Bank of Russia

The Role of Communication and Information Factors in the Emergence of Surprises in Bank of Russia Monetary Policy

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Abstract

In this paper, we examined how the quality of communication and the general information background influence the predictability of the Bank of Russia's decisions on the key rate. Contrary to expectations, the start of the publication of the key rate trajectory did not lead to an increase in predictability, as suggested in previous papers. We show that this can hardly be explained by increased uncertainty, which had only limited impact on decision predictability in 2015-2021. Miscommunication (the difference in focus of Bank of Russia and analysts' messages) and verbal interventions (Bank of Russia speeches in the weeks before the decision to "correct" market expectations) also showed almost no significance in the occurrence of surprises.

At the same time, we found a significant asymmetry in Bank of Russia communication and market perception. The source of this asymmetry was, among other things, the central bank's greater confidence in achieving the 4% target over the entire time horizon, while analysts began to build their materials around the topic of inflation only from 2019 (and this time roughly coincides with the "anchoring" of their expectations on the target).

Our analysis renders as the most plausible explanation of surprises is the Bank of Russia's "information advantage" over the entire inflation targeting period. The information advantage in the literature refers both to the better models and analysis tools of the central bank and to the market's belief that a central bank can have such an advantage. As the experience of other central banks shows, this advantage wanes and the predictability of decisions increases with the development of communication tools.

Key words: monetary policy, communication, text analysis, High-Frequency Identification, uncertainty.

JEL classification: E52, E58, C53, D81, G14.

1. Introduction

In this study, we present a systematic view of the role of communication in the emergence of surprises in the monetary policy of the Bank of Russia.

We are aware of three papers that have raised the topic of the predictability of Bank of Russia decisions. The first is from the IMF, which notes that the Bank of Russia is one of the most unpredictable in the world (World Economic Outlook: Challenges to steady growth (2018, chapter 3)). In the 2010–2018 period, 27% of key rate decisions were not expected by the market. At the same time, the unpredictability of the decisions of other developing countries was noticeably lower: 19% for Brazil, 13% for Turkey and India, and 9% for Thailand. The central banks of the developed countries are very predictable. For example, the US Federal Reserve did not present any surprises in the same period – all of its decisions were expected by the market.[1]

Isakov et al. (2018) continue the topic. Their work also provides data on the share of key rate decisions correctly predicted by analysts, but for the 2015–2018 period, that is, for the period of inflation targeting. The average unpredictability in these years was 35%, compared with 10% for New Zealand (the country is selected for comparison due to its successful experience in publishing the future trajectory of the rate, and this is the main recommendation of the work in terms of improving the communication of the Bank of Russia). It is noteworthy that after the start of the publication of the key rate trajectory in April 2021, the predictability of the decisions of the Bank of Russia has not increased, but decreased.

Table 1. By how many basis points on average per year were Bloomberg consensus analysts wrong?

Year	b.p.
2015	34,4765
2016	7,4445
2017	11,8601
2018	7,0184
2019	2,1483
2020	6,5856
2021[2]	15,4597

[1] According to Bloomberg consensus forecasts.
[2] The start of the publication of the key rate trajectory was in April 2021

Nevertheless, in this paper we suggest that the publication of the key rate trajectory may have had a positive effect on decision predictability through an improved verbal intervention mechanism (see Section 4).

After these studies, the discussion continued at forums and in the media. In recent years, the topic has often been raised in the largest Russian media outlets, both in analysts' columns and in editorial materials[3]. The controversy tends to intensify after decisions that were predicted by less than half of analysts according to Bloomberg and Reuters polls. At the time of writing, in 2021, there had been three such decisions, out of six decisions in total, in March, April, September and October.

Why is the predictability of key rate decisions so important? Woodford (2003), Bernanke (2004b), Blinder (2004), Issing (2005), Trichet (2005), and Blinder et al. (2008) argue that the predictability of decisions is an important and effective component of inflation targeting. As King (2000) notes, a successful central bank should be boring. The predictability of decisions speaks to the correctness of the perceptions of economic agents about the central bank's policies, which, through expectations, contributes to the achievement of the goal of price stability. In turn, effective communication makes a crucial contribution to the predictability of decisions. Blinder et al. (2008): 'Successful central bank communication should make its policies more predictable and market expectations for future rates more precise.'

In this study, we aim to present a systematic view of the role of communication in the emergence of surprises in the Bank of Russia's monetary policy.

To do this, we address the following **issues**:

1) we assess the current level of predictability of decisions separately for professional analysts and for the money market;

2) on the basis of the observations made and the approaches available in the literature, we form hypotheses on the possible causes of Bank of Russia monetary policy surprises in terms of the role of communication;

3) we test our hypotheses;

4) we develop recommendations to improve communication.

This work's contribution to the literature is its provision of systematic analysis of the predictability of the Bank of Russia's monetary policy decisions in terms of the efficiency of communication. No such systematic studies have been conducted to date. In addition, we contribute to the literature on the development of tools for textual analysis, modelling the level of macroeconomic uncertainty through a news index and modelling

[3] What's wrong with the Central Bank's communication with the market. Financier Sergey Romanchuk on the problem of word games with the market // Vedomosti. - 2019. - May 6. (only in Russian)
The Bank of Russia unexpectedly raised the rate for the first time since 2018 // Vesti.Ru. - 2021. - March 19. (only in Russian)
The Bank of Russia unexpectedly raised its key rate to 7.5% // Interfax. - 2018. - September 14. (only in Russian)
Undervalued data: why the decision of the Bank of Russia surprised the market // Prime. - 2021. - March 22. (only in Russian)
Cry poor more persuasive. Central Bank raised the key rate to 5% per annum to avoid consumer rally // Kommersant. - 2021. - April 23. (only in Russian)
Hawkish decision: why central bank changed its policy // Forbes. - 2021. - March 20. (only in Russian)

narrative communication gaps between the central bank and professional analysts. The methods proposed may be used in future studies of the efficiency of communication. We also propose methods adapted to the characteristics of financial markets in developing countries for the assessment of central banks' information advantage, which may be used in the construction of appropriate models for central bank communication in other developing countries.

The paper is structured as follows. In Section 2, we describe the data that we use in our models and assess the current level of decision predictability separately for professional analysts and the financial market. Based on the observations and available approaches in the literature, we hypothesize about the possible causes of monetary policy surprises. In Sections 3-6, we test these hypotheses. Section 7 contains recommendations to improve communication and general conclusions of the paper.

2. Data and hypotheses

In this paper, we study the following types of monetary policy surprises:

1. Surprises for professional analysts. To estimate them, we used several approaches:

1) the average deviation in basis points of the Bloomberg consensus from the key rate decision;

2) the share of analysts who incorrectly predicted the decision;

3) a binary variable that takes a value of 1 if more than half failed to predict the decision correctly, and 0 if otherwise. The choice of the specific variable in each case will be explained in the relevant sections.

2. Surprises for financial markets. A surprise occurs if the rates in financial markets are significantly adjusted within a short period of time following a central bank decision.

We consider the data for each group of surprises individually.

2.1. Surprises for professional analysts

First of all, we evaluate surprises for professional analysts according to Bloomberg surveys through the deviation in basis points of the consensus from the key rate decision.

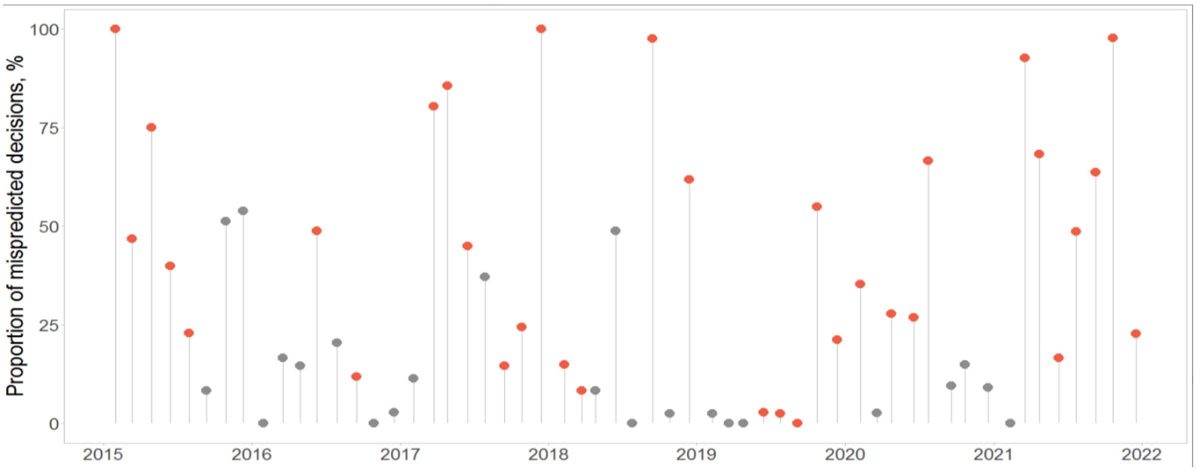
The Bank of Russia moved to inflation targeting starting in 2015. Thus, the most volatile period of 2014 remains outside our study.

In the 2015–2021 period analysts in the Bloomberg survey could not correctly predict the Bank of Russia's key rate decisions by an average of 12.14 basis points.

In analysing the predictability of the Bank of Russia's decisions, we divide by type of event.

First of all, by the principle of maintaining or changing the rate. Were analysts equally mistaken in the case of a rate change and its remaining unchanged? These data are presented in Figure 1. According to the results for 2015–2021, analysts are significantly more likely to make mistakes when the Bank of Russia changes the key rate (the average error is 17.06 bps). In other words, analysts find it quite difficult to predict the specific step of the key rate change.

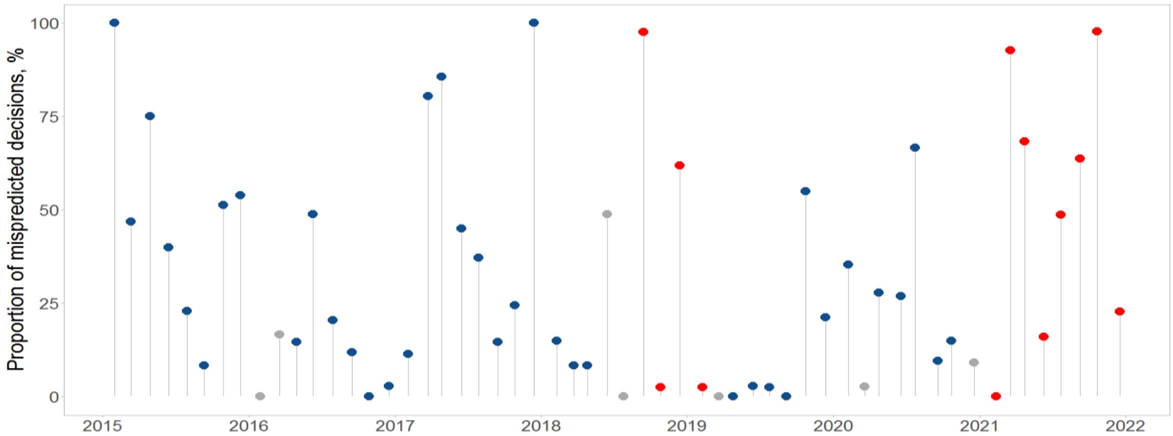
Figure 1. Monetary policy surprises for professional analysts (orange color – decisions on changing the rate; grey – decisions on maintaining the rate)[4]



Sources: Bloomberg, authors' calculations.

A second way to divide surprises by event type is by 'hawkish' and 'dovish' decisions. For hawkish decisions, analysts are wrong more often on average: the error is 13.68 bps versus 8.73 bps for dovish decisions. We consider decisions to reduce the key rate and/or decisions with signals of a future reduction to be 'dovish' decisions, while 'hawkish' ones are correspondingly decisions on key rate increases and/or decisions with signals of a future increase. Neutral decisions are decisions that give no clear signal of a future decision (data dependent) or signal the need to assess the feasibility of continuing the cycle, or decisions that prepare reversals in policy by stating a strongly changed situation compared to the baseline forecast.

Figure 2. Monetary policy surprises for professional analysts (blue color – 'dovish' decisions; red – 'hawkish' decisions; grey – other)



Sources: Bloomberg, authors' calculations.

[4] Decision on January 2015 is an outlier and therefore excluded.

Since the start of the inflation targeting regime, we have recorded 15 surprises (cases in which more than 50% of analysts made a mistake in the rate forecast), of which 13 correspond to decisions involving a change in the rate and only 2 to decisions involving its preservation. A detailed list of these surprises is given in Annex 1.

In 11 cases out of 15, analysts expected the Bank of Russia to be more cautious in its decision-making than it was in the end. This may indicate that there are different reaction functions among analysts and at the Bank of Russia.

2.2. Surprises for financial markets

To detect surprises for the financial market, we used a common method of high-frequency event-study analysis, as described, for example, in the work of Kuttner (2001). In this paper, Fed Funds Futures are used to assess the impact of monetary policy on US Treasury bond rates. The author concludes that the impact of expected policy changes on bond yields is zero, while the impact of unexpected changes is high and significant.

Further development of the method is proposed by Gürkaynak et al. (2005), breaking down monetary policy surprises into two components. The first reflects surprise about the decision made directly (target shock), and the second – surprise regarding the future trajectory of the key rate (path shock). The authors conclude that the US Federal Reserve's actions have a much lower impact on financial markets than its words, especially for medium- and long-term bonds. Buraschi and Whelan (2016) update the results of this study and come to similar conclusions. We follow this approach (breakdown into target shock and path shock) in identifying Bank of Russia surprises.

The impact of monetary policy on financial markets has also been assessed for other central banks. Leombroni et al. (2021) assess the surprises of the ECB, and Pescatori (2018), the surprises of the Bank of Chile. Regarding the assessment of the Bank of Russia's monetary policy surprises for financial markets, this is partly addressed in the work of Tishin (2019). The author designs a series of monetary policy surprises from currency futures and used them to evaluate the monetary policy transmission mechanism over the 2002–2018 sample.

It is worth noting that in emerging market economies, the analysis of surprises is complicated due to the lack of a developed and highly liquid derivatives market on the interbank loan rate. In particular, the futures market for interbank lending rate is not as developed in Russia, so we use two indicators to evaluate monetary policy surprises. The first one ROISfix indicative rate[5], which is formulated by the National Financial Association on the basis of quotes announced by the participants in fixing – several of the largest Russian banks. The 1 week to 6 month rates have been available since 2011, and hence they capture the fluctuations in the short term rates. The second indicator is the OFZ index, which is the index of federal loan bonds issued by the Russian government. We use bonds with the term of one, two and five years.

[5] ROISfix – RUONIA Overnight Interest Rate Swap – is the indicative rate (fixing) for interest rate swap operations on the RUONIA rate. It is published daily at 12.30 on the basis of a morning survey of the largest banks. For more information, please see the association's website.

We define a monetary policy surprise as a market rate change during the day of the meeting. Since the ROISfix rate is published in the morning of the each business day, we subtract the ROISfix rate on the board meeting day from the rate on the following business day. For most meetings, this is equivalent to[6]:

$$Monetary\ policy\ surprise\ (\%\ per\ annum) = ROISfix_{Monday\ morning} - ROISfix_{Friday\ morning} \quad (1)$$

For the OFZ indexes, it is fairly the same:

$$Monetary\ policy\ surprise\ (\%\ per\ annum) = OFZ_{Friday\ close} - OFZ_{Thursday\ close} \quad (2)$$

This definition of surprise is based on several assumptions. First, the execution of the RUONIA interest rate swap contract takes place on the next business day after the conclusion of the transaction. In other words, the contract concluded according to Friday morning quotes come into effect on Monday. Second, we assume that there are no other events in one business and two non-business days that could significantly affect the expected rates of the money market or government bonds market. Indeed, the US market opens seven hours later and, in theory, events on it may affect three-, six-, and twelve-month money market rates. Nonetheless, analysis of changes in short-term rates in the US on these days shows that no significant events occurred.

Our sample begins in 2015 and comprises 56 observations. During this period, the Bank of Russia mainly reduced the key rate, so surprises tended to be more downwards than upwards. The average surprise value is from 3 to 7 p.p. depending on the term. Particularly large surprises were observed in 2015[7], in June 2016[8], in the midst of the pandemic in 2020, and during policy normalisation in 2021[9].

If we consider the cumulative value of surprises, the longer the term of the instrument, the smaller the surprise, and it is largest for the weekly ROISfix. A possible explanation of this phenomenon is given in the works of Gürkaynak et al. (2005) and Bernanke and Kuttner (2005). Markets may expect a key rate change in the near future and be mistaken about the specific date of the upcoming change.

The formation of surprises according to the method of Gürkaynak et al (2005) consists of two steps. In the first step, we combine the ROISfix surprises with terms of one week, of two, three, and six months, and OFZ surprises of one, two and five years into one dataset and get a 56x7 matrix. Next, using principal component analysis, we reduce the dimensionality of the matrix to two. This is possible due to the fact that the two new components together account for around 90% of the cumulative variation for surprises across all seven terms[10].

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[6] However, for four meetings, the window was more than two days, and for two meetings, it was less, since either they were held not on a Friday or there were public holidays.

[7] In particular, on 30 January 2015, when the Bank of Russia unexpectedly reduced the rate by 200 bp from 17.00% to 15.00% per annum, the surprise was from -1.20 to -1.54 pp.

[8] The Bank of Russia unexpectedly reduced the rate by 50 bp from 11.00% to 10.50% after it had been unchanged for almost a year.

[9] See additional details in Annex 2.

[10] 68% and 22% for the first and second component respectively

The problem with the principal components is that they do not have a direct economic interpretation. We achieve this in the second step by rotating them in such a way that the first component, with white noise precision, becomes equal to the ROISfix surprise with a term of one week, while the second component remains orthogonal to the first. Accordingly, we interpret the first of them as surprise linked to an unexpected decision or target shock, and the second as surprise linked to future decisions due to new communication or path shock[11].

Figure 3 shows the monetary policy surprises for the financial market in relation to the Bank of Russia decisions and communications. The two type of surprises (target shock и path shock) are highly correlated[12] and in most cases have the same sign. This is consistent with economic logic, since the Bank of Russia usually accompanies an unexpected decision with an unexpectedly milder or harsher signal. Particularly large surprises were observed in 2015, in June 2016, in the midst of the pandemic in 2020, and during the rate increase in 2021. In addition, the constructed target shock indicator has a high correlation (about 0.75) with analysts' forecast errors on the rate from Section 2.1.

Figure 3. Monetary policy surprises for the financial market regarding Bank of Russia decisions and communications

Taking into account the observations made and the approaches available in the literature to assess the role of communication in the emergence of surprises (which are discussed in the relevant sections below), we form the following hypotheses about the emergence of Bank of Russia monetary policy surprises:

[11] For a technical description of the composition of the rotation matrix and its multiplication by components, see Annex 1 to the article by Gürkaynak et al. (2005).
[12] It is worth noting that the orthogonality of vectors does not exclude the possibility of correlation. For example, see Brereton (2016)

The high role of uncertainty/information shocks. In this hypothesis, we consider whether information shocks and macroeconomic and financial uncertainty have an impact on the emergence of monetary policy surprises. It can be assumed that in the context of high uncertainty and frequent information shocks, it is more difficult for the central bank to conduct timely analysis and communicate its vision of the changing situation to the market. This hypothesis is tested in Section 3.

Verbal interventions. In Section 4 we tested the hypothesis that the predictability of decisions depends on the verbal interventions of the members of the Board of Directors of the Bank of Russia**.**

Miscommunication. The central bank may place incorrect emphasis on its communication, which leads to market errors in reading information which is critical for forecasting decisions. In this case, there are narrative gaps between the analysis of the situation by analysts and the rationale for the central bank's decision. Analysis of this topic can be found in Section 5.

'Information advantage' or the central bank's information channel. This is an assumption that the central bank may possess certain additional non-public economic data or models that the market does not have and therefore cannot correctly predict the decision. This topic is discussed in Section 6.

3. The hypothesis of the high role of uncertainty and information shocks

One of the most popular and intuitive explanations for unpredictable decisions is increased macroeconomic and/or financial uncertainty. When the situation is difficult to predict and is characterised by an increased number of information shocks, it is more difficult for the central bank to make decisions, as well as to explain to the market its vision of the changing situation.

As Conway (2000) observes, while inflation-targeting central banks have done much to create a transparent system of operation for monetary policy, the uncertainty of the environment in which inflation has to be managed has grown alongside this process. This uncertainty comes from different angles: central banks can never be completely certain of the structure and state of the economy, while statistical information often presents surprises. In addition, unexpected events occur from time to time, and the future is inherently unpredictable. Bloom (2009) shows that strong uncertainty shocks pose a serious challenge to macroeconomic authorities, including central banks. The efficiency of monetary and fiscal policies is significantly reduced during uncertainty shocks. Poole and Rasche (2003) also observe that the central bank, as well as the real sector, may occasionally face situations of heightened uncertainty. If the regulator has no influence on these events, it must strive by all means to reduce the uncertainty of its future decisions. The same conclusion is reached by Mendes et al. (2017) after an analysis of the experience of the Bank of Canada. Blattner et al. (2008) point in this regard to the need to improve central bank communication, which takes on unprecedented importance in an environment of high uncertainty.

High uncertainty as a factor of monetary policy surprises (primarily in terms of external risks) has also been pointed out by representatives of the Bank of Russia in an interview[13]. Under these conditions, the central bankers advised the market not to wait for signals from the regulator, but to independently analyse the rapidly changing situation and proceed directly from the logic of key rate decision-making[14].

Methods for measuring the level of uncertainty and information shocks are developed in several works. The most popular techniques are those proposed by Bachmann, Elstner, and Sims (2013), Jurado, Ludvigson, and Ng (2015), Rossi and Sekhposyan (2016), and Baker, Bloom, and Davis (2016). These methods have been improved in later works. The approach of Bachmann, Elstner, and Sims (2013) is to measure the variance of estimates of the economic situation. Rossi and Sekhposyan (2016) propose the use of an index based on the determination of errors in real GDP forecast relative to the sample distribution of errors in forecasts of the same variable. Jurado, Ludvigson, and Ng (2015), as well as several other researchers, estimate uncertainty by calculating the conditional volatility of forecast errors for a large number of U.S. macroeconomic indicators. Finally, Baker, Bloom, and Davis (2016) apply modern methods of textual analysis. They evaluate a news index of economic policy uncertainty, which reflects the frequency with which words such as ‘economy’ and ‘uncertainty’ are used together in reports in leading media. The experience of applying this approach for Russia was implemented as part of the Index of Global Economic Policy Uncertainty in 2016 by a group of researchers from the University of Chicago and Stanford University. We use it as the base model for our own news index, which is described below.

There are also operational indicators of uncertainty for financial markets. The most famous of these is the VIX, the so-called ‘fear index,’ calculated by the Chicago Option Exchange. It represents market expectations of the 30-day future volatility of the US stock market for the S&P 500 Index. The Russian analogue of this index is the RVI for the RTS market, which has been calculated by the Moscow Exchange since the end of 2013. The principle of its calculation is based on the volatility of actual RTS option prices. In the calculation of the RVI, the nearest and following options with terms to expiration of more than 30 days are used.

Given the research experience described and the data available for Russia, we consider the following models for estimating uncertainty and information shocks:

1. For macroeconomic uncertainty – an estimate based on the variance of Bloomberg analysts’ forecast estimates[15] for key macro variables (Model 1):

$$\begin{gathered} S = \alpha + \beta_0 * GDP + \varepsilon, \\ S = \alpha + \beta_1 * \pi + \varepsilon, \\ S = \alpha + \beta_2 * P + \varepsilon, \\ S = \alpha + \beta_3 * I + \varepsilon, \\ S = \alpha + \beta_4 * Un + \varepsilon, \\ S = \alpha + \beta_5 * SI + \varepsilon, \end{gathered} \tag{3}$$

[13] Dynamics of the ruble exchange rate. ’Head of the Department of Monetary Policy of the Central Bank – on currency purchases and interest rates’. 2019. Rossiyskaya Gazeta. No. 5(7763).

[14] Central Bank of the Russian Federation: decisions on the rate depend on market conditions // Rambler. – 2018. – 15 October.

[15] Bloomberg provided data on individual analysts' forecasts, which makes it possible to estimate variance.

where S – значение сюрприза (for analysts – Bloomberg data[16], ; for the money market – target shock and path shock);
GDP – variance of analysts' forecasts of GDP;
π – variance of analysts' forecasts of inflation;
P – variance of analysts' forecasts of industrial production;
I – variance of analysts' forecasts of real wages;
Un – variance of analysts' forecasts of unemployment rate;
Sl – variance of analysts' forecasts of real retail sales[17];
α, β_0, β_1, β_2, β_3, β_4, β_5, ε – coefficients.

2. For information shocks – News index based on textual analysis tools (Model 2).

To build the news index, we use the Russian news database described in our work Karpov and Evstigneeva (2022 forthcoming). For the assessment, we use economic news from January 2014 to December 2021, a total of about 1.47 million news items. This database contains 28 major Russian media resources, while the Index of Global Economic Policy Uncertainty (which we use as a base model) includes only the newspaper 'Kommersant'.

To extract the level of uncertainty from the news base, uncertainty topic tokens are used (for more information, see Section 5). The news uncertainty index for a specific month is calculated as the ratio of the number of articles containing uncertainty tokens to the total number of articles in the given month.

We verify the validity of the news index obtained using the Pearson correlation coefficient with the Moscow Exchange RVI. It is 0.5450077, versus 0.2986799 for the Index of Global Economic Policy. So our index is a better reflection of financial market volatility.

[16] In these models, we chose as the dependent variable the size of the "miss" of analysts, that is, the difference between the actual decision and the Bloomberg consensus, because, in our opinion, it is more consistent with the difference in the estimates of macro variables.
[17] The models include variances with lags up to one year.

Figure 4. Moscow Exchange RVI (left) and News Uncertainty Index (right)

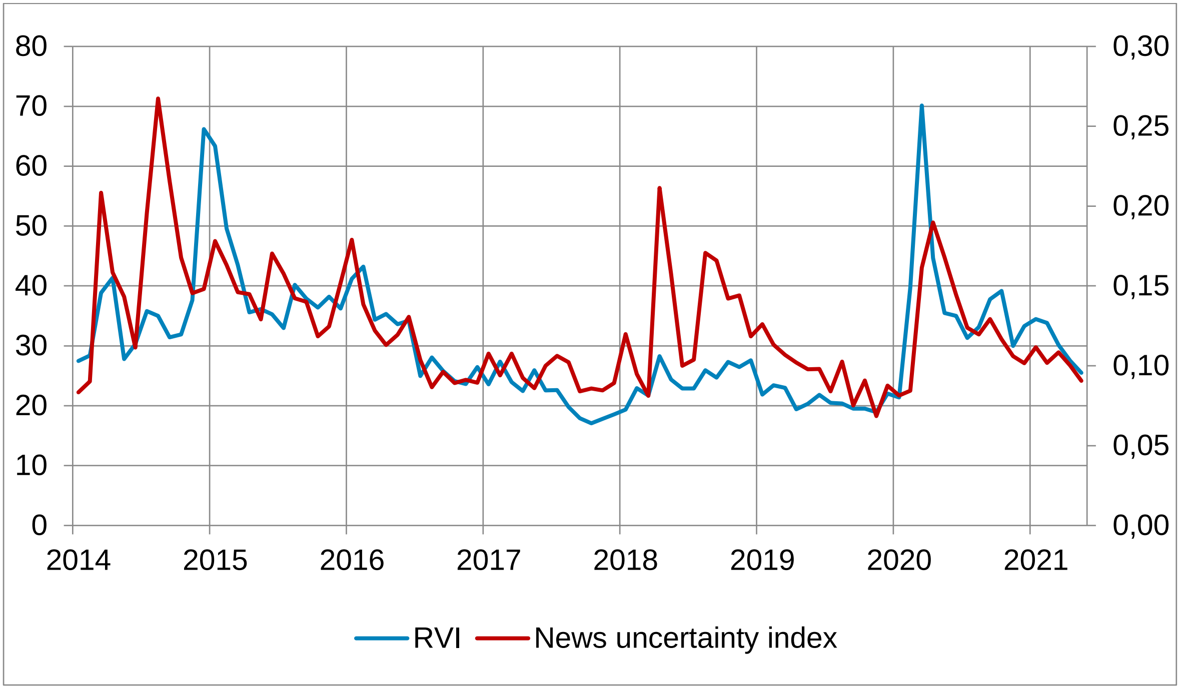
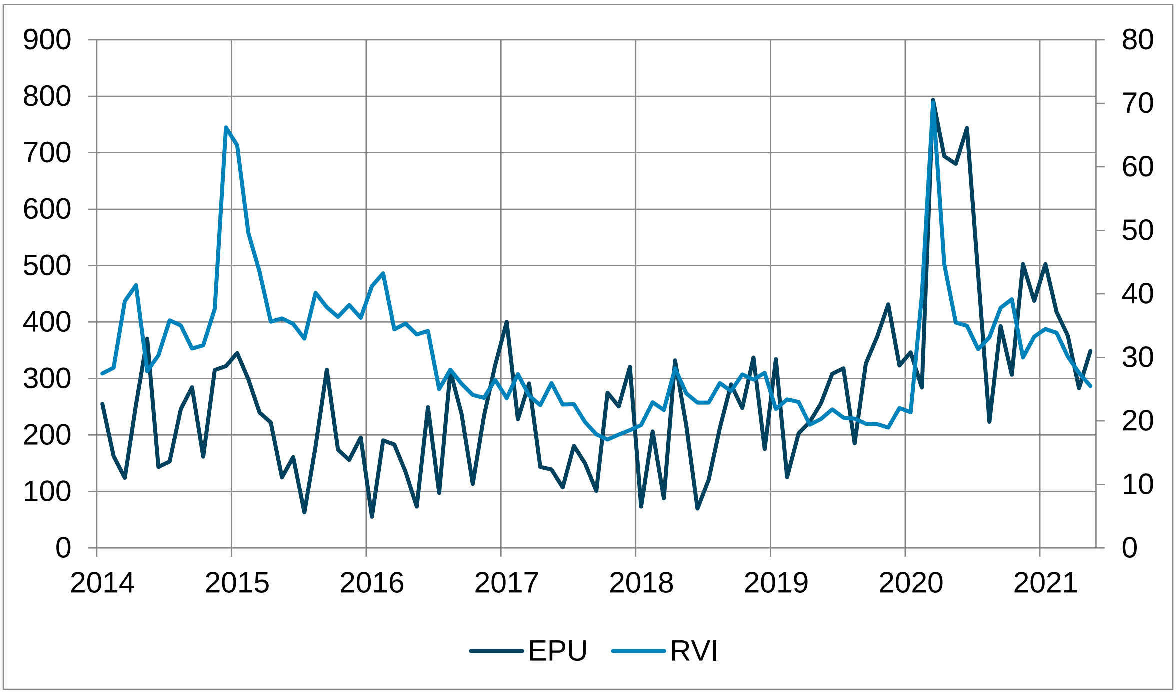


Figure 5. Moscow Exchange RVI (right) and Index of Global Economic Policy (left)



To test the possible impact of the information shocks measured by our News Uncertainty Index, we consider the following model:

$$S = \alpha + \beta^* \text{ NUI } + \varepsilon, \quad (4)$$

where S – surprise value (for analysts – Bloomberg surprises, or, for the money market – target shock and path shock);

NUI – value equal to the value of the News Uncertainty Index on the eve of a key rate decision;
α, β, ε – coefficients.

Having evaluated the models obtained (the technical results are presented in Annex 3), we come to the following results.

Uncertainty has a minimal impact on the predictability of monetary policy. The hypothesis about the influence of information shocks (news index uncertainty as a dependent variable) on the predictability of decisions (model 2) is not confirmed even at 10%-level of significance. The hypothesis about the impact of macrovariable variance (model 1) is confirmed at the 5% significance level for current decisions in terms of the impact of real wage forecast variance, at the 5% significance level for the key rate curve in terms of the impact of industrial production forecast variance, and at the 10% significance level for current decisions in terms of the impact of unemployment forecast variance. Notably, there is no impact from the variance of inflation and GDP forecasts, which are typically the key factors in key rate decisions.

4. The Verbal Interventions Hypothesis

Predictability of decisions can be determined by more active and transparent communication of the Bank of Russia. In the initial stage of inflation targeting in Russia (2015–2021), there were many episodes of increased volatility (falling oil prices, sanctions, geopolitical risks, weakening of the ruble, etc.), during which the Bank of Russia had to explain in detail the principles of its response to extraordinary events.

However, this explanation may be criticised. In the early stage of inflation targeting in 2015–2021, the Bank of Russia expanded its communication tools gradually, and such important decisions as holding press conferences after each decision, publishing the trajectory of the key rate, and the section of the website about the model apparatus fell late in the period, in 2021–2021. Until then, communication was limited to press releases on the key rate and the Monetary Policy Report, which, according to the criteria of Dincer and Eichengreen (2014) and Al-Mashat et al. (2018), is clearly not enough to consider communication exemplary transparent.

To answer this question for sure, we build another model that estimates the impact of verbal interventions by Bank of Russia representatives before the week of silence (that is, 2–3 weeks before key rate decisions) on the emergence of surprises. Thus, we test the hypothesis of whether more active communication by the Bank of Russia in the run-up to a decision has an effect on the predictability of decisions.

The impact of verbal interventions by Bank of Russia representatives on various indicators of financial markets has been considered in a number of works: Kuznetsova and Ulyanova (2016; 2018), Merzlyakov and Khabibullin (2017), and Zhemkov and Kuznetsova (2017).

Following the logic of the works listed, verbal interventions are understood as verbal statements by representatives of the Bank of Russia which contain hints about a future key rate decision. In this, we take into account all possible forms of interventions: press scrums, press conferences, interviews, speeches at public events, articles, and columns.

As speakers, we select those who most frequently comment on monetary policy on behalf of the Bank of Russia: E.S. Nabiullina (Governor of the Bank of Russia), A.Yu. Simanovsky (Advisor to the Governor of the Bank of Russia), K.V. Yudaeva (First Deputy Governor of the Bank of Russia), S.A. Shvetsov (First Deputy Governor of the Bank of Russia till 21 March 2022), D.V. Tulin (First Deputy Governor of the Bank of Russia), I.A. Dmitriev (Director of the Monetary Policy Department of the Bank of Russia until June 2018), A.B. Zabotkin (Director of the Monetary Policy Department, Deputy Governor of the Bank of Russia since June 2020), and K.V. Tremasov (Director of the Monetary Policy Department since June 2020).

A list of interventions grouped according to decision, as well as examples thereof, is provided in Annex 4. We take verbal interventions as a factor variable which takes a value of 1 if interventions are carried out and 0 if they are not.

To assess the following relationship, we use the probit model:

$$Pr(S=1|IN) = F(\alpha + \beta{*}IN), \quad (5)$$

where S – a factor variable for surprises for professional analysts which takes a value of 1 if the proportion of correctly predicted decisions is <50% and 0 if otherwise[18];
IN – a binary variable for interventions, which takes the value 1 if there was one or more interventions, and 0 otherwise;
F(...) is a Gaussian distribution function;
α, β, ε –coefficients.

Based on the results of the evaluation (Table 2), we find that verbal interventions are associated, at the 10% significance level, with the occurrence of monetary policy surprises – that is, verbal interventions before a decision correspond to lower predictability of the subsequent decision. Thus, we reject the hypothesis that the slightly higher predictability of decisions during periods of increased volatility is associated with active explanatory communication before a decision. This is consistent with the findings in the work of Hwang, Lustenberger, and Rossi (2021). It proves that intensive communication, as measured by the number of speeches from central bankers, worsens the impact of the central bank. Too much communication can be dangerous because of the "noise pollution" of the information space and growing costs of processing the increased volume of information from the central bank. An alternative interpretation might be the assumption that in periods of high uncertainty verbal interventions may become more intensive. But at least for the available data for Russia we do not observe this (see Figure 7), because the correlation between verbal interventions and episodes of high uncertainty is negative.

[18] In this case, we chose dummy as the dependent variable because, first, it corresponds to the idea of the probit model, and second, it takes into account the perception of the decision in the media environment (the media calls the decision a surprise, even if its direction was correctly guessed by the market, but the step size was predicted incorrectly).

Table 2. Assessment of the impact of verbal interventions before a decision on the emergence of Bank of Russia monetary policy surprises

	Dependent variable:
	Surprises
Interventions	0.599*
	(0.351)
Constant	-0.168
	(0.230)
Observations	54
Log Likelihood	-35.803
Akaike Inf. Crit.	75.607
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

At the same time, it should be noted that in 2021 (see Figure 6), verbal interventions worked properly: in all cases (at the time of writing, six meetings had been held), decisions were more predictable in the presence of preliminary interventions. This can serve as another confirmation of the initial stage of the formation of communication tools by the Bank of Russia. It takes a significant amount of time for the market to learn to correctly understand the signals of the regulator. Also, the high probability of "triggering" of interventions could be influenced by the expansion of the communication "menu" of the Bank of Russia, including the publication of the forecast trajectory of the key rate.

Figure 6. The role of verbal interventions in the emergence of monetary policy surprises

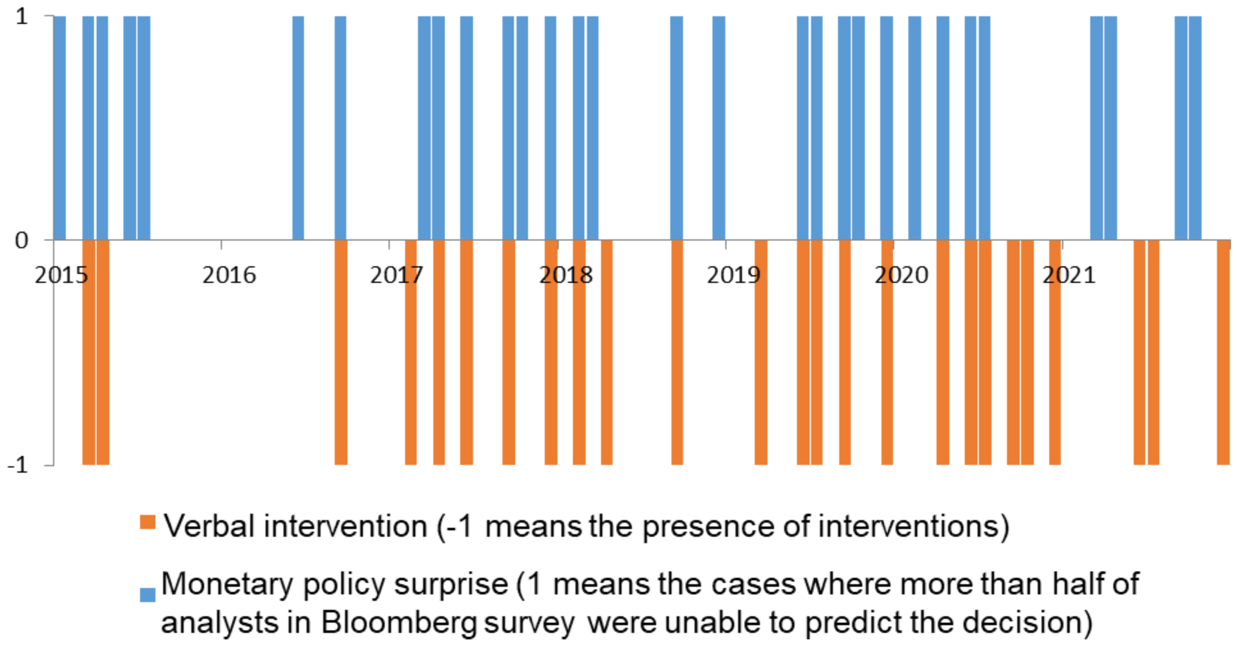
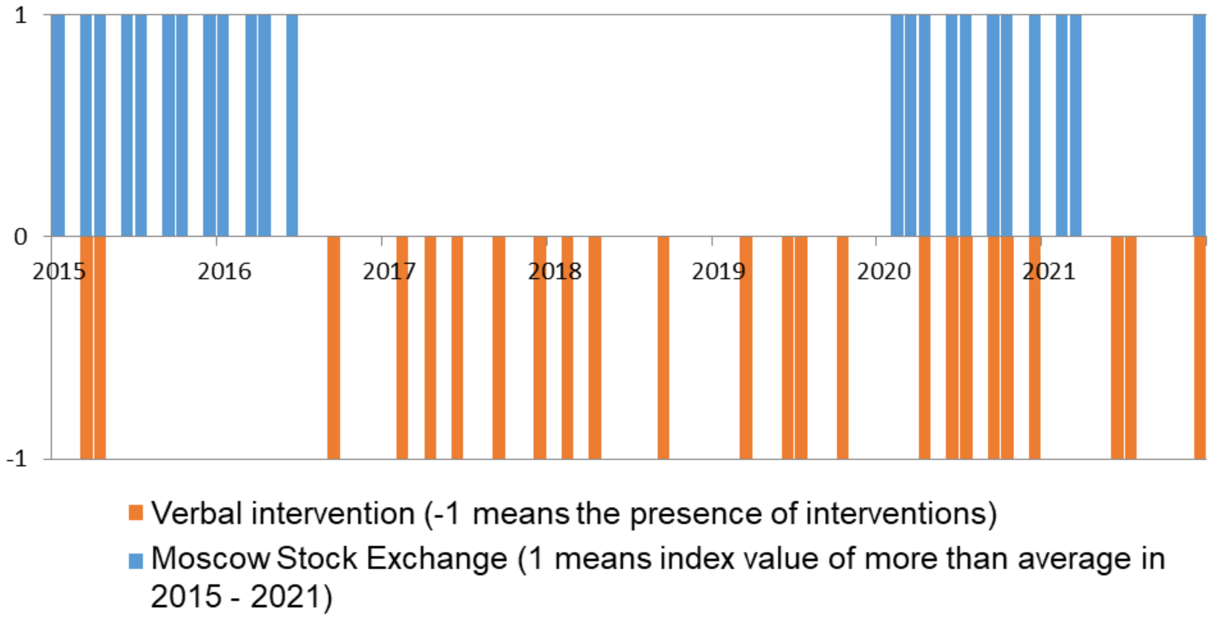


Figure 7. Verbal Interventions and Moscow Stock Exchange RVI



5. Miscommunication hypothesis

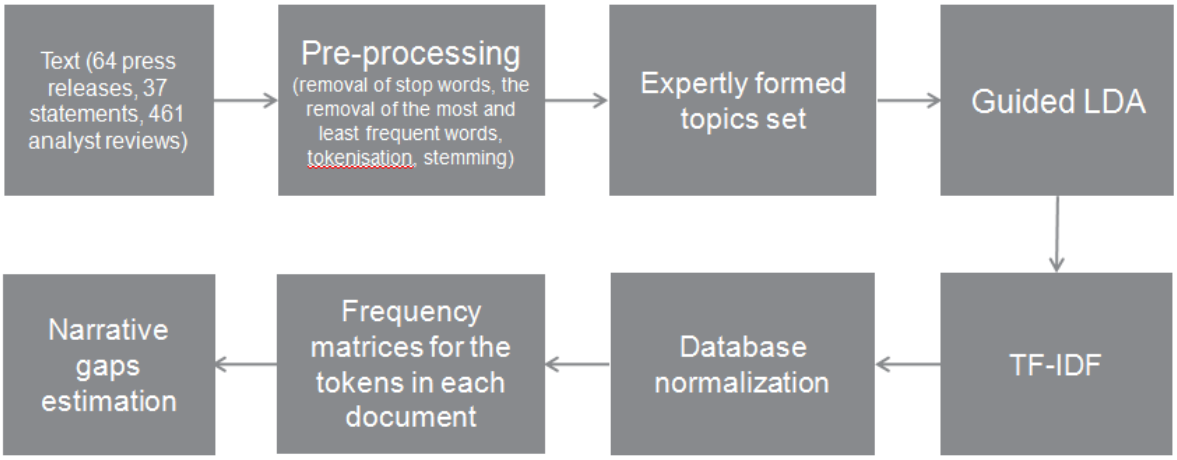
In this section, we test the assumption that monetary policy surprises may be based on differing assessments of the economic situation by the central bank and by analysts. For example, if the central bank attaches particular importance to a particular factor, while analysts do not, this may cause that factor to be underestimated by the market and, accordingly, contribute to the emergence of an unexpected decision. We are particularly interested in situations where the central bank systematically overestimates or underestimates certain factors in comparison with the market. This situation can lead to sustained miscommunication and a shift in its focus.

We know of only one example of similar work in the scientific literature. Ter Ellen et al. (2019), using a textual analysis method based on Latent Semantic Indexing (LSI) with a teacher, evaluate central bank narrative surprises to the media using the experience of Norges Bank as a case study. They come to the conclusion that, although a strong link between narrative communication gaps and monetary policy surprises has not been identified, narrative assessment can provide the central bank with important additional information about the quality of communication and its focus. In addition, narrative gaps significantly affect the media’s interest in the topic of rate decisions.

Additionally, we rely on the techniques described by Luangaram and Wongwachara (2016). In this work, key communication topics are modelled for 12 inflation-targeting central banks. For this purpose, Luangaram and Wongwachara use one of the most popular algorithms of thematic modelling today: Latent Dirichlet Allocation (LDA). The possibilities of using textual analysis tools for central banks are described in more detail in a review by Bholat et al. (2015).

Based on these works, we have developed the following algorithm for modelling narrative gaps:

Figure 8. 'Conveyor' of narrative gap modelling



For modelling, we collected the following datasets: on the one hand, press releases and statements from the Governor after the Bank of Russia Board of Directors' meetings on monetary policy, and on the other hand, reviews of professional analysts with forecasts of Bank of Russia decisions. The data cover the period from February 2014 to September 2021. The corpus contains a total of 64 press releases, 37 statements, and 461 analyst reviews. Since analyst reviews are available mainly in English, and the Bank of Russia's communication on the key rate is officially translated, we use English as the working language of the study.

Having collected the data, we carry out standard pre-processing, which includes the removal of stop words, the most and least frequent words, and tokenisation (splitting the text into individual elements); then, we perform stemming (that is, we replace words with their 'root' bases, for example, inflation → inflat). This allows the concentration of words with common roots.

Then it is necessary to highlight the topics. Since we have a relatively small dataset, which is not enough for machine learning algorithms to work fully without a teacher, we combine two techniques: guided LDA and a dictionary-based approach. At the same time, our initial definition of topics, as in ter Ellen et al (2019), is made subjectively based on the Bank of Russia's allocation of decision factors and the configuration of the extended Taylor rule for a small open economy with inflation targeting (Gali and Monacelli, 2005; Svensson, 2010). We also take into account the long periods of increased volatility in the Bank of Russia's inflation targeting experience and the coronavirus crisis that began in 2020. Thus, the following topics are expertly formed:

1) inflation;
2) inflation expectations;
3) economy;
4) volatility;
5) monetary conditions;
6) Government (fiscal policy and other government measures);

7) Covid-19.

To primarily identify the set of tags for each of the topics, we apply Guided LDA to the entire corpus. This technique extends the classical LDA of Blei et al. (2003) and Pritchard et al. (2000), which is based on the simple idea that the probability of associating a text with a certain topic is related to the frequency of certain words in it. That is, the word ‘ball’ is more easily found in the topic ‘sport’ than in the topic ‘medicine’. LDA is a hierarchical Bayesian model in which a multinomial variable with a Dirichlet a priori distribution is responsible for the distribution of topics. LDA is used mainly as a method for the thematic modelling of large sets of texts without a teacher, where it shows the best results. Guided LDA is an attempt to apply LDA to small corpora of texts by applying a teacher-assisted training algorithm. The method is described and applied by Toubia et al. (2014). There is also a similar variation of the method called Labelled LDA (Ramage, 2009).

The key advantage of these innovations is the ability to control the LDA algorithm, primarily through a predefined set of tags incorporated into the model. At the same time, the output of the model is also a probabilistic structure of the words in the topic. The expert set of key tags passed into the model guide it, but do not determine the results. In this, the probability of the appearance in topics of service words that are common to a variety of topics is quite high. Having obtained the set of words that identify a topic, we clear it of the service parts of speech and the words with the highest and lowest frequencies, thus increasing the concentration of the substantive part of the topic, as well as connecting related topics – for example, those related to the acceleration and deceleration of inflation. (In our study, these are all included in a single, more general topic: ‘Inflation’). As a result, we obtain the following set of topic-identifying tokens (table 3).

Table 3. Topic-identifying words

#	Topic	Tags
Topic 0	Inflation	'inflat', 'consum', 'price', 'acceler', 'season', 'annual', 'proinflationari', 'disinflationari', 'factor', 'slow', 'pressur', 'overheat', 'cost', 'inflationari', 'spiral', 'product', 'servic', 'basket'
Topic 1	Volatility	'foreign', 'geopolit', 'volatil', 'extern', 'risk', 'global', 'shock', 'oil', 'currenc', 'dollar', 'barrel', 'opec', 'sanction', 'sovereign', 'harvest', 'commod', 'world', 'concern', 'uncertainti'
Topic 2	Economy	'econom', 'economi', 'growth', 'dynam', 'compani', 'recoveri', 'recov', 'demand', 'invest', 'product', 'import', 'export', 'sector', 'suppli', 'develop', 'aggreg', 'weaken', 'busi', 'unemploy', 'labour'
Topic 3	Monetary conditions	'rate', 'pace', 'yield', 'ofz', 'monetari', 'condit', 'deposit','save', 'debt', 'mortgag', 'loan', 'financi'
Topic 4	Inflation expectations	'household', 'inflat', 'expect', 'peopl', 'citizen', 'famili', 'unanchor', 'elev', 'consum', 'activ', 'food', 'petrol', 'incom'
Topic 5	Government	'govern', 'budget', 'fiscal', 'rule', 'tax', 'infrastructur'
Topic 6	Covid-19	'pandem', 'coronavirus', 'vaccin', 'lockdown', 'epidem'

Next, we compile frequency matrices for the tokens in each document (press releases and statements or analyst reviews on a particular decision), normalise them by median (because we are dealing with exponential frequency distributions), and estimate the difference in weight of each of the seven topics in Bank of Russia communications and in economic analyst reviews from before the decisions. The results of these narrative gaps by topic are presented in Figures 8–14, and the general picture is presented in Figure 15.

Based on the data obtained, we made the following observations:

1. The narrative gaps in Bank of Russia communications are substantial. However, they can be associated with different views on the situation in the economy compared to those of analysts, and they are largely determined by the specifics of the Bank of Russia’s materials. In particular, they can be associated with the template structure of Bank of Russia materials. For example, in the press release on the key rate, there is always a paragraph on the economy. Analyst reviews are more situational. This may explain the steadily significant gaps in the ‘Economy’ topic.

2. The narrative gaps in the ‘Inflation’ and ‘Inflation expectations’ topics are strongly correlated by both the Bank of Russia and analysts. That is, both analysts and the Bank of Russia interpret these topics in close connection. Moreover, the correlation of these topics in later periods even increases. The significant gaps in the coverage of these topics between April 2016 and July 2017 can probably be explained by analysts’ lesser interest in these topics during the period of deceleration of inflation/reduction of inflation expectations. It is important to note that, while before 2019, the Bank of Russia steadily gave inflation expectations and inflation more importance in its communications than analysts, then later analysts began to pay much more attention to these indicators, building their pre-decision notes around these topics. This sustained attention by analysts to the topic of inflation virtually coincides with the "anchoring" of their inflation expectations at the 4% target.

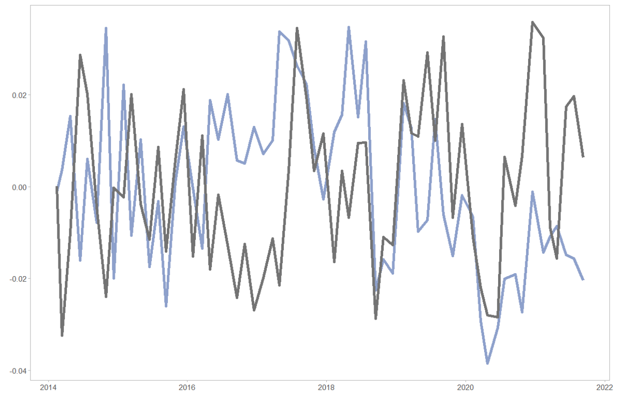
3. It is noteworthy that the Bank of Russia assesses the risks associated with the coronavirus significantly higher than analysts (except for in the very beginning of the pandemic, when analysts still responded faster and showed greater concern).

4. The biggest positive gap is in the averages on the ‘Monetary conditions’ topic (in other words, this topic plays a bigger role in Bank of Russia’s communication), while the largest negative gap is on the ‘Inflation expectations’ topic (respectively, this topic appears steadily more often in analysts’ notes).

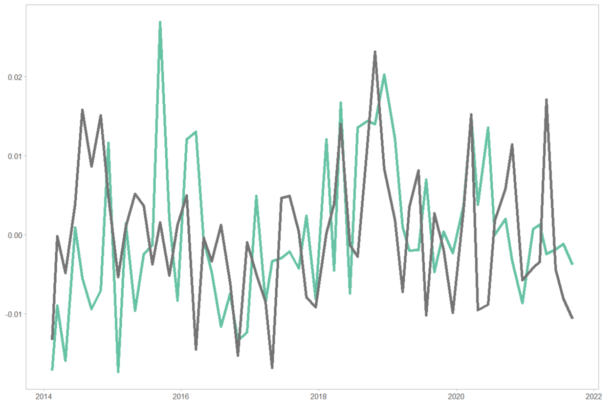
Figures 9–15. Narrative gaps in Bank of Russia communications (coloured lines – Bank of Russia; grey lines – analysts)

Frequency of 'Inflation' terms

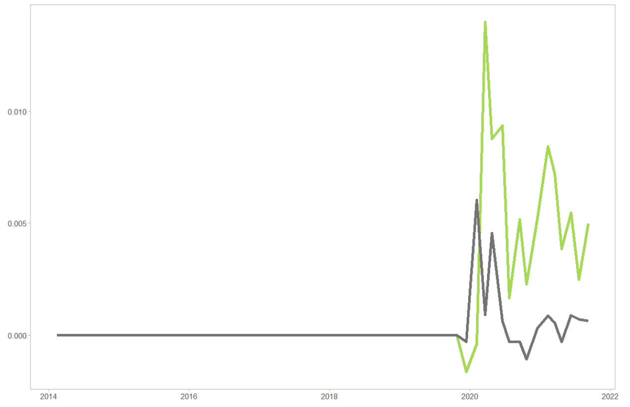
Frequency of 'Inflation expectations' terms



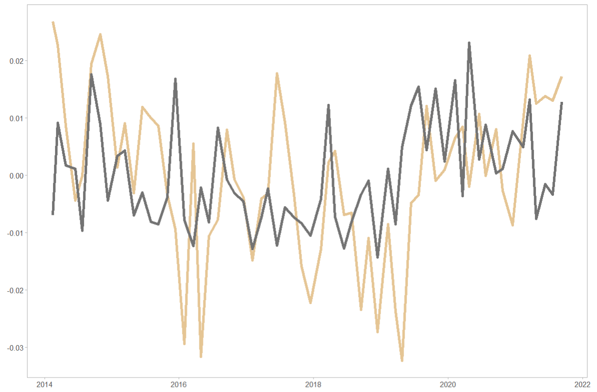
Frequency of 'Volatility' terms



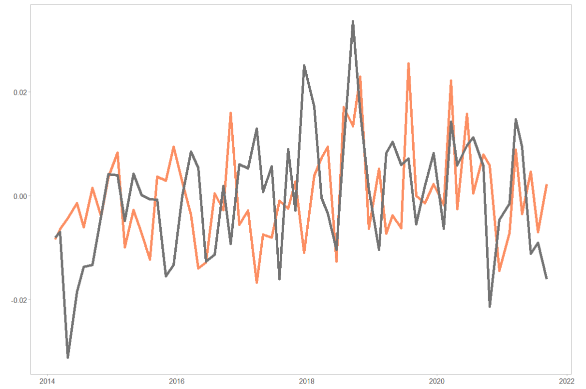
Frequency of 'Covid-19' terms



Frequency of 'Economy' terms



Frequency of 'Monetary conditions' terms



Frequency of 'Government' terms

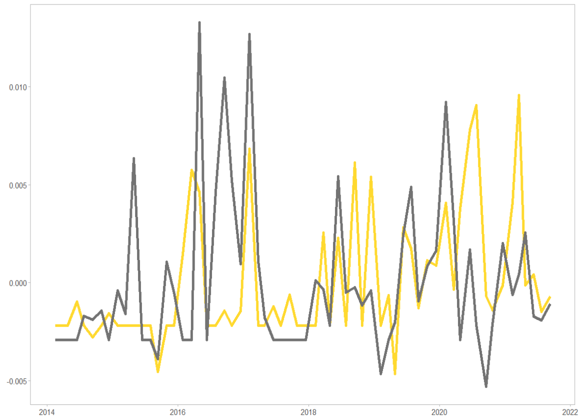
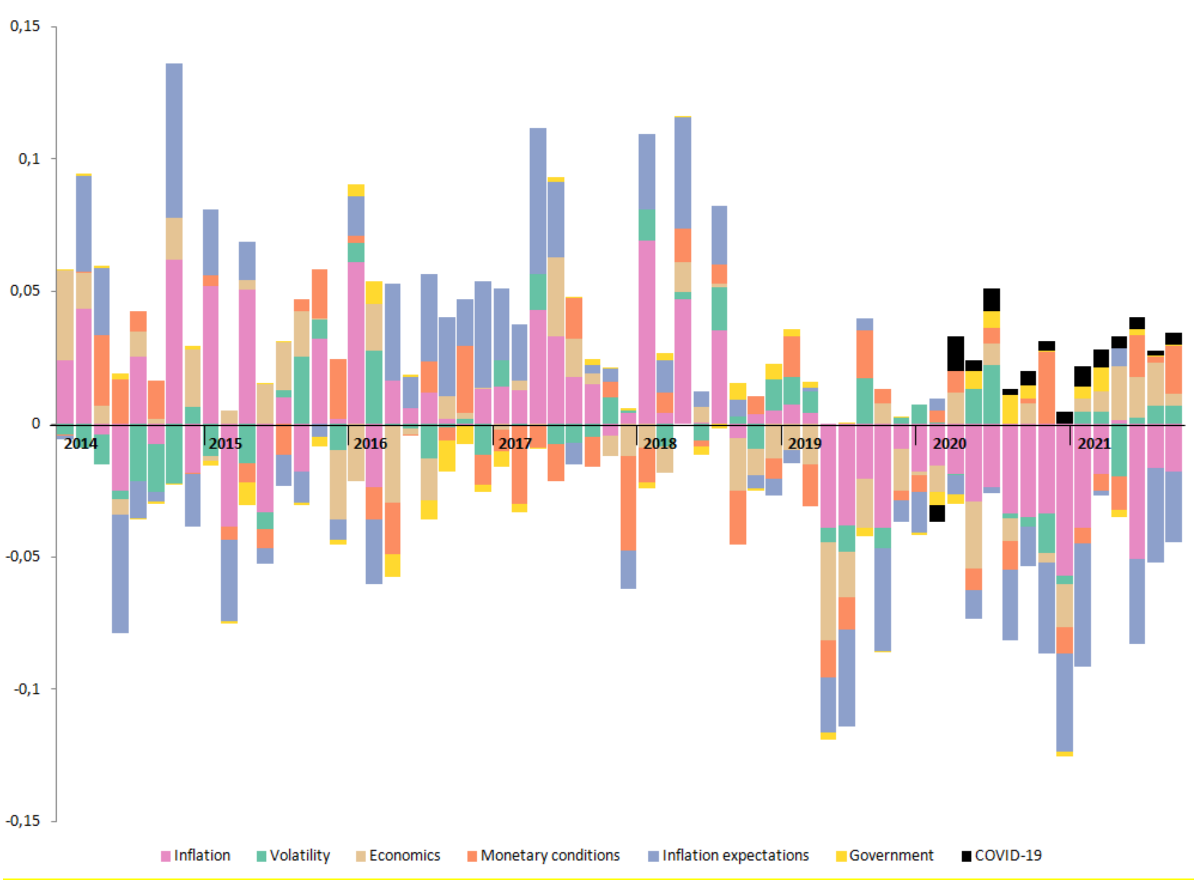


Figure 16. Narrative gaps in Bank of Russia communications and analysts' assessments of the situation
(upward deviation from zero on the Y-axis – the Central Bank attaches more importance to the factor than analysts; downward deviation from zero on the Y-axis – analysts attribute more importance to the factor than the Central Bank)



To assess the possible relationship between narrative gaps and monetary policy surprises, we perform a regression analysis:

$$S_t = \alpha + \beta * nd_t + \varepsilon, \quad (6)$$

where S_t – classically measured normalised monetary policy surprises at date t, measured as the share of analysts who incorrectly predicted the key rate decision [19];
nd_t – narrative gaps at date t (analyst reviews before the decision and the Bank of Russia decision itself);
α, β, ε – coefficients.

As ndt, both each of the types of gaps separately and their entirety throughout the sum of the modules are considered.

Judging by the results of the regression analysis, narrative gaps may explain a very modest part of the surprises. This is in line with the results obtained by ter Ellen et al. (2019).

Narrative gaps in inflation and volatility are most important in predicting surprises (5% significance; see Table 4). From this, we can conclude that monetary policy surprises are probably not based on different assessments of the economic situation by the central bank and analysts, although assessments of inflation and volatility do make a (very limited, but statistically significant) contribution.

Table 4. Assessment of the influence of narrative gaps in terms of inflation and volatility on the occurrence of surprises in Bank of Russia monetary policy

	Dependent variable:		*Dependent variable:*
	Unpredictability		Unpredictability
Infl_diff_corr	294.414**	Volatil_diff_corr	-760.077**
	(146.774)		(377.891)
Constant	35.005***	Constant	34.354***
	(4.158)		(4.100)
Observations	61	Observations	62
R^2	0.064	R^2	0.063
Adjusted R^2	0.048	Adjusted R^2	0.048
Residual Std. Error	32.452 (df = 59)	Residual Std. Error	32.285 (df = 60)
F Statistic	4.024** (df = 1; 59)	F Statistic	4.046** (df = 1; 60)

Note: *p<0.1; **p<0.05; ***p<0.01

[19] In this case, we chose the proportion of analysts who guessed the decision incorrectly as the dependent variable, since this, in our opinion, is more consistent with narrative gaps.

6. The hypothesis of the central bank's information advantage

One of the reasons for occurrence of monetary policy surprises investigated in the literature is related to the information being transmitted. Market participants receive certain additional information on the central bank's assessment of the economic situation from monetary policy decisions and their communication (Hoesch, Rossi, and Sekhposyan, 2020). New information influences the correction of their expectations and forecasts.

The key assumption is the hypothesis of information advantage of the central bank. It is assumed that this advantage allows the central bank to better forecast macroeconomic indicators and assess the situation in the economy. The presence of this information advantage may be due to the belief of the market, as well as an objective advantage of the central bank in terms of analysis and forecasting.

In the case that the central bank has a proven information advantage, it is possible to draw conclusions about communication gaps in terms of decision-making logic and the analytical and instrumental apparatus. In a pronounced situation of informational advantage of the central bank, the market does not try to predict decisions based on publicly available information about the state of the economy, but waits for new inputs from the central bank on the economic situation, which appear along with its monetary policy decision. A situation of informational advantage is characterised by counterintuitive market behaviour: when the central bank raises the rate, the market does not lower its inflation forecasts, counting on the effectiveness of the regulator in achieving the goal of price stability, but rather increases them, thinking that the actions of the regulator are related to an upward revaluation of inflation forecasts. When the central bank is as open as possible in terms of publishing its model and analytical apparatus, the information channel comes to naught. This is proven for the US Federal Reserve by Hoesch, Rossi, and Sekhposyan (2020). These authors directly link the disappearance of the Federal Reserve's information advantage to the development of communication.

Several research articles have been devoted to testing the presence of an information advantage at central banks and assessing the reaction of analysts' forecasts to monetary policy decisions. In particular, Romer and Romer (2000) examine the US Federal Reserve's information advantage and the impact of monetary policy decisions on commercial forecasts. Based on the results of the study, the authors conclude that in 1970–1991, the US Federal Reserve had information advantage in forecasting inflation and GDP at horizons of up to 6 quarters. At the same time, analysts' inflation forecasts shifted upward as monetary policy tightened.

In the study of central banks' information advantage, most authors look at the US Federal Reserve, even though their forecasts were previously published with a five-year lag. Hubert (2009) draws attention to this problem. The author investigates the presence and sources of information advantage in five countries (Great Britain, Japan, Sweden, Canada and Switzerland). As a result of the analysis, the author makes a conclusion about the existence of information advantage only for the Swedish Riksbank from the late 1990s to 2007. The study also showed that during this time period in Britain and Switzerland, analysts' inflation forecasts for a year or more ahead were more accurate than the central banks' forecasts. Boero, Smith and Wallis (2008) draw a similar conclusion for Britain using a different source of analyst predictions.

In addition to information asymmetries, Hubert (2009) assesses the impact of the disclosure of central bank forecasts on inflation and GDP forecasting by analysts. This topic is also analysed in works by Morris and Shin (2002), Svensson (2006), and Amador and Weill (2010). In addition, the author analyses the mutual influence of central bank and analyst forecasts.

The work of Romer and Romer (2000) serves as the basis for a later study of information asymmetry in the United States by Hoesch, Rossi, and Sekhposyan (2020). The authors slightly modify the methodology and check how the presence of an information advantage changed over time using the rolling window method on two time intervals (1979–2003 and 2004–2014). The study shows that the Federal Reserve's information advantage in forecasting inflation and GDP disappeared on mid-term horizons in the early 1990s, and on short-term horizons in the early 2000s. The information advantage is also estimated by Fair and Shiller (1989; 1990) and Sims (2002).

In assessing the information advantage, the authors of these studies pay attention to the rationality of forecasts in general. Often, the forecasts of macroeconomic indicators become a separate subject of research. Blix, Wadefjord, Wienecke and Adahl (2001) analyse 1990s forecasts of various macro-variables from 250 sources in five countries. The results of the analysis show that it is more difficult to predict economic growth than inflation. At the same time, inflation forecasts are overestimated, and growth forecasts are underestimated. Patton and Timmermann (2012) and Rossi and Sekhposyan (2015) focus on estimating and analysing the rationality of forecasts.

Some authors attribute the existence of a central bank's information advantage not to early access to statistical information, but to a more advanced forecasting apparatus (Romer and Romer, 2000; Hubert, 2009). The lack of information advantage or its disappearance is explained by the central banks' level of transparency and its increase (Hubert, 2009; Hoesch, Rossi, and Sekhposyan, 2020; Laséen, 2020). The more information the central bank discloses, the smaller the difference in the perception of the economic situation between it, the market, and analysts. Consequently, the number of monetary policy surprises is also decreasing.

When testing the hypothesis of the Bank of Russia's information advantage, we rely on research on information advantage, mainly the classic work of Romer and Romer (2000).

To test the rationality of the forecasts and the hypothesis of the Bank of Russia's information advantage, we used the Bank of Russia's annual inflation forecasts and the Bloomberg consensus from March 2015 to October 2021 (for forecasts for the current year). For forecasts for the next year, the sample is limited to October 2022; for the two-year forecast horizon, the sample is limited to December 2019. This is due to the fact that the evaluation of these regressions requires actual data, which are currently available for 2021 at the latest.

The Bank of Russia presents forecasts of macro indicators on a three-year horizon. However, these are not included in the study, as analyst forecasts for more than two years ahead are not available in Bloomberg. In addition, the Bank of Russia publishes forecasts

4 times a year (except for 2019, when 5 forecasts were published), which also serves as a limitation on the sample size. The number of observations for current-year forecasts is 29, for the next year, 25, and for the two-year period, 21. As forecast values, we use point forecasts or the middle of the interval if the forecast was published as a range.

In testing the hypothesis of the existence and rationality of a Bank of Russia informational advantage in predicting inflation, we focus on the dates of the Monetary Policy Report (when the forecast was published as part of it) and the dates of the medium-term forecast from when it began to be published separately the week before the reports were published as part of the press release on the key rate. Analysts' forecasts were collected for the corresponding dates. Charts of inflation forecasts and errors in the Bank of Russia's and analysts' forecasts are given in Annex 5.

6.1. Verification of forecast rationality

Verification of the hypothesis about the rationality of forecasts is required to test our hypotheses of interest about the existence of an information advantage. We proceed from the assumption that it is possible to draw correct conclusions about the presence of an information advantage if the prerequisites of this hypothesis are met (Romer and Romer, 2000).

In testing the hypothesis of the rationality of forecasts and further researching information advantage, we focus only on inflation forecasts. The forecasts of this indicator are of the greatest interest, since maintaining price stability is the goal of the monetary policy of the Bank of Russia.

Before testing the hypotheses, we construct scatter diagrams of the Bank of Russia's and analysts' inflation forecasts. The charts are given in Annex 6. The diagrams are constructed to include forecasts for December 2014. Since then, the Bank of Russia has been publishing medium-term macroeconomic forecasts as part of the Monetary Policy Report. However, the charts show that these points are clearly outliers. We do not include them in the calculations when testing this hypothesis and the information advantage hypothesis.

For the initial comparison of the forecasts of the Bank of Russia and those of the analysts, we calculate the mean squared errors of the inflation forecasts. The mean squared errors in the Bank of Russia's inflation forecasts for the end of the current year are much smaller than the errors in the analysts' forecasts. The errors of forecasts for the next year are similar. For the two-year horizon, the errors of the analysts' forecasts are slightly lower. A table is provided in Annex 6.

In the following regressions, we include actual and forecast inflation values. We test the hypothesis of inflation forecasts accuracy:

$$\pi = \alpha + \beta\hat{\pi}_{BR\ or\ Analysts} + \varepsilon, \qquad (7)$$

where π – the actual inflation;

$\hat{\pi}_{BR\ or\ Analysts}$ – inflation forecast of the Bank of Russia or the analysts (Bloomberg consensus).

Inflation forecasts are rational if α = 0 and the coefficient in the inflation forecast is 1. The coefficients in the Bank of Russia forecasts are significant at the horizons of the current year and the two-year period. The significance of the regression is confirmed only when forecasting for the current year. However, when testing this hypothesis, the size of the coefficients is important. Therefore, in addition to evaluating the regressions, we performed an F-test for the double hypothesis that α = 0 and β = 1. The hypothesis cannot be rejected only for forecasts for the current year.

The coefficients for the analysts' forecasts are significant for the same horizons: for the current year and for two years ahead. However, according to the F-test for equality of the coefficient to one and the free term to zero, the hypothesis is rejected for all types of predictions. The results of the regression evaluation and the F-test are presented in Annex 6.

According to the data obtained, rationality is confirmed for the forecasts of the central bank on horizons of up to three quarters (for the current year).

6.2. Testing the hypothesis of the Bank of Russia's information advantage

Next, we check the main hypothesis of information advantage in inflation forecasting. We consider the following regression:

$$\pi = \alpha + \beta_1 \hat{\pi}_{BR} + \beta_2 \hat{\pi}_{Analysts} + \varepsilon, \quad (8)$$

where π – the actual inflation,

$\hat{\pi}_{BR}$ – the Bank of Russia's inflation forecast,

$\hat{\pi}_{Analysts}$ – the analysts' inflation forecast (Bloomberg consensus).

We assume that the central bank has an informational advantage over analysts if the coefficient in its forecasts is meaningfully different from zero.

The results of the regression evaluation are presented in Annex 7. According to the data obtained, the Bank of Russia has information advantage or an information advantage in forecasting inflation on horizons of up to three quarters. The coefficient for the Bank of Russia forecasts for the current year is more than one and is statistically significant. However, the results of the regression estimation for the longer forecast horizons led to other conclusions. The existence of an information asymmetry in forecasting inflation for the next year and the two years ahead is not confirmed. The forecast rationality hypothesis is also rejected for these forecast horizons. When testing the hypothesis of information advantage, we find the presence of serial correlation. All regressions are estimated taking into account robust standard errors.

To analyse the information advantage in dynamics and validate the findings, we also evaluate the regressions for the forecasts for the current year and next year using a rolling window method with a size of 16 observations. The evaluation was performed according to the methodology proposed by Hoesch, Rossi, and Sekhposyan (2020). However, the use of this method has several limitations. The small number of observations for the forecast horizons analysed (29 and 25 respectively) does not allow for a larger window size. But its decrease may also affect the correctness of the results. In this case, regressions with fewer than 16 observations will be evaluated for each window.

The rolling window regression evaluation confirms the previous findings. The Bank of Russia had an informational advantage in forecasting inflation over short-term horizons throughout the period under study (2015–2021). A detailed description of the results and charts of the t-statistic values obtained are presented in Annex 7.

On the basis of the information received, we draw the following conclusions. The Bank of Russia has an information advantage in forecasting inflation in comparison with analysts on horizons of up to three quarters. In other words, the central bank has additional information or tools to predict inflation more accurately.

6.3. Testing the hypothesis of the impact of monetary policy decisions on analysts' forecasts

The assessment of this hypothesis allows us to understand how the Bank of Russia's key rate decisions affect analysts' forecasts in the presence of an information asymmetry. In other words, we investigate whether the Bank of Russia's information advantage is revealed through its monetary policy decisions.

It is important to note that the data sample is slightly different from that used in the previous block. The regression does not include actual inflation values, allowing for the expansion of the sample to include forecasts for 2022 and 2023. The number of observations for the forecasts for the current and next years is 29 units and 24 units for two years. Slightly different dates are used for the analysts' forecasts. We take the difference between the analysts' forecast a week after the Bank of Russia Board of Directors' meetings on the key rate and the forecast the day before. The dates of the Bank of Russia forecasts are still tied to the dates of the Monetary Policy Report and the publication of the medium-term forecast. Key rate decisions are measured through dummy variables, where -1 is a decision to reduce the rate (mitigation), 1 is a decision to increase the rate (monetary tightening), and 0 is a decision to maintain the rate.

The following regression is evaluated to test the hypothesis:

$$\Delta\hat{\pi}_{Analysts} = \alpha + \beta_1 Decision + \beta_2 \Delta\hat{\pi}_{BR} + \varepsilon, \tag{9}$$

where $\Delta\hat{\pi}_{Analysts}$ – the difference between the analysts' forecasts one week after the key rate decisions and the day before,

$\Delta\hat{\pi}_{BR}$ – the difference between the current and previous Bank of Russia inflation forecasts,

$Decision$ – a key rate decision (dummy variable).

Key rate decisions indicate a disclosure of information advantage if the coefficient in the decision is significantly different from zero. For example, if it is greater than zero, then a tightening of monetary policy leads to an increase in analysts' inflation forecasts. The results of the regression analysis are provided in Annex 8.

Based on the results, we can draw the following conclusions. As the key rate rises, analysts' inflation forecasts do shift upward, although the impact is rather limited. This applies to inflation forecasts for the current year and the next year – the coefficients differ significantly from zero. This conclusion is not confirmed at the two-year forecasting horizon. This probably indicates analysts' high confidence that the Bank of Russia will return inflation to the target on the medium-term horizon. However, a conclusion about the possible impact of information asymmetry on upward adjustments of forecasts can only be drawn for short-term forecasts. This is due to the fact that the existence of an information advantage is confirmed only for this forecasting horizon.

Based on these findings, we can conclude that the Bank of Russia, in the opinion of the market, has a significant information advantage in terms of forecasting and estimating inflation. To reduce the unpredictability of decisions, the Bank of Russia should disclose in its communication many more details of its model and analytical apparatus, to which the market currently has no access.

Conclusions

In this study, we assessed the influence of communication and other information factors on the occurrence of monetary policy surprises.

According to the findings, the stage of early inflation targeting in Russia (2015-2021) is quite clearly divided into two periods: 2015 – mid-2020 and after mid-2020. During the first period, the Bank of Russia communication was being adjusted, the market was adapting to the new conditions and learning to perceive the central bank signals, which inevitably affected the level of predictability of decisions. We drew these conclusions on the basis of hypothesis tests on narrative gaps and verbal interventions.

Regarding narrative gaps or miscommunication, the first period is characterized by increased noisiness: the market was trying to understand what factors are important in predicting key rate decisions. The second stage is anchoring: analysts are firmly entrenched in the topics of inflation and inflation expectations when forecasting decisions. These topics make a statistically significant contribution to the formation of the monetary policy surprises. Analysts' sustained attention to the topic of inflation virtually coincides with the anchoring of their inflation expectations on the 4% target.

As for verbal interventions, they did not work “correctly” until about the middle of 2020 - that is, they didn’t prevent monetary policy surprises. In the second period, interventions began to work more correctly. According to our estimates, this can be attributed to the development of the Bank of Russia's communication policy, including the launch of the publication of the forecast trajectory of the key rate. It should be noted that the publication of the key rate trajectory by itself did not lead to an improvement in the predictability of decisions. Apparently, there is a more complex transmission mechanism. The development of communication tools first leads to an improvement in the work of communication itself, which in our case is noticeable in the sharply improved perception of verbal interventions. Then it increase the predictability of monetary policy decisions.

In addition to the lack of improvement in the predictability of decisions after the start of the publication of the key rate trajectory, we found other unexpected effects. In particular, high macroeconomic and financial uncertainty and the increase in the number of information shocks do not seem to make a statistically significant contribution to the occurrence of monetary policy surprises. Moreover, this applies to the variance of analysts' inflation and GDP forecasts, which are the most significant factors of any key rate decision.

We conclude that surprises are mostly attributable to information advantage. According to the data obtained, the Bank of Russia has such an advantage. In other words, market suppose that it has some non-public information about inflation and/or has more advanced models of its forecasting. As it is proved in the literature, with the development of communication as an inflation targeting tool, the information advantage of the central bank comes to naught. In other words, the more information a central bank publishes about its mechanism of analysis and forecasting, the closer the perception of its decisions by the market is to the fact is a sign of the formation stage of the inflation targeting in Russia and communication as its tool.

Based on our research, we suggest the following recommendations that the Bank of Russia could use to improve the predictability of monetary policy decisions through the development of communication as a tool:

1. to disclose more details of the forecasting and analytical framework, which are currently not available to the market. This makes it possible to gradually negate the information advantage;

2. to reduce the narrative gaps in communication, to move away from the template structure of the main materials on the key rate in favor of a situational structure. That way, the market will be able to better assess the relative weight of the arguments in the decision. The current template structure creates miscommunication risks. For example, the paragraph about the economy is always present in the press release and occupies about the same place or volume in it, even if the situation in the economy was not a factor for the decision.

3. to strengthen the discussion of how the inflation forecast influences the key rate decisions, giving more detailed forecasts and explaining the reasons for their revisions. This can be done, if not in the press releases on the key rate, but in auxiliary publications (e.g. Monetary Policy Report).

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Annexes

Annex 1. Bank of Russia decisions and analysts' expectations

No.	Surprise date	Surprise type (0 – unexpected retention; 1 – unexpected change)	Details
1	30 January 2015	1	Analysts expected the rate to remain the same, that is, a more cautious decision. The Bank of Russia reduced the rate sharply from 17 to 15 per cent, predicting a faster slowdown than in previous forecasts and also considering the growing risks to the economy.
2	30 April 2015	1	Analysts expected a more cautious decision. The Bank of Russia reduced the rate from 14% to 12.5%, analysts expected a decrease of only 100 bp, to 13%.
3	30 October 2015	0	Analysts expected a less cautious decision. Analysts were almost evenly split, but a formal majority (51.3%) expected a rate reduction to 10.5%, while the Bank of Russia kept it at 11%.
4	11 December 2015	0	Analysts expected a less cautious decision. The situation repeated itself in the next round: analysts, by a slight margin (53.9%), expected a rate reduction to 10.5%, while the Bank of Russia kept it at 11% again.
5	24 March 2017	1	Analysts expected a more cautious decision. Analysts expected the rate to remain at 10%, but the Bank of Russia reduced it to 9.75%.
6	28 April 2017	1	Analysts expected a more cautious decision. Analysts expected a smoother rate reduction of 25 bp, while the Bank of Russia cut it by 50 bp to 9.25%.
7	15 December 2017	1	Analysts expected a more cautious decision. Analysts expected a smoother rate reduction of 25 bp, while the Bank of Russia reduced it by 50 bp to 7.75%.
8	14 September 2018	1	Analysts expected a more cautious decision. Analysts expected the rate to remain unchanged, while the Bank of Russia raised it by 25 bp.
9	14 December 2018	1	Analysts expected a more cautious decision. Analysts expected the rate to remain unchanged, while the Bank of Russia raised it by 25 bp.
10	25 October 2019	1	Analysts expected a more cautious decision. Analysts expected a reduction of the rate by 25 bp, while the Bank of Russia reduced it by 50 bp.
11	24 July 2020	1	Analysts expected a less cautious decision. The Bank of Russia reduced the rate by 25 bp, while the market expected a more aggressive reduction of 50 bp.
12	19 March 2021	1	Analysts expected a more cautious decision. The Bank of Russia raised the rate by 25 bp, while the market expected it to remain unchanged.
13	23 April 2021	1	Analysts expected a more cautious decision. The Bank of Russia raised the rate by 50 bp, while the market expected a smoother increase of 25 bp.
14	10 September 2021	1	Analysts expected a less cautious decision. The Bank of Russia raised the rate by 25 bp, while the market expected a more aggressive increase of 50 bp.
15	22 October 2021	1	Analysts expected a more cautious decision. The Bank of Russia raised the rate by 75 bp, while the market expected a smoother increase of 50 bp.

Annex 2. Additional details on surprises from financial markets

Figure 16. The changes in ROISFIX and OFZ index on monetary policy meeting dates

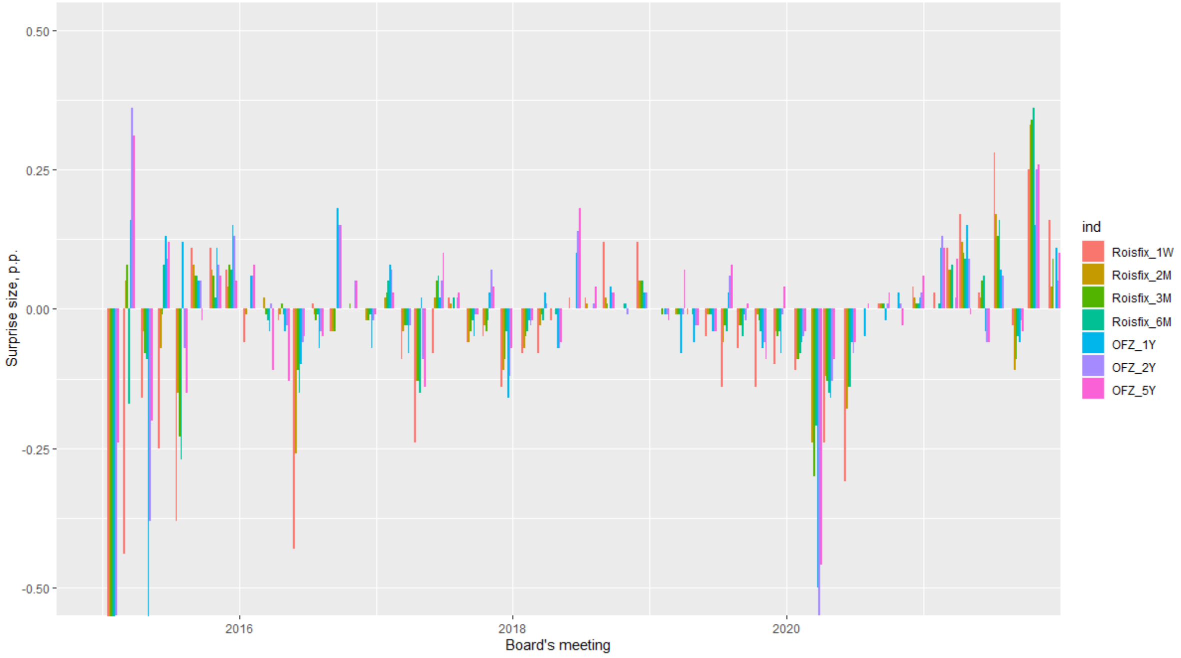
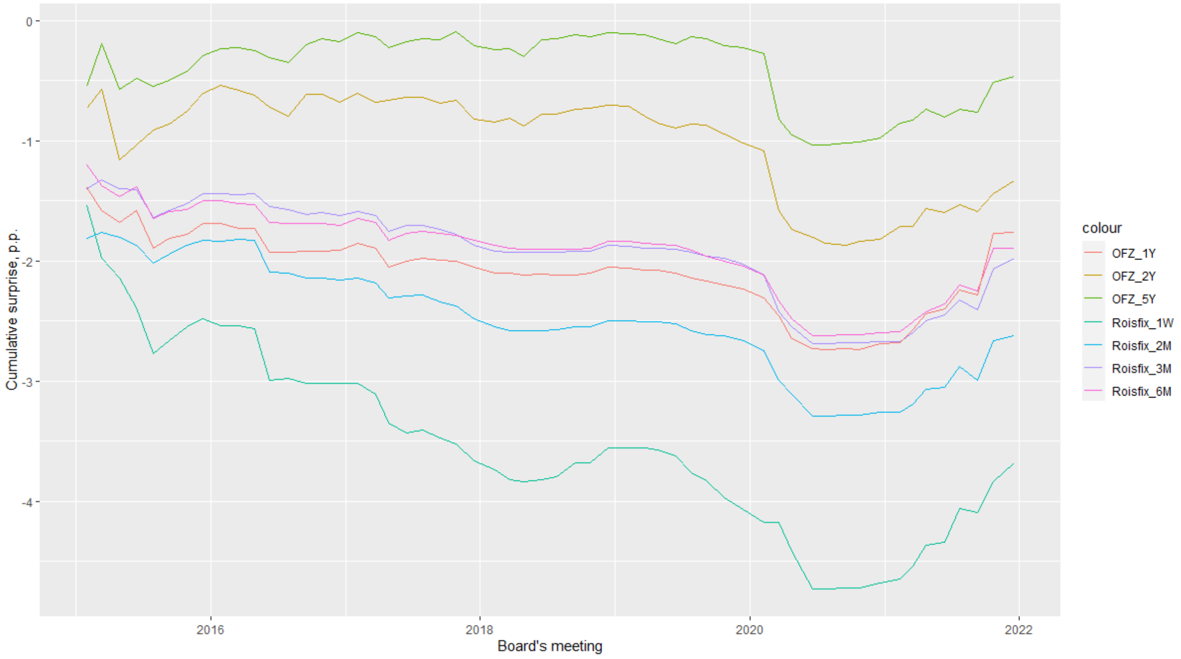


Figure 17. The cumulative changes in ROISFIX and OFZ index in monetary policy meeting dates



Annex 3. Assessments of models of the high role of uncertainty and information shocks

Model 1. Assessment of the impact of variance of Bloomberg analysts' forecasts of key macro variables

Inflation

	Dependent variable:	*Dependent variable:*	*Dependent variable:*
	Bloomberg Surpises	Target.shock	Path.shock
Inflation	0.185	-0.118	-0.072
	(0.201)	(0.203)	(0.048)
Constant	0.000	-0.000	-0.073
	(0.197)	(0.199)	(0.047)
Observations	26	26	26
R^2	0.034	0.014	0.085
Adjusted R^2	-0.006	-0.027	0.047
Residual Std. Error	1.003 (df = 24)	1.014 (df = 24)	0.242 (df = 24)
F Statistic	0.850 (df = 1; 24)	0.336 (df = 1; 24)	2.231 (df = 1; 24)
Note:	*p<0.1; **p<0.05; ***p<0.01	*p<0.1; **p <0.05; ***p<0.01	*p<0.1; **p<0.05; ***p<0.01

GDP

	Dependent variable:	*Dependent variable:*	*Dependent variable:*
	Bloomberg Surpises	Target.shock	Path.shock
GDP	-0.165	0.118	0.008
	(0.201)	(0.203)	(0.051)
Constant	0.000	-0.000	-0.073
	(0.197)	(0.199)	(0.050)
Observations	26	26	26
R^2	0.027	0.014	0.001
Adjusted R^2	-0.013	-0.027	-0.041
Residual Std. Error	1.007 (df = 24)	1.013 (df = 24)	0.253 (df = 24)
F Statistic	0.669 (df = 1; 24)	0.340 (df = 1; 24)	0.025 (df = 1; 24)
Note:		*p<0.1; **p<0.05; ***p<0.01	

Industrial production

	Dependent variable:	*Dependent variable:*	*Dependent variable:*
	Bloomberg Surpises	Target.shock	Path.shock
Production	0.208	-0.260	**-0.120****
	(0.200)	(0.197)	(0.044)
Constant	0.000	-0.000	-0.073
	(0.196)	(0.193)	(0.043)
Observations	26	26	26
R^2	0.043	0.067	0.236
Adjusted R^2	0.003	0.028	0.204
Residual Std. Error	0.998 (df = 24)	0.986 (df = 24)	0.221 (df = 24)
F Statistic	1.083 (df = 1; 24)	1.733 (df = 1; 24)	7.397** (df = 1; 24)
Note:		*p<0.1; **p<0.05; ***p<0.01	

Real Salary

	Dependent variable:	*Dependent variable:*	*Dependent variable:*
	Bloomberg Surpises	**Target.shock**	Path.shock
Salary	0.041	**-0.396****	-0.059
	(0.204)	(0.187)	(0.049)
Constant	0.000	-0.000	-0.073
	(0.200)	(0.184)	(0.048)
Observations	26	26	26
R^2	0.002	0.157	0.057
Adjusted R^2	-0.040	0.122	0.017
Residual Std. Error	1.020 (df = 24)	0.937 (df = 24)	0.246 (df = 24)
F Statistic	0.041 (df = 1; 24)	4.461** (df = 1; 24)	1.445 (df = 1; 24)
Note:		*p<0.1; **p<0.05; ***p<0.01	

Unemployment

	Dependent variable:	*Dependent variable:*	*Dependent variable:*
	Bloomberg Surpises	**Target.shock**	Path.shock
Unemployment	0.043	**-0.358****	-0.031
	(0.204)	(0.191)	(0.050)
Constant	0.000	-0.000	-0.073
	(0.200)	(0.187)	(0.049)
Observations	26	26	26
R^2	0.002	0.128	0.016
Adjusted R^2	-0.040	0.092	-0.025
Residual Std. Error	1.020 (df = 24)	0.953 (df = 24)	0.251 (df = 24)
F Statistic	0.044 (df = 1; 24)	3.534* (df = 1; 24)	0.383 (df = 1; 24)
Note:		*p<0.1; **p<0.05; ***p<0.01	

Real retail sales

	Dependent variable:	*Dependent variable:*	*Dependent variable:*
	Bloomberg Surpises	Target.shock	Path.shock
Demand	-0.137	0.058	-0.013
	(0.202)	(0.204)	(0.051)
Constant	0.000	-0.000	-0.073
	(0.198)	(0.200)	(0.050)
Observations	26	26	26
R^2	0.019	0.003	0.003
Adjusted R^2	-0.022	-0.038	-0.039
Residual Std. Error	1.011 (df = 24)	1.019 (df = 24)	0.253 (df = 24)
F Statistic	0.461 (df = 1; 24)	0.080 (df = 1; 24)	0.071 (df = 1; 24)
Note:		*p<0.1; **p<0.05; ***p<0.01	

Model 2. Assessment of the impact of the News Uncertainty Index (NUI) on the emergence of Bank of Russia monetary policy surprises

	Dependent variable:	*Dependent variable:*	*Dependent variable:*
	Bloomberg Surpises	Target.shock	Path.shock
NUI	0.367	0.045	0.025
	(1.342)	(0.691)	(0.260)
Constant	-0.130	0.115	-0.032
	(0.223)	(0.113)	(0.044)
Observations	43	37	41
R^2	0.002	0.0001	0.0002
Adjusted R^2	-0.023	-0.028	-0.025
Residual Std. Error	0.950 (df = 41)	0.451 (df = 35)	0.176 (df = 39)
F Statistic	0.075 (df = 1; 41)	0.004 (df = 1; 35)	0.009 (df = 1; 39)
Note:		$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$	

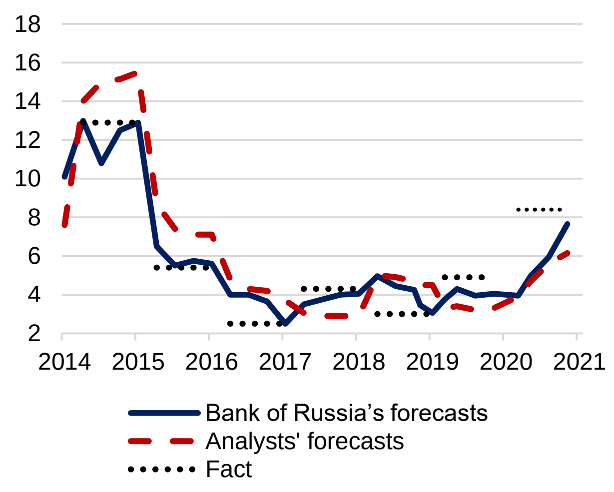
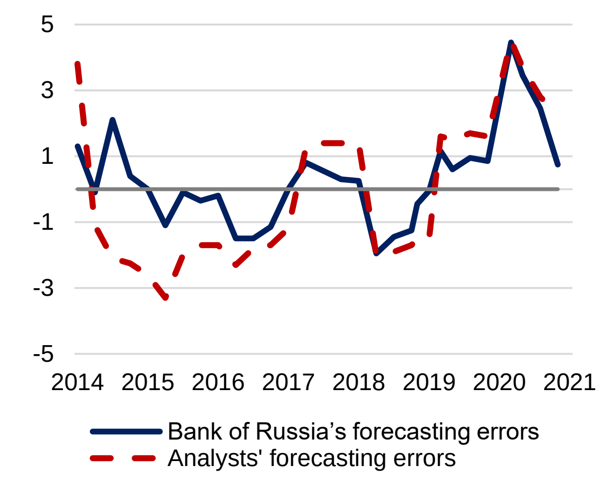
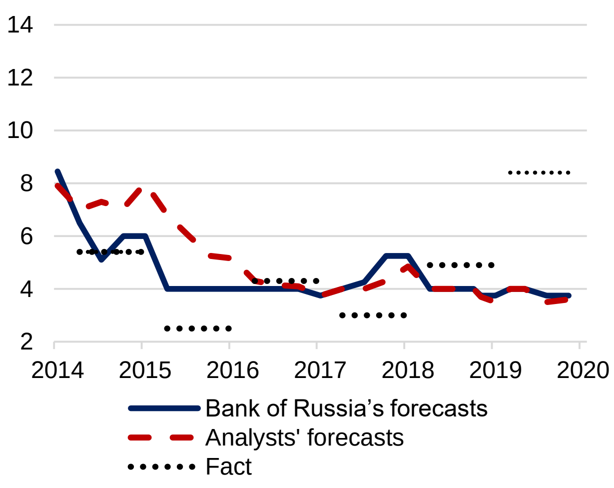
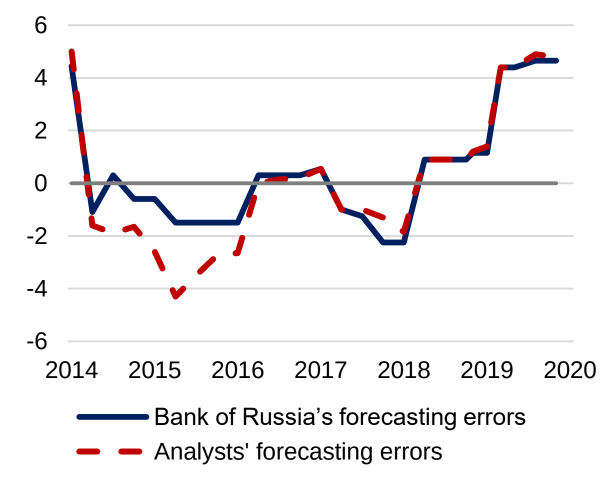
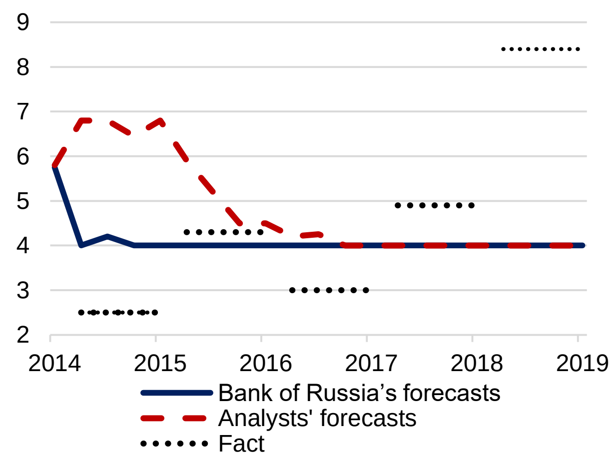
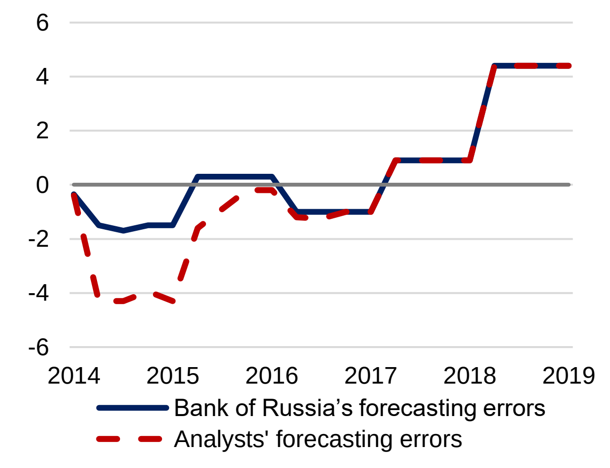
Annex 4. Verbal interventions of the Bank of Russia before decisions

Decision date	Interventions in the period before the decision
30 January 2015	–
13 March 2015	Simanovsky 'According to the economist, on 13 March, the Central Bank of Russia will decide whether to keep the rate at the current 15 per cent or start reducing it.'
30 April 2015	Tulin 'Representative of the Central Bank Dmitry Tulin said that the Bank of Russia plans to reduce the current key rate, which is now 14 per cent.'
15 June 2015	–
31 June 2015	–
11 September 2015	–
30 October 2015	–
11 December 2015	–
29 January 2016	–
18 March 2016	–
29 April 2016	–
10 June 2016	–
29 July 2016	–
16 September 2016	Nabiullina 'The head of the Central Bank warned in this regard that the Central Bank's monetary policy remains 'moderately tight' and will remain so in the future.'
28 October 2016	–
16 December 2016	–
3 February 2017	Yudaeva 'Right now, inflation is still above the target, inflation expectations are even more elevated, and for inflation and inflation expectations to come down, real rates need to be 2–3 percentage points above that level.'
24 March 2017	–
28 April 2017	Nabiullina 'A faster decline in inflation opens up room for us to lower the key rate as early as April. I even assume that at the next Board meeting in a week, there may be a discussion about reducing the rate by between 25 and 50 basis points.'
16 June 2017	Nabiullina 'We will consider two options (a 25 bp and a 50 bp reduction). We will make our decision on the basis of the traditional analysis of inflation indicators, inflation expectations, the situation in the economy, and unemployment. There is now intensive preparation for this meeting in progress, and we will be choosing'
28 July 2017	–
15 September 2017	Nabiullina The Bank of Russia sees room for a key rate reduction, most likely, discussion will proceed between rate reductions of 0.25 pp and 0.5 pp, said the regulator's head Elvira Nabiullina in an interview with Bloomberg on 7 September.
27 October 2017	–
15 December 2017	Nabiullina At the end of November, Central Bank governor Elvira Nabiullina said that the recent slowdown in inflation was due to a stronger ruble on the back of rising oil prices and a record grain harvest. At the same time, she once again confirmed that the recently observed inflation rate does not require a correction of monetary policy, since low inflation rates are largely due to 'positive factors that can exhaust their effect', and in general, inflation is 'near the target.'

Decision date	Interventions in the period before the decision
9 February 2018	Nabiullina 'We see room for a softening of monetary policy. And, of course, the size of the step will be considered next week and at the board meeting. But now we see that the devaluation risks associated with external factors have weakened, so we do not exclude that we will move to a neutral monetary policy a little faster than we had previously assumed'
23 March 2018	–
27 April 2018	Dmitriev 'We are talking about approaching the neutralisation point. And then, depending on the inflation forecast and on how short-term trends develop, the question is whether we will remain at this point of neutralisation. The restriction on the impossibility of increasing the rate is already lifted. Depending on the inflation forecast it may go up, may go down, or may spend some time around neutral levels'
15 June 2018	–
27 July 2018	–
14 September 2018	Nabiullina 'There are few factors right now that would speak in favour of a rate reduction. There are a significant number of factors that speak in favour of keeping the rate, and several factors have emerged that allow the question of a possible rate increase to be put on the table.'
26 October 2018	–
14 December 2018	–
8 February 2019	–
22 March 2019	Several statements.
26 April 2019	–
14 June 2019	Nabiullina 'We believe it is possible to return to rate reduction in Q2 or Q3,' she stressed, noting that 'the pro-inflationary factors that required our intervention have largely exhausted themselves.'
26 July 2019	Nabiullina At the beginning of July, the regulator's head, Elvira Nabiullina, did not rule out that the key rate could be lowered by 50 bp at once.
6 September 2019	–
25 October 2019	Nabiullina 'We see that our key rate may be not just reduced, but that we can act more decisively'
13 December 2019	–
7 February 2020	–
20 March 2020	–
24 April 2020	Nabiullina According to Central Bank head Elvira Nabiullina, a rate increase is unlikely, and the possibility of a rate cut is the main option to be considered on 24 April.
19 June 2020	Nabiullina In public speeches in May and early June, the Central Bank head, Elvira Nabiullina, June repeatedly pointed to the room for significant further monetary policy softening and even noted that one of the options at the June meeting would be to reduce the rate by 100 bp at once – from 5.5% to 4.5%.
24 July 2020	Nabiullina 'We now have the opportunity to lower the key rate based on low inflation'

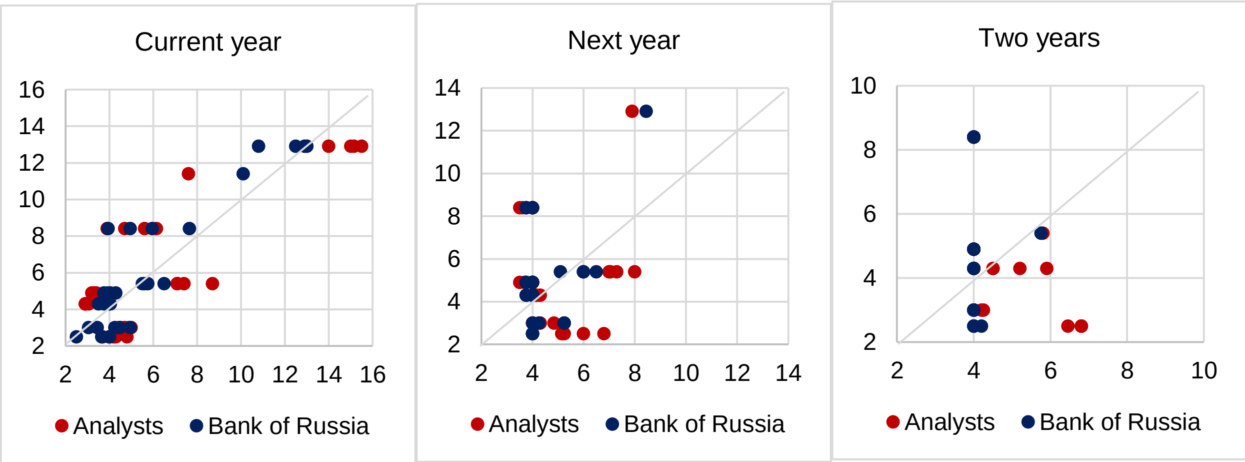
Decision date	Interventions in the period before the decision
18 September 2020	Nabiullina On 8 September, speaking at the Moscow Financial Forum, E. Nabiullina reported that the Central Bank will assess not only when to use this room to soften monetary policy, but also the appropriateness of using this space in general.
23 October 2020	Zabotkin An interview with Alexey Zabotkin, Deputy Governor of the Bank of Russia, made it clear that no changes are to be expected from the next meeting. The deputy head of the Central Bank of Russia said that the same factors as before will be taken into account when making a decision on the rate in October. On the basis of this message, it can be concluded that the rate will remain unchanged.
18 December 2020	Nabiullina 'This gives us room for additional policy softening, but the decision depends on many factors. The situation is very uncertain.'
12 February 2021	–
19 March 2021	–
23 April 2021	–
11 June 2021	Yudaeva On 11 June, the Central Bank's Board of Directors will consider options to raise the rate by 25 or 50 bp. There is less chance of keeping the rate unchanged, said First Deputy Governor of the Bank of Russia Ksenia Yudaeva last week.
23 July 2021	Nabiullina 'We will carefully study the new data, revise our forecast in July and make a decision on the size of the step. I think we can discuss an increase of from 25 basis points to 1 percentage point'.
10 September 2021	–
22 October 2021	–
17 December 2021	Nabiullina "The rate forecast for the rest of the year, which we gave in October, suggests a step from zero to one percentage point. Of course, the latest data on inflation, in general, say that zero is quite unlikely, 0.25 percentage points is also not the most likely scenario, but then we will look at the relevant data and analyze them, make estimates for next year and make a decision," Nabiullina said when asked about the Central Bank decision at the meeting in December.

Annex 5. Forecast and forecasting error charts

Inflation forecasts for the current year	Forecasting errors
	
Inflation forecasts for the next year	**Forecasting errors**
	
Inflation forecasts for two year	**Forecasting errors**
	

Annex 6. Results of evaluation of the forecast rationality hypothesis

Figure 18. Scatter diagrams of inflation forecasts



Note: X axis – inflation forecasts of the Bank of Russia and analysts; Y axis – actual inflation.

Table 5. Mean squared errors of inflation forecasts

Forecasts	Bank of Russia	Analysts
For the current year	1.46	2.84
For the next year	3.11	3.04
For the next two years	4.08	2.97

Results of regression evaluation. Rationality of inflation forecasts of the Bank of Russia

$$\pi = \alpha + \beta\hat{\pi}_{BR} + \varepsilon \quad (10)$$

where π – the actual inflation,
$\hat{\pi}_{BR}$ – the Bank of Russia's inflation forecast.

Table 6. Results of regression evaluation (Bank of Russia)

	Forecasts for the current year	Forecasts for the next year	Forecasts for two years
	Dependent variable:	*Dependent variable:*	*Dependent variable:*
	Fact	Fact	Fact
BR	1.063***	0.040	-10.139***
	(0.047)	(0.725)	(3.970)
Constant	-0.231	4.427*	45.083***
	(0.566)	(3.703)	(16.673)
Observations	28	24	19
R^2	0.871	0.0003	0.055
Adjusted R^2	0.866	-0.045	-0.001
Residual Std. Error	1.255 (df = 26)	1.841 (df = 22)	1.991 (df = 17)
F Statistic	175.644*** (df = 1; 26)	0.007 (df = 1; 22)	0.982 (df = 1; 17)
Note:	*p<0.1; **p<0.05; ***p<0.01		

F-test to evaluate the rationality of Bank of Russia forecasts. Hypothesis being tested: $\alpha = 0$ and $\beta = 1$.

Table 7. F-test results (Bank of Russia)

Forecasts for the current year:

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Res.Df	2	27.000	1.414	26	26.5	27.5	28
Df	1	2.000		2.000	2.000	2.000	2.000
F	1	2.094		2.094	2.094	2.094	2.094
Pr(> F)	1	0.144		0.144	0.144	0.144	0.144

Forecasts for the next year:

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Res.Df	2	23.000	1.414	22	22.5	23.5	24
Df	1	2.000		2.000	2.000	2.000	2.000
F	1	1.536		1.536	1.536	1.536	1.536
Pr(> F)	1	0.237		0.237	0.237	0.237	0.237

Forecasts for two years:

Statistic	N	Mean	St. Dev.	Min	Pctl (25)	Pctl (75)	Max
Res.Df	2	18.000	1.414	17	17.5	18.5	19
Df	1	2.000		2.000	2.000	2.000	2.000
F	1	-192,144,435,630		-192,144,435,630	-192,144,435,630	-192,144,435,630	-192,144,435,630
Pr(> F)	1	1.000		1.000	1.000	1.000	1.000

The hypothesis that α = 0 and β = 1 cannot be rejected for forecasts for the current year. For other forecasts the assumption of a normal distribution of residuals is not fulfilled.

Results of regression evaluation. Rationality of analysts' inflation forecasts

$$\pi = \alpha + \beta\hat{\pi}_{Analysts} + \varepsilon \tag{11}$$

where π – the actual inflation,
$\hat{\pi}_{Analysts}$ – the analysts' inflation forecast (Bloomberg consensus).

Table 8. Results of regression evaluation (analysts)

	Forecasts for the current year	Forecasts for the next year	Forecasts for two years
	Dependent variable:	*Dependent variable:*	*Dependent variable:*
	Fact	Fact	Fact
Analysts	0.752***	-0.189	-1.074**
	(0.054)	(0.321)	(0.376)
Constant	1.100	5.526***	9.743***
	(0.822)	(2.068)	(1.841)
Observations	28	24	20
R^2	0.749	0.021	0.311
Adjusted R^2	0.740	-0.024	0.273
Residual Std. Error	1.750 (df = 26)	1.822 (df = 22)	1.817 (df = 18)
F Statistic	77.656*** (df = 1; 26)	0.469 (df = 1; 22)	8.143** (df = 1; 18)
Note:	*p<0.1; **p<0.05; ***p<0.01		

F-test results to evaluate the rationality of analysts' forecasts. Hypothesis being tested: α = 0 and β = 1.

Table 9. F-test results (analysts)

Forecasts for the current year:

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Res.Df	2	27.000	1.414	26	26.5	27.5	28
Df	1	2.000		2.000	2.000	2.000	2.000
F	1	22.970		22.970	22.970	22.970	22.970
Pr(> F)	1	0.00000		0.00000	0.00000	0.00000	0.00000

Forecasts for the next year:

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Res.Df	2	23.000	1.414	22	22.5	23.5	24
Df	1	2.000		2.000	2.000	2.000	2.000
F	1	13.817		13.817	13.817	13.817	13.817
Pr(> F)	1	0.0001		0.0001	0.0001	0.0001	0.0001

Forecasts for two years:

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Res.Df	2	19.000	1.414	18	18.5	19.5	20
Df	1	2.000		2.000	2.000	2.000	2.000
F	1	3,968.119		3,968.119	3,968.119	3,968.119	3,968.119
Pr(> F)	1	0.000		0.000	0.000	0.000	0.000

The hypothesis that α = 0 and β = 1 is rejected for all forecast horizons.

Annex 7. Evaluation of regressions for the Bank of Russia information advantage hypothesis

$$\pi = \alpha + \beta_1 \hat{\pi}_{BR} + \beta_2 \hat{\pi}_{Analysts} + \varepsilon \quad (12)$$

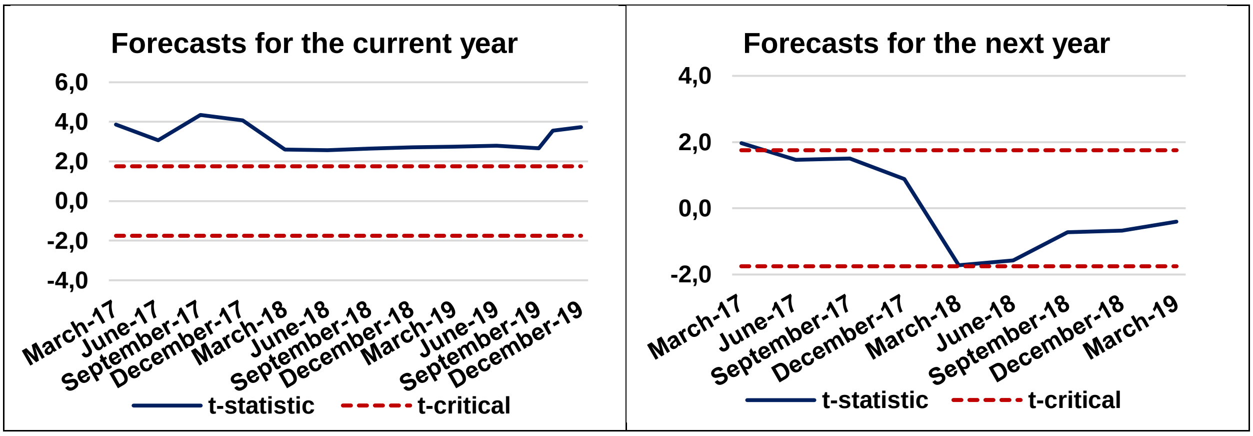
where π – the actual inflation,
$\hat{\pi}_{BR}$– the Bank of Russia's inflation forecast,
$\hat{\pi}_{Analysts}$ – the analysts' inflation forecast (Bloomberg consensus).

Table 10. Results of regression evaluation

	Forecasts for the current year	Forecasts for the next year	Forecasts for two years
	Dependent variable:	*Dependent variable:*	*Dependent variable:*
	Fact	Fact	Fact
Analysts	-0.293	-0.483	-0.838***
	(0.212)	(0.332)	(0.242)
BR	1.431***	0.584	-0.377
	(0.241)	(0.955)	(0.857)
Constant	-0.490	4.385	9.779**
	(0.402)	(3.768)	(1.959)
Observations	28	24	18
R^2	0.881	0.063	0.287
Adjusted R^2	0.871	-0.026	0.192
Residual Std. Error	1.232 (df = 25)	1.824 (df = 21)	1.611 (df = 15)
F Statistic	92.136*** (df = 2; 25)	0.705 (df = 2; 21)	3.024* (df = 2; 15)
Note:	*p<0.1; **p<0.05; ***p<0.01		

The coefficient for Bank of Russia forecasts is significantly different from zero only for short-term forecasts (at the end of the current year).

Figure 19. Evaluation of information advantage by rolling window method



Note: the X-axis shows the central observations for each window. The window size is 16. The sample for the current year forecasts includes observations from 2015 to 2021. The samples for the next year forecasts include forecasts until 2020.

Annex 8. Evaluation of regressions for the hypothesis of the influence of monetary policy decisions on analysts' forecasts

$$\Delta\hat{\pi}_{Analysts} = \alpha + \beta_1 Decision + \beta_2 \Delta\hat{\pi}_{BR} + \varepsilon \quad (13)$$

where $\Delta\hat{\pi}_{Analysts}$– the difference between the analysts' forecasts one week after the key rate decisions and the day before;
$\Delta\hat{\pi}_{BR}$– the difference between the current and previous Bank of Russia inflation forecasts;
Decision – a key rate decision (dummy variable).

Table 11. Results of regression evaluation

	Forecasts for the current year	Forecasts for the next year	Forecasts for two years
	Dependent variable:	*Dependent variable:*	*Dependent variable:*
	Delta_Analysts	Delta_Analysts	Delta_Analysts
Decision_dummy	0.073**	0.029***	-0.006
	(0.029)	(0.008)	(0.010)
Delta_BR	0.020	0.007	-0.002
	(0.014)	(0.010)	(0.006)
Constant	0.012	0.003	-0.009
	(0.024)	(0.007)	(0.007)
Observations	29	29	24
R^2	0.277	0.242	0.008
Adjusted R^2	0.221	0.183	-0.086
Residual Std. Error	0.118 (df = 26)	0.044 (df = 26)	0.062 (df = 21)
F Statistic	4.975** (df = 2; 26)	4.145** (df = 2; 26)	0.086 (df = 2; 21)
Note:	*p<0.1; **p<0.05; ***p<0.01		

The coefficient for Bank of Russia decisions is significantly different from zero for the short- and medium-term forecasts (at the end of the current year and next year).