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# **Development of Short-term Forecasting Models for Non-oil GDP**

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# Development of Short-term Forecasting Models for Non-Oil GDP

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## Abstract

Short-term forecasting of non-oil GDP is essential for preparing its medium-term projections. This paper evaluates the performance of three key forecasting models—Vector Autoregression (VAR), Mixed Data Sampling (MIDAS), and Dynamic Factor Models (DFM)—in predicting quarterly growth of non-oil GDP. The empirical results show that most models outperform the AR(1) benchmark in quarterly forecasts. To leverage the strengths of each model, the study also examines combined forecast results. A forecast combination based on mean squared error (MSE) weights improves forecast accuracy compared to individual models. Overall, the findings highlight the advantages of a multi-model forecasting strategy for enhancing the accuracy of short-term GDP growth predictions in Azerbaijan’s dynamic economic environment. The results emphasize the practical benefits of using combination methods to strengthen the reliability of short-term forecasts.

**Keywords:** short-term forecasting, non-oil GDP, forecast combination

**JEL:** C32, E52, O40

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## I. Introduction

As of 2022, the Central Bank of the Republic of Azerbaijan (CBAR) developed the Forecasting and Policy Analysis System (FPAS) to support monetary policy and financial stability committee. The forecasting process in FPAS consists of three phases: nowcasting, short-term forecasting, and medium-term forecasting. Medium-term projections rely on insights from nowcasting and short-term forecasting (primarily one or two quarters ahead). Consequently, accurate and well-performing short-term forecasts are critical for CBAR to generate reliable medium-term predictions for key macroeconomic variables such as inflation and economic growth.

This paper aims to identify the best-performing model for short-term forecasting of non-oil Gross Domestic Product (GDP) in Azerbaijan. Non-oil GDP forecasting presents unique challenges, particularly due to the volatility of economic conditions and the mixed frequencies of available economic indicators. To address these challenges, several forecasting models have been developed, each offering distinct strengths. Vector Autoregression (VAR) models, for instance, capture the interdependencies among multiple economic variables over time, while Mixed Data Sampling (MIDAS) models integrate high-frequency indicators, such as monthly industrial production, into quarterly GDP forecasts. Dynamic Factor Models (DFM) condense a wide range of economic indicators into a few latent factors that drive GDP growth.

However, no single model consistently performs well under all economic conditions. Forecast combination methods have emerged as a powerful tool in recent literature, leveraging the strengths of various models to improve forecast accuracy and mitigate individual weaknesses. By combining forecasts based on their performance, these methods provide more reliable and robust predictions. For example, Timmermann (2006) demonstrated that forecast combination could reduce model misspecification and adjust to structural changes in the economy.

This research aims to contribute to the growing body of literature on GDP forecasting by employing a combination of VAR, MIDAS, and DFM models to forecast Azerbaijan's non-oil GDP. Through a comparative analysis of these models and the implementation of an MSE-weighted forecast combination approach, this study seeks to determine the most effective forecasting methodology for Azerbaijan's non-oil sector. The findings of this research will provide valuable insights for policymakers, enhancing their ability to make informed decisions in a dynamic and complex economic environment.

Our results reveal that most models outperform the benchmark across all forecast horizons, with the DFM consistently providing the most accurate forecasts. While VAR models excel in short-term forecasts, their performance declines as the horizon extends. MIDAS models offer moderate improvements over the benchmark, but their advantage is less pronounced. Moreover, forecast combinations further enhance accuracy across all forecast horizons. The MSE weights method, though not surpassing DFM, remains closely aligned with the top-performing model for each forecast horizon, making it a robust approach for short-term forecasting in Azerbaijan. These findings underscore the importance of using multiple models and forecast combinations to improve short-term GDP growth forecasting in a dynamic and complex economic environment.

The remainder of this paper is structured as follows: Section 2 provides a brief review of the relevant literature. In Section 3, we present the forecasting models and the forecast combination methodology along with a description of the data utilized. Section 4 outlines the results and offers a comprehensive interpretation. Finally, Section 5 concludes the paper by summarizing the key findings and discussing their implications.

## **II. Literature review**

The academic literature on short-term forecasting of GDP is vast and has suggested a large number of different forecasting models. The use of MIDAS, DFM or ML models are the most popular methods implemented by many central banks for nowcasting and short-term forecasting.

To determine the optimal model for short-term forecasting in a specific period and country can be challenging. This difficulty arises because the models often produce significantly different results for different countries and samples. Given the challenge of selecting the best model, recent academic research has increasingly focused on combining multiple models and forecasts. Timmermann's (2006) paper stands out as a seminal work among these studies. Timmermann conducts a theoretical analysis highlighting the benefits of forecast combination, such as aggregating a broad dataset without compromising model quality, adapting to structural changes, and increasing robustness against misspecification and forecast errors (2006). He also suggests incorporating time-varying weights and excluding the poorest-performing models from the combined approaches to enhance forecast accuracy.

Currently forecast combination is a well-developed approach in the academic literature and is extensively applied to the majority of macroeconomic indicators.

The paper "MIDAS versus mixed-frequency VAR: nowcasting GDP in the euro area" by Vladimir Kuzin, Massimiliano Marcellino, and Christian Schumacher compares two approaches for nowcasting GDP in the euro area: Mixed Data Sampling (MIDAS) and mixed-frequency Vector Autoregressions (VAR). They find that both methods can effectively handle mixed-frequency data, but there are differences in their performance across various conditions and horizons. MIDAS models are simpler and can be estimated quickly, making them suitable for high-frequency data integration. In contrast, mixed-frequency VAR models, while more complex, provide a richer dynamic structure that can capture more intricate relationships between variables. The empirical results show that combining forecasts from both approaches can lead to more accurate nowcasts. The study underscores the importance of using multiple models and techniques to improve forecast accuracy, especially in the context of economic indicators that are reported at different frequencies.

The paper "Nowcasting Russian GDP using forecast combination approach" by Michael Zhemkov outlines a method for short-term forecasting of Russia's GDP. This method involves combining nearly 500 models that integrate high-frequency predictors and scenario indicators to forecast GDP by expenditure components. The findings suggest that combining forecasts, particularly using mixed-frequency data and dynamic factor models, provides more accurate and reliable GDP nowcasting than individual models alone.

Short-term forecasting of economic growth is crucial for CBAR as well as it provides timely insights necessary for effective monetary policy decisions. Unfortunately, there is limited research on this topic, and there is a notable gap in studies exploring forecast combination methods which highlights the importance of our research.

### **III. Methodology**

This section provides an overview of the modeling framework to forecast real non-oil GDP growth in Azerbaijan: vector autoregression (VAR), mixed data sampling (MIDAS), and dynamic factor model (DFM).

#### **i. VAR**

We employed popular approach for forecasting real non-oil GDP growth, the Vector Autoregression (VAR) model. It is a multivariate statistical model that captures the linear interdependencies among multiple time series data. The VAR model is particularly suited for

economic forecasting because it allows for the endogeneity of all variables, meaning that each variable in the system is treated as potentially influenced by past values of itself and all other variables. The model is specified as follows:

$$Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + \dots + A_p Y_{t-p} + u_t$$

where  $Y_t$  is a vector of endogenous variables at time  $t$ ,  $A_1, A_2, \dots, A_p$  are matrices of coefficients to be estimated,  $p$  is the number of lags,  $u_t$  is a vector of error terms (white noise).

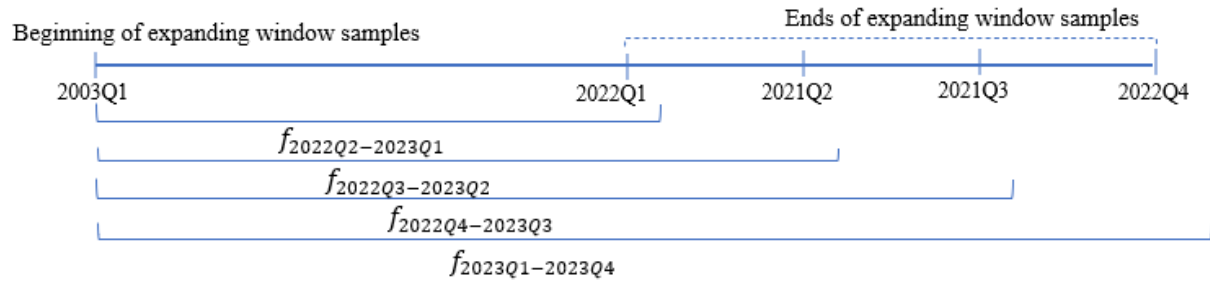
In this study we have three particular VAR models used to forecast non-oil GDP and we develop them at two steps. At first step, numerous VAR models are estimated using a pool of variables and their forecasts are stored. Then, the models are ranked according to their forecasting performances: the ones with the lowest MSEs are selected.

#### ✓ *Building the VAR Models*

In VAR based forecasting procedure, at first stage, a pool of 66 endogenous variables (Appendix 1) is designed in order to capture the fundamental dynamics of the economy. Clearly, the variable of interest, real non-oil GDP, is included in all models. The remaining 65 variables are reduced to 31 by Lasso variable selection method to only consider the variables that may potentially have high predictive power. Estimated VAR models consist of three to five endogenous variables. Each model draws its variables from these selected variables in such a way that budget expenditures and consumption variables are included at the same time in all the model. At the end, we had approximately 200 VAR models. We want to note that stationary forms of the variables are used in the models. The nonstationary variables are stationarized by taking quarterly percentage change.

#### ✓ *Forecasting using the VAR Models*

At first stage, a total number of 200 VAR models are estimated and 200 real non-oil GDP growth forecasts are obtained at each recursion in pseudo sample period. At the second stage, we look at the forecast accuracy of each models. Diagram 1 depicts the forecasting procedure for a VAR model for four quarters ahead.

**Diagram 1.** Forecasting procedure for  $h=4$ 

$f_t, t = 2022Q2, \dots, 2023Q4$ , stands for the forecast of non-oil GDP growth rate at time  $t-1$ . Using the sample 2003Q1 :  $t-1$ , non-oil GDP growth forecast for  $t$  is obtained.

The MSE of each model is calculated as:

$$MSE_h^i = \frac{\sum_{t=2022Q1+h}^{2023Q4} (\hat{y}_t - y_t)^2}{T}$$

where  $h=1, \dots, 4$  quarters,  $i$  ( $i=200$ ) represents the model,  $T$  is the out-of-sample size and equals to 4.  $\hat{y}_t$  denotes the forecast and  $y_t$  is the realized value of the non-oil GDP growth. In this way, MSE of 200 models is obtained and ranked from the lowest to the highest at each horizon. Based on the MSE, three models with the lowest forecast errors are selected. At the end, we set up three VAR models, namely VAR1, VAR2 and VAR3. The VAR1 model includes real net export, real retail trade turnover, real budget expenditures, M2, and electricity production. The VAR2 model contains the variables in the VAR1 except real net export and the number of employees additionally. The VAR3 model includes real industrial production, real household consumption, and real budget expenditures.

## ii. MIDAS

The alternative framework which used in the paper is the MIDAS model. The distinguishing feature of MIDAS models is that the predictors are included in the regression at the original observation frequency. In particular, MIDAS models relate low-frequency variables, such as quarterly GDP growth, to lags of high-frequency variables, such as monthly, weekly or even daily indicators. The basic MIDAS model with a single explanatory variable takes the following form:

$$Y_t^l = \beta_0 + \beta_1 B(L^{1/h}; \theta) X_t^h + \varepsilon_t \quad (2)$$

where  $Y_t^l$  is the lower-frequency variable (e.g., quarterly).  $B(L^{1/h}; \theta)$  is the lag polynomial (with the lag structure represented by the parameter  $\theta$ ) of the high-frequency indicator  $X_t^h$  (e.g., monthly,  $h = 3$ ).

In this paper, we will refer to unrestricted MIDAS (U-MIDAS) approach that does not impose a specific functional form on the lag structure but does assume linearity. A U-MIDAS model can be written:

$$Y_t^Q = \beta_1 + \varphi_1 Y_{t-1}^Q + \dots + \varphi_p Y_{t-p}^Q + \sum_{j=1}^3 \gamma_{1,j} X_t^{M_j} + \dots + \sum_{j=1}^3 \gamma_{q+1,j} X_{t-q}^{M_j} + \omega_t \quad (3)$$

where  $Y_t^Q$  is a quarterly variable of interest, and  $X_t^{M_j}$  is a monthly indicator. In equation (3), the dependent variable is assumed to follow an  $AR(p)$  process, while  $q$  lags of the explanatory variable are also included.

The literature related to the MIDAS model suggests various approaches to selecting the lag structure of the independent variables. Foroni, Marcellino and Schumacher (2011) use the Bayesian information criterion (BIC), while Koenig, Dolmas and Piger (2003) use a constant specification with five lags of the monthly variables. Our U-MIDAS specification includes three lags of the monthly indicators.

In MIDAS model, we adhere to a methodological approach similar to that utilized in the VAR model. Here, we set up two MIDAS models: MIDAS1 and MIDAS2. The MIDAS1 model includes real budget expenditures, M2, electricity production, real household consumption, and the number of employees while the MIDAS2 model contains the variables in the MIDAS1 except the number of employees.

### iii. DFM

The Dynamic Factor Model (DFM) is a multivariate time series model that is designed to capture the co-movements of several time series by explaining the observed variables through a small number of unobserved common factors. The dynamic nature of the model allows for the evolution of both the common factors and the idiosyncratic components over time. This section outlines the theoretical framework, estimation procedure, and model validation techniques employed in constructing the DFM for this study.

### ✓ *Model Specification*

Let  $Y_t$  denote an  $n \times 1$  vector of observed time series at time  $t$ , where  $t = 1, 2, \dots, T$ . The Dynamic Factor Model assumes that the observed time series can be decomposed as:

$$Y_t = \Lambda F_t + u_t$$

where  $F_t$  is an  $r \times 1$  vector of unobserved common factors, with  $r \ll n$ , implying that a few common factors drive the dynamics of the large number of observed time series,  $\Lambda$  is an  $n \times r$  matrix of factor loadings, which captures the relationship between the observed series and the common factors and  $u_t$  is an  $n \times 1$  vector of idiosyncratic disturbances or noise that is assumed to be weakly correlated.

The dynamics of the factors are governed by a vector autoregressive (VAR) process:

$$F_t = A(L)F_{t-1} + \varepsilon_t$$

where  $A(L)$  is a matrix lag polynomial, and  $\varepsilon_t \sim IID(0, Q)$  is an  $r \times 1$  vector of innovations to the common factors.

In the DFM framework, non-oil GDP is forecasted by separately forecasting the seven key sectors (agriculture, production, construction, retail, tourism, transport and communication, and social sectors) of the non-oil economy. These sectoral forecasts are then aggregated to obtain the total non-oil GDP forecast.

Quarterly data on real non-oil GDP components by sectors, along with nominal explanatory variables, are employed. The model calibration process involves assessing the Akaike Information Criterion and the variance explained through principal component analysis. For each sector, the optimal model specification is determined by selecting the parameter set that minimizes the mean squared forecast error. Once the models for all sectors are finalized, forecasts are generated individually and combined to derive the total non-oil GDP forecast.

#### **iv. Forecast Combination**

To combine forecasts of individual models, it is necessary to assign a weight to each model. In this paper, the weights are calculated based on forecast accuracy measured in terms of the inverse of the mean squared forecast errors (MSEs) of the respective models relative to the sum of the MSEs of all models (Timmermann, 2006):

$$\omega_{j,k} = \frac{1/MSE_{j,k}}{\sum_{j=1}^n 1/MSE_{j,k}}$$

$$Y_{combined}^{fi} = \sum_{j=1}^n \omega_{j,k} * y_{t_k}^j$$

where  $Y_{combined}^{fi}$  is the combined forecast of the  $i^{th}$  component,  $y_{t_k}^j$  is the final out of sample forecasts of the  $j$  model for the period  $t_k \in \{T_0 + 1, \dots, T_0 + k\}$ .

#### IV. Data

For the short-term forecasting of real non-oil GDP growth, we utilize a broad range of indicators spanning the period from January 2003 to December 2023 for the first stage of estimation. This comprehensive dataset consists of 66 indicators, including macroeconomic variables, labor market statistics, and financial data (Appendix 1). These indicators are generally available at higher frequencies and with shorter publication lags compared to GDP data.

For the VAR and MIDAS analysis, variable selection is conducted using a two-step approach: first, by applying LASSO to reduce dimensionality, and second, by evaluating forecast errors. This process results in a final selection of eight variables: net exports, budget expenditures, retail trade turnover, consumption, the number of employees, industrial production, electricity production, and M2. Data for non-oil GDP, retail trade turnover, consumption, the number of employees, industrial production, and electricity production are sourced from the State Statistical Committee of the Republic of Azerbaijan (SSCRA). Meanwhile, data on net exports, budget expenditures, and M2 are obtained from the Central Bank of the Republic of Azerbaijan (CBAR). Except for non-oil GDP and net exports, all variables are available on a monthly basis.

For the DFM analysis, the production side of non-oil real GDP components is analyzed alongside nominal explanatory variables (Appendix 1). The quarterly real non-oil GDP data, viewed from a production perspective, encompasses the following sectors: agriculture, production, construction, retail, tourism, transport and communication, and social sectors.

#### V. Results

The accuracy of the forecasts is evaluated using the relative Mean Square Error (MSE), which is the ratio of the MSE of the models or combination method to that of the benchmark. The relative MSE greater than 1 indicates that the alternative models perform worse than the benchmark, while the relative MSE less than 1 signifies better performances compared to the

benchmark. Table 1 displays the relative performances of the models for different forecast horizons (1 to 4 quarters ahead).

**Table 1.** MSEs Relative to the Benchmark

	Forecast Horizon			
	h=1	h=2	h=3	h=4
<b>Individual Model Forecasts</b>				
AR1 (benchmark)	1.00	1.00	1.00	1.00
VAR1	0.69	0.67	0.71	0.94
VAR2	0.66	0.74	1.06	0.88
VAR3	0.49	0.77	0.96	0.86
MIDAS1	0.98	0.90	0.79	0.83
MIDAS2	1.00	0.85	0.76	0.85
DFM	<b>0.36</b>	<b>0.45</b>	<b>0.27</b>	<b>0.58</b>
<b>Forecast Combination</b>				
Simple Average	0.44	0.48	0.56	0.61
MSE Weights	<b>0.41</b>	<b>0.45</b>	<b>0.53</b>	<b>0.56</b>

The results indicate that most models provide more accurate forecasts than the benchmark for all forecast horizons. The DFM consistently outperforms all individual models across all forecast horizons. This superior performance highlights DFM's ability to integrate a wide range of sectoral and nominal indicators, effectively capturing the underlying dynamics of non-oil GDP growth. Notably, the DFM exhibits remarkable accuracy for medium-term horizons (h=3), where its MSE (0.27) significantly outperforms other models, underscoring its robustness in capturing co-movements across economic sectors.

The VAR-based models, in particular, demonstrate robust performance, with the VAR3 model yielding the lowest relative MSE for the 1-quarter-ahead forecast. This suggests that the VAR3 model is highly effective in capturing the short-term dynamics of non-oil GDP growth. However, as the forecast horizon extends, the performance of the VAR models tends to decline. For instance, VAR2, which performs well for the 1-quarter-ahead forecast, exhibits a relative MSE above 1 for the 3-quarter-ahead forecast, indicating a deterioration in accuracy. This trend highlights a common challenge in economic forecasting: the difficulty in maintaining accuracy over longer horizons due to the increasing uncertainty and complexity of economic variables.

In contrast, the MIDAS models, while generally outperforming the benchmark, show less pronounced improvements. The relative MSEs for MIDAS1 and MIDAS2 hover around 0.98 to

1.00 for the 1-quarter-ahead horizon but improve slightly as the horizon extends. This suggests that while MIDAS models are useful, their advantage over the benchmark is less significant compared to DFM and VAR models.

Combining forecasts through simple averaging or MSE-weighted methods enhances predictive accuracy across all horizons compared to the benchmark. However, it is notable that the accuracy of these combination methods declines slightly as the forecast horizon extends. This decline might be due to the increasing divergence among individual models as uncertainty grows over longer periods.

Among the combination methods, the MSE weights approach demonstrates slightly better performance. The use of MSE weights effectively capitalizes on the strengths of the most accurate models, thereby enhancing the overall forecast accuracy. This method's ability to adaptively assign higher weights to more accurate models make it particularly effective in the context of short-term economic forecasting, where precision is critical.

**Figure 1. Actual and forecast for h=4**

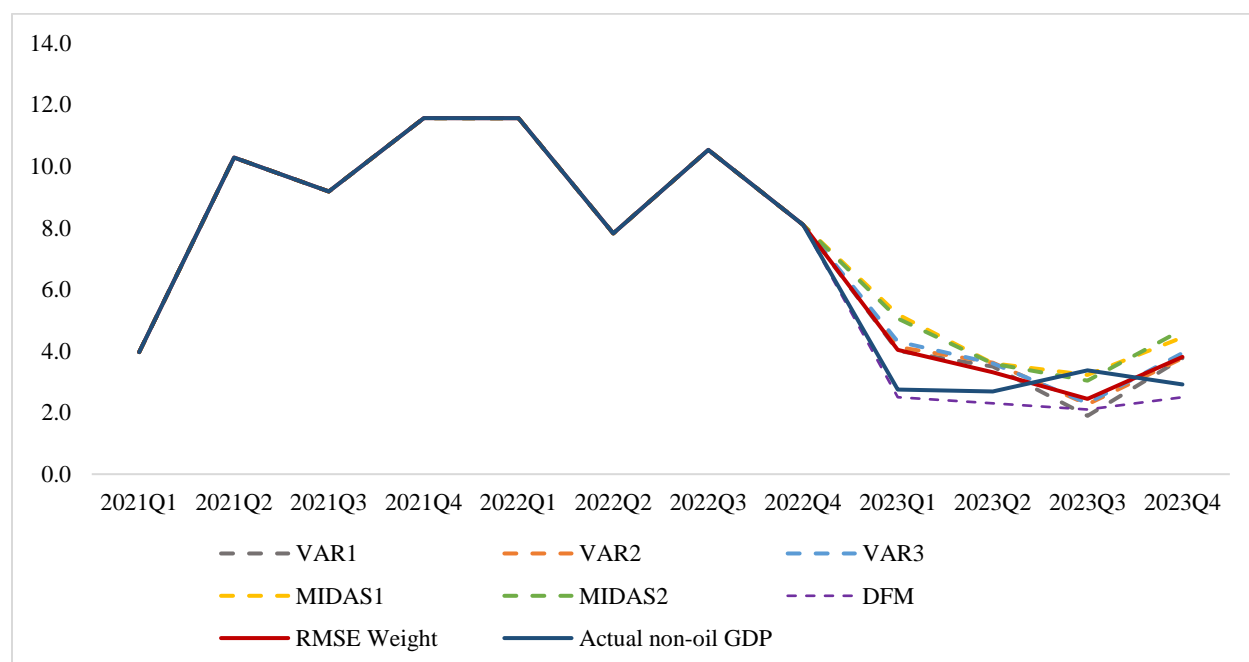


Figure 1 illustrates the non-oil GDP growth forecasts alongside the actual values for a 4-quarter-ahead horizon. The figure underscores the capability of the DFM and the MSE weights method to closely track actual economic performance, even as the forecast horizon extends. This alignment with actual values highlights the practical utility of these forecasting methods for

policymakers and analysts aiming to make informed decisions based on reliable short-term GDP growth projections.

## **VI. Conclusion**

In conclusion, this study highlights the importance of combining multiple forecasting models to improve the accuracy of short-term non-oil GDP growth forecasts for Azerbaijan. Among the models, the DFM model showed superior performance across all forecast horizons. However, to capture the diverse strengths of different models, forecast combination remains a valuable approach.

The forecast combination methods, particularly the MSE-weighted approach, demonstrated the ability to further improve forecast accuracy by integrating the strengths of various models. This method offers a more reliable and adaptive tool for short-term economic forecasting, helping policymakers and analysts make informed decisions based on robust projections.

Future research could extend this work by exploring alternative model combinations and integrating new machine learning techniques to address the limitations observed in longer forecast horizons.

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## Appendix

<b>N</b>	<b>Variables</b>	<b>Frequency</b>	<b>Publication lag (days)</b>
1	Non-oil GDP	Quarterly	>90
2	Freight turnover	Monthly	up to 15
3	Electricity production	Monthly	up to 15
4	Investment	Monthly	up to 15
5	Non-oil investment	Monthly	up to 15
6	Public investment	Monthly	up to 15
7	Private investment	Monthly	up to 15
8	Budget expenditure	Monthly	up to 15
9	Current expenditure	Monthly	up to 15
10	Capital expenditure	Monthly	up to 15
11	Budget revenue	Monthly	up to 15
12	Non-oil tax revenue	Monthly	up to 15
13	Retail trade turnover	Monthly	up to 15
14	Retail trade turnover-food	Monthly	up to 15
15	Retail trade turnover-non food	Monthly	up to 15
16	Public services	Monthly	up to 15
17	Paid services to population	Monthly	up to 15
18	Consumption (15+16+17)	Monthly	up to 15
19	Nominal income	Monthly	up to 15
20	NEER	Monthly	up to 15
21	REER	Monthly	up to 15
22	M0	Monthly	up to 25
23	M1	Monthly	up to 25
24	M2	Monthly	up to 25
25	M3	Monthly	up to 25
26	Claims on economy	Monthly	up to 25
27	Export	Quarterly	>90
28	Import	Quarterly	>90
29	Net export	Quarterly	>90
30	Industrial production	Monthly	up to 15
31	Industrial production, non-oil	Monthly	up to 15
32	Agricultural production	Monthly	up to 15
33	Labor force	Monthly	up to 15
34	Number of employees	Monthly	up to 15
35	Russian GDP	Monthly	>90
36	Turkey GDP	Monthly	>90
37	Cement production	Monthly	up to 15
38	Cargo transportation with airline	Monthly	up to 15

39	Passenger transportation with metro	Monthly	up to 15
40	Official foreign reserves	Monthly	up to 25
41	Loans, business	Monthly	up to 25
42	Loans, consumer	Monthly	up to 25
43	Loans, mortgage	Monthly	up to 25
44	Loans, trade and services sector	Monthly	up to 25
45	Loans, agriculture, forestry and fisheries sector	Monthly	up to 25
46	Loans, building and construction sector	Monthly	up to 25
47	Loans, industry and manufacturing sector	Monthly	up to 25
48	Loans, transportation and communication sector	Monthly	up to 25
49	Loans, households	Monthly	up to 25
50	Remittances	Monthly	up to 25
51	RTGS, amount of transactions	Monthly	up to 25
52	LVPCSS, amount of transactions	Monthly	up to 25
53	Number of payment cards	Monthly	up to 25
54	Transactions with debit and credit cards	Monthly	up to 25
55	Monthly average volume of operations per ATM	Monthly	up to 25
56	Monthly average volume of operations for POS-terminals	Monthly	up to 25
57	Number of bank customers	Monthly	up to 25
58	Number of bank customers, individuals	Monthly	up to 25
59	Number of bank customers, engaged in entrepreneurial activity	Monthly	up to 25
60	Number of bank customers, legal entities	Monthly	up to 25
61	Number of customer accounts	Monthly	up to 25
62	Number of customer accounts, transaction account	Monthly	up to 25
63	Number of customer accounts, credit accounts	Monthly	up to 25
64	Number of customer accounts, deposit accounts	Monthly	up to 25
65	Total deposits	Monthly	up to 25
66	Mortgage rate	Monthly	up to 25