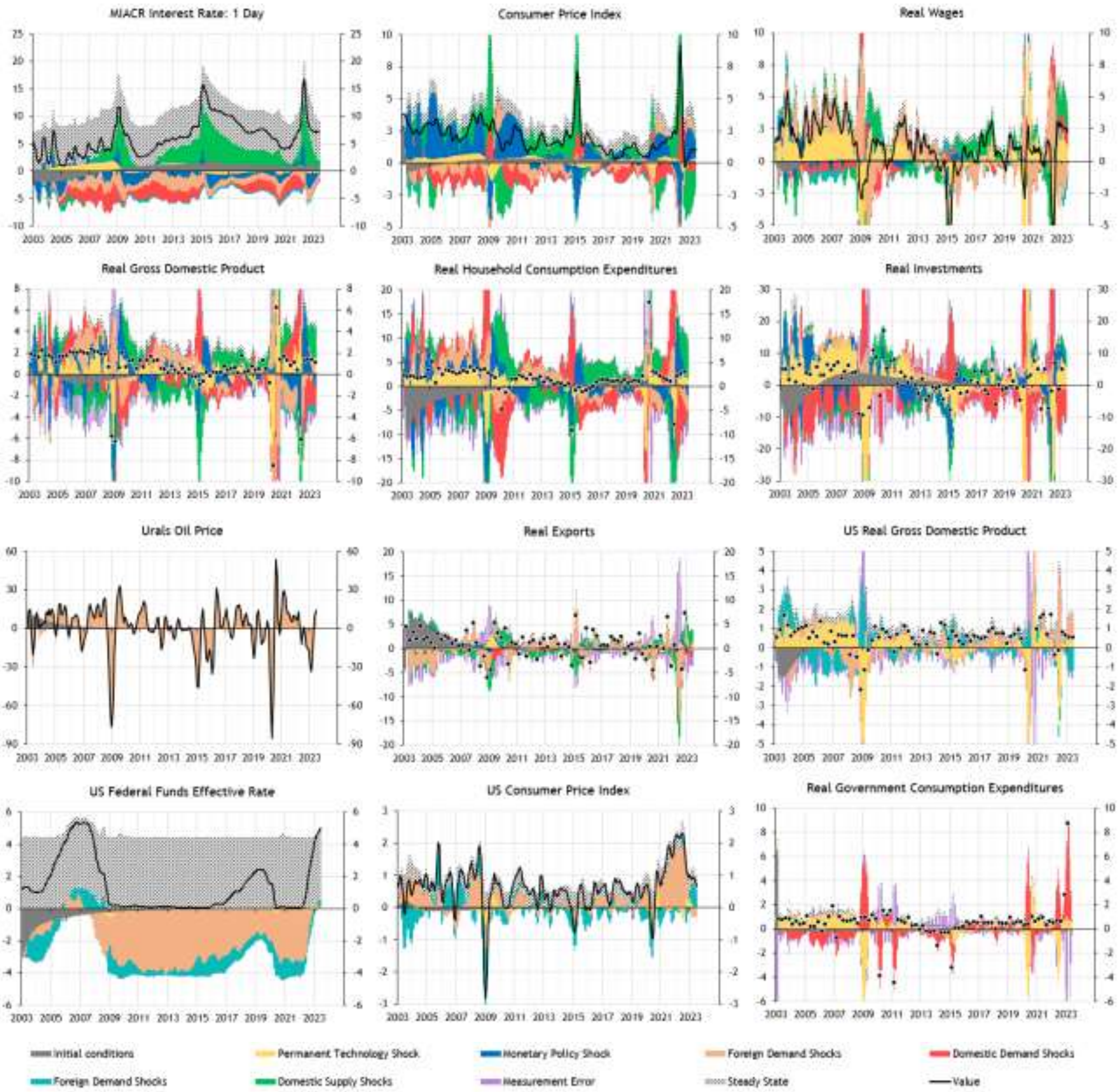


Figure C1 (cont.)



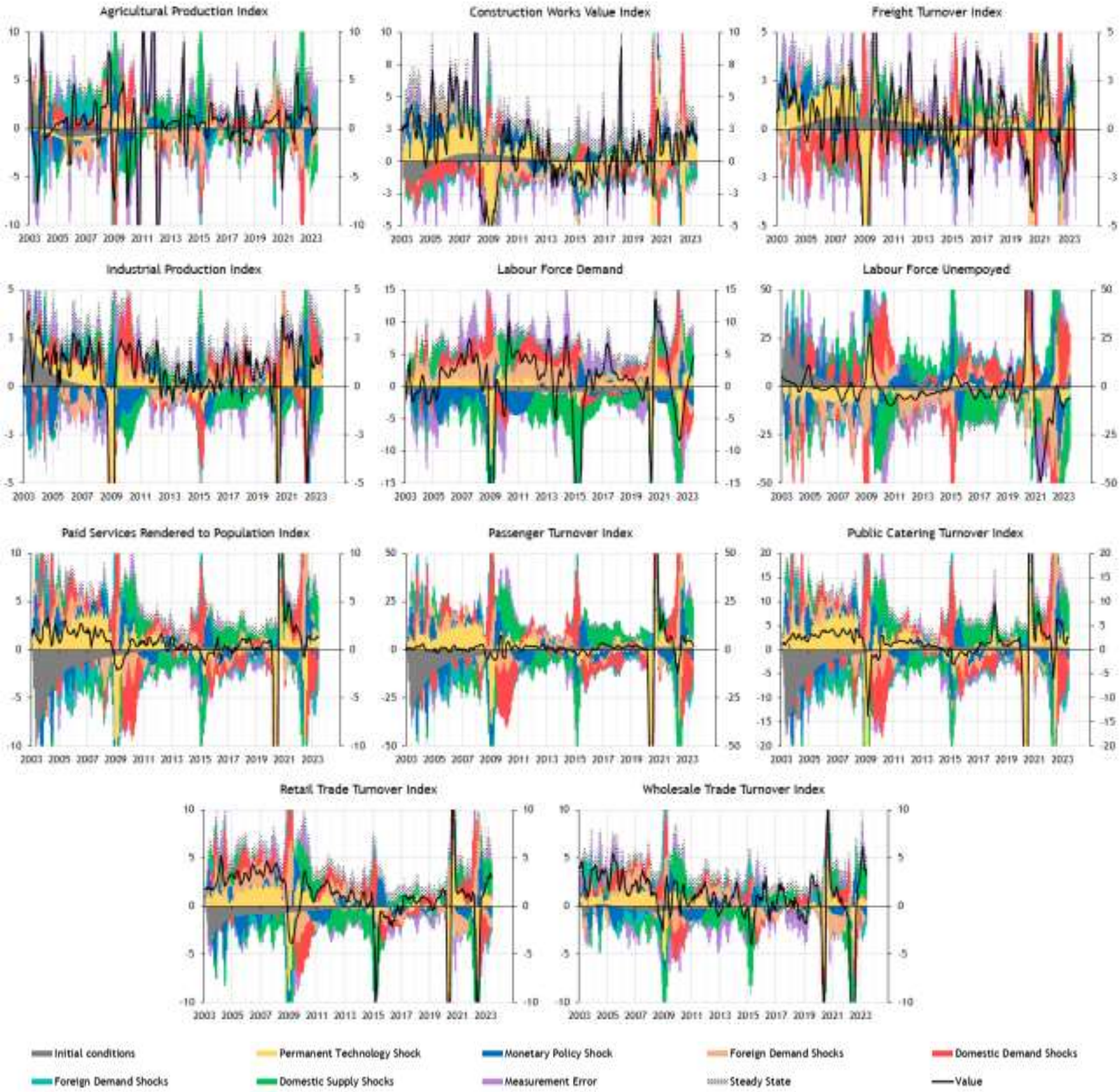
Source: author's calculations.

Figure C2. Historical decomposition of modelled variables into structural shocks



Source: author's calculations.

Figure C3. Historical decomposition of non-modelled variables ("hard") into structural shocks



Source: author's calculations.

Figure C4. Historical decomposition of non-modelled variables ("soft") into structural shocks

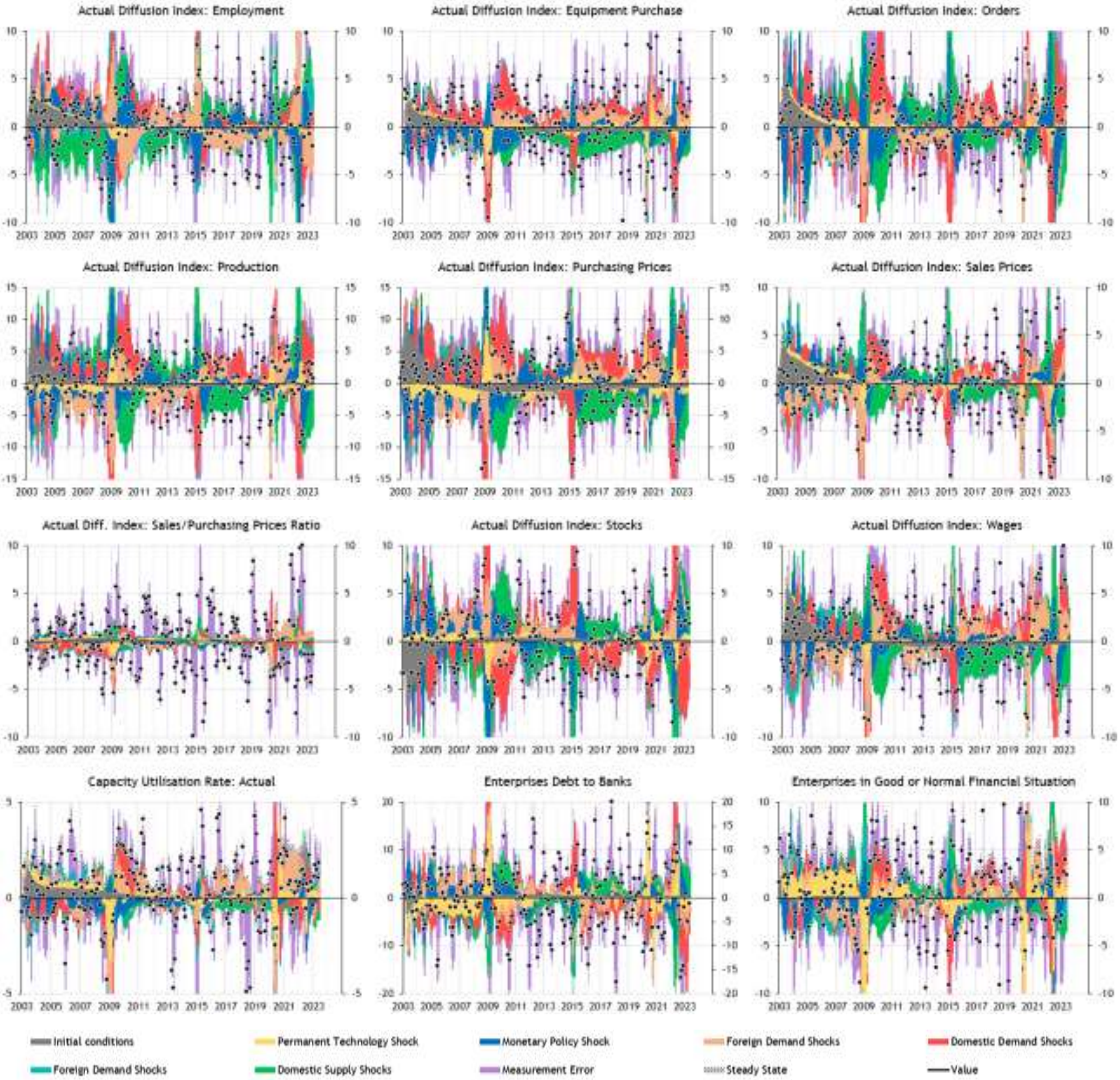


Figure C4 (cont.)

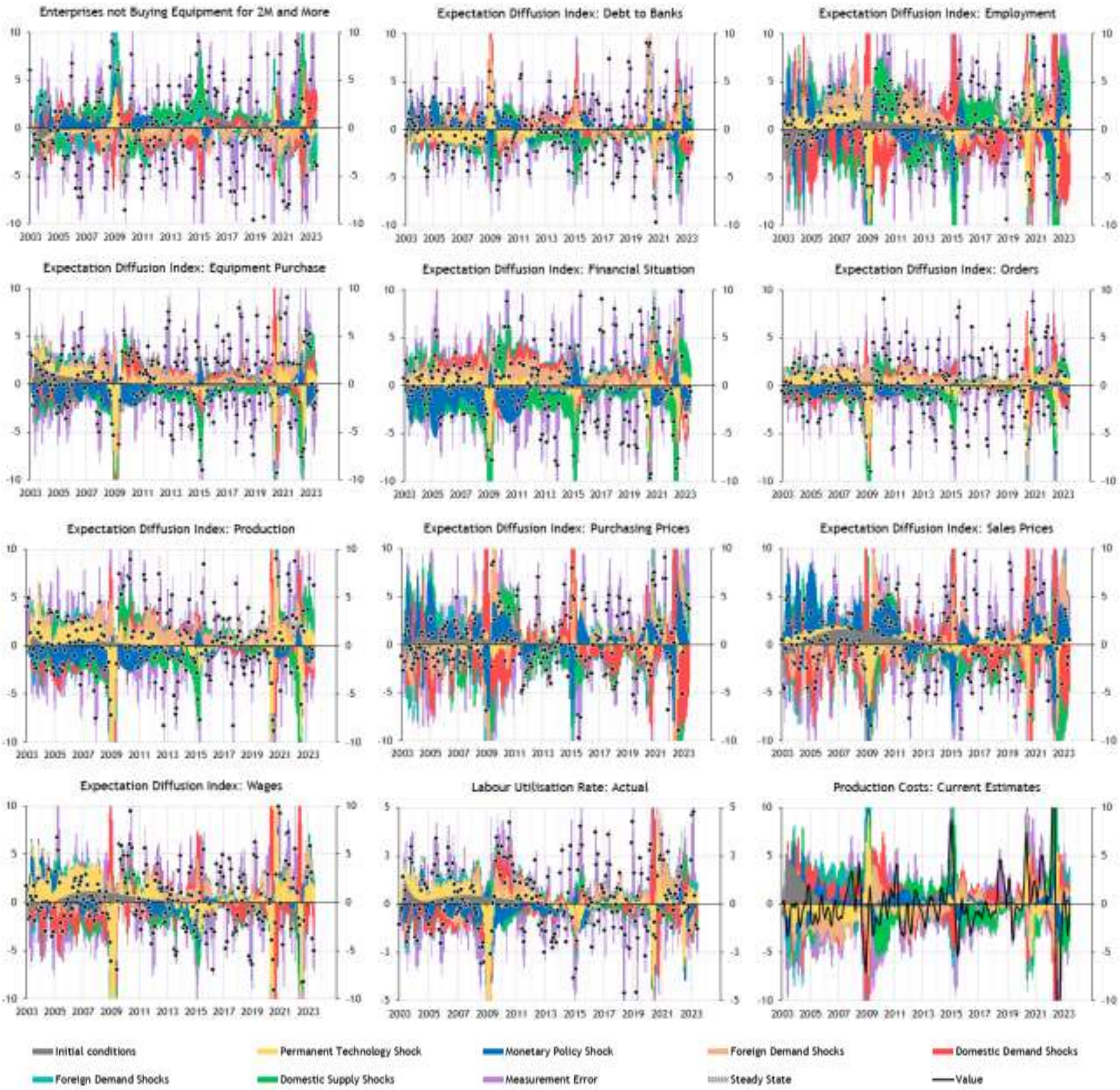
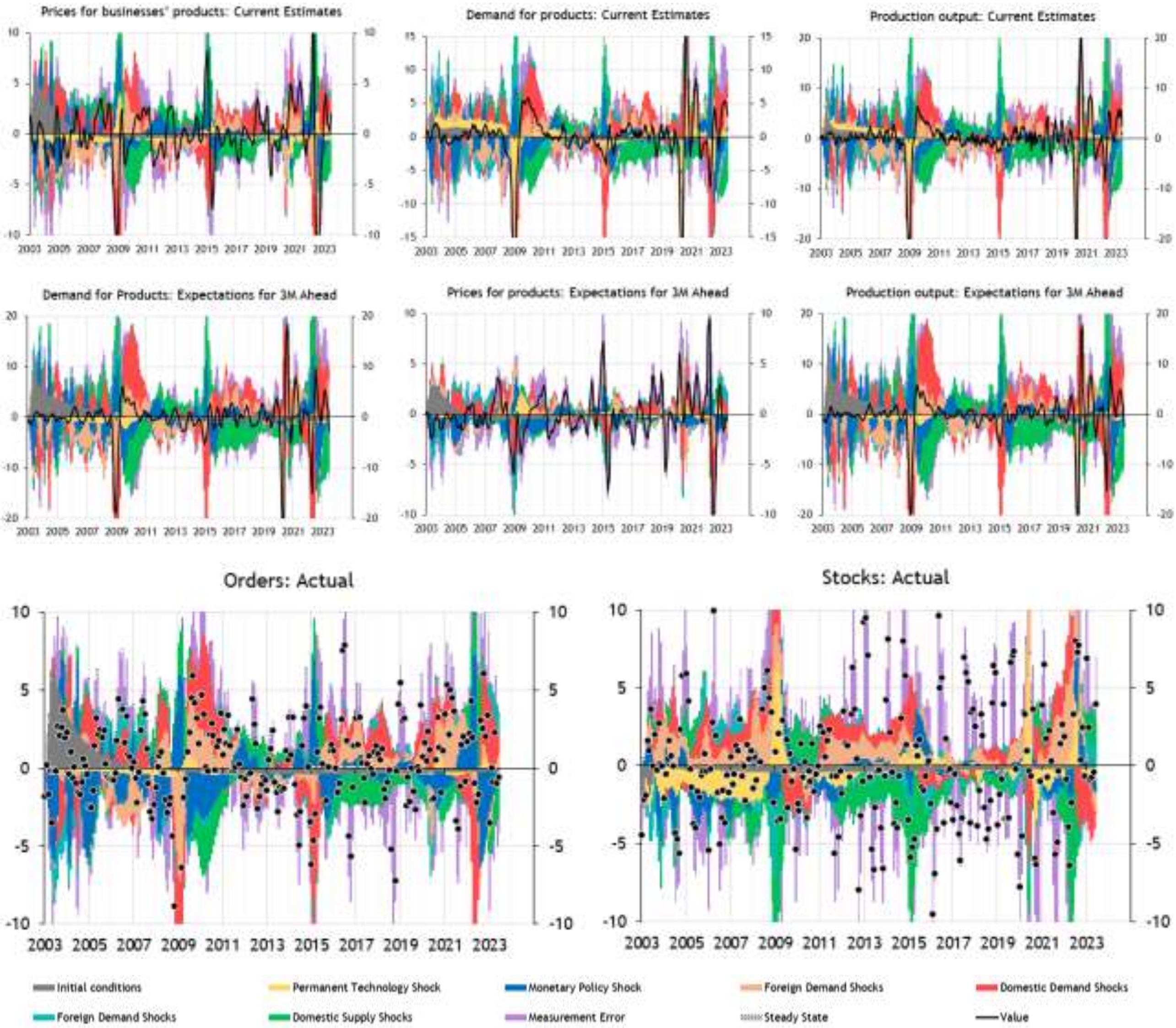
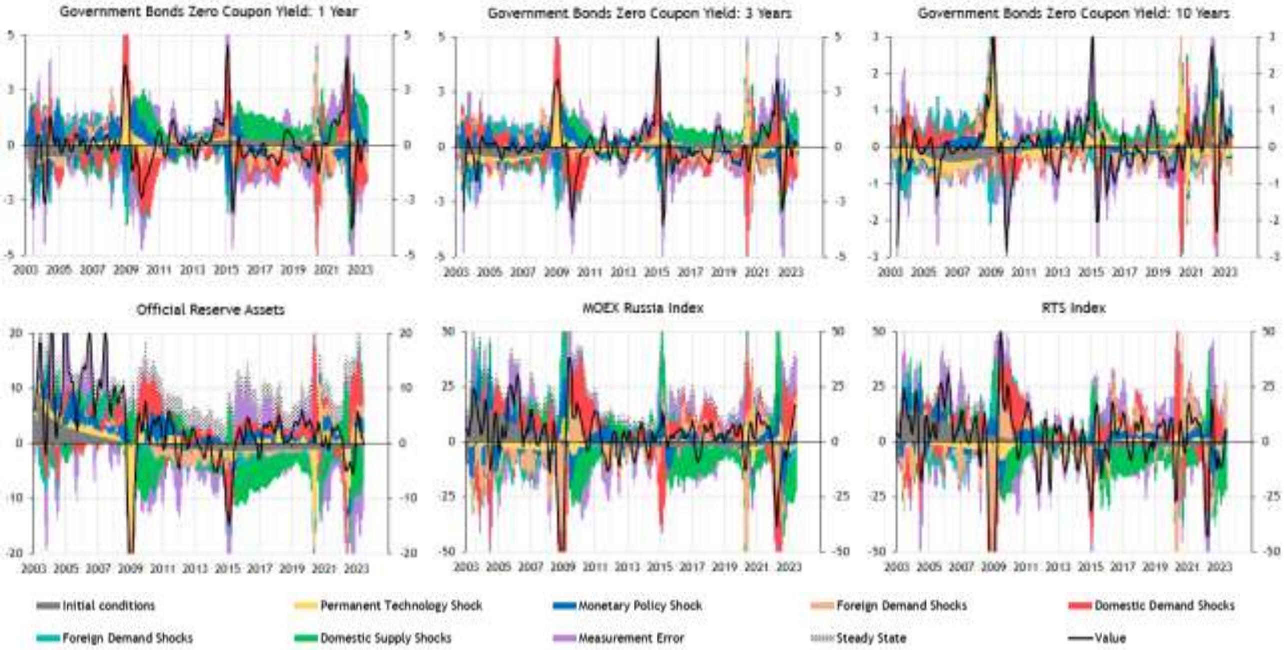


Figure C4 (cont.)



Source: author's calculations.

Figure C5. Historical decomposition of non-modelled variables ("financial") into structural shocks



Source: author's calculations.

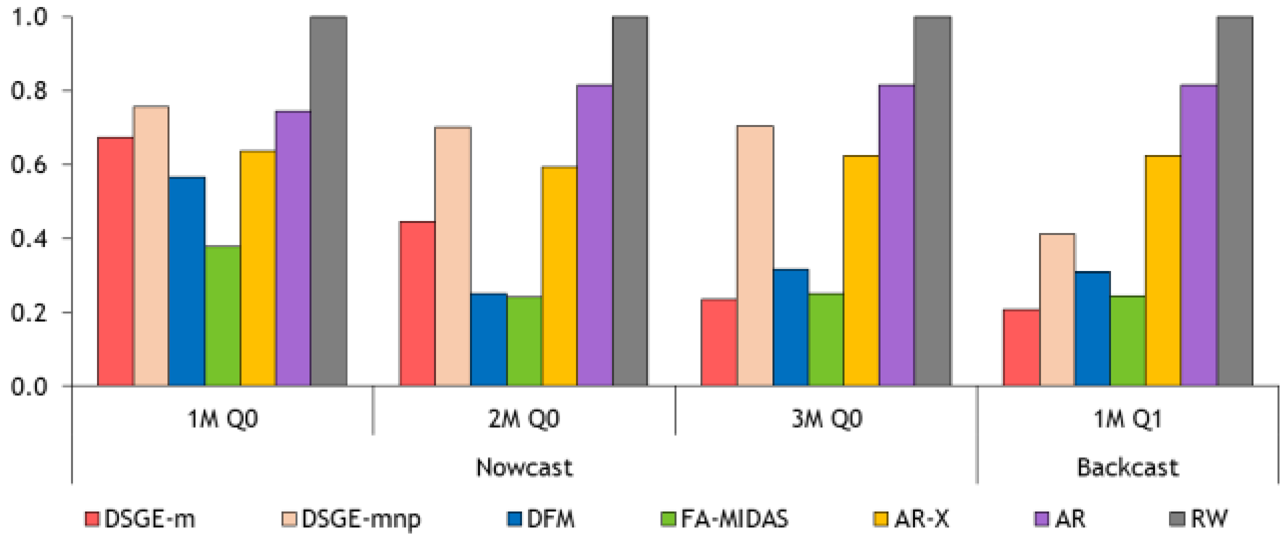
Table C3. Point estimates of the parameters of the matrix Λ connecting modelled and non-modelled variables

Non-modelled variable \ Modelled variable	MIACR Rate	CPI	Real Wages	GDP	Real Consumption	Real Investments	Urals Oil Price	Real Exports	US GDP	FFR	US CPI	Real Gov. Cons. Expen.
Agricultural Production Index	0.16	0.03	-0.15	1.18	-0.11	-0.23	0.12	-0.47	-0.71	-0.02	0.01	-0.10
Construction Works Value Index	-0.10	0.14	0.42	-0.09	-0.21	0.26	-0.10	-0.02	0.31	0.17	0.14	-0.01
Freight Turnover Index	0.08	0.01	-0.23	0.20	0.00	0.49	0.18	0.30	0.04	-0.03	0.09	0.09
Industrial Production Index	0.03	-0.11	-0.08	1.13	-0.32	-0.12	0.01	0.00	0.02	-0.02	0.15	0.02
Labour Force Demand	-0.27	-0.31	-0.24	0.45	0.25	0.20	0.05	-0.06	-0.14	-0.07	0.08	-0.01
Labour Force Unempoyed	-0.12	0.06	0.09	0.43	-0.57	-0.36	0.35	-0.40	-0.19	-0.01	-0.57	0.12
Paid Services Rendered to Population Index	0.01	0.00	-0.11	0.12	0.46	-0.06	-0.09	-0.07	0.57	0.05	0.06	-0.09
Passenger Turnover Index	0.08	-0.05	-0.19	0.09	0.60	0.02	-0.08	-0.04	0.48	0.01	0.04	-0.10
Public Catering Turnover Index	0.05	-0.01	-0.10	0.15	0.49	0.05	-0.08	-0.06	0.49	0.04	0.04	-0.10
Retail Trade Turnover Index	-0.15	-0.10	0.07	0.43	0.48	-0.11	-0.05	-0.07	0.10	0.05	-0.05	-0.10
Wholesale Trade Turnover Index	-0.09	-0.11	0.09	0.43	0.36	-0.16	0.10	0.17	0.01	0.01	-0.31	-0.01
Actual Diffusion Index: Employment	-0.06	0.14	-0.25	0.28	-0.49	-0.02	-0.04	0.26	0.38	0.03	0.08	0.20
Actual Diffusion Index: Equipment Purchase	-0.16	-0.21	-0.13	0.44	-0.25	0.02	0.07	-0.07	0.18	-0.05	0.04	-0.04
Actual Diffusion Index: Orders	0.16	-0.09	0.09	0.86	-0.53	-0.34	0.35	-0.22	0.15	-0.04	-0.08	0.01
Actual Diffusion Index: Production	-0.04	0.03	-0.16	0.81	-0.44	-0.42	0.22	-0.08	0.11	0.00	0.07	0.04
Actual Diffusion Index: Purchasing Prices	-0.19	-0.10	-0.17	0.76	-0.36	-0.47	0.02	-0.05	-0.08	-0.04	0.00	0.18
Actual Diffusion Index: Sales Prices	-0.04	0.06	-0.06	0.33	-0.29	-0.09	0.18	0.18	0.20	0.01	-0.14	0.13
Actual Diffusion Index: Sales/Purchasing Prices Ratio	0.04	0.00	-0.07	-0.16	-0.09	0.13	-0.01	0.07	0.21	0.00	0.12	0.01
Actual Diffusion Index: Stocks	-0.08	0.02	-0.09	-0.54	0.44	0.43	-0.28	0.14	0.15	0.04	0.16	-0.21
Actual Diffusion Index: Wages	-0.12	-0.03	-0.33	0.70	-0.31	-0.08	-0.01	0.10	0.10	-0.01	0.21	0.10
Capacity Utilisation Rate: Actual (Normal Monthly Level = 100)	0.01	-0.10	-0.10	0.16	-0.23	0.22	0.28	0.07	0.07	-0.04	0.23	-0.01
Enterprises Debt to Banks (Normal Monthly Level = 100)	-0.01	0.08	0.15	-0.88	0.22	0.14	0.29	0.20	-0.08	0.04	0.04	-0.25
Enterprises in Good or Normal Financial Situation	0.04	-0.06	-0.02	0.32	-0.20	-0.04	0.13	-0.09	0.45	-0.02	0.06	0.12
Enterprises not Buying Equipment for 2 Months and More	0.09	0.14	0.32	-0.42	-0.12	-0.23	0.03	-0.08	0.27	0.05	-0.12	0.02
Expectation Diffusion Index: Debt to Banks	-0.23	0.08	0.04	-0.66	0.10	0.09	-0.29	0.26	0.03	0.06	0.07	-0.09
Expectation Diffusion Index: Employment	0.06	-0.10	-0.11	-0.17	0.30	0.64	-0.02	0.22	-0.30	-0.04	0.13	-0.09
Expectation Diffusion Index: Equipment Purchase	-0.02	-0.23	0.07	0.40	-0.20	0.18	-0.02	0.06	-0.16	-0.07	0.10	0.07
Expectation Diffusion Index: Financial Situation	-0.04	-0.32	-0.09	0.49	0.07	0.08	0.14	-0.18	-0.10	-0.11	-0.07	-0.02
Expectation Diffusion Index: Orders	-0.01	-0.18	-0.03	0.18	-0.05	0.29	-0.06	0.03	0.02	-0.07	0.08	-0.03
Expectation Diffusion Index: Production	0.03	-0.27	-0.09	0.55	-0.05	0.30	-0.09	-0.01	-0.20	-0.12	0.11	0.04
Expectation Diffusion Index: Purchasing Prices	-0.14	0.11	-0.70	0.09	0.34	0.47	0.00	0.39	-0.22	-0.01	0.04	-0.07
Expectation Diffusion Index: Sales Prices	-0.18	0.17	-0.37	-0.14	-0.02	0.54	-0.14	0.30	0.04	0.03	0.06	-0.07
Expectation Diffusion Index: Wages	-0.03	-0.06	-0.17	0.22	-0.09	0.49	-0.21	0.18	0.05	-0.04	0.16	0.12
Labour Utilisation Rate: Actual (Normal Monthly Level = 100)	0.07	-0.13	-0.07	0.44	-0.24	0.30	0.23	-0.08	-0.13	-0.06	0.10	-0.02
Production Costs: Current Estimates	-0.05	0.13	-0.20	0.56	-0.23	-0.33	-0.01	0.08	-0.23	0.02	0.11	-0.08
Demand for businesses' products (services): Current Estimates	-0.05	-0.12	0.02	0.39	-0.53	-0.11	0.43	-0.18	0.66	-0.02	-0.06	0.05
Prices for businesses' products (services): Current Estimates	-0.02	0.05	-0.16	0.99	-0.33	-0.41	0.11	0.04	-0.15	-0.01	-0.12	0.03
Production output: Current Estimates	-0.03	-0.05	0.01	0.49	-0.61	-0.21	0.46	-0.22	0.63	0.00	-0.08	0.08
Demand for Businesses' Products: Expectations for 3 Months Ahead	-0.14	-0.05	0.02	0.34	-0.98	-0.16	0.57	-0.12	0.45	-0.01	-0.10	0.15
Prices for businesses' products: Expectations for 3 Months Ahead	0.07	-0.13	-0.06	0.93	0.01	-0.30	-0.19	0.03	-0.42	-0.06	0.08	0.02
Production output: Expectations for 3 Months Ahead	-0.13	-0.06	0.01	0.42	-1.01	-0.17	0.58	-0.16	0.40	-0.02	-0.10	0.18
Orders: Actual (Normal Monthly Level = 100)	0.04	-0.19	-0.13	0.93	-0.45	-0.17	0.30	-0.13	-0.28	-0.08	0.17	0.09
Stocks: Actual (Normal Monthly Level = 100)	-0.22	-0.10	-0.11	-0.37	0.24	0.04	-0.13	0.05	-0.04	0.01	0.36	-0.10
Government Bonds Zero Coupon Yield: Redemption Term 1 Year	0.23	0.19	-0.18	0.07	0.71	-0.05	-0.28	0.20	-0.42	0.04	0.05	-0.09
Government Bonds Zero Coupon Yield: Redemption Term 3 Years	0.14	0.15	-0.27	0.31	0.65	-0.21	-0.21	0.04	-0.50	0.02	0.00	-0.07
Government Bonds Zero Coupon Yield: Redemption Term 10 Years	0.17	0.11	-0.19	0.63	0.37	-0.49	-0.11	-0.13	-0.52	0.00	0.02	0.00
MOEX Russia Index	-0.39	0.15	0.14	0.42	-0.35	-0.03	0.05	0.04	-0.02	0.18	0.14	0.15
Official Reserve Assets	-0.26	0.03	-0.08	0.25	-0.61	-0.15	0.37	0.21	0.44	0.05	-0.17	0.01
RTS Index	-0.25	0.02	-0.02	-0.22	-0.48	0.11	0.60	0.17	0.44	0.06	-0.04	0.04

Source: author's calculations.

Appendix D

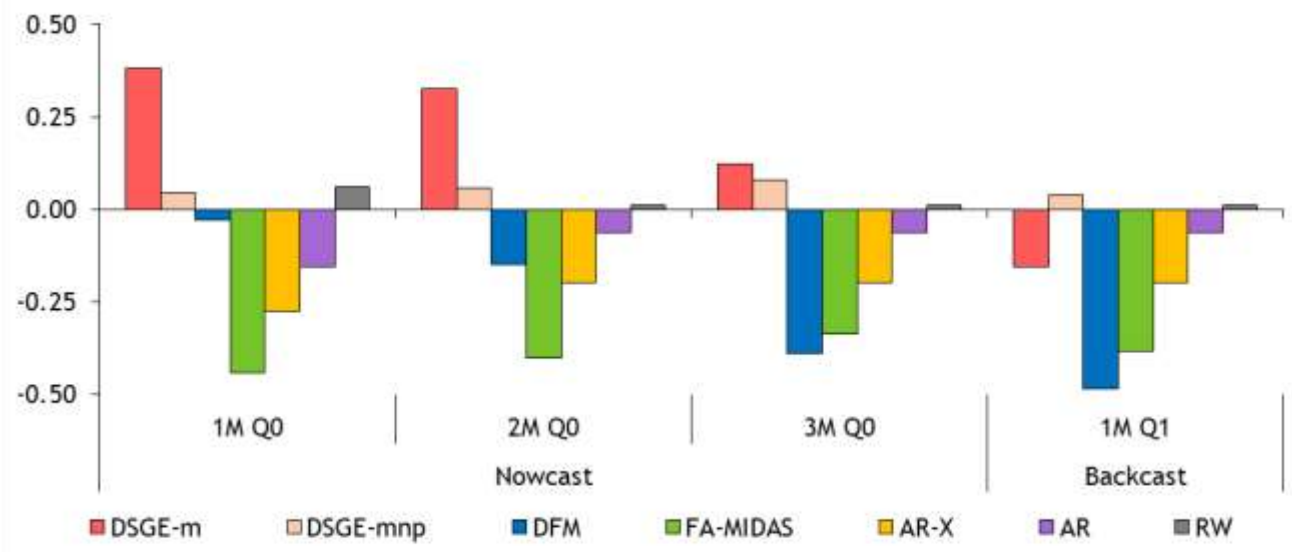
Figure D1. Relative root mean squared forecast error (RMSFE) in a DSGE-m model, competing models and benchmark models



Notes. Q0 represents the current quarter, while Q1 refers to the next quarter.
1M, 2M, and 3M indicate the end of the first, second, and third months, respectively.
Results for each model are shown relative to the RMSFE of the RW model. A value less (more) than one indicates that the model performs better (worse) than the RW model.

Source: author's calculations.

Figure D2. Mean forecast error (MFE) in a DSGE-m model, competing models and benchmark models



Notes. Q0 represents the current quarter, while Q1 refers to the next quarter.
1M, 2M, and 3M indicate the end of the first, second, and third months, respectively.

Source: author's calculations.

Table D1. Results of the Diebold and Mariano (1995) pairwise test for statistical differences in forecasting accuracy between a DSGE-m model, competing models, and benchmark models

		DSGE-m	DSGE-mnp	DFM	FA-MIDAS	AR-X	AR	RW
1M Q0	DSGE-m							
	DSGE-mnp							
	DFM		–*					
	FA-MIDAS		–*					
	AR-X				+**			
	AR				+**			
	RW	+*		+**	+**	+**	+**	
2M Q0	DSGE-m							
	DSGE-mnp	+*						
	DFM		–**					
	FA-MIDAS		–**					
	AR-X			+**	+**			
	AR	+**		+*	+*			
	RW	+**	+*	+*	+*	+*	+**	
3M Q0	DSGE-m							
	DSGE-mnp	+**						
	DFM		–**					
	FA-MIDAS		–**	–**				
	AR-X	+**		+**	+**			
	AR	+**		+*	+*			
	RW	+**		+*	+*	+*	+*	
1M Q1	DSGE-m							
	DSGE-mnp	+*						
	DFM	+*						
	FA-MIDAS	+*						
	AR-X	+**		+**	+**			
	AR	+*		+*	+*			
	RW	+**	+*	+*	+*	+*	+*	

Notes. Q0 represents the current quarter, while Q1 refers to the next quarter.
1M, 2M, and 3M indicate the end of the first, second, and third months, respectively.
"+" means that the column model has a significantly lower mean squared prediction error than the row model.
"–" means that the column model has a significantly higher mean squared prediction error than the row model.
An empty cell (" ") means that the test finds no evidence of a significant difference in forecasting accuracy between the models.
** is the 5% significance level.
* is the 10% significance level.

Source: author's calculations.

Figure D3. Nowcasting Russian GDP quarterly growth rates (seasonally adjusted) in different models for the test sample (2017 Q1 – 2023 Q2)

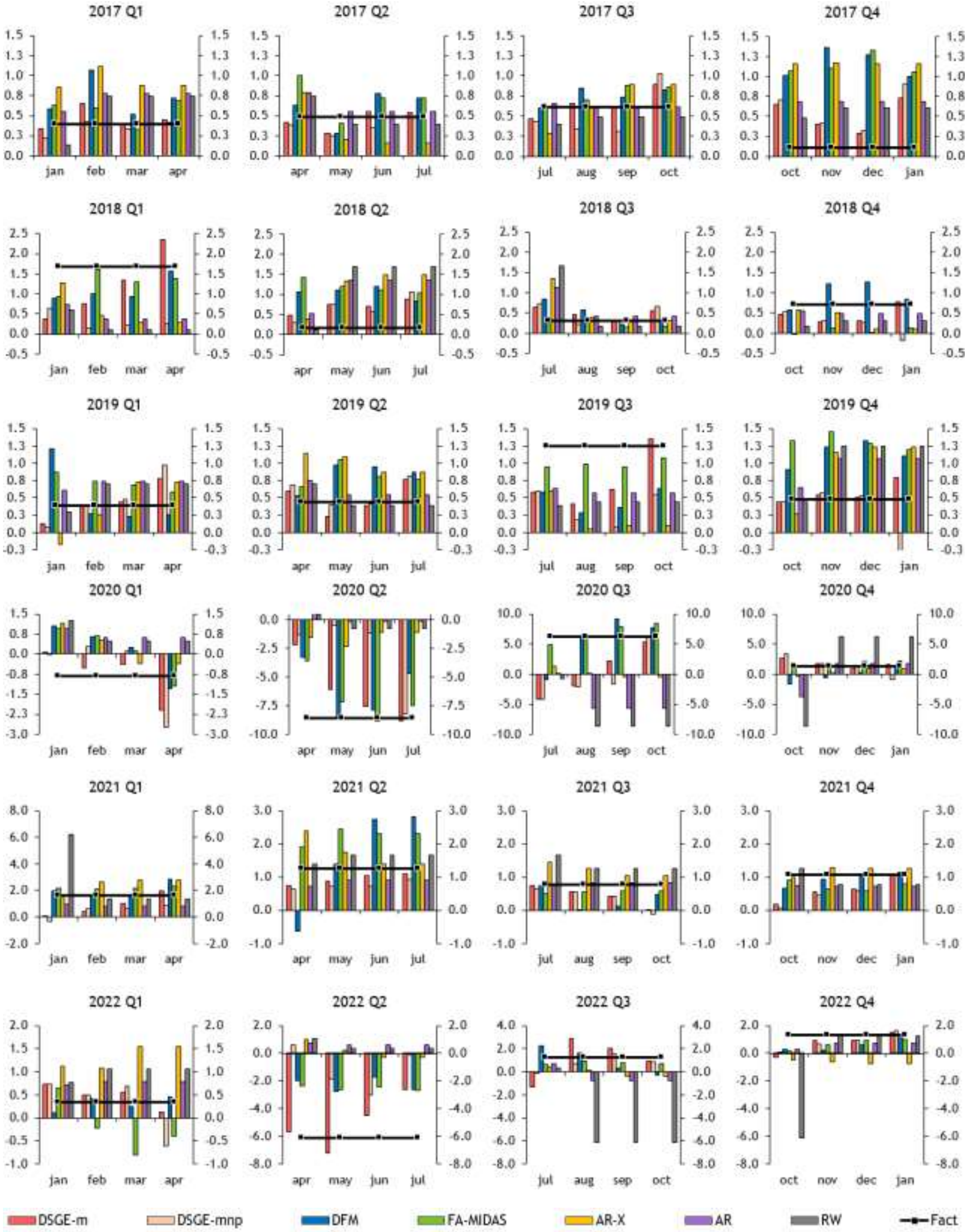
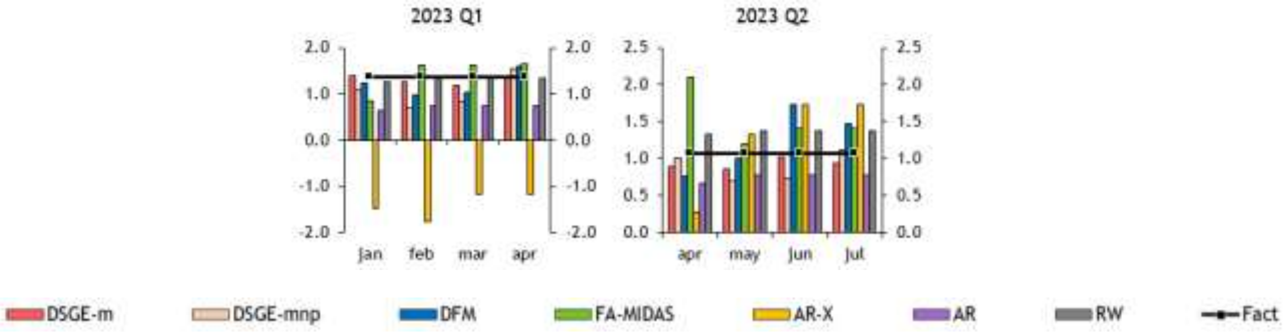


Figure D3 (cont.)



Source: author’s calculations.

Table D2. Relative root mean squared forecast error (RMSFE) for dynamic factor models (DFM) with different number of common factors (r) and lags (p)

Specification	Nowcast			Backcast
	1M Q0	2M Q0	3M Q0	1M Q1
r=1, p=1	0.77	0.48	0.31	0.34
r=1, p=2	0.65	0.28	0.29	0.33
r=1, p=3	0.63	0.28	0.29	0.34
r=1, p=4	0.59	0.31	0.33	0.34
r=1, p=5	0.61	0.28	0.29	0.34
r=1, p=6	0.61	0.27	0.29	0.34
r=2, p=1	0.70	0.60	0.34	0.31
r=2, p=2	0.61	0.27	0.33	0.32
r=2, p=3	0.57	0.27	0.32	0.31
r=2, p=4	0.56	0.34	0.39	0.32
r=2, p=5	0.61	0.28	0.31	0.31
r=2, p=6	**0.56**	**0.25**	**0.32**	**0.31**
r=3, p=1	1.60	0.60	0.28	0.39
r=3, p=2	1.57	0.27	0.43	0.40
r=3, p=3	1.05	0.28	0.42	0.39
r=3, p=4	0.96	0.42	0.51	0.40
r=3, p=5	1.22	0.38	0.44	0.39
r=3, p=6	1.12	0.36	0.45	0.39
r=4, p=1	2.05	0.52	0.34	0.28
r=4, p=2	1.02	0.33	0.59	0.27
r=4, p=3	0.93	0.29	0.55	0.26
r=4, p=4	1.24	0.51	0.57	0.25
r=4, p=5	0.92	0.35	0.63	0.26
r=4, p=6	0.98	0.36	0.63	0.26
r=5, p=1	2.63	0.45	0.60	0.33
r=5, p=2	0.80	0.43	0.79	0.31
r=5, p=3	0.72	0.39	0.84	0.31
r=5, p=4	1.02	0.55	0.84	0.30
r=5, p=5	0.64	0.40	0.88	0.32
r=5, p=6	0.73	0.40	0.87	0.32
r=6, p=1	2.68	0.50	0.60	0.40
r=6, p=2	0.81	0.41	0.75	0.38
r=6, p=3	1.00	0.37	0.81	0.37
r=6, p=4	1.17	0.50	0.81	0.37
r=6, p=5	0.87	0.37	0.86	0.40
r=6, p=6	1.02	0.38	0.88	0.40

Notes. Q0 represents the current quarter, while Q1 refers to the next quarter.
1M, 2M, and 3M indicate the end of the first, second, and third months, respectively.
The specification used to present the main results is highlighted in red.
Results for each model are shown relative to the RMSFE of the RW model. A value less (more) than one indicates that the model performs better (worse) than the RW model.

Source: author’s calculations.

Table D3. Relative root mean squared forecast error (RMSFE) for a mixed-frequency factor regression (FA-MIDAS) with different numbers of common factors (r) and lags (p)

Specification	Nowcast			Backcast
	1M Q0	2M Q0	3M Q0	1M Q1
r=1, p=1	0.43	0.28	0.29	0.26
r=1, p=2	0.41	0.27	0.29	0.26
r=1, p=3	0.41	0.27	0.29	0.26
r=1, p=4	0.40	0.26	0.30	0.26
r=1, p=5	0.41	0.26	0.29	0.26
r=1, p=6	0.41	0.26	0.29	0.26
r=2, p=1	0.59	0.28	0.25	0.30
r=2, p=2	0.38	0.26	0.26	0.24
r=2, p=3	0.37	0.25	0.26	0.24
r=2, p=4	0.37	0.24	0.26	0.24
r=2, p=5	0.37	0.24	0.25	0.24
r=2, p=6	**0.38**	**0.24**	**0.25**	**0.24**
r=3, p=1	0.61	0.31	0.30	0.33
r=3, p=2	0.54	0.29	0.28	0.32
r=3, p=3	0.54	0.28	0.27	0.32
r=3, p=4	0.64	0.26	0.27	0.32
r=3, p=5	0.68	0.26	0.26	0.33
r=3, p=6	0.82	0.26	0.26	0.32
r=4, p=1	0.62	0.31	0.27	0.33
r=4, p=2	0.56	0.27	0.28	0.34
r=4, p=3	0.41	0.26	0.27	0.29
r=4, p=4	0.64	0.26	0.28	0.35
r=4, p=5	0.43	0.27	0.28	0.28
r=4, p=6	0.53	0.30	0.27	0.28
r=5, p=1	0.61	0.33	0.30	0.34
r=5, p=2	0.54	0.29	0.27	0.34
r=5, p=3	0.51	0.28	0.27	0.34
r=5, p=4	0.65	0.28	0.28	0.34
r=5, p=5	0.68	0.28	0.28	0.34
r=5, p=6	0.89	0.29	0.27	0.34
r=6, p=1	0.61	0.34	0.28	0.33
r=6, p=2	0.55	0.31	0.28	0.34
r=6, p=3	0.39	0.30	0.28	0.29
r=6, p=4	0.42	0.29	0.28	0.29
r=6, p=5	0.43	0.29	0.28	0.29
r=6, p=6	0.51	0.31	0.27	0.28

Notes. Q0 represents the current quarter, while Q1 refers to the next quarter.
1M, 2M, and 3M indicate the end of the first, second, and third months, respectively.
The specification used to present the main results is highlighted in red.
Results for each model are shown relative to the RMSFE of the RW model. A value less (more) than one indicates that the model performs better (worse) than the RW model.

Source: author's calculations.

Table D4. Mean forecast error (MFE) for dynamic factor models (DFM) with different number of common factors (r) and lags (p)

Specification	Nowcast			Backcast
	1M Q0	2M Q0	3M Q0	1M Q1
r=1, p=1	-0.32	-0.31	-0.34	-0.36
r=1, p=2	-0.27	-0.25	-0.31	-0.36
r=1, p=3	-0.27	-0.25	-0.31	-0.36
r=1, p=4	-0.27	-0.24	-0.30	-0.36
r=1, p=5	-0.26	-0.24	-0.30	-0.36
r=1, p=6	-0.26	-0.24	-0.30	-0.36
r=2, p=1	-0.29	-0.14	-0.37	-0.49**
r=2, p=2	-0.17	-0.09	-0.36	-0.49**
r=2, p=3	-0.09	-0.13	-0.37	-0.48**
r=2, p=4	-0.05	-0.14	-0.40	-0.49**
r=2, p=5	-0.01	-0.13	-0.39	-0.49**
r=2, p=6	**-0.03**	**-0.15**	**-0.39**	**-0.48****
r=3, p=1	0.42	-0.13	-0.25	-0.11
r=3, p=2	0.65	-0.08	-0.16	-0.11
r=3, p=3	0.39	-0.15	-0.18	-0.10
r=3, p=4	0.30	-0.18	-0.22	-0.10
r=3, p=5	0.68	0.00	-0.14	-0.08
r=3, p=6	0.62	-0.05	-0.17	-0.08
r=4, p=1	0.89	-0.03	-0.08	-0.16
r=4, p=2	0.24	-0.25	-0.14	-0.19
r=4, p=3	0.30	-0.20	-0.10	-0.18
r=4, p=4	0.72	0.01	-0.04	-0.19
r=4, p=5	0.35	-0.15	0.00	-0.19
r=4, p=6	0.53	-0.09	0.02	-0.18
r=5, p=1	1.51	0.10	0.28	-0.04
r=5, p=2	0.13	-0.34	0.04	-0.08
r=5, p=3	0.22	-0.25	0.12	-0.07
r=5, p=4	0.70	-0.04	0.23	-0.08
r=5, p=5	0.18	-0.23	0.21	-0.07
r=5, p=6	0.45	-0.11	0.25	-0.06
r=6, p=1	1.52	0.03	0.18	-0.12
r=6, p=2	0.13	-0.35	-0.08	-0.14
r=6, p=3	0.44	-0.26	0.03	-0.14
r=6, p=4	0.91	-0.04	0.13	-0.14
r=6, p=5	0.42	-0.27	0.09	-0.12
r=6, p=6	0.71	-0.20	0.14	-0.13

Notes. Q0 represents the current quarter, while Q1 refers to the next quarter.
1M, 2M, and 3M indicate the end of the first, second, and third months, respectively.
The specification used to present the main results is highlighted in red.
"* (**)" is the significant at 10% (5%) level difference of MFE from zero in two-sided t-test for equality to zero of mean forecast error.

Source: author's calculations.

Table D5. Mean forecast error (MFE) for a mixed-frequency factor regression (FA-MIDAS) with different numbers of common factors (r) and lags (p)

Specification	Nowcast			Backcast
	1M Q0	2M Q0	3M Q0	1M Q1
r=1, p=1	-0.58*	-0.47**	-0.32	-0.43**
r=1, p=2	-0.56*	-0.44**	-0.31	-0.43**
r=1, p=3	-0.52*	-0.44**	-0.32	-0.44**
r=1, p=4	-0.51*	-0.42**	-0.31	-0.44**
r=1, p=5	-0.52*	-0.41**	-0.30	-0.44**
r=1, p=6	-0.51*	-0.41**	-0.31	-0.44**
r=2, p=1	-0.23	-0.50**	-0.35*	-0.49**
r=2, p=2	-0.52*	-0.47**	-0.33	-0.38**
r=2, p=3	-0.50*	-0.44**	-0.32	-0.38**
r=2, p=4	-0.46*	-0.42**	-0.33*	-0.38**
r=2, p=5	-0.47*	-0.40**	-0.33*	-0.38**
r=2, p=6	**-0.44**	**-0.40****	**-0.34***	**-0.38****
r=3, p=1	-0.23	-0.51**	-0.43*	-0.47*
r=3, p=2	-0.24	-0.48**	-0.28	-0.47*
r=3, p=3	-0.21	-0.46**	-0.30	-0.47*
r=3, p=4	-0.10	-0.41**	-0.33	-0.47*
r=3, p=5	-0.07	-0.39*	-0.33	-0.47*
r=3, p=6	0.00	-0.35*	-0.30	-0.46*
r=4, p=1	-0.31	-0.53**	-0.39*	-0.52**
r=4, p=2	-0.33	-0.47**	-0.36*	-0.53**
r=4, p=3	-0.62*	-0.43**	-0.40*	-0.45**
r=4, p=4	-0.21	-0.39*	-0.43**	-0.55**
r=4, p=5	-0.47	-0.34*	-0.42**	-0.45**
r=4, p=6	-0.39	-0.27	-0.38*	-0.43**
r=5, p=1	-0.29	-0.54**	-0.47**	-0.51**
r=5, p=2	-0.33	-0.47**	-0.34	-0.51**
r=5, p=3	-0.34	-0.44**	-0.38*	-0.53**
r=5, p=4	-0.18	-0.43**	-0.41*	-0.52**
r=5, p=5	-0.13	-0.40*	-0.41*	-0.52**
r=5, p=6	0.03	-0.35	-0.38*	-0.52**
r=6, p=1	-0.27	-0.54**	-0.40*	-0.49*
r=6, p=2	-0.27	-0.49**	-0.34	-0.49*
r=6, p=3	-0.53*	-0.46**	-0.37*	-0.43*
r=6, p=4	-0.44	-0.42*	-0.41*	-0.43**
r=6, p=5	-0.40	-0.39*	-0.40*	-0.43*
r=6, p=6	-0.29	-0.35	-0.37*	-0.42*

Notes. Q0 represents the current quarter, while Q1 refers to the next quarter.
1M, 2M, and 3M indicate the end of the first, second, and third months, respectively.
The specification used to present the main results is highlighted in red.
"* (**)" is the significant at 10% (5%) level difference of MFE from zero in two-sided t-test for equality to zero of mean forecast error.

Source: author's calculations.

Table D6. Relative root mean squared forecast error (RMSFE) for benchmark models with different numbers of lags (p)

Specification	AR-X				AR			
	Nowcast			Backcast	Nowcast			Backcast
	1M Q0	2M Q0	3M Q0	1M Q1	1M Q0	2M Q0	3M Q0	1M Q1
p=1	**0.64**	**0.59**	**0.62**	**0.62**	**0.74**	**0.81**	**0.81**	**0.81**
p=2	0.65	0.60	0.63	0.63	0.73	0.87	0.87	0.87
p=3	0.67	0.62	0.64	0.64	0.72	0.89	0.89	0.89
p=4	0.68	0.63	0.64	0.64	0.73	0.91	0.91	0.91
p=5	0.69	0.63	0.64	0.64	0.73	0.92	0.92	0.92
p=6	0.69	0.63	0.64	0.64	0.73	0.93	0.93	0.93

Notes. Q0 represents the current quarter, while Q1 refers to the next quarter.
1M, 2M, and 3M indicate the end of the first, second, and third months, respectively.
The specification used to present the main results is highlighted in red.
Results for each model are shown relative to the RMSFE of the RW model. A value less (more) than one indicates that the model performs better (worse) than the RW model.

Source: author's calculations.

Table D7. Mean forecast error (MFE) for benchmark models with different numbers of lags (p)

Specification	AR-X				AR			
	Nowcast			Backcast	Nowcast			Backcast
	1M Q0	2M Q0	3M Q0	1M Q1	1M Q0	2M Q0	3M Q0	1M Q1
p=1	**-0.27**	**-0.20**	**-0.20**	**-0.20**	**-0.15**	**-0.06**	**-0.06**	**-0.06**
p=2	-0.30	-0.19	-0.18	-0.18	-0.22	-0.03	-0.03	-0.03
p=3	-0.26	-0.16	-0.15	-0.15	-0.18	0.01	0.01	0.01
p=4	-0.24	-0.14	-0.14	-0.14	-0.20	0.05	0.05	0.05
p=5	-0.23	-0.15	-0.15	-0.15	-0.19	0.07	0.07	0.07
p=6	-0.25	-0.16	-0.16	-0.16	-0.21	0.08	0.08	0.08

Notes. Q0 represents the current quarter, while Q1 refers to the next quarter.
1M, 2M, and 3M indicate the end of the first, second, and third months, respectively.
The specification used to present the main results is highlighted in red
"* (**)" is the significant at 10% (5%) level difference of MFE from zero in two-sided t-test for equality to zero of mean forecast error.

Source: author's calculations.