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 uses 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 likely counteracts the general expectations [Nakamura and Steinsson 2018].

Recent developments in the field suggest text analysis for study of informational effects of 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 of high frequency monetary shocks in developing economies are not as numerous: Mallick and Sousa 2012 have come to similar conclusions about for 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 the 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 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 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 existence is verified by case study analysis and the evidence of financial market response (MAYBE NOT!!!!!!!!!!!). 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]

[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 processing.

We have downloaded all texts of 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 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/ because we could not find another consistent source that would publish financial analysis of Russian economy throughout 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 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 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:

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. Than 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 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 from provided by open community Hugging Face. The models, present for 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 as computational linguistic tool - mainly for topic modelling - to include the

[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.

results into VAR framework. Though, 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 has 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 develop links between word 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 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 the expectation of the last term in the equation is zero, private sector's rational expectations of key rate would follow the rule:

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

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

[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.

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 monetary policy shock - an implementation error that creates deviation from the interest rate, desired by 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 amount of variables in the data (1024 for Sbert model and ??? for Ruberta) 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 is 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 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 question about model overfitting in Stage 3. Though, 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 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, 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 instrument, are significant instruments in first stage regression, therefore we decided to leave 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 is 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. Though, 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 enough.

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 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:

$$\left(\frac{E_{t,\tau+20}[S_{t+T}] - S_{t,\tau+20}}{S_{t,\tau+20}} - \frac{E_{t,\tau-10}[S_{t+T}] - S_{t,\tau-10}}{S_{t,\tau-10}}\right) \times \frac{365}{T} = i^d_{t,\tau+20} - i^d_{t,\tau-10}$$

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 and interesting substitution for the Federal Fund futures.

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 ans 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 is justified.

Basic model of small economy consists of 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. Though, our measure of credit spread does include it.

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.

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.

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

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.

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 the new information, and the present movement is created by small fraction of market participants, who did not "guess correctly" Central 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 a positive market reaction. Which counteracts conventional mechanism: in theory, if the interest rate is unexpect-

[5]Except for the futures that replicates 15-year bond. As 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 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.

edly increased, the return on bonds is not sufficiently high, which should drive the bond prices down.

As 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. Though, 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 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???????

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%[7].

5

6 SVAR analysis

Base specification. Based on multiple verifications with serial autocorrelation tests, information criteria, and residual normality tests, the appropriate model is VAR()

Open economy specification. VAR(2)

References

Akiba, Takuya et al. (July 25, 2019). *Optuna: A Next-generation Hyperparameter Optimization Framework*. arXiv:1907.10902. type: article. arXiv. DOI: 10.48550/arXiv.1907.10902. arXiv: 1907.10902[cs,stat]. URL: http://arxiv.org/abs/1907.10902 (visited on 06/12/2022).

Bannikova, Viktoria and Anna Pestova (2021). "The Effects of Monetary Shocks on Inflation: High-Frequency Approach". In: *Voprosy Ekonomiki* 6. ISSN: 0042-8736. DOI: 10.32609/0042-8736-2021-6-47-76. URL: http://elibrary.ru/item.asp?id=46256858 (visited on 05/29/2022).

Cai, Yong, Santiago Camara, and Nicholas Capel (Nov. 11, 2021). "It's not always about the money, sometimes it's about sending a message: Evidence of Informational Content in Monetary Policy Announcements". In: *arXiv:2111.06365 [econ, q-fin]*. arXiv: 2111.06365. URL: http://arxiv.org/abs/2111.06365 (visited on 11/25/2021).

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

[7] The reaction of bond market can be deduced.?????????????????????

Caldara, Dario and Edward Herbst (Jan. 2019). "Monetary Policy, Real Activity, and Credit Spreads: Evidence from Bayesian Proxy SVARs". In: *American Economic Journal: Macroeconomics* 11.1, pp. 157–192. ISSN: 1945-7707. DOI: 10.1257/mac.20170294. URL: https://www.aeaweb.org/articles?id=10.1257/mac.20170294 (visited on 06/15/2022).

Cesa-Bianchi, Ambrogio, Gregory Thwaites, and Alejandro Vicondoa (2020). "Monetary policy transmission in the United Kingdom: A high frequency identification approach". In: *European Economic Review* 123 (C). Publisher: Elsevier. ISSN: 0014-2921. URL: https://econpapers.repec.org/article/eeeeecrev/v_3a123_3ay_3a2020_3ai_3ac_3as0014292120300076.htm (visited on 06/12/2022).

David Lucca and Francesco Trebbi (2009). *Measuring Central Bank Communication: An Automated Approach with Application to FOMC Statements — NBER*. URL: https://www.nber.org/papers/w15367 (visited on 06/12/2022).

Devlin, Jacob et al. (May 24, 2019). *BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding*. arXiv:1810.04805. type: article. arXiv. arXiv: 1810.04805[cs]. URL: http://arxiv.org/abs/1810.04805 (visited on 06/02/2022).

Doh, Taeyoung, Sungil Kim, and Shu-Kuei Yang (Feb. 11, 2021). "How You Say It Matters: Text Analysis of FOMC Statements Using Natural Language Processing". In: *The Federal Reserve Bank of Kansas City Economic Review*. ISSN: 01612387. DOI: 10.18651/ER/v106n1DohKimYang. URL: https://www.kansascityfed.org/research/economic-review/how-you-say-it-matters-text-analysis-of-fomc-statements-using-natural-language-processing/ (visited on 11/08/2021).

Doh, Taeyoung, Dongho Song, and Shu-Kuei Yang (Oct. 15, 2020). "Deciphering Federal Reserve Communication via Text Analysis of Alternative FOMC Statements". In: *The Federal Reserve Bank of Kansas City Research Working Papers*. ISSN: 19365330. DOI: 10.18651/RWP2020-14. URL: https://www.kansascityfed.org/research/research-working-papers/deciphering-federal-reserve-communication-via-text-analysis/ (visited on 11/07/2021).

Gertler, Mark and Peter Karadi (Jan. 2015). "Monetary Policy Surprises, Credit Costs, and Economic Activity". In: *American Economic Journal: Macroeconomics* 7.1, pp. 44–76. ISSN: 1945-7707. DOI: 10.1257/mac.20130329. URL: https://www.aeaweb.org/articles?id=10.1257/mac.20130329 (visited on 05/29/2022).

Giannone, Domenico, Michele Lenza, and Giorgio E. Primiceri (Apr. 1, 2021). *Economic Predictions with Big Data: The Illusion of Sparsity*. SSRN Scholarly Paper 3835164. Rochester, NY: Social Science Research Network. DOI: 10.2139/ssrn.3835164. URL: https://papers.ssrn.com/abstract=3835164 (visited on 06/12/2022).

Handlan, Amy (2020). "Text Shocks and Monetary Surprises:" in: p. 65.

Hansen, Stephen and Michael McMahon (2016). "Shocking language: Understanding the macroeconomic effects of central bank communication". In:

Journal of International Economics. 38th Annual NBER International Seminar on Macroeconomics 99, S114–S133. ISSN: 0022-1996. DOI: 10.1016/j.jinteco.2015.12.008. URL: https://www.sciencedirect.com/science/article/pii/S0022199615001828 (visited on 01/11/2022).

Hansen, Stephen, Michael McMahon, and Andrea Prat (May 1, 2018). "Transparency and Deliberation Within the FOMC: A Computational Linguistics Approach*". In: *The Quarterly Journal of Economics* 133.2, pp. 801–870. ISSN: 0033-5533, 1531-4650. DOI: 10.1093/qje/qjx045. URL: https://academic.oup.com/qje/article/133/2/801/4582916 (visited on 11/10/2021).

Jarociński, Marek and Peter Karadi (Apr. 2020). "Deconstructing Monetary Policy Surprises—The Role of Information Shocks". In: *American Economic Journal: Macroeconomics* 12.2, pp. 1–43. ISSN: 1945-7707. DOI: 10.1257/mac.20180090. URL: https://www.aeaweb.org/articles?id=10.1257/mac.20180090 (visited on 05/29/2022).

Ke, Shikun, José Luis Montiel Olea, and James Nesbit (2021). "Robust Machine Learning Algorithms for Text Analysis". In: p. 50.

Ke, Zheng Tracy, Bryan T. Kelly, and Dacheng Xiu (Sept. 30, 2020). *Predicting Returns with Text Data*. SSRN Scholarly Paper 3389884. Rochester, NY: Social Science Research Network. DOI: 10.2139/ssrn.3389884. URL: https://papers.ssrn.com/abstract=3389884 (visited on 06/15/2022).

Mallick, Sushanta and Ricardo Sousa (Sept. 1, 2012). "Real effects of monetary policy in large emerging economies". In: *Macroeconomic Dynamics* 16, pp. 190–212. DOI: 10.1017/S1365100511000319.

Miranda-Agrippino, Silvia and Giovanni Ricco (July 2021). "The Transmission of Monetary Policy Shocks". In: *American Economic Journal: Macroeconomics* 13.3, pp. 74–107. ISSN: 1945-7707. DOI: 10.1257/mac.20180124. URL: https://www.aeaweb.org/articles?id=10.1257/mac.20180124 (visited on 06/12/2022).

Nakamura, Emi and Jón Steinsson (2018). *High Frequency Identification of Monetary Non-Neutrality: The Information Effect*. Working Paper 19260. Series: Working Paper Series. National Bureau of Economic Research. DOI: 10.3386/w19260. URL: https://www.nber.org/papers/w19260 (visited on 06/15/2022).

Swanson, Eric T. and John C. Williams (Oct. 2014). "Measuring the Effect of the Zero Lower Bound on Medium- and Longer-Term Interest Rates". In: *American Economic Review* 104.10, pp. 3154–3185. ISSN: 0002-8282. DOI: 10.1257/aer.104.10.3154. URL: https://www.aeaweb.org/articles?id=10.1257/aer.104.10.3154 (visited on 06/13/2022).

Tishin, Alexander (2019). "Monetary Policy Surprises in Russia". In: *Dengi i Kredit* 4. ISSN: 0130-3090. DOI: 10.31477/rjmf.201904.48. URL: http://elibrary.ru/item.asp?id=41552774 (visited on 05/29/2022).