Analysing Russian Central Bank Communication Impact on Monetary Policy Effectiveness With Natural Language Processing

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1 Introduction

The Central Banks in developed countries use interest rate as a tool for stabilising economic activity and inflation. In order to make correct decisions in setting the rate, they need to know how it will affect macroeconomic variables. It should be noted that the rate is changed to stabilise the economy state, which makes it difficult to separate the cause and the effect. To conquer this problem, a brunch of monetary policy literature has exploited the usage of high frequency changes in prices of futures contracts during tight windows around key monetary events as external instruments for monetary policy. Under the assumption that no other news could impact the markets within these small time windows, the price changes would reflect solely the market reaction to the monetary news.

Nevertheless, as emphasised by Nakamura and Steinsson 2018, Jarociński and Karadi 2020, and Doh, Song, and Yang 2020 among others, the information about the economic state, revealed along with the decision on the interest rate, impacts the private sector decisions as well. The direction of the impact this information component has on the economic variables is likely to counteract what would be expected in general theory [Nakamura and Steinsson 2018].

Recent developments in the field suggest text analysis for study of informational effects of the Central Bank monetary policy announcements. This section of literature has multiple branches: Z. T. Ke, Kelly, and Xiu 2020 and Doh, Song, and Yang 2020 use sentiment scores with information content of FOMC statements to estimate the market response to monetary policy tightening; Handlan 2020, Hansen and McMahon 2016, and Hansen, McMahon, and Prat 2018 focus on differences between median expert predictions of the key rate and the modelled expectations, built on FOMC statements texts; Cai, Camara, and Capel 2021 model expectations with FOMC statements and news articles to compute the difference. Their findings are that stock market responds negatively to an unexpected monetary policy tightening.

While different aspects of FOMC informational policy have drawn a lot of attention from researches, studies on high frequency monetary shocks in developing economies are not as numerous: Mallick and Sousa 2012 have come to similar conclusions about large emerging economies while Tishin 2019 has detected a "price puzzle" in the case of Russian economy (situation when policy tightening causes uplift in the inflation) even with the use of external instruments. Bannikova and Pestova 2021 argue that this effect appears with addition of Russian crisis of 2014-2015. While mentioned works exploit advances in high frequency identification (HFI) literature, no studies incorporate the information component, which is argued to counteract the main effect of monetary policy shocks [**nakamura˙high˙2015**, Jarociński and Karadi 2020]. To our knowledge, this paper is the first to implement text analysis into monetary shock identification framework for developing economies.

In this paper we use the method, developed by Cai, Camara, and Capel 2021 to decompose the high frequency movements into information component (which responds to the information about future economic outlook) and pure monetary shock. We do that by modelling public expectations with the use of information from newspapers and from press releases. The former represents public expectations about the "natural"[1] key rate before the press release and the latter public expectations after they learned what view Central bank has on the future economic outlook. This paper incorporates the insight from Cai, Camara, and Capel 2021: they propose that the information component of the monetary shock is a function of a difference of these expectations. That is to say that the informational component exists if the expectations based on the available information are different.

After derivation of the component, its existence is verified by case study analysis. We found that our news component measure is interpretable and can partly explain high frequency changes of prices in Russian markets.

Moreover, we argue that the high frequency surprise, cleared of derived informational component is a more appropriate measure for monetary shock in comparison to ordinary high frequency price changes, that are used in literature on high frequency identification. This notion is supported by estimation of the transmission mechanism of a "purified" monetary component - captured monetary shock without informational component.

2 Data

This section describes three main types of data used: (i) text data from CB official site and articles; (ii) financial variable data used to compute high frequency shocks; (iii) macroeconomic data used to trace the transmission mechanism of monetary component.[2]

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[1] Here, "natural" key rate - the rate considered optimal by the market provided all available information as in Nakamura and Steinsson 2018.

[2] All links and data descriptions can be found at `https://github.com/tssorokina/information_component_of_monetary_shocks` along with notebooks for data scraping and

We have downloaded all texts of the Bank of Russia press releases along with dates from their official web page. The sample consists of 68 observations from 17 October 2013 to 17 December 2021, which is considerably less than what is available for the US data. Cai, Camara, and Capel 2021 use economic and financial analysis from New York Times paper to model public expectations before press release publication along with federal funds rate predictions. We use general news from economic and financial columns of https://www.rbc.ru/ due to unavailability another consistent source that would publish financial analysis of Russian economy throughout the whole period. The timeframe for each press release date is 96 hours or less before publication time.

For high frequency shock construction we utilise data on several instruments: futures on baskets of government bonds, replicating bonds with exercise dates in two, four, six, ten, and fifteen years; closest to press release dates one-month futures on currency pairs US dollar/ruble and euro/ruble; we also use spot rates of currency pairs US dollar/ruble and euro/ruble to construct a new instrument for monetary policy shocks, proposed by Bannikova and Pestova 2021. All data on financial instruments was taken from Finam investment holding.

For the SVAR analysis we use: monthly data on industrial production and consumer price index growth rate, weighted average of mortgage rate; daily data on credit spread (averaged difference between Corporate Russian bonds of 30 companies with highest capitalisation and zero-coupon bonds of the Russian government with the same maturity), nominal effective exchange rate (weighted exchange rate of domestic currency to a weighted geometric average of exchange rates for a basket of other selected currencies over a period of time), global volatility index (index, dependent on market expectations of near-term price changes of the SP 500 Index), yield to maturity of government five-year zero-coupon bonds - all averaged over the month.

3 Methodology

In this section, we specify the three-stage process of extracting the informational content of the high frequency movements around press-release publication. The process is based on methodology of Cai, Camara, and Capel 2021 and adapted to the data in use. It can be summarised as follows:

processing.

Stage 1: **Document Embedding.** We use a transformer-based model for text embedding to convert documents into vectors.

Stage 2: **Constructing Proxy Expectations.** The vector representations of the texts from previous Stage are used to predict the key rate for public and Central bank of Russia data. Under rational expectation assumption, we interpret the predictions of the estimated functions as expected policy decisions, based on the information available to the private sector and Central Bank respectively.

Stage 3: **Extracting Informational Content.** Suppose that with all information available to the private sector, the prices in the market reflect the public assumptions about the economy state and the public expectations are already incorporated into it. Then, the high frequency movements around the release are supposed to be the market response to updated information about economy. Therefore, informational effect can be derived by projecting high frequency movements onto the difference in expectation of the private sector and the Central Bank.

Afterwards, we build a structural autoregressive model using difference between high frequency monetary shocks and isolated informational component as instruments to trace the transmission mechanism of a pure monetary component.

3.1 Stage 1: Document Embedding

In this section we convert every press release and news article into a 1024-dimension vectors using BERT model (Bidirectional Encoder Representations from Transformers, Devlin et al. 2019)

We used pretrained BERT models provided by open community Hugging Face. The models, present for the Russian language are not as developed as for English and there is no public agreement on which embedding model has better performance. Therefore it was decided to use two embedding models: from repository sberbank-ai (`https://huggingface.co/sberbank-ai/sbert_large_mt_nlu_ru`) and DeepPavlov (`https://huggingface.co/DeepPavlov/rubert-base-cased-sentence`). It should be noted that all results presented further in the paper are derived with 'SBERT' model by sberbank-ai because they were more stable.[3]

We note that some articles [Hansen, McMahon, and Prat 2018, Hansen and McMahon 2016, David Lucca and Trebbi 2009] use Latent Dirichlet Allocations

[3]The expectations, modelled with the use of embeddings from DeepPavlov model were usually overfitted ($E[KR_t|X] \approx KR_t$) or underfitted ($E[KR_t|X] \approx \frac{1}{T}\sum_{t-1}^{T} KR_t$) for one of the predictions, which is complicates the interpretation.

as computational linguistic tool - mainly for topic modelling - to include the results into VAR framework. Nevertheless, the results are highly dependent on the prior specification [S. Ke, Olea, and Nesbit 2021], and that can be detrimental in small datasets. Our data have fewer observations than what was available for mentioned authors, which can make LDA predictions unstable. Therefore, it was decided to use BERT model for embedding as in Doh, Song, and Yang 2020, Doh, Kim, and Yang 2021, Cai, Camara, and Capel 2021, Handlan 2020.

Before vectorising the texts, we conducted certain preprocessing steps. We deleted stop words - such as prepositions - as they do not contain any information and may confuse the model. We relied on the stop-word list, provided by 'nltk' library. Then we tokenised the words with the tokenisers provided by sberbank-ai and DeepPavlov repositories respectively as it would stabilise the outputs of the models - the text would be adapted to the training dataset of the model. The tokenisation of the sentences means division into smaller parts - usually one-to-five-word windows, which allows the model to develop links between words and phrases.

Moreover, the cleaning process removes all dates and number from the text. This precaution will ensure that the model would not be able to trace the policy rates or their forecasts from the vector representations and would rely solely on the beliefs about economy.

The outcomes of this stage are 1x1024 size vectors for each press release date t. The news embeddings are averaged over the dates of press releases[4].

3.2 Stage 2: Constructing Proxy Expectations

Following the original methodology of Cai et al., we suppose that the key rate (KR_t), set during the meeting t can be presented as a function of the information available to the Central Bank of Russia and private sector:

$$KR_t = f^{news}(X_t^{news}) + \varepsilon_t^{news}$$
$$KR_t = f^{CBR}(X_t^{CBR}) + \varepsilon_t^{CBR},$$

$$E[\varepsilon_t^{news}|KR_t] = 0, \ E[\varepsilon_t^{CBR}|KR_t] = 0$$

This assumption can be interpreted as follows. Suppose that news embeddings X_t^{news} capture all information available to private sector before the press release time. Then, considering that the expectation of the last term in the equation is zero, private sector's rational expectations of the key rate would follow the rule:

$$E[KR_t|X_t^{news}] = f^{news}(X_t^{news}).$$

[4]We note that it would be preferential to collect news - or financial and economic analyses - from different sources and average their embeddings, which could be interpreted as average market prediction of economic outlook. Unfortunately, this could not be done with Russian data, but might be replicated with US.

Where $f^{news}(X_t^{news})$ is a determined relation function. In this case, ε_t^{news} would represent the expectation error of public sector. It should tend to zero on average: the expectations are not systematically biased. This justifies the conditional mean assumption.

Similar reasoning concludes that ε_t^{CBR} can be viewed as a monetary policy shock - an implementation error that creates deviation from the interest rate, desired by the Bank of Russia. The representation then $E[KR_t|X_t^{CBR}] = f^{CBR}(X_t^{CBR})$ characterises the new public expectations about the optimal rate, updated after press release publication.

As in Cai et al., we assume linear form of the function $f^i(X_t^i)$ ($i \in \{news, CBR\}$) for simplicity:

$$f^{news}(X_t^{news}) = \alpha^{news} + \beta^{news\prime} X_t^{news}$$
$$f^{CBR}(X_t^{CBR}) = \alpha^{CBR} + \beta^{CBR\prime} X_t^{CBR}$$

Where parameters $(\alpha^{news}, \beta^{news}), (\alpha^{CBR}, \beta^{CBR})$ are obtained with the use of elastic net model:

$$(\hat{\beta}^i, \hat{\alpha}^i) = \underset{\alpha^i, \beta^i}{\operatorname{argmin}} \|KR - \alpha^i - \beta^{i\prime} X^i\|_2^2 + \gamma\eta(\|\alpha^i\|_1 + \|\beta^i\|_1) + \gamma(1-\eta)(\|\alpha^i\|_2^2 + \|\beta^i\|_2^2)$$

Elastic net parameter optimisation incorporates both LASSO and ridge regularisation. With properly chosen parameters (η^i, λ^i) it will both set the unnecessary coefficients to zero (because of L1 regularisation) and penalise the model for excessively large coefficients (L2 regularisation). It is argued that elastic net regularisation may be more appropriate for the economic data Giannone, Lenza, and Primiceri 2021. Moreover, taking in account number of variables in the data (1024 for Sbert model) using elastic net regularisation allows flexibility in model identification without over-fitting.

Elastic net parameters are selected with the use of ‘optuna‘ library [Akiba et al. 2019] by implementing Bayesian optimization algorithm. This algorithm samples parameter combinations, concentrating on the areas where the hyperparameters give better results. They are chosen by targeting the coefficient of determination R^2 in Stage 3.

3.3 Stage 3: Extracting Informational Content

In this section we use key rate expectations $E[KR_t|X_t^i]$ to decompose high frequency movements around Bank of Russia press release into news component ($News_t$) and pure monetary shock ($Monetary_t$).

Let ΔR_t be the high frequency movement of the real interest rate around press release publication. Part of this movement is due to private sector updating its information about the economy state. Cai et al. propose that this component is a function of the difference in the expectations of the natural rate before and after release of Central Bank information. Moreover, they argue that if the press did not contain anything unexpected for the public sector, this component was 0. Then, the high frequency movement of the natural rate can be described as:

$$\Delta R_t = \zeta + \theta \Delta E[KR_t] + \nu_t,\ E[\nu_t | \Delta E[KR_t]] = 0 \tag{1}$$

Where $\Delta E[KR_t] := E[KR_t | X_t^{CBR}] - E[KR_t | X_t^{news}]$ is the change in the expectations of the private sector after receiving new information from the press release. The regression residual ν_t can be interpreted as the pure monetary shock ($Monetary_t$) and the predictions of the model are viewed by authors as the informational component of the monetary shock ($News_t$).

Estimation of this variables depends on the selection of parameters in Stage 2: $\Delta \widehat{E[KR_t]}(\eta^{news}, \lambda^{news}, \eta^{CBR}, \lambda^{CBR})$. Therefore, Cai et al. propose choosing parameters of the elastic net to maximise coefficient of determination R^2 in (1) as it would not let the model neither overfit nor underfit in Stage 2. Otherwise, the differences in expectation would be zero and the R^2 in Stage 3 would be zero as well.

This identification rises the question about model overfitting in Stage 3. Nevertheless, as the regression (1) has only two parameters, it is believed that the excess overfitting should not rise a great concern.

3.4 High Frequency Identification of Monetary Shocks

We suppose that private sector bases its beliefs about economy state on all available news. The prices in the market reflect their beliefs and incorporate all available information by efficient market hypothesis (EMH). We also suppose that in the determined window around the press release publication there is no news that would impact market prices except for the press release (which is a strong assumption for some of the instruments in use, which will be discussed later).

The ideal instrument for constructing monetary surprises would be a liquid contract based on the key rate. In HFI literature for US data, conventional instruments of monetary shock construction are Federal Funds Futures. Unlike the case of Fed Funds for United States, Russian financial market does not have an instrument, explicitly based on the key rate. Similar to Cesa-Bianchi, Thwaites, and Vicondoa 2020 we decided to work with one-month currency futures on pairs USD/RUB and EUR/RUB with excersise dete closest to the preview date. These futures are liquid instruments, dependent on domestic interest rate; therefore, they are eligible for further monetary shock construction.

Russian financial market has also futures for the baskets of government bonds, replicating the bonds with exercise dates of two, four, six, ten, and fifteen years. The problem with these instruments is that the data on prices is present only with a daily frequency. Bannikova and Pestova 2021 have rejected this instrument because of this reasoning. However, Tishin 2019 uses these instruments to construct monetary surprises, which strains the assumption about orthogonality of the high frequency movements to non-monetary shocks: there might be more non-monetary news published during the day, that could affect the prices of the instruments. The monetary shocks, built with this asset, are significant instruments in the first stage regression, therefore we decided to keep them in further analysis.

The optimal window length in HFI literature was determined as 30 minutes (10 minutes before the FOMC statement publication and 20 minutes after) [Nakamura and Steinsson 2018, Miranda-Agrippino and Ricco 2021]. The studies on HFI of monetary shocks for Russian market Bannikova and Pestova 2021, have also used this window length.

Using all of the above, high frequency surprises for currency futures are constructed as:

$$s_t = \frac{\frac{1}{p_{t,t+20}} - \frac{1}{p_{t,t-10}}}{\frac{1}{p_{t,t-10}}} = \frac{p_{t,t-10} - p_{t,t+20}}{p_{t,t+20}}.$$

Where s_t - is an instrument for a monetary shock; $p_{t,\tau+20}$ - the price of a chosen instrument in the end of 30-minute window, 20 minutes after the release; $p_{t,\tau-10}$ - the price of a chosen instrument in the beginning of 30-minute window, 10 minutes before the release. Consequently, $\frac{1}{p_{t,\tau}}$ represents the rate of exchange for domestic currency, while p_t, τ would be a reverse exchange rate. We make the transformation to the reverse futures price for easier interpretation: here, positive sign of s_t would mean ruble strengthening and negative sign - its weakening. We note that the futures for currency pair euro/ruble are not as liquid. Nevertheless, as there are enough transactions during the day, we simply "widen" the window to the latest transaction before $(t, \tau - 10)$ and the earliest transaction after $(t, \tau + 20)$.

Prices for futures on government bonds are presented for the end of the day session. We suppose that if the monetary shock is present, then there was at least one transaction at the day of press-release. The instrument for monetary shock would be then:

$$s_t = \frac{p_{t,\tau} - p_{t,\tau-1}}{p_{t,\tau-1}}.$$

Where s_t - is an instrument for a monetary shock; $p_{t,\tau}$ - the price of the chosen instrument by the end of the press release day t; $p_{t,\tau-1}$ - the price of the chosen instrument after the last transaction before the press release day t. On certain press release dates there were no transactions at all. In that case we suppose that the monetary shock is 0 as it was not strong enough to influence market participants significantly.

Bannikova and Pestova 2021 have proposed new instrument for measuring monetary shock, which allows us to work with available instruments within our small window assumption. It is built on uncovered interest rate parity (UIRP). If in 30-minute window we suppose perfect capital mobility, perfect exchange between foreign and domestic capital and UIRP compliance, the UIRP formula will be as follows:

$$s_t = \frac{E_t[S_{t+T}] - S_t}{S_t} \times \frac{365}{T} = i_t^d - i_t^f$$

Where S_t is reverse spot rate of domestic currency; $E_t[S_{t+T}]$ - expected at t spot rate of domestic currency in T days; i_t^d - interest rate for domestic assets; i_t^f - interest rate for foreign assets; and T - amount of days until exercise date. The interpretation is that the difference between domestic and foreign interest rates equals to the expected rate of domestic currency depreciation.

Then, if we write this equation for both times $(t, \tau - 10)$ and $(t, \tau + 20)$ and suppose constant interest rate in the US, we get the following:

$$(\frac{E_{t,\tau+20}[S_{t+T}] - S_{t,\tau+20}}{S_{t,\tau+20}} - \frac{E_{t,\tau-10}[S_{t+T}] - S_{t,\tau-10}}{S_{t,\tau-10}}) \times \frac{365}{T} = i_{t,\tau+20}^d - i_{t,\tau-10}^d$$

The advantages of this instrument are that, in theory, it is based on the domestic rate, which should make it a good external instrument for monetary shocks. In addition, the currency futures are relatively liquid even in developing financial markets, which could make it an interesting substitution for the Federal Fund futures.

Gertler and Karadi 2015 in their work use the first principle component of high frequency shock in federal funds rate, federal funds rate futures, and several currency futures. Therefore, we have decided to construct a first principle component on currency and bonds futures to create a measure that would account for the market volatility.

3.5 Econometric Framework for Structural VAR Model

In this section, we describe the econometric framework used to trace the transmission mechanism of the identified pure monetary shocks. The main procedure follows the structural vector autoregressive (SVAR) model with external instruments from Gertler and Karadi 2015 and Cesa-Bianchi, Thwaites, and Vicondoa 2020. In the empirical section, we estimate the base model first with 4 economic and financial variables (similar to original Gertler and Karadi 2015 specification), then - with 7 variables (modified version of Cesa-Bianchi, Thwaites, and Vicondoa 2020).

Let Y_t be a vector of economic and financial variables, C and $A_j, j \geq 1$ - coefficient matrices, and ε_t - vector of structural white noise shocks with variance-covariance matrix $\Sigma_\varepsilon = I_\varepsilon$. The structural form of the $VAR(p)$ model is then:

$$CY_t = \sum_{i=1}^{p} D_i Y_{t-i} + \varepsilon_t.$$

Reduced form representation of the model can be derived as:

$$Y_t = \sum_{i=1}^{p} A_i Y_{t-i} + u_t$$

Where $A_i = C^{-1}D_i$, and u_t is a reduced form shock (innovations of the model) - linear transformation of structural shocks: $u_t = A^{-1}\varepsilon_t = B\varepsilon_t$ with variance-covariance matrix:

$$E[u_t u_t'] = E[BB'] = \Sigma_u \tag{2}$$

For simplicity let us consider $VAR(1)$ model. We can represent vector of endogenous variables Y_t as (r_t', X_t') with r_t' - vector of monetary policy variable and X_t' - other variables. The structural VAR form is then:

$$\begin{pmatrix} r_t \\ X_t \end{pmatrix} = \begin{pmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{pmatrix} \times \begin{pmatrix} r_{t-1} \\ X_{t-1} \end{pmatrix} + \begin{pmatrix} B_{11} & B_{12} \\ B_{21} & B_{22} \end{pmatrix} \times \begin{pmatrix} \varepsilon_t^r \\ \varepsilon_t^X \end{pmatrix} \tag{3}$$

Then it is possible to compute impulse responses to a monetary shock from the equation:

$$Y_t = \sum_{i=1}^{p} A_i Y_{t-i} + B\varepsilon_t^r. \tag{4}$$

We are not interested in impulse responses to other shocks, therefore we have to identify only vector $(B_{11}, B_{21})'$ in (3), which can be done with two-stage least squares methodology.

Let Z_t be a vector of exogenous instruments correlated with monetary policy variable and orthogonal to other structural shocks:

$$E[\varepsilon_t^r Z_t'] \neq 0 E[\varepsilon_t^X Z_t'] = 0 \tag{5}$$

In the first stage, we estimate matrix A and residuals u_t in reduced form VAR model. Then, we regress the estimated residuals for monetary policy variables u_t^r on the instrument set Z_t to obtain $\widehat{u_t^r}$, cleared of structural shocks influence - the variation in $\widehat{u_t^r}$ is only due to monetary shocks ε_t^r. The second stage part then implies regression:

$$u_t^X = \frac{B_{21}}{B_{11}} \widehat{u_t^r} + \xi_t.$$

Where $\widehat{u_t^r}$ is orthogonal to ξ_t given the assumption (5). The coefficients $\widehat{B_{11}}, \widehat{B_{21}}$ can be isolated using assumptions (5) and (2) and compute responses in monetary surprises in (4).

As discussed above, in HFI literature, the set of potential external instruments usually consists of surprises in fed funds and Eurodollar futures on FOMC dates. Furthermore, Bannikova and Pestova 2021 use high frequency surprises in currency futures and their constructed instrument based on uncovered interest rate parity for similar analysis of Russian data; [Tishin 2019] uses daily changes in futures on government bonds; Cai, Camara, and Capel 2021 use pure monetary shock, cleared of the news component.

Preferred indicator for monetary policy rate in literature is an indicative central bank rate [Bannikova and Pestova 2021, Tishin 2019] or a two-year government bond rate [Gertler and Karadi 2015, Swanson and Williams 2014] to account for forward guidance. We suppose that effects of forward guidance are incorporated in our informational component measure, therefore usage of official key rate as monetary policy indicator is justified.

A basic model of small economy consists of a monetary policy indicator, industrial production growth to the last period, monthly inflation, and credit spread (Caldara and Herbst 2019 argue that credit spread inclusion is crucial for the correct identification of monetary policy shocks, as monetary policy responds to financial conditions as well as to the current state of the economy). In the original paper, Gertler and Karadi 2015 use credit spread, without default risk. Tishin 2019, in his analysis uses arithmetic difference between prices of corporate and government bonds with the same maturities, which is difficult for interpretations. Our measure of credit spread is weighted sum of differences between corporate and government bonds of same duration. Therefore, it is more related to Gertler and Karadi 2015, though includes default risk premia as well.

The model of an open economy includes all variables referenced above with an addition of nominal effective exchange rate and mortgage spread as endogenous variable and global volatility index as exogenous variable. We construct a mortgage spread measure as an arithmetical difference between weighted average mortgage rate and yield to maturity of a five-year government bond.

4 Results

Firstly, we present summary statistics for Stage 3 in Table 1. We find weak, but mostly significant connection between high frequency monetary shocks and the difference in expectations before and after press release publication. The determination coefficient, which was maximised in Stage 3 is relatively low. It can be explained by the fact that most high frequency movement around publication time is a response to pure monetary shock.

It might be also the case that everything that is disclosed in a press release and, in general, all of the information that Central Bank possesses, is already known in public sector beforehand (it is not reasonable to suggest that economic analysts in private sector are less competent than economists in the Central Bank, therefore, the information pull should be similar in both sectors). But the Central Bank might have incentives to pay more attention to one of the economic variables in certain periods, which would be hard to predict for private sector. Moreover, the data, available to the market, is too diverse and most participants arrive to different conclusions. Then, we can suppose that the most part of the market would not react to new information, and the present movement is created by small fraction of market participants, who did not "guess correctly" Central

Table 1: Summary Statistics for Stage 3

Shock	R^2	$\hat{\theta}$	$S.E.$	t-stat	p-value
OFZ2	0.091	0.0020	0.001	2.563	0.013
OFZ4	0.175	0.0068	0.002	3.742	0.000
OFZ6	0.179	0.0086	0.002	3.793	0.000
OFZ10	0.091	0.0228	0.009	2.564	0.013
OFZ15	0.065	-0.0014	0.001	-2.133	0.037
F RUB/USD	0.133	-0.0002	0.000	-3.186	0.002
F RUB/EUR	0.009	-0.0612	0.034	0.766	0.447
PCA	0.130	-0.6504	0.207	-3.138	0.003
UIP (USD)	0.242	0.0392	0.009	4.517	0.000
UIP (EUR)	0.237	0.0567	0.013	4.453	0.000

Column $\hat{\theta}$ refers fo the coefficient of the regression in Stage 3, where we regress instrument from the first column on difference in constructed key rate expectations; column R^2 - to the determination coefficient; $S.E.$ - standard deviation; t-stat - student criterion; p-value - probability of t-stat being higher than empirically computed, reference level - $\alpha = 0.05$; OFZ2 - futures on government bond basket, replicating two-year bond; OFZ4, OFZ6, OFZ10, OFZ15 - for four, six, ten, and fifteen years respectively; F RUB/USD - $1/p$, where p is a price of one-month futures on currency pair US dollar/ruble; F RUB/EUR - for currency pair euro/ruble; PCA - first principle component of OFZ2, OFZ4, OFZ6, OFZ10, F RUB/USD variation; UIP (USD) - high frequency difference in rates, built on UIRP with futures on currency pair US dollar/ruble and spot rate of dollar; UIP (EUR) - for euro.

Bank's perception on the economic outlook. This proposition would explain such a moderate response.

It should be noted that the coefficient $\hat{\theta}$ is significantly positive for shocks, constructed with futures on government bonds[5]. The sign of the coefficient can be interpreted as follows: the positive difference in expectations of the key rate (it is the case when the private sector increases expectations about natural key rate after information disclosure) creates an increase of prices in the bond market. Which counteracts conventional mechanism: in theory, if the interest rate is unexpectedly increased, the return on bonds is not sufficiently high, which should drive the bond prices down.

As it can be seen from Table 2, the estimated expectation of the key rate before press release publication is constant, therefore, it is not reasonable to explain the coefficients $\hat{\theta}$ for currency futures. Nevertheless, if we suppose, that the true sign of the coefficient is negative, it would mean that positive difference of key rate expectations weakens domestic currency. This again contradicts general open economy theory and confirms findings from Nakamura and Steinsson

[5]Except for the futures that replicates 15-year bond. As it can be seen from Table 2, the prediction for $E[KR_t|X^{news}]$ is constant, for $E[KR_t|X^{CBR}]$ - near constant. Their difference cannot be interpreted as described in the previous section. Therefore, despite the coefficient being statistically significant with probability of making type I error $\alpha = 0.05$, it cannot be considered in the following analysis.

Table 2: Summary Statistics for Stage 2

Shock	η^{news}	λ^{news}	R^2_{news}	η^{CBR}	λ^{CBR}	R^2_{CBR}
OFZ2	0.3744	0.0143	0.868	0.0012	0.0009	1.0
OFZ4	0.0777	0.0318	0.8324	0.0186	0.0053	0.9986
OFZ6	0.0182	0.0294	0.8635	0.0819	0.0010	0.9999
OFZ10	0.58425	6.2197	0.0	0.0563	3.8966	0.064
OFZ15	0.0617	0.0002	0.9999	0.7392	0.5360	0.0483
F RUB/USD	0.0181	0.1002	0.0	0.5099	0.0043	0.2043
F RUB/EUR	0.1099	3.1264	0.0	0.0872	4.0527	0.0099
PCA	0.0007	0.8906	0.7966	0.0216	0.4219	0.9998
UIP (USD)	0.3197	0.0264	0.7839	0.0255	0.0072	0.9996
UIP (EUR)	0.3432	0.0286	0.7613	0.0927	0.0028	0.9966

(η^i, λ^i) - hyper-parameters of Elastic net model, chosen to maximise R^2 in Stage 3. The Elastic net models for news and CBR press-releases were constructed by regressing official CBR Key Rate, set during the meeting, on the embeddings of news and CBR press-releases respectively. Then predictions were used to construct differences in expectations of the Key Rate. High frequency monetary shock from first column was then regressed on previously derived variable. OFZ2 - futures on government bond basket, replicating two-year bond; OFZ4, OFZ6, OFZ10, OFZ15 - for four, six, ten, and fifteen years respectively; F RUB/USD - $1/p$, where p is a price of one-month futures on currency pair US dollar/ruble; F RUB/EUR - for currency pair euro/ruble; PCA - first principle component of OFZ2, OFZ4, OFZ6, OFZ10, F RUB/USD variation; UIP (USD) - high frequency difference in rates, built on UIRP with futures on currency pair US dollar/ruble and spot rate of dollar; UIP (EUR) - for euro.

2018.

As first principle component is composed with several elements, its interpretation is complicated. What we can say, is that the main variation of its elements can be explained by difference in key rate expectations by about 16%.

For the measure built on UIRP, positive coefficient $\hat{\theta}$ can be interpreted as follows. The positive difference in the key rate expectations augments the real rate. This instrument is the only one that can be interpreted in line with general macroeconomic theory.

From 2, we should note that for significant regressions determination coefficients in Second Stage are higher for information after press release publication. If we consider the graphic representations of these expectations, the expectations after release publication would be closer to the official key rate, and expectations based solely on news articles - further from the key rate and more volatile.

This results confirm findings from Nakamura and Steinsson 2018, who have estimated that in response to a policy news shock that 2-year nominal forward[6] rises by 1%, the SP500 index falls by 6.5% with a standard error of 3.3% The coefficient direction coincides with results of Cai, Camara, and Capel 2021.

[6]They use 2-year nominal forward rate as a monetary policy variable in their SVAR model to account for forward guidance component.

5 Evidence of Informational Component

5.1 Case Study Analysis

In this section, we will focus on selected events and follow all monetary shock measures to show that our identified news component is reasonable.

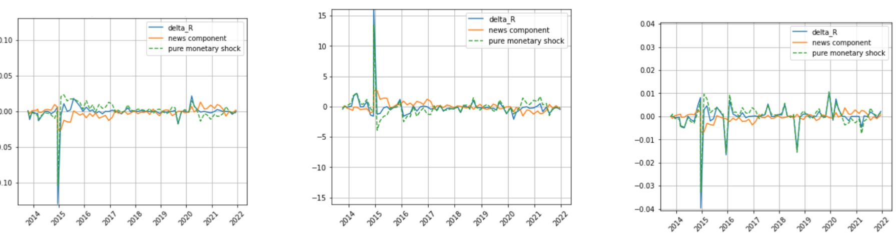

Figure 1: Time series of OFZ_t (left), PCA_t (center), and $UIP(USD)_t$ decomposition into news component and pure monetary shock.

30 January 2015: this meeting was held after unexpected key rate increase to 17% on 16 December 2014. During it, the rate was lowered to 15%; captured high frequency movements were positive[7] for all instruments. Nevertheless, the information component is moderately negative in all cases. The experts forecast was of key rate kept on the same level of 17% [8] because of high inflation risks. THe press release included remarks on possible production cuts and inflation growth due to oil price lowering and ruble weakening. According to general theory, unexpected lowering in the key rate should lead to higher government bonds prices and increase in economic activity, which can be also seen in 5.1. According to our measure, the expectations of the economic outlook dropped after press release publication (as $\hat{\theta}$ is positive for $OFZ4_t$ and $UIP(USD)_t$, and negative for PCA, it can be deduced from Figure 5.1 that the difference in expectations is negative), which had a negative impact on the market. Therefore, we can conclude that pure monetary shock was actually much higher than what is evident from high frequency price changes because it had to overcome this news component in order to create a positive response from the market.

18 December 2020: experts anticipated that the Bank of Russia would lower or keep the key rate the same; CBR did the latter - the key rate was kept at 4.25%. Moreover, estimated yearly inflation was higher than the set key rate. As it can be seen from Figure 5.1, the high frequency price change was close to zero while informational component was positive for all instruments. In the rbc.ru article on expert views[9], no mentions of future economic outlook are

[7] In this subsection, "positive" connotation means the direction that aligns with positive market movements and economic activity increase. Subsequently, "negative" connotation is opposite.

[8] https://www.rbc.ru/finances/27/01/2015/54c67afc9a79473f51457555

[9] The article that was included into dataset can be found here (in Russian) https://www.rbc.ru/finances/15/12/2020/5fd71a709a794790c707ba02.

present, though they remarked on the increase of inflation over CBR predictions. They also note the reduction in probability of key lowering in the next few months. Included in press release[10] are the notions of: lower yield to maturity of government bonds, higher inflation risks, pause in economic activity recovery after COVID-19 restrictions, but also mention of slowdown of the GDP decrease and hopefulness about vaccine production. Positive value of news shock might imply that news about overcoming COVID-19 effects met a positive market response. And negative pure monetary shock can be explained by the fact that a more dovish stance was needed (and expected) in the context of production slump but was not implemented because of the inflation risks, which caused a negative market response and counteracted the positive news shock.

5.2 Channels of Information Transmission

To understand how the information from Central bank statements translates into markets, Cai, Camara, and Capel 2021 propose an identification scheme, which resembles Stages 2 and 3 of news component construction.

Let $Y_{i,t}$ be a general economic variable. Then it can be represented as a fuction of all available information and some expectation error ε:

$$Y_{i,t} = f^{news}(X_t^{news}) + \varepsilon_t^{news}$$
$$Y_{i,t} = f^{CBR}(X_t^{CBR}) + \varepsilon_t^{CBR},$$

$$E[\varepsilon_t^{news}|Y_{i,t}] = 0,\ E[\varepsilon_t^{CBR}|Y_{i,t}] = 0$$

And Stage 3 can be transformed to account for variable autoregression if we would want to represent adaptive:

$$\Delta R_t = \zeta + \sum_{i=1}^{p} \theta_i \Delta E[Y_{i,t}] + \nu_t, \tag{6}$$

The estimations for the case of rational expectations are presented in Table 3. The determination coefficients for industrial production growth are relatively large for the high frequency shocks $OFZ4$, $OFZ6$, $OFZ15$, PCA - presumably, industrial production monthly growth depends more on medium and long term rates. As the coefficients are positive, the positive difference in industrial production expectations before and after press release publication (that is if the expectations of industrial production growth were lower before the press release), it augments the price of the futures. As for inflation, the determination coefficient is relatively high only for $OFZ4$, $OFZ6$, and PCA shocks, which might imply that the moderate connection exists between CPI expectations and medium term rates. The positive sign implies that positive difference in inflation expectations triggers price surge in the bond market response.

[10] `https://cbr.ru/press/pr/?file=18122020_133000Key.htm`

Table 3: Results for industrial production and inflation

Shock	R^2_{IP}	$\hat{\theta}_{IP}$	p-value, IP	R^2CPI	$\hat{\theta}_{CPI}$	p-value, CPI
OFZ2	0.033	0.0006	0.183	0.033	0.0006	0.187
OFZ4	0.201	0.0132	0.001	0.197	0.0075	0.001
OFZ6	0.152	0.0097	0.003	0.153	0.0029	0.003
OFZ10	0.079	0.0004	0.038	0.017	0.0119	0.341
OFZ15	0.170	0.0005	0.002	0.000	0	-
PCA	0.112	-0.7889	0.013	0.111	-0.7930	0.013
UIP (USD)	0.061	-0.2776	0.070	0.057	-3.4656	0.079
UIP (EUR)	0.066	-0.0174	0.058	0.067	-0.0171	0.057

Column $\hat{\theta}$ refers to the coefficient of the regression in Stage 3, where we regress instrument from the first column on difference in constructed key rate expectations; column R^2 - to the determination coefficient; $S.E.$ - standard deviation; t-stat - student criterion; p-value - probability of t-stat being higher than empirically computed, reference level - $\alpha = 0.05$; OFZ2 - futures on government bond basket, replicating two-year bond; OFZ4, OFZ6, OFZ10, OFZ15 - for four, six, ten, and fifteen years respectively; F RUB/USD - $1/p$, where p is a price of one-month futures on currency pair US dollar/ruble; F RUB/EUR - for currency pair euro/ruble; PCA - first principle component of OFZ2, OFZ4, OFZ6, OFZ10, F RUB/USD variation; UIP (USD) - high frequency difference in rates, built on UIRP with futures on currency pair US dollar/ruble and spot rate of dollar; UIP (EUR) - for euro.

6 SVAR analysis

Base specification. Based on multiple verifications with serial autocorrelation tests, information criteria, and residual normality tests, the appropriate model is VAR(3). Most of the external instruments were insignificant in the first stage regression of reduced form residuals. The only statistically significant instruments were $OFZ2$ high frequency shocks, constructed on the futures on basket of government bonds. Both pure monetary shock and and general high frequency movements were significant, though F-statistic for the former was 3.772 on 1 and 79 degrees of freedom (with p-value 0.05567) and for the latter - 3.04 on 1 and 79 degrees of freedom (with p-value 0.08512). Therefore, we can conclude that pure monetary component is a stronger instrument for structural VAR model.

According to the results from the model built with pure monetary component as an external instrument (Figure 6), monetary shock lowers the inflation by 1% in 3 month. Afterwards, the monthly inflation stays negative and after 10 months setlles on -0.1% per month. Response of monthly industrial production growth rate is more volatile in the beginning: firstly rising by 4%, then falling by 4% next month, returning to zero growth the third month and then settling on the downward trend, declining every month by 4% (comparing to the last month). The credit spread augments by 0.5% first month as a response to official rate increase, and then its growth lowers until it settles in a downward trend on -0.1% each month. It should be noted that the used software did not provide

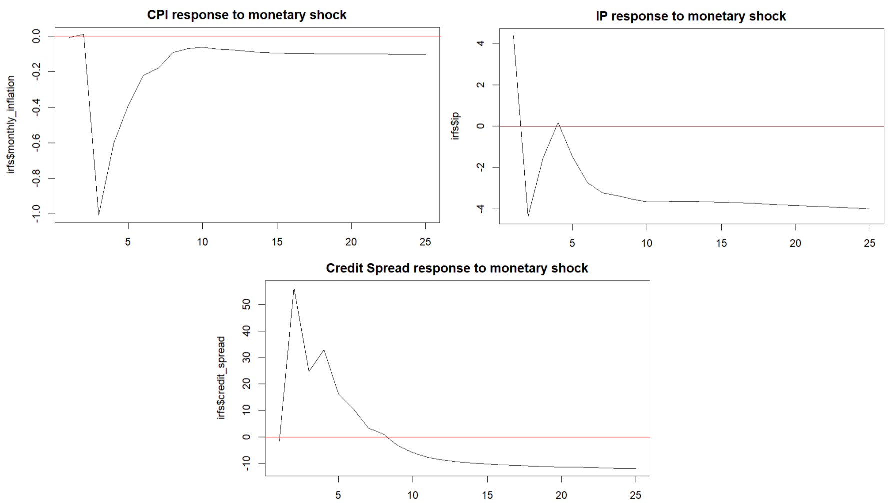

Figure 2: Response functions of base model with four variables: monthly data on industrial production growth in percentage terms, inflation - in percentage terms, credit spread - in base points, and monetary policy indicator (official key rate of Bank of Russia) - in percentage terms. Identifications of SVAR model - with external instruments of constructed pure monetary component based on $OFZ2$ instrument. The order of the reduced form model (p=3) was chosen depending on the Akaike and Schwarz information criteria, residuals were tested for normality and homoskedasticity.

any confidence intervals[11]. Therefore, it is hard to judge the significance of the results.

Open economy specification. In this specification significant, instruments were: pure monetary component, built on $OFZ2$ high frequency price changes, and general high frequency movements, built on $OFZ6$. However, again F-statistic was higher on pure instrument with 5.799 on 1 and 68 degrees of freedom (with p-value 0.01876) against 2.872 on 1 and 70 degrees of freedom (with p-value 0.09457) for the general component.

The result interpretation for open economy specification is more complicated. The response of CPI to a raise of key rate by 1% in the model with pure monetary component as external instrument (Figure 6) is at first negative, but after 4 months we can see the "price puzzle" - the inflation is positive because of monetary policy tightening. Nevertheless, it lowers down and after fifteen months inflation growth is close to zero or negative, this result can be a signal of wrong model specification. The industrial production rises at first and despite high volatility settles on zero growth after fifteen months, which again is counter-

[11] This section was done in RStudio. Better option for structural VAR analysis is matlab software, therefore this section will be redone in future.

intuitive. Reactions of credit spread and mortgage spread are negative in the first fifteen months, though they settle down on positive values afterwards, which again is not an obvious response to nominal rate rise. Reaction of nominal exchange rate is opposite as well: after domestic nominal rate rise there should be a capital inflow to the country, which should rise the demand for domestic currency and, as a result, drive the nominal effective exchange rate up. All of this shows the inadequate model specification.

Results for the model built with general high frequency price shocks are in part more intuitive: for mortgage and credit spreads the response spread an uplift after two months, though it gets back to negative for credit spread after five months. NEER is negative for sixteen months and the "price puzzle" is present in the model again.

Therefore, we can conclude that both model specifications were inadequate for the open economy models from Cesa-Bianchi, Thwaites, and Vicondoa 2020; and either more variables are needed, or the model construction should be revisited.

7 Conclusion

In this paper, we have identified several measures of high frequency shocks, building upon a corpus of existing HFI techniques. After that, we have used a state-of-the-art transparent model to pick out a news component of the Bank of Russia and verified its existence with event study analysis. We support the argument that the market response depends not only on the information provided by Central Bank, but on the difference in expectations of public sector. Consequently, we build public expectations on texts of news and press releases in assumption that it is all information available to public sector before and after releases. We find that high frequency price changes in Russian financial markets can be, in part, explained by our measure of differences in expectations.

We also stress that omitting this information component would lead to bias. To show that, we implement popular in HFI structural VAR model identification with extracted monetary shocks as external instruments. We find that our pure monetary component is a stronger instrument is first stage regression. Results of SVAR analysis for small economy coincide with findings of similar paper for developed countries. Nevertheless, the SVAR identification for open economy needs further revision.

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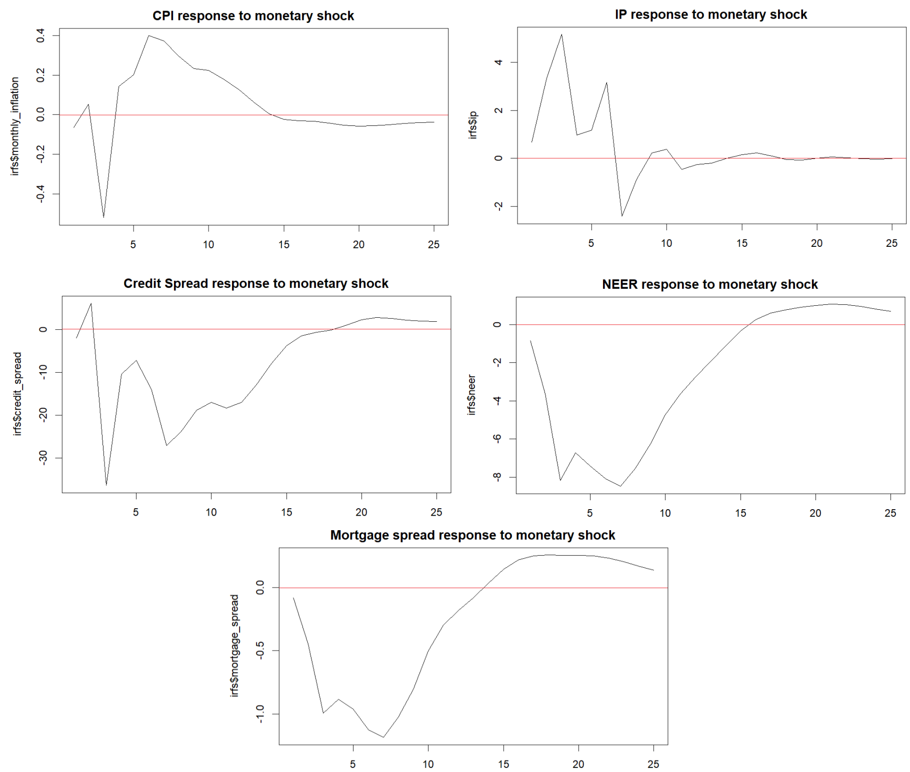

Figure 3: Response functions of base model with seven variables: monthly data on industrial production growth in percentage terms, inflation - in percentage terms, credit spread - in base points, global volatility index, nominal effective exchange rate - in percentage terms to the base in 2010, constructed measure for mortgage rate in percentage terms, and monetary policy indicator (official key rate of Bank of Russia) - in percentage terms. Identifications of SVAR model - with external instruments of constructed pure monetary component based on $OFZ2$ instrument. The order of the reduced form model (p=3) was chosen depending on the Akaike and Schwarz information criteria and instrument significance.

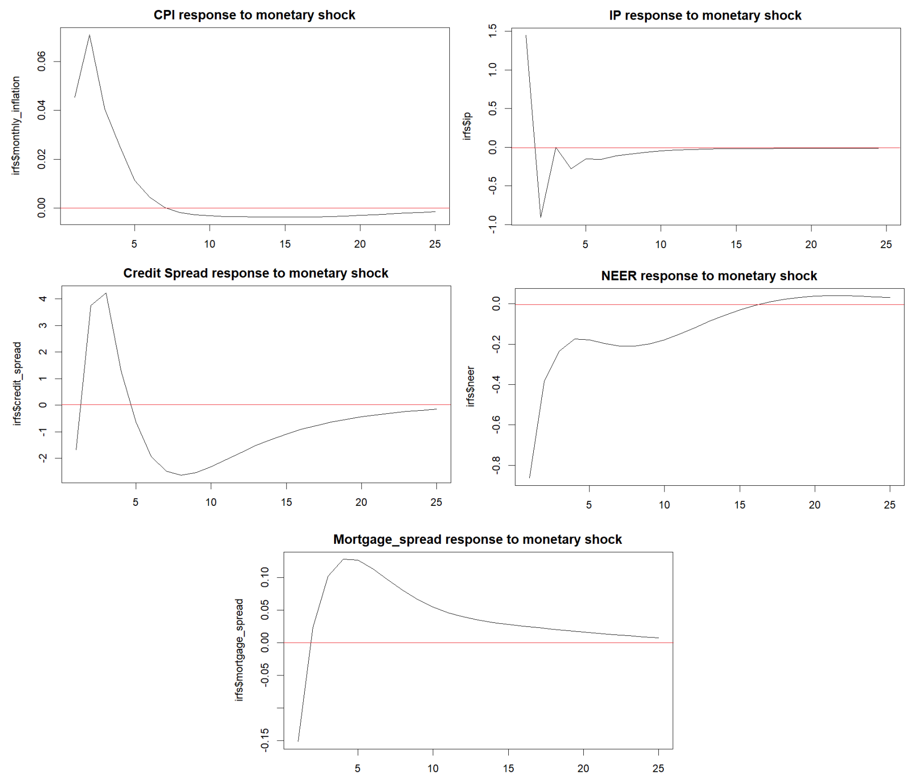

Figure 4: Response functions of base model with seven variables: monthly data on industrial production growth in percentage terms, inflation - in percentage terms, credit spread - in base points, global volatility index, nominal effective exchange rate - in percentage terms to the base in 2010, constructed measure for mortgage rate in percentage terms, and monetary policy indicator (official key rate of Bank of Russia) - in percentage terms. Identifications of SVAR model - with external instruments of constructed general high frequency price changes based on $OFZ6$ instrument. The order of the reduced form model (p=3) was chosen depending on the Akaike and Schwarz information criteria and instrument significance.