Bank of Russia

Monetary Policy REVIEW

LESSONS FROM CRISES FOR BETTER BANK OF RUSSIA COMMUNICATION WITH FINANCIAL MARKETS

WORKING PAPER

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Contents

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The views expressed herein are solely those of the authors. Our findings are preliminary; they are published to stimulate discussion and seek feedback for potential follow-up improvements of the study. The contents and findings of this research should not be construed or quoted in any publications as the official position of the Bank of Russia or an indication of its official policy or decisions. Any errors in this work are solely those of the authors.

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LESSONS FROM CRISES FOR BETTER BANK OF RUSSIA COMMUNICATION WITH FINANCIAL MARKETS

Summary

This study is an assessment of the impact of Bank of Russia communication on volatility in financial markets, both in crisis episodes and in calmer times.

This impact is analysed in terms of six characteristics of communication: volume, the intensity of signal correction, commitment to the target, the degree of invariance of communication (further, invariance), the presence or absence of a signal, and the degree of communication confidence (further, confidence). Our methods are regression models, Granger causality tests, and the PCMCI algorithm – a more advanced method to determine causal relationships in arrays with linear and non-linear dependencies for time series, allowing for mutual influence lags.

We find significant differences in how financial markets perceive Bank of Russia communication, and all the variables above have an effect. In times of increased volatility, communication has a stabilising impact on markets. Outside of these episodes, its impact is rather destabilising, probably owing to the communication noise that emerges in the media landscape. In relatively quiet times, market players do not expect extraordinary communication from the central bank and may well be disconcerted by the unexpected release of such communication. Our findings are aligned with those of Caiazza et al. (2022) and Hwang, Lustenberger, and Rossi (2021).

Furthermore, we discover that the Bank of Russia's impact on the markets tends to be negative when it releases large volumes of monetary policy documents, while signal corrections and communication in between policy meetings tend to have a positive effect. At the same time, markets respond better to more specific *Delphic* forward guidance than to the absence of forward guidance. The communication of a commitment to the inflation target is particularly important for markets in times of crisis.

Importantly, while communication has an influence on financial markets, the state of financial markets has a significant impact on the central bank's communication tactics. Specifically, strong market fluctuations may spur the central bank's intent to give a signal and may increase the frequency of pronouncements by Bank of Russia executives on key factors of monetary policy.

Introduction

Effective communication with financial markets is of critical importance to inflation targeting. In shaping the opinions of market players, the central bank helps bring about the transfer curves that improve the possibility of delivering on inflation targets through the monetary policy transmission mechanism.

Communication with markets in times of crisis is a real challenge for central banks. Its success defines, for example, the speed of economic adjustment to a change in conditions, as well as the depth and duration of shocks. As noted by Siklos (2018), the 2008 global financial crisis fundamentally transformed the communication strategies of central banks. When central banks' policies aiming to put their economies on course for recovery hit the zero lower bound, communication remained one of the few effective tools at their disposal. It enabled regulators to shape market sentiment without changing rates and even without additional monetary policy measures at all.

A textbook example of how powerful communication can be is the famous 'whatever it takes' speech[1] by European Central Bank head Mario Draghi in July 2012, in which he insisted that that the regulator would do whatever it took to save the euro. At the time, the ECB's resolve led to a rapid response from traders, sending yields on the bonds of non-core European economies lower. A week later, the ECB unveiled a programme for purchasing the bonds of the struggling countries, which came to be known as Outright Monetary Transactions, but the need to use it did not arise. The handful of words Draghi said at the right time and in the right place were enough to produce a stabilising effect.

Communication between the central bank and the market in the midst of a crisis is essential to ensuring macroeconomic and financial stability.

Since the start of its inflation targeting in 2015, the Bank of Russia has confronted several crisis episodes, namely in 2015, 2020, and 2022, and its approach to communication has been different every time. A detailed account of market developments surrounding the Bank of Russia's transition to inflation targeting as it moved away from the exchange rate band is presented in this RBC article. Based on this and other accounts of the events of November 2014, one key problem was the lack of communication from the regulator or conflicting signals. Judging by the subsequent crisis episodes, especially the 2020 pandemic, the Bank of Russia had taken the experience into account and adopted a totally different tactic. In the course of the pandemic, the regulator held press conference every two weeks. Thereafter, eight monetary policy briefings were held instead of four (following each rate decision). In addition, the Bank of Russia introduced a Q&A section on its website, while also providing increasingly more information to markets, including on the key rate path. Overall, the period of inflation targeting has seen a drastic increase in the transparency of its monetary policy. Our calculations, based on the popular methodology for assessing central bank transparency by Al-Mashat et. al. (2018), show that the Bank of Russia's transparency score between 2014 and 2022 went up from 6.2 to 9.8 points (of 20 possible points).

This work **aims** to assess the effectiveness of Bank of Russia communication with financial markets both during episodes of high volatility and in normal times. The patterns we have discovered may be taken into account by the Bank of Russia as it improves the efficiency of its communication.

We address several issues to help us achieve our objective:

- identify the episodes of increased volatility in financial markets
- explore the academic literature and the global experience of central banks in crisis communication and the quantification of communication
- set up our own set of variables to be used as characteristics of communication with the help of the machine processing of natural languages among other methods
- further identify the variables that characterise financial market volatility and which may be indicative of the response to key rate decisions

[1] 'Within our mandate, the ECB is ready to do whatever it takes to preserve the euro. And believe me, it will be enough.'

- formulate and test hypotheses using econometric methods.

This study contributes to the relevant academic literature as follows: first, it introduces two unique variables for communication (invariance and confidence), which can be used to compare the communication practices of central banks or to test the hypotheses about the impact of communication on the real sector. Second, we create a detailed map of Bank of Russia communications between key rate decisions in 2015–2022, which can also be used in follow-up studies of verbal interventions. Third, we elaborate on the theme of central bank communication in times of crisis, measuring various effects of communication on financial markets. There has been scant research in this area to date. In addition, we confirm the existing findings about the negative impact of 'overcommunicating' because of noise in the media landscape.

The study is structured as follows. Section 2 is a review of the literature on the subject. Section 3 presents hypotheses about differences in the impact of communication on financial markets in various periods. Section 4 presents a detailed description of the data used to test the hypotheses in terms of both communication and the response of financial markets. Section 5 outlines the methods used to test the hypotheses. Section 6 summarises the results of the estimation of the models. Finally, Section 7 concludes and presents a summary of our findings alongside key discussion points and highlights potential follow-up studies in the area.

Literature review

What makes crisis communication different from regular communication? The articles we have been able to find on the subject provide examples of impactful anti-crisis communication and case studies of failures of communication. They all constitute background reading in addressing this issue.

Checkley and Piris (2020) present the following core recommendations to central banks: explain the objectives of decisions as clearly as possible; talk about problems in conjunction with solutions; provide enough information on the state of the economy; and communicate decisions and changes in the vision without delay. The authors of other works arrive at similar conclusions. For example, Musard-Gies (2006) draws an important conclusion about the preliminary preparation of the market via communication ahead of monetary policy decisions. The author highlights the importance of providing market professionals with intensive, high-frequency, highly detailed communication in order to minimise the market volatility following sharp and unexpected decisions by the central bank. Vayid (2013) notes the particular importance of the timely communication of the targets when unconventional monetary instruments are resorted to. Garbers and Unsal (2021) argue that the understanding of public communication in times of crisis has critical implications for the execution of the crisis response.

Hallvarsson & Halvarsson (2010) presents a detailed analysis of Riksbank's communication during the challenging period of 2008–2009. The report identifies the following key mistakes: ‘a lot information in them, but little communication’, a belated response to shocks, fragmented information on risks, and the abundance of unnecessary technicalities.

Practice shows that central banks’ crisis communication (‘speak’) differs from non-crisis communication in being more ‘aggressive’ (Siklos, 2013). On the other hand, Blinder et al. (2017) show that past crises did not change the approach to communication in any way in a number of countries. In a later study, Siklos (2018) concludes that a communication policy that works in a normal economy may be counterproductive in times of crisis. At the same time, the Bank of Russia's communication strategy is not changed by crises but by the methods to overcome them. Cieslak and Schrimpf (2019) show that the response of financial markets in the midst of financial crises and in early recovery periods is in large part determined by non-monetary news.

Based on the conclusions of prior studies, the takeaway for central banks is that they should report problems and their decisions aimed at restoring stability in an open and prompt manner and communicate with great focus and absolute clarity, seeking to minimise the risks of misinterpretation. No less important are efforts to prepare the market well in advance of monetary policy decisions, especially when non-standard measures are imminent.

There are several papers focused on the relevance of trust in the perception of communication, including in times of crisis. Naghdaliyev (2011), Ehrmann, Soudan, and Stracca (2013), and Hayo and Neuenkirch (2015) conclude that a higher level of public confidence in the central bank ensures optimal communication, while Freedman and Laxton (2009) note that the more trust there is in the central bank, the closer current inflation is to the target.

Most academic articles on crisis communication essentially describe case studies of central bank communication practices, and many such articles leave econometric models out of their scope. A relatively substantial pool of works create models on the basis of regular market surveys about analysts’ trust in monetary policy. No such data exist for Russia. These are the two reasons why only a small number of studies use quantified parameters for communication such as those on which this paper is grounded (in line with our objective of conducting an econometric test of hypotheses about differences in Bank of Russia communication in crisis periods and in normal times).

These articles include the work of Born et al. (2014), who provide a quantification of the tone of central bank communication, the work of Bennani et al. (2020), which features a set of factor variables for signals, and the work of Do Hwang et al. (2021), who present an assessment of the volume of public presentations by central bank representatives. We have drawn on these findings to shortlist the main variables for communication: intensity, tone, and two-factor variables representing the presence or absence of a signal and of a commitment to the target. We add the unique invariance variable, with the methodology for its calculation presented in Section 4.

The subject of the impact of communication on financial markets is better covered in the academic literature than the subjects described above. Ranaldo and Rossi (2010) confirm the importance of speeches and interviews for price dynamics in financial markets. The importance of communication is also stressed by Musard-Gies (2006), who draws on the example of the ECB to establish that crises make financial market players more sensitive to the general tone of press conferences and clarifications of forward guidance. Vague language can strengthen expectations for an abrupt shift to monetary tightening, which is evidenced by positive returns on equity.

High-frequency event study analysis is a common method for assessing the impact of central bank communication on financial markets. It involves the analysis of changes in financial markets in the short periods of time before and after policy announcements in order to measure their effects. Kuttner (2001) applies this method, using Fed funds futures to measure the impact of monetary policy on Treasury security rates, and concludes that monetary surprises are the true difference maker in the impact of policy on financial markets. Gürkaynak et al. (2005) suggest distinguishing two variables: target shock – a surprise relative to the recent decision – and path shock – a surprise over the future key rate path – based on principal component analysis. The analysis of these variables leads the authors to conclude that it is language (statements), rather than the Fed's actions, that has the primary impact on US financial markets. Evstigneeva, Shchadilova, and Sidorovskiy (2022) also use this approach to identify *Bank of Russia surprises* in order to test several hypotheses about regulator communication. We calculate shock variables in the same way.

Jianguo Liu et al. (2022) draw on the example of the People's Bank of China to analyse the yields on government bonds and find that communication may influence the temporal structure of interest rates but that its impact on the stock market may be limited. Additionally, current communication is somewhat akin to a *lemon market*[2] with asymmetric information (Akerlof, 1970), in which the general public is unable to correctly interpret the importance and content of information, while the credibility of information turns out to be more important than content.

[2] This metaphor illustrates the asymmetry of available information and reflects the situation of the seller knowing more about product quality than the buyer. George Akerlof, Michael Spence, and Joseph Stiglitz were awarded the 2001 Nobel Prize in economics for their analysis of markets with asymmetrical access to information.

Hypotheses

Taking into account the above findings of previous researchers, we formulate and test the following hypotheses about the effectiveness of Bank of Russia communication in crisis and non-crisis times:

H1: The perception of Bank of Russia communication by financial markets in episodes of increased volatility is markedly different from perception in normal times.

H2: Financial markets are more receptive to Bank of Russia communication in episodes of increased volatility.

H3: More intense communication from the Bank of Russia has a stabilising effect on financial markets.

H4: The confidence of communication has a stabilising effect on financial markets.

H5: The communication of a commitment to the target has a stabilising effect on financial markets in episodes of increased volatility.

Data

We collect two datasets with different frequencies for our research.

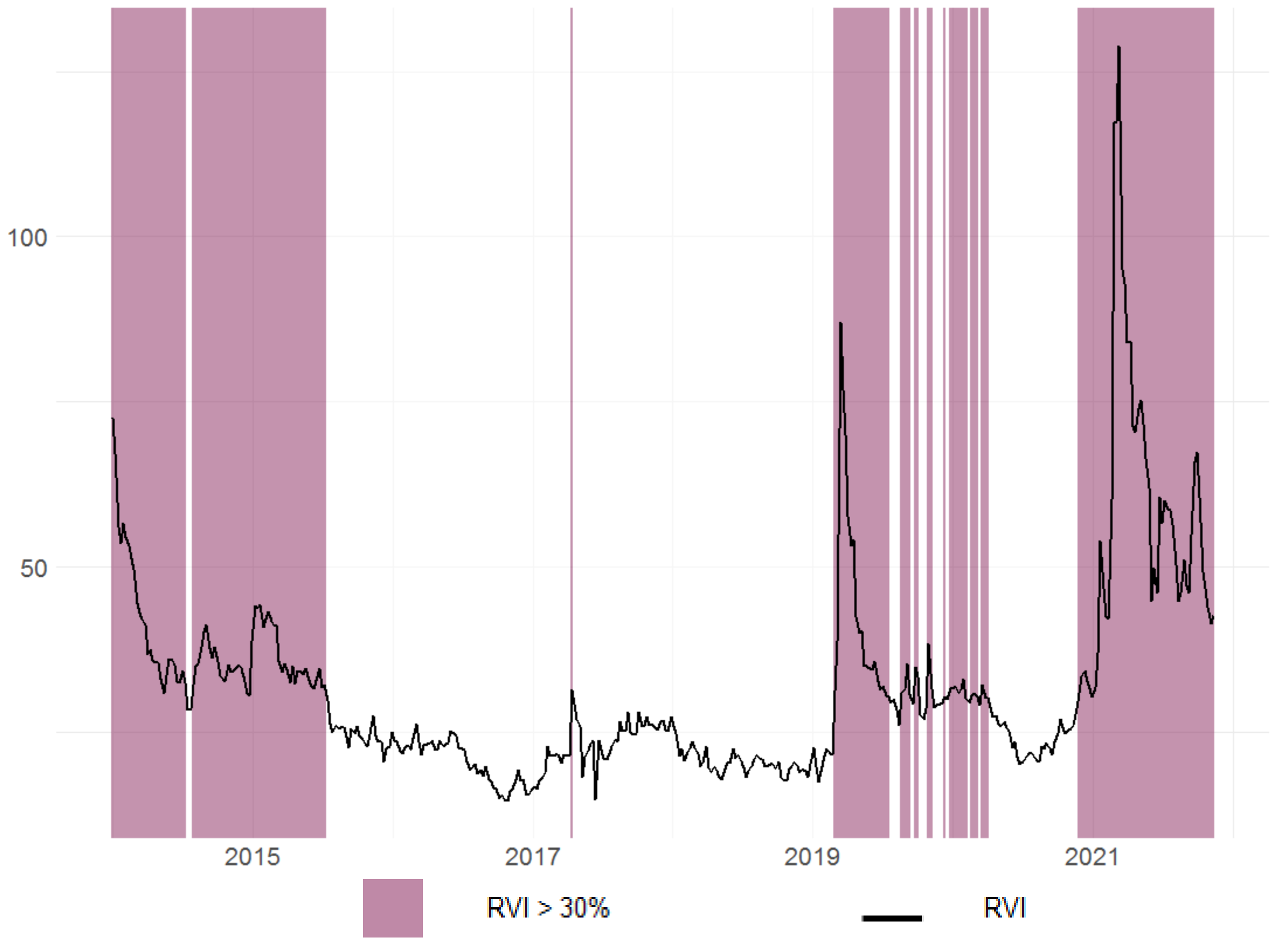
- **Dataset 1** (weekly data)

Dataset 1 is further divided into *crisis* and *non-crisis* subsamples.

Inasmuch as we explore communication with financial markets, *crisis episodes* are defined as weeks of increased volatility in financial markets. To this end, we use the RVI ('fear') index, which reflects the expected level of volatility in the stock market. The RVI index is calculated based on the volatility of the actual prices for options on the RTS Index. Its calculation is based on the nearest and following series of options with maturities of more than 30 days before expiration. The crisis factor is assigned to weeks with RVI values of more than 30%. The weeks of 2015–2016, spring 2020, and the whole of 2022 (Figure 1) are classified as crisis episodes.

Dataset 1 includes 406 observations between January 2015 and November 2022. The dataset strips out the three weeks of the period (when the Moscow Exchange suspended trading), due to the lack of data for several response variables, about which further details are discussed below.

FIGURE 1. CRISIS EPISODES OF 2015–2022 IDENTIFIED BY RVI



Source: Authors' calculations.

- **Dataset 2** (frequency consistent with the dates of key rate decisions).

The sample size of Dataset 2 is smaller, at just 63 observations (from the key rate press release of 30 January 2015 to the press release of 16 September 2022). This is a constraint on the construction of the model, and the data for this dataset are not divided into subsamples. This dataset also excludes data as of 28 February 2022 and 18 March 2022 since the Moscow Exchange was closed for business on these days (trading was suspended between 28 February and 24 March 2022).

Characteristics of communication

This subsection describes the characteristics of communication we quantify and use in the models.

A. Intensity of communication correction

The intensity of signal correction is measured as the frequency of information correction in key topics of monetary policy by Bank of Russia executives. This occurs between key rate meetings. Detailed weekly data from 2015 to 2022 are presented in Appendix 1. Among the key topics are inflation, inflation expectations, the state of the economy (GDP), monetary conditions and financial markets, the situation in the oil market, external conditions and the ruble exchange rate, budget and government policies, and forward guidance. In the table, '1' corresponds to a public Bank of Russia communication containing a meaningful correction of information on the key topics; '0.5' corresponds to a minor correction. We strip out instances of information fully repeated from previous communications. For cases in which information about inflation changed several times in the reporting week, the value of '1' in the corresponding field is left unchanged. The search for information messages is enabled by the search engines of the principal Russian news agencies: TASS, RIA Novosti, Prime, Interfax, and RBC. The only sources of information are personalised statements by Bank of Russia executives (presentations at forums, statements to the media, briefings, interviews, etc.).

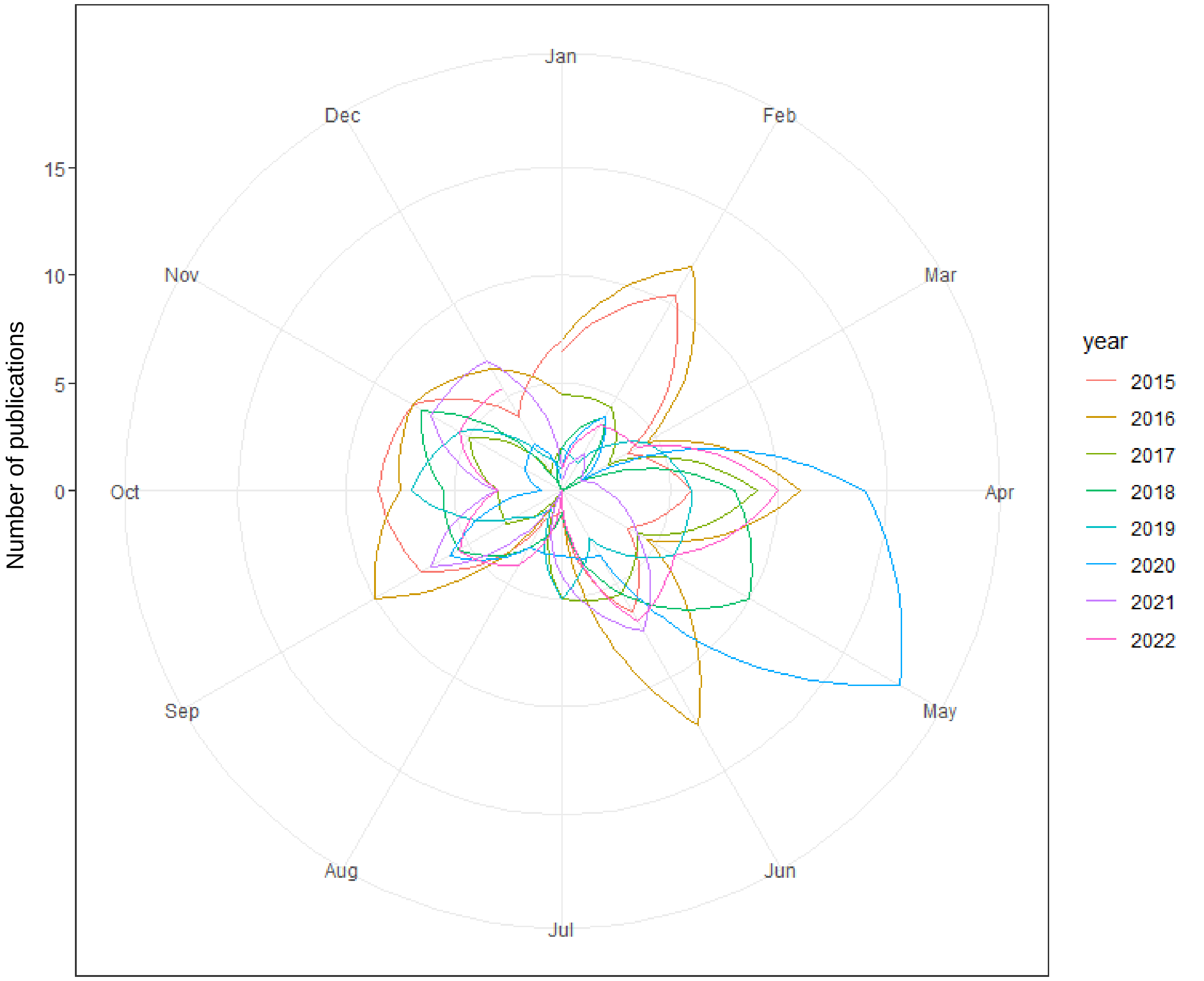
Several preliminary observations can be made based on the data we obtain. First, the Bank of Russia tends to correct its communication more often during crises: 8.26 correction messages between key rate decisions about monetary policy factors, compared with 5.81 communications in more quiet times.

Second, communications are marked by seasonality. The average intensity of communication in the 2015 to 2022 period was above average in February, in April–June, and in September–November. The intensity in January, March, July–August, and December was below average. If the *black swan* episodes are stripped out, a correlation with the seasonality of business activity emerges, as well as with the schedule of major forums in Russia: the SPEF and the IFC both occur in the spring and early summer, and 'Russia Calling!' and the Moscow Financial Forum are held in autumn. As they participate in these events, Bank of Russia representatives have more opportunities for communication and greater access to the media.

B. Volume of communication

The measure for the volume of communication is the number of pages of documents published per week. The volume of communication includes press releases about the key rate, statements by the Governor following key rate decisions, Monetary Policy Reports, Monetary Policy Guidelines, the 'Regional Economy: Commentaries by Bank of Russia Main Branches' reports, the 'Consumer Price Dynamics, 'Inflation Expectations and Consumer Sentiment', 'Monitoring of Businesses: Assessments, Expectations and Comments', 'Balance of Payments of the Russian Federation', and 'Monetary Conditions and Monetary Policy Transmission Mechanism' information and analytical reviews, as well as ad-hoc publications dedicated to specific subjects in the Analytics subsection. For text documents, the *volume of communication* variable is the number of pages in the original publication.

FIGURE 2. SEASONALITY OF BANK OF RUSSIA COMMUNICATIONS



Source: Authors' calculations.

C. Invariance of communication

This indicator is calculated by methods of textual analysis: press releases on the key rate from period *t* are automatically compared with those from period *t-1*. The measure is the proportion of sentences that remain essentially unchanged from release to release (changes of up to 5% are tolerable). A '1' denotes a press release that repeats 95% of the previous one, while a '0' is a press release that is completely different from the previous one. The calculations use Stanza, a natural language machining library in Python (Qi et al., 2020).

D. Confidence

The *confidence of communication* indicator is also calculated by textual analysis methods: for the text of every press release on the key rate and every statement by the Governor following a decision, divided into unigrams and bigrams (one or two consecutive words that often come together), we calculate the number of matches with a dictionary of strong words (Appendix 2) created on the basis of Loughran and Mcdonald's (2011) dictionary. The measure of the confidence of communication is calculated according to the following formula:

$$\text{Confidence of Communication} = \frac{\text{Number of Strong Words in Text}}{\text{Total Words in Text}}$$

The text is processed with the help of the NLTK library (Loper, Bird, 2002) and pymorphy2 (Korobov, 2015) in Python.

E. Signal

The factor variable of the type of signal is determined based on press releases about the key rate and public presentations by Board members. As a rule, the signal includes the Bank of Russia's view of future changes in the key rate, provided that the baseline scenario materialises, or a view of factors that may affect the Bank of Russia's decision on the key rate in the future.

The variable for Dataset 1 is binary, as it reflects the presence or absence of a signal in central bank communications. It is calculated as follows:

$$\text{Presence of Signal} = \begin{cases} 1, & \text{Delphic Signal} \\ 0, & \text{No Signal} \end{cases}$$

The literature distinguishes two types of forward guidance, Delphic and Odyssean (Campbell et al., 2012). The first involves a central bank commitment to particular certain decisions in the future, while the second is a signal of future decisions to be made, with no firm commitment as to their execution. We divide Bank of Russia forward guidance (signal) into three types: Delphic, Odyssean, and signals without clear commitment. Since the Bank of Russia has not used Odyssean signals, we retain only two signal categories: 1) unclear commitment and 2) Delphic. The signal type variable for data with a frequency corresponding to that of key rate decisions is therefore calculated as follows:

$$\text{Signal Type} = \begin{cases} 1, & \text{Delphic Signal} \\ 0, & \text{Without Clear Commitment} \end{cases}$$

An example of a signal of unclear commitment is: 'Moving forward, the Bank of Russia will make decisions on the level of the key rate depending on the change in the balance of inflation risks and the risks of economic cooling.' An example of the Delphic signal is: 'The Bank of Russia will be ready to continue reducing its key rate as inflation risks weaken.'

F. Commitment to target

The binary *commitment to the target* variable is calculated as follows:

$$\text{Commitment to Target} = \begin{cases} 1, & \text{Commitment to Target Communicated} \\ 0, & \text{Otherwise} \end{cases}$$

A commitment to the target in this case is understood as the presence, in the text of a press release or public statement, of a timeline to deliver on the target for inflation, for example: 'The Bank of Russia forecasts that, given the monetary policy stance, annual inflation will decline to 5–7% in 2023 and return to 4% in 2024.'

Response variables

This subsection describes the dependent variables that characterise volatility in the financial market and which can capture the market's response to central bank communication.

The response variables in Dataset 1 (weekly data) for the regressions we take have a one-week lag, that is, the characteristics of communication in period *t* are consistent with the response variables in period *t+1.*

In Dataset 2, all the response variables (in addition to the target shock and the path shock) are taken as *surprises*, that is, for each indicator selected, the difference is calculated between the values for one day before the key rate decision is made and for the day the decision is announced. This presentation of the dependent variables makes it possible to assess the effect of the decision and its communication on financial markets. It is communication that has the greatest impact on the surprise in the reaction of the long end of the yield curve (Gürkaynak et al., 2005).

A. RVI

The RVI (an index of financial market volatility) variable is selected as one of the dependent variables and reflects the expected level of stock market volatility. We identify two variables based on this index: 1) the average closing value of the index for the week and 2) the difference between the maximum and minimum closing values of the index for the week.

B. Spread between RUONIA and key rate and its standard deviation

RUONIA is an interest rate indicator. It is the weighted average interest rate that Russian credit institutions on the list of RUONIA participants approved by the Bank of Russia (the RUONIA list) use for unsecured overnight lending in rubles. The spread between RUONIA and the key rate (further, RUONIA–key rate spread) is the difference between them, and the standard deviation of the RUONIA–key rate spread is calculated as the standard deviation of the difference between RUONIA and the key rate for the week.

The spread itself and its standard deviation are missing one value for the first week of 2016. It should also be mentioned that the data for the standard deviation of the RUONIA–key rate spread, in addition to the above-mentioned gaps, identify three values involving division by zero, which are replaced by the median value of the four observations closest to the gap: the values of the standard deviation of the spread for the two weeks before the gap and for the two weeks thereafter.

C. OFZ bonds of different maturities and their standard deviation

The yields on OFZ bonds with maturities of 1–3 and 5–10 years can also reflect the response to monetary policy communication. We use the average yield for the week and the standard deviation of the yield for the week.

D. Monetary policy surprises

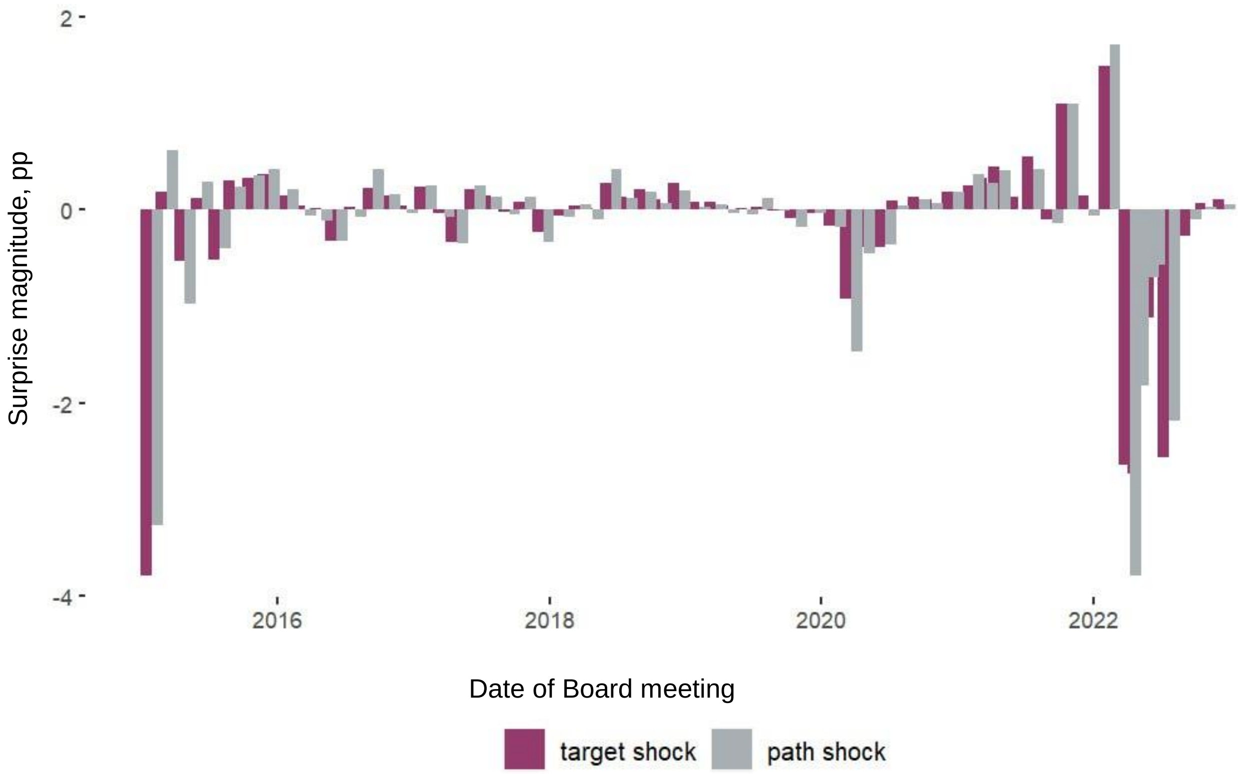
The variables for monetary policy surprises (the target shock and the path shock) are calculated consistent with the dates of the press releases. The target shock variable reflects a surprise over the decision made, while the path shock variable reflects a surprise over the future key rate path. Monetary policy surprises are assessed with the help of two indicators. These are the indicative ROISfix[3] rate with maturities of 1 week, 2 months, 3 months, and 6 months and the index of federal loan bonds (OFZs) with maturities of 1, 2, and 5 years. Surprises are calculated as the change in the rate over the course of the day of a Board meeting. In the first stage, surprises with all maturities are combined into one dataset. Then, we use principal component analysis to reduce the dimension of the matrix to two. These new components explain more than 90% of the cumulative variation in surprises with all seven maturities. Accordingly, the target shock is due to a decision made unexpectedly, while the path shock is a surprise of future decisions due to new communication. In our opinion, both variables can significantly depend on the tactic of central bank communication with the market.

E. Trading volume

We further assume that the transmission mechanism for the impact of central bank communication on the volatility of financial markets may be more complex and, for example, have an indirect impact in terms of trading volumes. To this end, we add the standard deviation of the MICEX's weekly trading volume alongside the standard deviation of the weekly MICEX index – as dependent variables – to the weekly frequency dataset and its subsamples. In Dataset 2, we use the surprises of MICEX trading volume and of the MICEX index.

[3] ROISfix–RUONIA Overnight Interest Rate Swap is the indicative rate (fixing) on RUONIA IR swaps.

FIGURE 3. BANK OF RUSSIA MONETARY POLICY SURPRISES



Source: Authors' calculations.

Data preprocessing

All the variables are subject to preliminary data analysis. As most of them do not have normal distributions (we conduct the Pearson (Pearson, 1900) and Shapiro-Wilk tests, (Shapiro, Wilk, 1965) and bar chart analysis), we bring the variables close to normal distributions where possible using mathematical series transformations, by finding the square root or the natural logarithm or via the Box-Cox transformation (Box and Cox, 1964).

It is important that the series be put in stationary form before estimating the models. This enables statistical conclusions to be drawn from the values observed, since stationarity implies unchanging statistical characteristics in time and rules out false correlations between the variables. The stationarity of the variables is also a key reason for the use of a VAR (vector autoregression) model in which the current values of a series depend on the previous values and, accordingly, the use of the Granger causality test (Granger, 1969) (to assess the significance of the influence of the previous values of the series on the current values).

The analysis of graphs and correlograms is a preliminary stage for assumptions about stationary processes. The graphs of the time series for all the samples are presented in Appendix 3. Formal tests are then carried out to find grounds to confirm the presence of stationarity: Dickey–Fuller (1979), KPSS (Hamilton, 1994), and Phillips–Perron (1988). The details of the data are presented in Appendix 4.

We deem the series stationary if they pass more than two of the three formal tests. The series of OFZ index yields and the invariance series are found to be non-stationary. Following previous research in related areas (McMahon et al., 2018; Máté et al., 2021), we use the first order difference to adjust the yield series, and, in the case of the invariance series, the sufficient transformation is to find the cube root.

Methods

To test our hypotheses, we must establish cause-effect relationships within our dataset, which is a set of several stationary time series. This problem is solved in a number of ways in the literature.

We select two-dimensional and multiple linear regressions as our basic method. Using a lag of one week for the explanatory variables, we check whether their response precedes a response change in the response variables.

Table 1 presents a summary view of the two-dimensional and multiple regressions for each dataset.

Table 1. REGRESSION MODELS: OVERALL VIEW

Data	Two-dimensional regressions	Multiple regressions
Dataset 1	$y_{t+1,j} = \beta_0 + \beta_i x_{t,i} + \varepsilon_t$	$y_{t+1,j} = \beta_0 + \sum \beta_i x_{t,i} + \varepsilon_t$
Dataset 2	$y_{t,j} = \beta_0 + \beta_i x_{t,i} + \varepsilon_t$	$y_{t,j} = \beta_0 + \sum \beta_i x_{t,i} + \varepsilon_t$

Index *j* for the dependent variable is the indicator of its type. In much the same way, index *i* for the explanatory variable indicates its type. Table 2 presents the variables used as dependent and explanatory for each dataset.

Our analysis must involve a test of the regression residues for normality (Pearson and Shapiro–Wilk tests) and for autocorrelation (Durbin–Watson (Durbin and Watson, 1971) and Ljung–Box tests (Ljung and Box, 1978)) as well as regression tests for heteroscedasticity (Breusch–Pagan test (Breusch and Pagan, 1979)) and for multicollinearity (VIF, the estimated growth in dispersion on the back of the mutual linear relationship of the factors).

If heteroscedasticity and multicollinearity are not observed in a model, the normality of the residues and the absence of their autocorrelation is rather an exception for all the subsamples. Problems with the normality of the residues are quite natural, as most of the original data do not have normal distributions, which is typical of yield series and, in particular, of their standard deviations. Robust regressions are directly used to overcome the autocorrelation of the residues on the weekly data, while robust residues are considered in the event of the autocorrelation of the residues for dataset models for key rate decisions on account of the limited number of observations. In this way, we achieve the dual goal of accounting for the autocorrelation of the residues and verifying the robustness of the results.

Another standard method of solving this problem is to use the Granger causality tests (Granger, 1969). To check causality and build the VAR model, the optimal order of lags is based on information criteria. To ensure the correct interpretation of the VAR model and of the Granger F-test for causality, we conduct a quality analysis resulting in all VAR inverse roots lying within the unit circle, that is, confirming that the processes are stationary (a necessary condition for the use of the model). We also conduct tests for normality and the autocorrelation of the residues.

Both of these methods have significant disadvantages and show poor performance in the case of non-linear dependencies. This leads us to additionally use the PCMCI algorithm. Its name reflects its two underlying methods: PC, after its creators (Peter-Clark and Spirtes, 2001), and MCI (the momentary conditional independence test). This method for identifying causal relationships in linear and nonlinear dependency arrays for time series accounts for the lag of mutual influence. The creators of the algorithm (Runge et al., 2019) use it to identify the causal relationships in multidimensional data arrays, in particular, for climate research (El Niño–Southern Oscillation). Comparing it with other widely used algorithms, the authors conclude that the PCMCI algorithm is less inclined to yield false positive relationships between the variables and that it has greater power to detect the relationship in multi-dimensional data arrays.

TABLE 2. LIST OF VARIABLES FOR DATASETS

Name of variable	Explained Y/Explanatory X
Weekly dataset (n = 406)	
Volume of communication	X
Intensity of communication correction	X
Presence of signal	X
Commitment to target	X
Average closing value of RVI Index	Y
Difference between maximum and minimum values of closing value of RVI Index	Y
RUONIA–key rate spread	Y
Standard deviation of RUONIA–key rate spread	Y
OFZ index, maturity 1–3 years	Y
Standard deviation of OFZ index, maturity 1–3 years	Y
OFZ index, maturity 5–10 years	Y
Standard deviation of OFZ index, maturity 5–10 years	Y
Standard deviation of MICEX trading volume	Y
Standard deviation of MICEX index	Y
Dataset with frequency of key rate decisions (n = 63)	
Volume of communication	X
Intensity of communication correction	X
Signal type	X
Commitment to target	X
Invariance	X
Confidence	X
RVI surprise	Y
Volatility of RUONIA–key rate spread	Y
Surprise of OFZ index, maturity of 1–3 years	Y
Surprise of OFZ index, maturity of 5–10 years	Y
Surprise of unexpected decision (target shock)	Y
Surprises of future decisions due to new communication (path shock)	Y
MICEX trading volume surprise	Y
MICEX index surprise	Y

The essence of the method is as follows. In the first (PC1, skeleton) stage, the algorithm applies a conditional independence strategy to identify potential dependencies between a variable at a certain point in time with all other variables within a pre-defined lag interval. That is, the algorithm first creates relationships between the variable under study and all the other variables. It builds a complete undirected graph. This is followed by a pairwise check of the link edges: if the matching variables are independent, the link edge is removed. An undirected relationship is added between each pair of variables that have been found to be free of conditional independence. Thereafter, directed colliders are added based on conditional probability checks. In the second stage (MCI), an instantaneous conditional independence test is used to clarify the causal relationships between variables in different time segments, taking into account autocorrelation and the boundaries incorrectly detected in the first stage (PC1 tends to create an excessive number of links).

Results

The estimation of the regression models is presented in detail in Appendix 5; the Granger causality tests are presented in Appendix 6, and the estimation of the PCMCI algorithm is presented in Appendix 7.

The results lead us to draw the following conclusions. First, we find significant differences in financial markets' perception of Bank of Russia communication from the standpoint of all of our communication variables. Specifically, in times of increased volatility, communication has a stabilising impact on markets and a rather destabilising impact in other times, which is due to the noise in the media space. In relatively quiet times, the markets do not expect extraordinary communication from the central bank and may find it disorienting if such communication does occur. Our findings are aligned with those of Caiazza et al. (2022) that frequent pronouncements from the central bank in the media space indicate increased instability in financial markets. Our findings are also consistent with the conclusions of Hwang, Lustenberger, and Rossi (2021) that intensive communication by a central bank may weaken its influence over markets.

The results show that voluminous monetary policy publication by the Bank of Russia is driven by increased volatility of the RUONIA–key rate spread. The Granger causality analysis also shows that the volume of communication is driven by the magnitude of the RUONIA spread, IMOEX volatility, and OFZ curve yields.

Second, the nuanced correction of signals and communication between key rate decisions in crisis times works to stabilise markets, reducing the yield of the OFZ curve at the short end. Conversely, intensive correction in quiet times is due to a rise in the yield of long-term OFZs and greater volatility of trading volumes. This may nonetheless also indicate the parallelism of the processes. This is evidenced by the results of the causality tests, where the intensity variable turns out to be central: on the one hand, it is highly influenced by almost all financial market indicators (this is understood as the central bank's logical intention to influence markets through its communication with the goal of stabilising them; the data suggest significant growth in the intensity of communication between decisions in times of increased volatility). On the other hand, it affects IMOEX volatility in and of itself.

Third, communicating a commitment to the target helps stabilise financial markets in times of crisis. This variable has a weak effect in normal times. It follows from the estimation of the regression models that the communication of a commitment to the target in crisis times precedes a reduction in the RUONIA–key rate spread. The PCMCI algorithm also indicates a probable stabilising effect on stock markets brought about by the communication of a commitment to the target (only for Dataset 2). This is aligned with the findings of case studies: in a crisis, a central bank must be very clear in its signal about the measures it is taking and their expected effects.

Finally, the presence of a signal in Bank of Russia communication in volatile periods is correlated with a reduction in the OFZ curve at its short end and in its standard deviation. The markets are more sensitive to Delphic forward guidance than to signal without clear commitment.

Importantly, the Granger tests and the PCMCI algorithm show that, while financial markets are affected by communication, the state of financial markets also has a strong impact on the central bank's communication tactics. In particular, strong fluctuations in the OFZ curve, the RVI, and on the Moscow Exchange may all strengthen the central bank's desire to give signals and may affect the frequency with which the Bank of Russia's leadership makes pronouncements on key factors of monetary policy.

The communication invariance variable does not have a statistically significantly effect on financial market indicators. However, the communication confidence variable is found to have a stabilising impact on the volatility of trading volume.

Therefore, we conclude that **in a crisis, communication, measured in different ways, works to reduce volatility, while in a quieter situation, intensified communication can introduce noise to the media space and confuse the markets**, which is confirmed by previous studies.

TABLE 3. RESULTS OF TESTS OF HYPOTHESES

<table>
<tr><th>No.</th><th>Hypothesis</th><th>Brief conclusion</th><th>Reference to model result</th></tr>
<tr><td rowspan="4">1</td><td rowspan="4">Financial markets’ perception of Bank of Russia communication in episodes of increased volatility is distinctly different from normal times.</td><td>Confirmed.

An increased volume of Bank of Russia communication has a negative impact on financial markets in quiet times (standard deviation of the RUONIA spread) and a positive impact in a crisis (standard deviation of the RUONIA spread).</td><td>Appendix 5, II, Table 3, III, Table 5</td></tr>
<tr><td>In times of crisis, the intensity of communication correction works to stabilise markets, reducing the yield of the OFZ curve at its short end. In contrast, in quiet periods, this variable is correlated with rising yields on long-term OFZs and trading volume volatility.</td><td>Appendix 5, II, Table 3, III, Table 5</td></tr>
<tr><td>Communicating a commitment to the target in a crisis stabilises financial markets by reducing the RUONIA–key rate spread and increases the volatility of trading volume and the IMOEX in a crisis.</td><td>Appendix 5, II, Table 3, III, Table 5. Appendix 7</td></tr>
<tr><td>In times of crisis, the presence of a signal in Bank of Russia communication reduces volatility in financial markets (yield on the OFZ index for maturities of 1–3 years and its standard deviation), while in quiet times, it increases the volatility of the RUONIA–key rate spread.</td><td>Appendix 5, II, Table 3, III, Table 5</td></tr>
<tr><td>2</td><td>Financial markets are more receptive to Bank of Russia communication in episodes of increased volatility.</td><td>Partially confirmed.

Most of the parameters of communication turn out to be significant both in crisis and in quiet times. Nonetheless, the number of response variables found to be sensitive to communication is higher in crisis times.</td><td>Appendix 5, Appendix 7</td></tr>
<tr><td>3</td><td>More intense communication from the Bank of Russia has a stabilising effect on the markets.</td><td>Partially confirmed.

An increase in the volume and frequency of signal correction has a multi-directional effect in crisis and in quiet times. In a crisis, intense communication has a stabilising effect on financial markets, while in normal times it can bring noise and increase uncertainty.</td><td>Appendix 5, II, Table 3, III, Table 5</td></tr>
<tr><td>4</td><td>Communication confidence has a stabilising effect on financial markets.</td><td>Confirmed.

The variable of communication confidence has a significant positive impact on the trading volume surprise.</td><td>Appendix 5, IV, Table 7</td></tr>
<tr><td>5</td><td>Communicating a commitment to the target has a stabilising effect on the markets in episodes of increased volatility.</td><td>Confirmed.

Communicating a commitment to the target in a crisis precedes a reduction in the RUONIA–key rate spread.</td><td>Appendix 5, II, Table 3, Appendix 7</td></tr>
</table>

Conclusion

This study is an assessment of the impact of Bank of Russia communication on volatility in financial markets in crisis episodes and in quieter times.

We analyse this impact in terms of six characteristics of communication. Four of these characteristics are fairly common in the literature: the volume of communication (measured as the number of pages of central bank documents per week), the intensity of signal correction (the frequency of pronouncements from Bank of Russia leadership between key rate decisions in which they adjust their views on key factors of monetary policy decisions), the presence or absence of a signal, and a commitment to the target (this is a binary variable equal to 1 if the Bank of Russia communicates a timeline for inflation to return to the target, and 0 otherwise). We have created two unique variables: the degree of communication invariance (extracted by methods of textual analysis of key rate press releases, it shows the degree to which a press release differs from the preceding release) and communication confidence (calculated as the share of ‘strong’ modal words in key rate press releases, reflecting the central bank’s confidence in current developments). The response variables are the wide range of variables characterising volatility in the financial market that can capture the market’s response to central bank communication. These are the RVI (‘fear’) index, the spread between RUONIA and the key rate, the rates at the short and long ends of the OFZ curve and their standard deviations, and the standard deviations of MICEX trading volume and the MICEX index. The data collected cover the January 2015 to November 2022 period.

We use three basic methods to test our hypotheses, with linear regression chosen as the basic method. Using a lag of one week for the explanatory variables, we check whether their reaction precedes the response of the response variables. We also use the Granger causality test, a standard test to solve such problems. However, given the multi-dimensional nature of our data and their nonlinear dependencies, we also apply the more advanced PCMCI algorithm. This algorithm is used to identify the causal relationships in arrays with linear and nonlinear dependencies for time series and takes into account the lags of mutual influence. The PCMCI algorithm tends to create fewer false positive relationships between variables and has greater power to detect relationships in multi-dimensional data arrays.

Following the results of the estimation of the models, we confirm four of the five hypotheses of this study, namely, that

- financial markets’ perception of Bank of Russia communication in episodes of increased volatility is distinctly different from perception in normal times.
- Financial markets are more receptive to Bank of Russia communication in episodes of increased volatility.
- More intense communication from the Bank of Russia has a stabilising effect on financial markets.
- Communication confidence has a stabilising effect on financial markets.
- The communication of a commitment to the target has a stabilising effect on financial markets in episodes of increased volatility.

In general, we conclude that communication in a crisis, measured in different ways, works to reduce volatility, while intense communication in times of lower volatility can introduce noise to the media space and drive growth in uncertainty.

Importantly, as follows from the Granger tests and the PCMCI algorithm, while communication has an influence on financial markets, the state of financial markets has a significant impact on the central bank’s tactics of communication. Specifically, strong fluctuations in the OFZ curves may spur the central bank’s intention to provide a signal, while high volatility in the markets has important implications for the frequency of pronouncements by Bank of Russia executives, in the media space, on the key drivers of monetary policy.

The contribution of our work to the literature is threefold. First, we propose two new unique variables for central bank communication (invariance and confidence) to compare the communication practices of various central banks or to test hypotheses about the impact of communication on the real sector. Second, we create a detailed map of Bank of Russia communications between key rate decisions in 2015–2022, which can be used in follow-up studies of verbal interventions. Third, we elaborate on the theme of central bank communication in times of crisis, measuring various effects of communication on financial markets. In addition, we confirm the researchers' existing findings of the negative impact of 'overcommunicating' due to noise in the media landscape.

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Appendices

Appendix 1. Map of Bank of Russia Communications, 2015–2022

Week start	Week end	Inflation	Inflation expectations[4]	Economy	Monetary conditions and financial markets	Oil	External conditions and the ruble	Budget and government policies	Forward guidance
01.01.2015	07.01.2015								
08.01.2015	14.01.2015		1			1			1
15.01.2015	21.01.2015	1	0.5						0.5
22.01.2015	28.01.2015	1				0.5			
29.01.2015	04.02.2015	1	0.5	1	1		1		
05.02.2015	11.02.2015	1	1	1	1	1	0.5		
12.02.2015	18.02.2015	1	1						0.5
19.02.2015	25.02.2015						1		
26.02.2015	04.03.2015	0.5		1					
05.03.2015	11.03.2015						0.5		
12.03.2015	18.03.2015	1		1	1				1
19.03.2015	25.03.2015	1				1		1	
26.03.2015	01.04.2015								
02.04.2015	08.04.2015	1		1		0.5	0.5		0.5
09.04.2015	15.04.2015								
16.04.2015	22.04.2015	1					1		0.5
23.04.2015	29.04.2015								

[4] Inflation expectations.

30.04.2015	06.05.2015	1	1	1	1	1	1	0.5	1
07.05.2015	13.05.2015								
14.05.2015	20.05.2015								
21.05.2015	27.05.2015	0.5	1				1		
28.05.2015	03.06.2015							1	
04.06.2015	10.06.2015	0.5	1	0.5	0.5		0.5		0.5
11.06.2015	17.06.2015	1	0.5	1	0.5	1	0.5	0.5	1
18.06.2015	24.06.2015	1		1	0.5		0.5		
25.06.2015	01.07.2015								
02.07.2015	08.07.2015						1		
09.07.2015	15.07.2015								
16.07.2015	22.07.2015								
23.07.2015	29.07.2015								
30.07.2015	05.08.2015	1		1	1		0.5	0.5	
06.08.2015	12.08.2015								
13.08.2015	19.08.2015								
20.08.2015	26.08.2015	0.5							0.5
27.08.2015	02.09.2015	0.5							
03.09.2015	09.09.2015						0.5		
10.09.2015	16.09.2015	1		1	1		1		0.5
17.09.2015	23.09.2015			1			1	1	
24.09.2015	30.09.2015	1		1	0.5	0.5	0.5		0.5
01.10.2015	07.10.2015	1	1	1			0.5	1	
08.10.2015	14.10.2015	1		1					
15.10.2015	21.10.2015	1		1					
22.10.2015	28.10.2015								
29.10.2015	04.11.2015	1	1	1	1		1		
05.11.2015	11.11.2015		1				0.5		

12.11.2015	18.11.2015	0.5				1	1		1
19.11.2015	25.11.2015								
26.11.2015	02.12.2015			1		1	1		
03.12.2015	09.12.2015						1		
10.12.2015	16.12.2015	1		1	1	0.5	0.5		1
17.12.2015	23.12.2015	0.5		0.5		1	1		
24.12.2015	30.12.2015								
31.12.2015	06.01.2016								
07.01.2016	13.01.2016								
14.01.2016	20.01.2016	1					1	1	1
21.01.2016	27.01.2016	0.5		0.5		1		1	
28.01.2016	03.02.2016	0.5	1	1		1	0.5	0.5	
04.02.2016	10.02.2016								
11.02.2016	17.02.2016			1	0.5	1	0.5		1
18.02.2016	24.02.2016	1		1		1			1
25.02.2016	02.03.2016	0.5	1	1		0.5	1		
03.03.2016	09.03.2016		1						
10.03.2016	16.03.2016	0.5							1
17.03.2016	23.03.2016	1	1	1	0.5	1	1	1	1
24.03.2016	30.03.2016	1							1
31.03.2016	06.04.2016								
07.04.2016	13.04.2016	1	1	1	1		1		1
14.04.2016	20.04.2016	1		1		0.5		1	0.5
21.04.2016	27.04.2016	1							
28.04.2016	04.05.2016	1	1	1	1	1	1	1	1
05.05.2016	11.05.2016								
12.05.2016	18.05.2016			0.5			0.5		0.5
19.05.2016	25.05.2016								

26.05.2016	01.06.2016	1			1			0.5	0.5
02.06.2016	08.06.2016								
09.06.2016	15.06.2016	1	1	1	1	1	1	0.5	1
16.06.2016	22.06.2016	1		1			1	1	0.5
23.06.2016	29.06.2016				1		1		
30.06.2016	06.07.2016	1	1	1	1	1		1	
07.07.2016	13.07.2016								
14.07.2016	20.07.2016								
21.07.2016	27.07.2016								
28.07.2016	03.08.2016	0.5	1	1	1			0.5	1
04.08.2016	10.08.2016								
11.08.2016	17.08.2016								
18.08.2016	24.08.2016								
25.08.2016	31.08.2016								
01.09.2016	07.09.2016								
08.09.2016	14.09.2016			0.5	1				0.5
15.09.2016	21.09.2016	1	1	1	0.5		0.5		1
22.09.2016	28.09.2016			1		1	0.5	1	1
29.09.2016	05.10.2016	1		0.5	0.5	0.5			1
06.10.2016	12.10.2016	1		1	0.5	0.5	1	1	0.5
13.10.2016	19.10.2016	1					1		
20.10.2016	26.10.2016								
27.10.2016	02.11.2016	1	0.5	1	1			0.5	1
03.11.2016	09.11.2016	0.5				1	1		1
10.11.2016	16.11.2016	0.5		1					1
17.11.2016	23.11.2016								
24.11.2016	30.11.2016	1				1			
01.12.2016	07.12.2016	1		1		1	0.5		1

08.12.2016	14.12.2016								1
15.12.2016	21.12.2016	1	1	1		0.5			1
22.12.2016	28.12.2016			0.5			0.5		
29.12.2016	04.01.2017								
05.01.2017	11.01.2017								
12.01.2017	18.01.2017			1			1		0.5
19.01.2017	25.01.2017	1				0.5	0.5		
26.01.2017	01.02.2017								
02.02.2017	08.02.2017	1	1	1				0.5	1
09.02.2017	15.02.2017	0.5	0.5			1		0.5	1
16.02.2017	22.02.2017	0.5					0.5		
23.02.2017	01.03.2017								
02.03.2017	08.03.2017								
09.03.2017	15.03.2017								
16.03.2017	22.03.2017						0.5		
23.03.2017	29.03.2017	1		1	1	0.5			1
30.03.2017	05.04.2017			1			0.5		0.5
06.04.2017	12.04.2017	1							1
13.04.2017	19.04.2017	1				1	1		1
20.04.2017	26.04.2017	1					1		1
27.04.2017	03.05.2017	1	1	1	1	1	1		1
04.05.2017	10.05.2017								
11.05.2017	17.05.2017								0.5
18.05.2017	24.05.2017			1			0.5		1
25.05.2017	31.05.2017					1			
01.06.2017	07.06.2017	1		0.5		1	0.5		1
08.06.2017	14.06.2017				0.5		0.5	0.5	
15.06.2017	21.06.2017	1	1	1	1				1

22.06.2017	28.06.2017								
29.06.2017	05.07.2017								
06.07.2017	12.07.2017								
13.07.2017	19.07.2017	1		0.5	1	1	0.5		1
20.07.2017	26.07.2017								
27.07.2017	02.08.2017	1	1	1	1	1		1	1
03.08.2017	09.08.2017								
10.08.2017	16.08.2017								
17.08.2017	23.08.2017								
24.08.2017	30.08.2017								
31.08.2017	06.09.2017								
07.09.2017	13.09.2017	1							
14.09.2017	20.09.2017	1	1	1	1	1	1	1	1
21.09.2017	27.09.2017	1							
28.09.2017	04.10.2017	1							
05.10.2017	11.10.2017								
12.10.2017	18.10.2017	1	1						
19.10.2017	25.10.2017	0.5							0.5
26.10.2017	01.11.2017	1	1	1	1		0.5	0.5	1
02.11.2017	08.11.2017								
09.11.2017	15.11.2017								
16.11.2017	22.11.2017	1		1		1			1
23.11.2017	29.11.2017						1		
30.11.2017	06.12.2017								
07.12.2017	13.12.2017								
14.12.2017	20.12.2017	1	1	1	1	1	0.5	0.5	1
21.12.2017	27.12.2017			0.5	0.5				
28.12.2017	03.01.2018								

04.01.2018	10.01.2018								
11.01.2018	17.01.2018			1		1			
18.01.2018	24.01.2018								
25.01.2018	31.01.2018								
01.02.2018	07.02.2018	1	1				1		1
08.02.2018	14.02.2018	1	1	1	1	1	0.5	0.5	1
15.02.2018	21.02.2018								
22.02.2018	28.02.2018								
01.03.2018	07.03.2018								
08.03.2018	14.03.2018								
15.03.2018	21.03.2018								
22.03.2018	28.03.2018	1	1	1	1	1	0.5	0.5	1
29.03.2018	04.04.2018								
05.04.2018	11.04.2018	0.5		1			1		
12.04.2018	18.04.2018	1					1		1
19.04.2018	25.04.2018	1					0.5		1
26.04.2018	02.05.2018	1	1	1	1	1	0.5	0.5	1
03.05.2018	09.05.2018								
10.05.2018	16.05.2018								
17.05.2018	23.05.2018	1		1		1			1
24.05.2018	30.05.2018	1		1	0.5				1
31.05.2018	06.06.2018	1		1		0.5			
07.06.2018	13.06.2018	1		1	1		0.5	1	1
14.06.2018	20.06.2018	1	1	1	1	1	1	1	1
21.06.2018	27.06.2018								
28.06.2018	04.07.2018								
05.07.2018	11.07.2018	0.5							
12.07.2018	18.07.2018				0.5				

19.07.2018	25.07.2018								
26.07.2018	01.08.2018	1	1	1	1	0.5	0.5	0.5	1
02.08.2018	08.08.2018								
09.08.2018	15.08.2018								
16.08.2018	22.08.2018								
23.08.2018	29.08.2018								
30.08.2018	05.09.2018	1					1		1
06.09.2018	12.09.2018						1		1
13.09.2018	19.09.2018	1	1	1	1	0.5	0.5	0.5	1
20.09.2018	26.09.2018	0.5					1		1
27.09.2018	03.10.2018						1		
04.10.2018	10.10.2018				0.5		0.5		
11.10.2018	17.10.2018	1		0.5				0.5	1
18.10.2018	24.10.2018	0.5		0.5			0.5		
25.10.2018	31.10.2018	1	1	1	1	0.5	0.5	0.5	1
01.11.2018	07.11.2018	0.5		1					1
08.11.2018	14.11.2018						0.5		
15.11.2018	21.11.2018	0.5				1	1		1
22.11.2018	28.11.2018	0.5						0.5	
29.11.2018	05.12.2018								
06.12.2018	12.12.2018								
13.12.2018	19.12.2018	1	1	1	1	1	1	0.5	1
20.12.2018	26.12.2018								
27.12.2018	02.01.2019								
03.01.2019	09.01.2019								
10.01.2019	16.01.2019	1					0.5		
17.01.2019	23.01.2019								
24.01.2019	30.01.2019								

31.01.2019	06.02.2019				0.5				
07.02.2019	13.02.2019	1	1	1	1	1	1		1
14.02.2019	20.02.2019								
21.02.2019	27.02.2019								
28.02.2019	06.03.2019	1			0.5				
07.03.2019	13.03.2019			1	1				
14.03.2019	20.03.2019								
21.03.2019	27.03.2019	1	1	1	1	0.5	1	0.5	1
28.03.2019	03.04.2019	0.5			1		1		
04.04.2019	10.04.2019	1		1			0.5		
11.04.2019	17.04.2019	1							0.5
18.04.2019	24.04.2019	1			1				
25.04.2019	01.05.2019	1	1	1	1	0.5	1	0.5	1
02.05.2019	08.05.2019								
09.05.2019	15.05.2019								
16.05.2019	22.05.2019	1		1					
23.05.2019	29.05.2019	1							
30.05.2019	05.06.2019			1	0.5			1	0.5
06.06.2019	12.06.2019	0.5							1
13.06.2019	19.06.2019	1	1	1	1	0.5	0.5	0.5	1
20.06.2019	26.06.2019								
27.06.2019	03.07.2019	1							
04.07.2019	10.07.2019	1	1	1		1			1
11.07.2019	17.07.2019								
18.07.2019	24.07.2019								
25.07.2019	31.07.2019	1	1	1	1	0.5	0.5	1	1
01.08.2019	07.08.2019			1					
08.08.2019	14.08.2019								

15.08.2019	21.08.2019								
22.08.2019	28.08.2019								
29.08.2019	04.09.2019								
05.09.2019	11.09.2019	1	1	1	1		0.5	1	1
12.09.2019	18.09.2019	1		0.5				1	
19.09.2019	25.09.2019								
26.09.2019	02.10.2019								
03.10.2019	09.10.2019	0.5			1			1	1
10.10.2019	16.10.2019	1		0.5		0.5			1
17.10.2019	23.10.2019								0.5
24.10.2019	30.10.2019	1	1	1	1		0.5	0.5	1
31.10.2019	06.11.2019								
07.11.2019	13.11.2019	1						1	1
14.11.2019	20.11.2019							1	1
21.11.2019	27.11.2019								
28.11.2019	04.12.2019						0.5		
05.12.2019	11.12.2019								0.5
12.12.2019	18.12.2019	1	1	1	1		0.5	0.5	1
19.12.2019	25.12.2019	0.5							1
26.12.2019	01.01.2020								
02.01.2020	08.01.2020								
09.01.2020	15.01.2020	0.5							0.5
16.01.2020	22.01.2020								
23.01.2020	29.01.2020								
30.01.2020	05.02.2020								
06.02.2020	12.02.2020	1	1	1	1		1	1	1
13.02.2020	19.02.2020	0.5			0.5				
20.02.2020	26.02.2020								

27.02.2020	04.03.2020	1		1			1		
05.03.2020	11.03.2020								1
12.03.2020	18.03.2020								
19.03.2020	25.03.2020	1	1	1	1		1		
26.03.2020	01.04.2020								
02.04.2020	08.04.2020	1		1			1		1
09.04.2020	15.04.2020	1		1	1	1			1
16.04.2020	22.04.2020	1		1	1		1		1
23.04.2020	29.04.2020	1	1	1	1		1		1
30.04.2020	06.05.2020								
07.05.2020	13.05.2020	1		1	1	1		1	1
14.05.2020	20.05.2020	1					1		1
21.05.2020	27.05.2020	1		1			1	1	1
28.05.2020	03.06.2020	1		1				1	1
04.06.2020	10.06.2020	1	1	0.5				0.5	0.5
11.06.2020	17.06.2020								
18.06.2020	24.06.2020	1	1	1	1		1	1	1
25.06.2020	01.07.2020								
02.07.2020	08.07.2020								
09.07.2020	15.07.2020	1			1				1
16.07.2020	22.07.2020								
23.07.2020	29.07.2020	1	1	1	1		1	1	1
30.07.2020	05.08.2020								
06.08.2020	12.08.2020			1					
13.08.2020	19.08.2020	1		1					
20.08.2020	26.08.2020								
27.08.2020	02.09.2020								
03.09.2020	09.09.2020			1			1		1

10.09.2020	16.09.2020	1		1					1
17.09.2020	23.09.2020	1	1	1	1		1	1	1
24.09.2020	30.09.2020								
01.10.2020	07.10.2020								
08.10.2020	14.10.2020								
15.10.2020	21.10.2020								
22.10.2020	28.10.2020	1	1	1	1		1	1	1
29.10.2020	04.11.2020	1							
05.11.2020	11.11.2020								1
12.11.2020	18.11.2020								
19.11.2020	25.11.2020								1
26.11.2020	02.12.2020								
03.12.2020	09.12.2020	1					1		0.5
10.12.2020	16.12.2020								
17.12.2020	23.12.2020	1	1	1	1		1	0.5	1
24.12.2020	30.12.2020								
31.12.2020	06.01.2021								
07.01.2021	13.01.2021								
14.01.2021	20.01.2021						0.5		
21.01.2021	27.01.2021								
28.01.2021	03.02.2021								
04.02.2021	10.02.2021								
11.02.2021	17.02.2021	1	1	1	1		1	1	1
18.02.2021	24.02.2021			1					1
25.02.2021	03.03.2021								
04.03.2021	10.03.2021	1							
11.03.2021	17.03.2021								
18.03.2021	24.03.2021	1	1	1	1		1	0.5	1

25.03.2021	31.03.2021								
01.04.2021	07.04.2021								
08.04.2021	14.04.2021	1					1		
15.04.2021	21.04.2021								
22.04.2021	28.04.2021	1	1	1	1		1	1	1
29.04.2021	05.05.2021								
06.05.2021	12.05.2021								
13.05.2021	19.05.2021	1		1					
20.05.2021	26.05.2021	1							
27.05.2021	02.06.2021			1					
03.06.2021	09.06.2021	1	1	0.5					1
10.06.2021	16.06.2021	1	1	1	1		1	0.5	1
17.06.2021	23.06.2021								0.5
24.06.2021	30.06.2021	1	1		1				0.5
01.07.2021	07.07.2021								1
08.07.2021	14.07.2021	1		1					
15.07.2021	21.07.2021		1						
22.07.2021	28.07.2021	1	1	1	1		1	0.5	1
29.07.2021	04.08.2021								
05.08.2021	11.08.2021								
12.08.2021	18.08.2021								
19.08.2021	25.08.2021								
26.08.2021	01.09.2021								
02.09.2021	08.09.2021	0.5							
09.09.2021	15.09.2021	1	1	1	1		1	0.5	1
16.09.2021	22.09.2021	1			1				1
23.09.2021	29.09.2021	1							
30.09.2021	06.10.2021	1		0.5		1			

07.10.2021	13.10.2021	0.5	0.5			1			1
14.10.2021	20.10.2021								
21.10.2021	27.10.2021	1	1	1	1		1	1	1
28.10.2021	03.11.2021								
04.11.2021	10.11.2021								
11.11.2021	17.11.2021	1			1				1
18.11.2021	24.11.2021	0.5							
25.11.2021	01.12.2021	1		0.5			1		1
02.12.2021	08.12.2021	1					1		1
09.12.2021	15.12.2021	1							1
16.12.2021	22.12.2021	1	1	1	1		1	0.5	1
23.12.2021	29.12.2021	1		1					
30.12.2021	05.01.2022								
06.01.2022	12.01.2022								
13.01.2022	19.01.2022	1							
20.01.2022	26.01.2022								
27.01.2022	02.02.2022								
03.02.2022	09.02.2022								
10.02.2022	16.02.2022	1	1	1	1		1	0.5	1
17.02.2022	23.02.2022	0.5							
24.02.2022	02.03.2022	1					1		1
03.03.2022	09.03.2022								
10.03.2022	16.03.2022	1							
17.03.2022	23.03.2022	1	1	1	1		1		1
24.03.2022	30.03.2022	1		1					1
31.03.2022	06.04.2022								
07.04.2022	13.04.2022	1	1	1	1				1
14.04.2022	20.04.2022	1		1	1				1

21.04.2022	27.04.2022								1
28.04.2022	04.05.2022	1	1	1	1		1		1
05.05.2022	11.05.2022								
12.05.2022	18.05.2022								
19.05.2022	25.05.2022	1							1
26.05.2022	01.06.2022	1			1		1		1
02.06.2022	08.06.2022								
09.06.2022	15.06.2022	1	1	1	1		1		1
16.06.2022	22.06.2022	1		1			1	1	
23.06.2022	29.06.2022	1			1		1		
30.06.2022	06.07.2022								
07.07.2022	13.07.2022								
14.07.2022	20.07.2022								
21.07.2022	27.07.2022	1	1	1	1		1	1	1
28.07.2022	03.08.2022								
04.08.2022	10.08.2022								
11.08.2022	17.08.2022	1		1			1		1
18.08.2022	24.08.2022								
25.08.2022	31.08.2022								
01.09.2022	07.09.2022								
08.09.2022	14.09.2022			1					
15.09.2022	21.09.2022	1	1	1	1		1	1	
22.09.2022	28.09.2022	1		1	1				
29.09.2022	05.10.2022	0.5		1					
06.10.2022	12.10.2022	1		0.5					0.5
13.10.2022	19.10.2022	1							
20.10.2022	26.10.2022								
27.10.2022	02.11.2022	1	1	1	1		1	1	

03.11.2022	09.11.2022			1	1				
10.11.2022	16.11.2022	1					1		
17.11.2022	23.11.2022	0.5					1		
24.11.2022	30.11.2022								
01.12.2022	07.12.2022								
08.12.2022	14.12.2022								
15.12.2022	21.12.2022	1	1	1	1		1	1	
22.12.2022	28.12.2022								

Source: Authors' estimates.

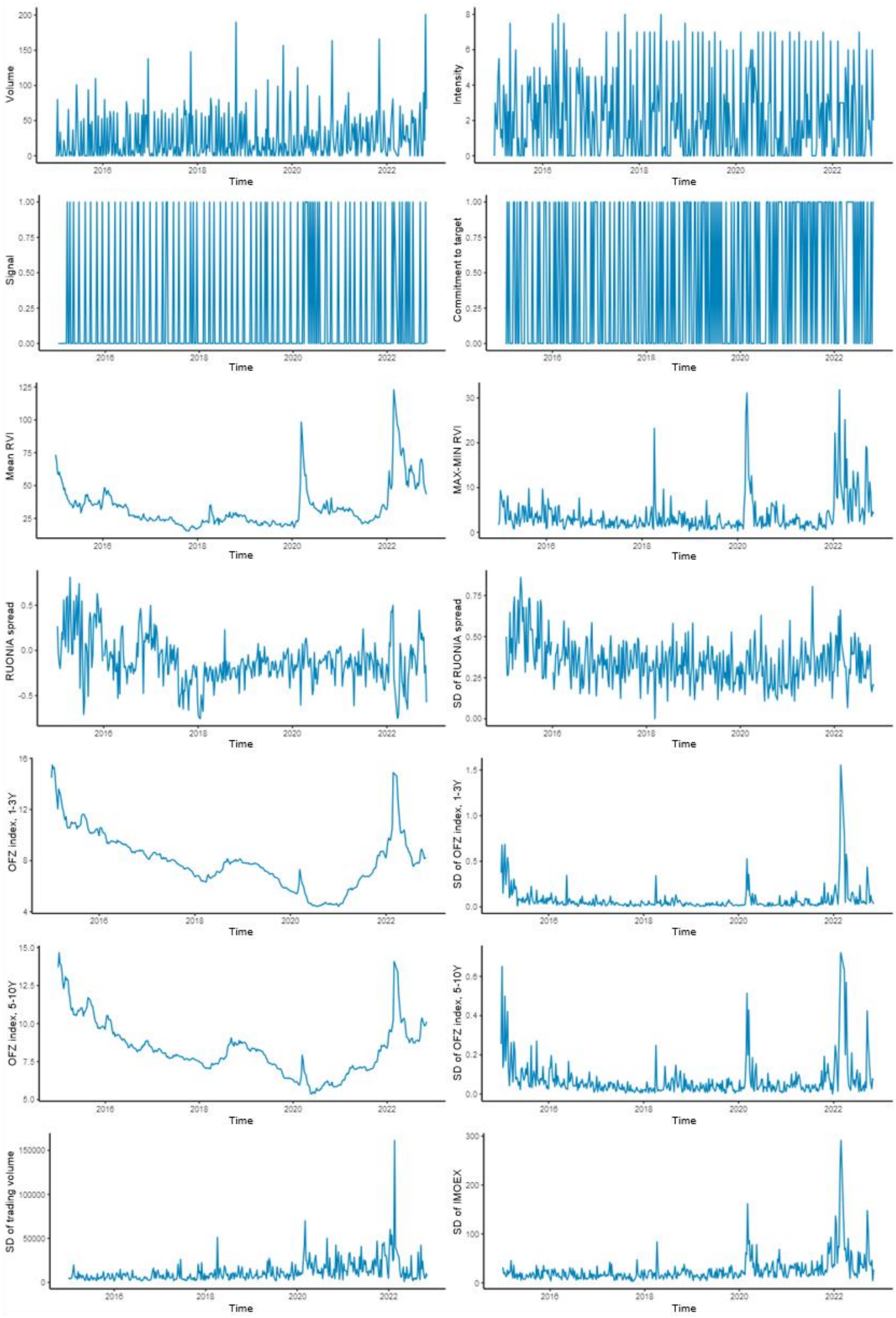
Appendix 2. Dictionary of strong words

- определенно [definitely]
- явно [clearly]
- явный [clear]
- однозначно [straightforwardly]
- отчетливо [distinctly]
- точно [precisely]
- наибольший [greatest]
- наименьший [least]
- должен [must]
- никогда [never]
- сильно [strongly]
- несомненно [undoubtedly]
- однозначно [straightforwardly]
- недвусмысленный [unambiguous]
- безусловно [certainly]
- невозможно [impossible]
- без сомнения [without doubt]
- наверняка [most certainly]
- всегда [always]
- как правило [as a rule]
- обычно [usually]

Source: Authors' proposals.

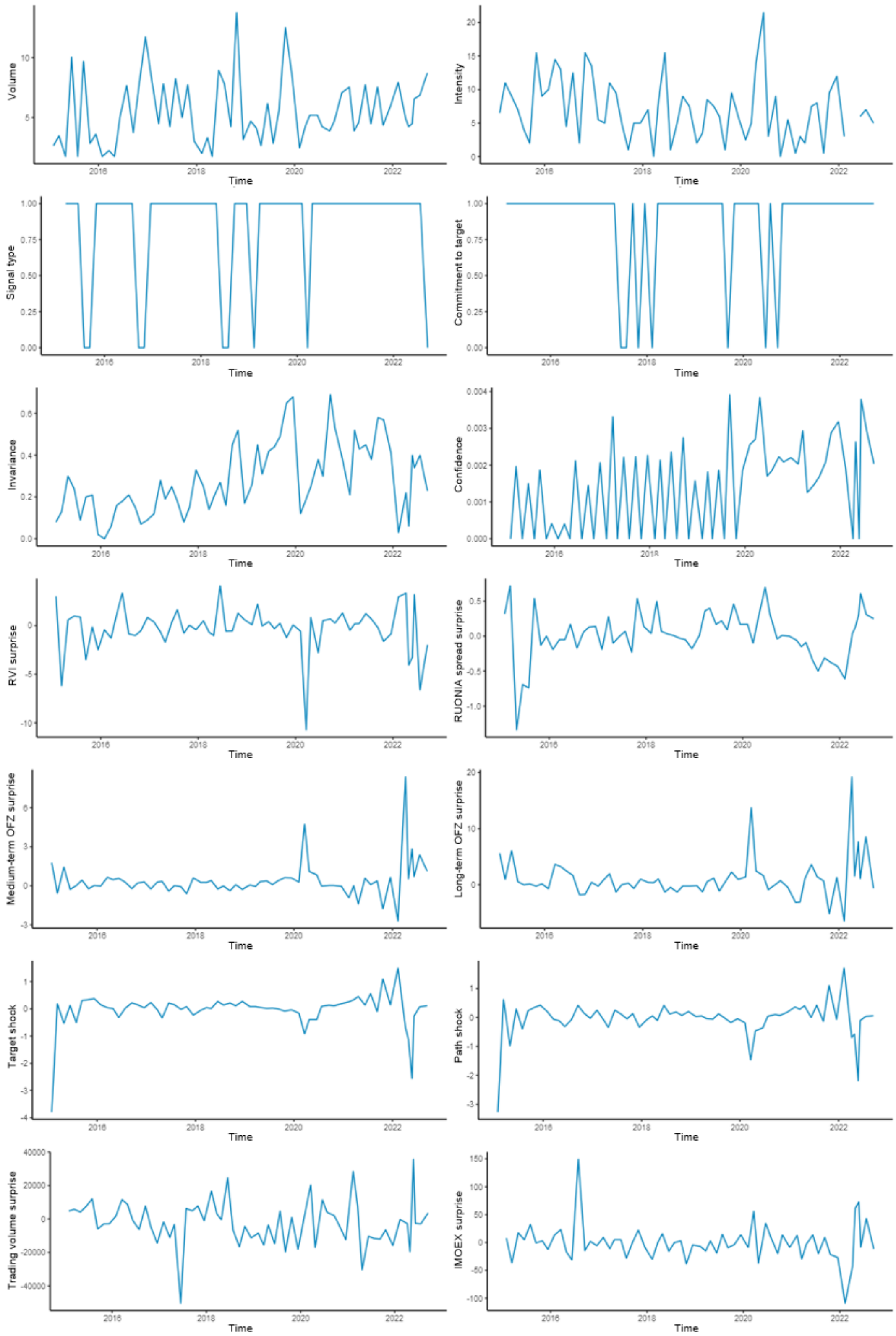
Appendix 3. Time series graphs

I. DATASET 1. WEEKLY DATA



Source: Authors' calculations.

II. DATASET 2. DATASET WITH FREQUENCY OF KEY RATE DECISIONS



Source: Authors' calculations.

Appendix 4. Stationarity tests

I. DATASET 1 (WEEKLY DATA)

Variable	D-F test H0 – not stationary	KPSS test H0: stationary	P-P test H0: not stationary	Conclusion: series stationary/not stationary
Volume of communication	p-value < 0.01	p-value < 0.01	p-value < 0.01	Series stationary
Intensity of communication	p-value < 0.01	p-value > 0.1	p-value < 0.01	Series stationary
Presence of signal	p-value < 0.01	p-value = 0.04586	p-value < 0.01	Series stationary
Commitment to target	p-value < 0.01	p-value < 0.01	p-value < 0.01	Series stationary
Average RVI	p-value = 0.03836	p-value < 0.01	p-value < 0.01	Series stationary
Max-min RVI	p-value < 0.01	p-value = 0.01231	p-value < 0.01	Series stationary
RUONIA spread	p-value < 0.01	p-value > 0.1	p-value < 0.01	Series stationary
Standard deviation of MICEX Spread	p-value < 0.01	p-value > 0.1	p-value < 0.01	Series stationary
OFZ index, 1–3 years	p-value = 0.5876	p-value < 0.01	p-value = 0.5805	Series not stationary
Standard deviation of OFZ index, maturity 1–3 years	p-value < 0.01	p-value = 0.05395	p-value < 0.01	Series stationary
OFZ index, 5–10 years	p-value = 0.5814	p-value < 0.01	p-value = 0.6296	Series not stationary
Standard deviation of OFZ index, maturity 5–10 years	p-value < 0.01	p-value = 0.04765	p-value < 0.01	Series stationary
Standard deviation of MICEX trading volume	p-value < 0.01	p-value < 0.01	p-value < 0.01	Series stationary
Standard deviation of MICEX index	p-value < 0.01	p-value < 0.01	p-value < 0.01	Series stationary

Source: Authors' calculations.

II. DATASET 2. DATASET WITH FREQUENCY OF KEY RATE DECISIONS

Variable	D-F test H0: series not stationary	KPSS test H0: series stationary	P-P test H0: series not stationary	Conclusion: series stationary/not stationary
Volume of communication	p-value < 0.01	p-value > 0.1	p-value < 0.01	Series stationary
Intensity of communication	p-value = 0.07579	p-value > 0.1	p-value < 0.01	Series stationary
Signal type	p-value = 0.02054	p-value > 0.1	p-value < 0.01	Series stationary
Commitment to target	p-value = 0.0923	p-value > 0.1	p-value < 0.01	Series stationary
Communication invariance	p-value = 0.1672	p-value < 0.01	p-value < 0.01	Series not stationary
Communication confidence	p-value = 0.01433	p-value < 0.01	p-value < 0.01	Series stationary
RVI surprise	p-value = 0.09955	p-value > 0.1	p-value < 0.01	Series stationary

RUONIA spread surprise	p-value = 0.1555	p-value > 0.1	p-value < 0.01	Series stationary
OFZ index surprise (OFZ maturity 1–3 years)	p-value = 0.08261	p-value > 0.1	p-value < 0.01	Series stationary
OFZ index surprise (OFZ maturity 5–10 years)	p-value = 0.02395	p-value > 0.1	p-value < 0.01	Series stationary
Target shock	p-value < 0.01	p-value > 0.1	p-value < 0.01	Series stationary
Path shock	p-value < 0.01	p-value > 0.1	p-value < 0.01	Series stationary
MICEX trading volume surprise	p-value = 0.1056	p-value > 0.1	p-value < 0.01	Series stationary
MICEX index surprise	p-value < 0.01	p-value > 0.1	p-value < 0.01	Series stationary

Source: Authors' calculations.

Appendix 5. Results of regression models

I. DATASET 1 (WEEKLY DATA)

TABLE 1. DUAL REGRESSION COEFFICIENTS AND THEIR SIGNIFICANCE**

	Average RVI	Max-min RVI	RUONIA spread	Standard deviation of RUONIA spread	OFZ index, 1–3 years	Standard deviation of OFZ index, OFZ maturity 1–3 years	OFZ index, 5–10 years	Standard deviation of OFZ index, maturity 5–10 years	Standard deviation of MICEX trading volume	Standard deviation of MICEX index
Volume of communication	0.004	0.0002	-0.051	0.009	0.004	-0.001	0.005	0.003	0.008	0.017
Intensity of communication	0.020	0.008	0.005	0.024	-0.002	0.001	0.003	0.003	0.015 *	0.002
Presence of signal	0.009	-0.001	-0.009	0.025 **	-0.002	-0.003	0.002	-0.002	0.010 .	0.003
Commitment to target	-0.001	-0.005	-0.021	-0.012	0.002	-0.003	0.004 .	-0.004	0.006	0.005

** Codes of significance: ** – 0.01, * – 0.05, . – 0.1.*
Source: Authors' calculations.

TABLE 2. MULTIPLE REGRESSION COEFFICIENTS AND THEIR SIGNIFICANCE*

	Average RVI	Max-min RVI	RUONIA spread	Standard deviation of RUONIA spread	OFZ index, 1–3 years	Standard deviation of OFZ index, OFZ maturity 1–3 years	OFZ index, 5–10 years	Standard deviation of OFZ index, maturity 5–10 years	Standard deviation of MICEX trading volume	Standard deviation of MICEX index
Volume of communication	0.003	0.007	-0.030	0.026	0.002	0.003	-0.0001	0.008	-0.0004	0.013
Intensity of communication	0.031	0.025 .	0.050	-0.001	-0.003	0.016 **	-0.001	0.016	0.011	-0.004
Presence of signal	-0.007	-0.012	-0.030	0.036 .	-0.002	-0.012 **	0.001	-0.009	0.002	0.003
Commitment to target	-0.006	-0.008	-0.020	-0.026 *	0.003	-0.003	0.004	-0.006	0.003	0.003

** Codes of significance: ** – 0.01, * – 0.05, . – 0.1.*
Source: Authors' calculations.

II. DATASET 1–1. CRISIS

TABLE 3. DUAL REGRESSION COEFFICIENTS AND THEIR SIGNIFICANCE*

	Average RVI	Max-min RVI	RUONIA spread	Standard deviation of RUONIA spread	OFZ index, 1–3 years	Standard deviation of OFZ index, OFZ maturity 1–3 years	OFZ index, 5–10 years	Standard deviation of OFZ index, maturity 5–10 years	Standard deviation of MICEX trading volume	Standard deviation of MICEX index
Volume of communication	0.016	-0.008	-0.123	-0.091 .	0.004	0.014	0.007	-0.012	-0.005	0.023
Intensity of communication	0.005	0.013	-0.042	0.037	-0.021 *	-0.009	-0.019	0.003	0.011	-0.015
Presence of signal	0.004	0.024	-0.027	0.007	-0.012 .	-0.012 .	-0.006	-0.014	0.011	0.003
Commitment to target	-0.008	-0.017	-0.089 **	-0.029	0.0003	-0.004	0.0004	-0.011	0.003	0.009

** Codes of significance: ** – 0.01, * – 0.05, . – 0.1.*
Source: Authors' calculations.

TABLE 4. MULTIPLE REGRESSION COEFFICIENTS AND THEIR SIGNIFICANCE*

	Average RVI	Max-min RVI	RUONIA spread	Standard deviation of RUONIA spread	OFZ index, 1–3 years	Standard deviation of OFZ index, OFZ maturity 1–3 years	OFZ index, 5–10 years	Standard deviation of OFZ index, maturity 5–10 years	Standard deviation of MICEX trading volume	Standard deviation of MICEX index
Volume of communication	0.026	0.008	-0.015	-0.074	0.003	0.021	0.007	-0.0002	-0.010	0.018
Intensity of communication	0.013	-0.001	0.017	0.088 .	-0.022	0.009	-0.030 .	0.048	0.0002	-0.042 *
Presence of signal	0.002	0.036	-0.005	-0.018	-0.003	-0.016 .	0.008	-0.034	0.011	0.016
Commitment to target	-0.015	-0.027 .	-0.089 **	-0.033	0.006	-0.004	0.004	-0.013	0.0004	0.013

** Codes of significance: ** – 0.01, * – 0.05, . – 0.1.*
Source: Author's calculations.

III. DATASET 1–2. NON-CRISIS

TABLE 5. DUAL REGRESSION COEFFICIENTS AND THEIR SIGNIFICANCE*

	Average RVI	Max-min RVI	RUONIA spread	Standard deviation of RUONIA spread	OFZ index, 1–3 years	Standard deviation of OFZ index, OFZ maturity 1–3 years	OFZ index, 5–10 years	Standard deviation of OFZ index, maturity 5–10 years	Standard deviation of MICEX trading volume	Standard deviation of MICEX index
Volume of communication	0.020	0.005	-0.002	0.076 .	0.001	-0.003	0.003	-0.002	0.018	0.010
Intensity of communication	0.004	0.003	0.011	0.020	0.005	0.003	0.008 *	0.006	0.018 *	0.002
Presence of signal	0.003	-0.003	0.0004	0.035 *	0.002	-0.001	0.003	0.004	0.011	0.001
Commitment to target	0.004	-0.002	0.014	-0.005	0.003	-0.001	0.004 **	-0.001	0.008	0.002

** Codes of significance: ** – 0.01, * – 0.05, . – 0.1.*
Source: Author's calculations.

TABLE 6. MULTIPLE REGRESSION COEFFICIENTS AND THEIR SIGNIFICANCE*

	Average RVI	Max-min RVI	RUONIA spread	Standard deviation of RUONIA spread	OFZ index, 1–3 years	Standard deviation of OFZ index, OFZ maturity 1–3 years	OFZ index, 5–10 years	Standard deviation of OFZ index, maturity 5–10 years	Standard deviation of MICEX trading volume	Standard deviation of MICEX index
Volume of communication	0.018	0.009	-0.025	0.097 *	-0.004	-0.003	-0.004	-0.004	0.006	0.009
Intensity of communication	-0.0004	0.017	0.040	-0.060 .	0.007	0.014 *	0.017 .	0.007	0.019	0.002
Presence of signal	0.0002	-0.013	-0.034	0.078 **	-0.003	-0.009 *	-0.010	0.001	-0.005	-0.001
Commitment to target	0.002	-0.002	0.019	-0.030 *	0.003	-0.0004	0.004 .	-0.003	0.005	0.001

** Codes of significance: ** – 0.01, * – 0.05, . – 0.1.*
Source: Author's calculations.

IV. DATASET 2 (WITH FREQUENCY OF KEY RATE DECISIONS)

TABLE 7. DUAL REGRESSION COEFFICIENTS AND THEIR SIGNIFICANCE*

	RVI surprise	Volatility of RUONIA–key rate spread	OFZ index surprise (OFZ maturity 1–3 years)	OFZ index surprise (OFZ maturity 5–10 years)	Target shock	Path shock	Trading volume surprise	MICEX index surprise
Volume of communication	0.060	0.068	-0.043	-0.077	0.111	0.116	-0.065	-0.040
Intensity of communication	-0.056	0.036	0.051	0.074	-0.042	-0.038	0.006	0.092
Signal type	0.087	-0.001	-0.032	0.008	0.005	0.011	-0.092	-0.020
Commitment to target	-0.030	-0.096	0.033	0.045	-0.016	-0.017	0.023	0.017
Communication invariance	0.053	0.071	0.042	0.033	0.046	-0.002	-0.156	-0.004
Communication confidence	-0.062	0.073	-0.035	-0.059	0.076	0.078	-0.141 *	-0.080

** Codes of significance: ** – 0.01, * – 0.05, . – 0.1.*
Source: Author's calculations.

TABLE 8. MULTIPLE REGRESSION COEFFICIENTS AND THEIR SIGNIFICANCE*

	RVI surprise	Volatility of RUONIA–key rate spread	OFZ index surprise (OFZ maturity 1–3 years)	OFZ index surprise (OFZ maturity 5–10 years)	Target shock	Path shock	Trading volume surprise	MICEX index surprise
Volume of communication	0.091	0.082	-0.046	-0.070	0.055	0.080	-0.046	-0.049
Intensity of communication	-0.092	0.052	0.087 .	0.101	-0.061	-0.064	-0.009	0.090
Signal type	0.101 .	-0.026	-0.070 *	-0.029	0.030	0.041	-0.087	-0.027
Commitment to target	-0.021	-0.107	0.014	0.034	0.007	-0.001	-0.006	0.023
Communication invariance	0.059	-0.005	0.081	0.087	-0.024	-0.091	-0.099	0.056
Communication confidence	-0.085	0.110	0.041	0.016	0.015	0.003	-0.088	-0.072

** Codes of significance: ** – 0.01, * – 0.05, . – 0.1.*
Source: Author's calculations.

Appendix 6. Granger causality analysis for Dataset 1

TABLE 1. RESULTS OF ANALYSIS

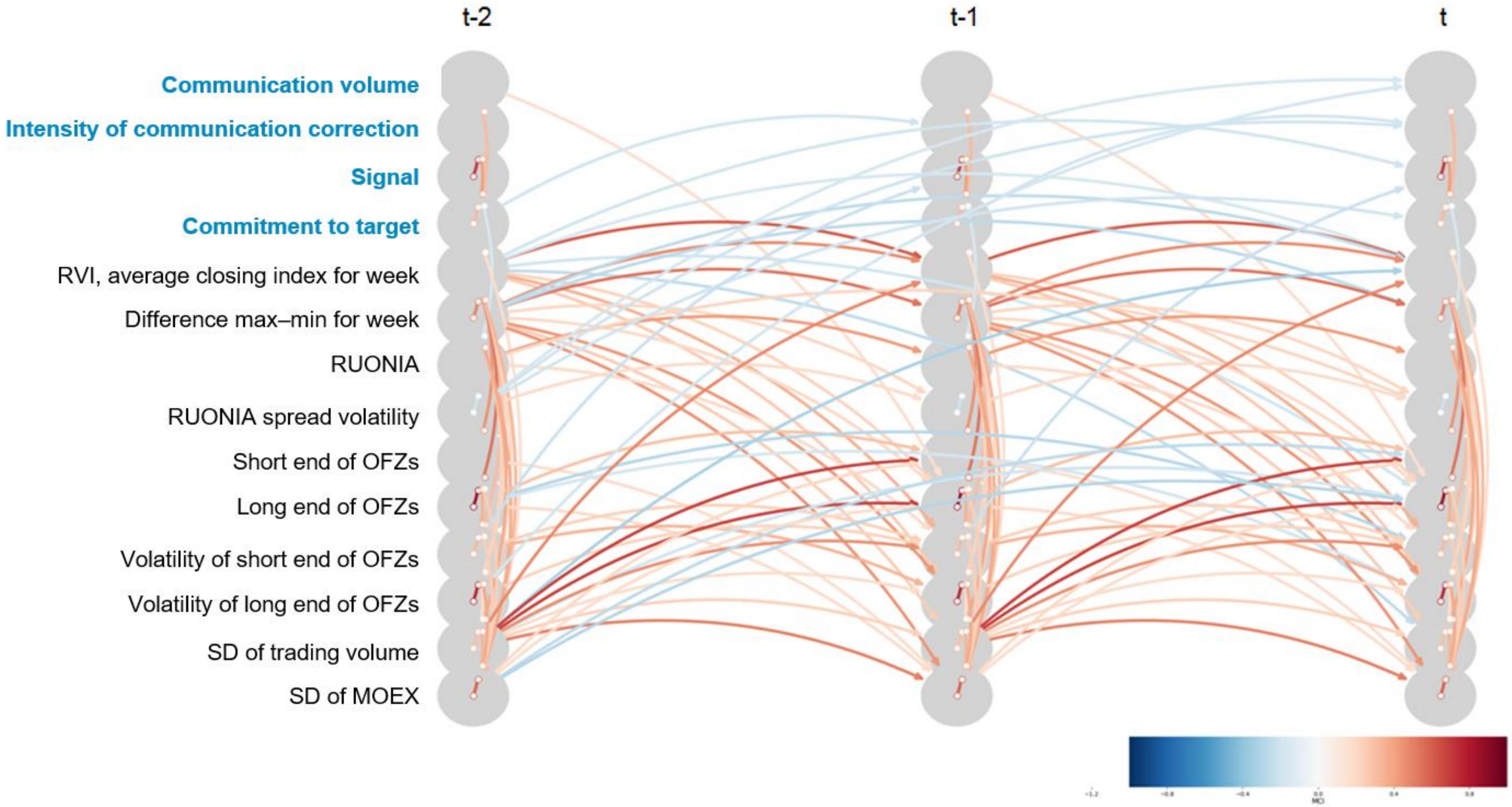
Direction of causality	F-statistics	P-value	Lag
Volume of communication → standard deviation of OFZ index (maturity 1–3 years)	4.997	0.026 *	1
Volume of communication → OFZ index (maturity 1–3 years)	2.789	0.096 .	1
Volume of communication → OFZ index (maturity 5–10 years)	4.853	0.028 *	1
Volume of communication → RUONIA–key rate spread	4.762	0.003 **	3
Volume of communication → standard deviation of IMOEX	5.726	0.017 *	1
Volume of communication → standard deviation of IMOEX	2.161	0.092 .	3
Volume of communication → OFZ index (maturity 5–10 years)	2.527	0.057 .	3
Intensity of communication → standard deviation of IMOEX	2.352	0.072 .	3
RUONIA–key rate spread → intensity of communication	2.861	0.037 *	3
RUONIA–key rate spread → commitment to target	2.313	0.076 .	3
Average RVI value → intensity of communication	3.120	0.074 .	1
Average RVI value → presence of signal	3.676	0.056 .	1
Average RVI value → intensity of communication	4.704	0.003 **	3
Average RVI value → commitment to target	2.105	0.099 .	3
Average RVI value → presence of signal	7.183	0.000 ***	3
Max-min RVI → intensity of communication	3.532	0.061 .	1
Max-min RVI → presence of signal	9.243	0.003 **	1
Max-min RVI → commitment to target	2.728	0.044 *	3
Max-min RVI → presence of signal	6.711	0.000 ***	3
Standard deviation of RUONIA–key rate spread → intensity of communication	2.415	0.066 .	3
Standard deviation of RUONIA–key rate spread → presence of signal	2.602	0.052 .	3
Standard deviation of OFZ index (1–3 years)–key rate spread → intensity of communication	3.142	0.025 *	3
Standard deviation of OFZ index (1–3 years) → presence of signal	3.302	0.020 *	3

OFZ index (5–10 years) → presence of signal	2.158	0.092 .	3
Standard deviation of OFZ index (5–10 years) → intensity of communication	3.365	0.019 *	3
Standard deviation of OFZ index (5–10 years) → presence of signal	3.544	0.015 *	3
Standard deviation of trading volume → commitment to target	3.677	0.056 .	1
Standard deviation of trading volume → presence of signal	2.829	0.038 *	3
Standard deviation of IMOEX → presence of signal	3.449	0.064 .	1
Standard deviation of IMOEX → presence of signal	3.204	0.023 *	3

** Codes of significance: ** – 0.01, * – 0.05, . – 0.1.*
Source: Author's calculations.

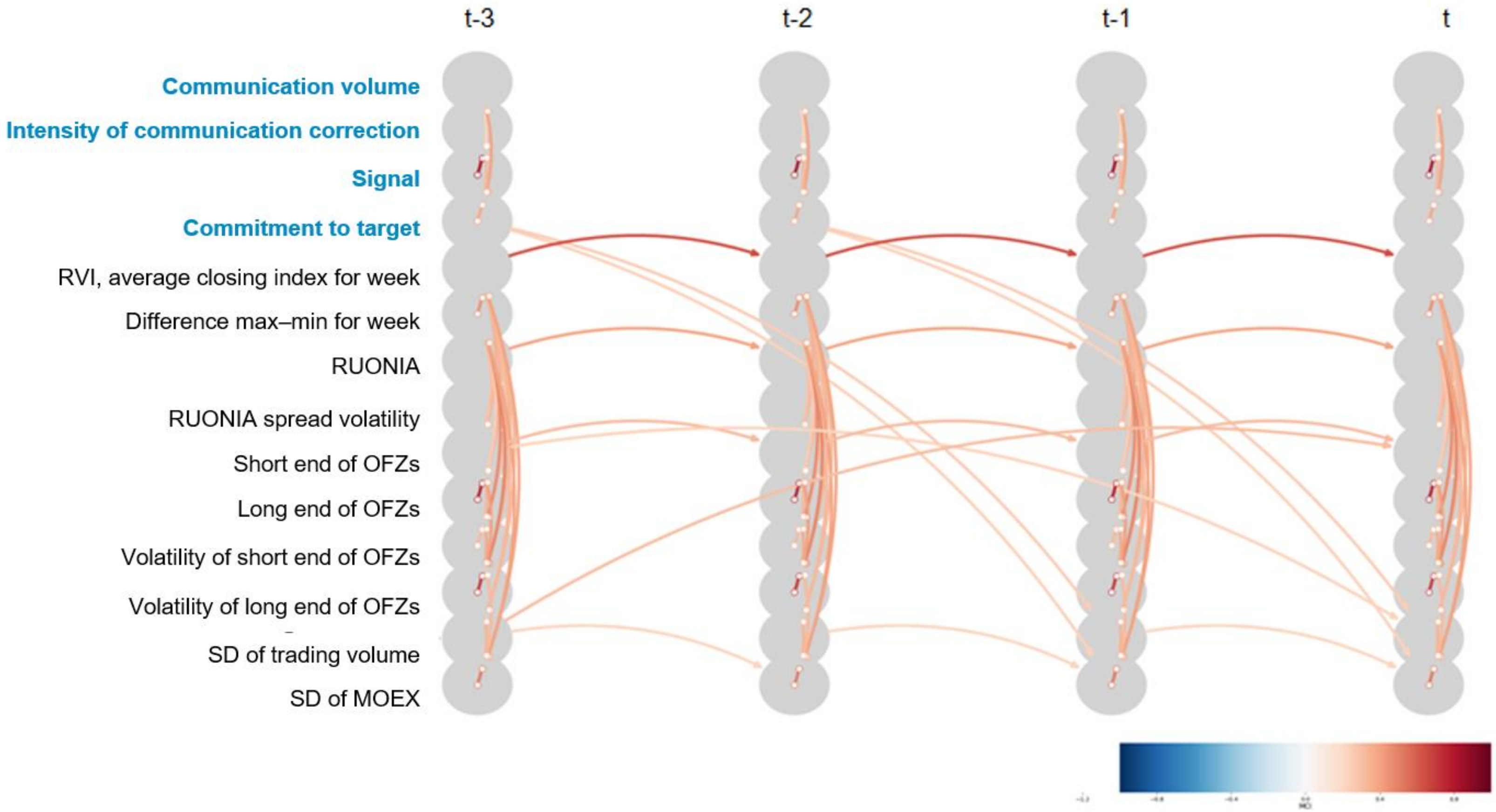
Appendix 7. Results of PCMCI algorithm

FIGURE 1. RELATIONSHIPS IN DATASET 1 VARIABLES, *CRISIS* SUBSAMPLE



Source: Author's calculations.

FIGURE 2. RELATIONSHIPS IN DATASET 1 VARIABLES, *NON-CRISIS* SUBSAMPLE



Source: Author's calculations.