# The Impact of Bank of Russia Monetary Policy Communication on the Stock Market

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# Research Background

- Communication by economic regulators influences social well-being and growth, in addition to direct effects of the policy (Algan and Cahuc 2014)
- The textual channel[1] of communication is the primary one:
  - low readability of reports **increases market volatility**, and only people with higher education understand them (Bruno 2017; Bulíř et al. 2012)
  - central banks' statements **affect media discourse** even several weeks after publication (Rybinski 2019)
  - voice tone of FED Chair's statements **affects share prices** (Gorodnichenko et al. 2021)
  - stock market is **sensitive to tone sentiment**, embedded in textual reports (Oshima and Matsubayashi 2018; Tumala 2019; Lee et al. 2019)

[1] It can be decomposed down to various indices: readability, sentiment, transparency etc.

# Research Question

- Linguistic and especially sentiment analysis of regulators' speech is limited to dictionary approach[2] or simple counting methods
- Natural language processing (NLP) models give more accurate results, closer to real perception (Smetanin and Komarov 2019)
- Bank of Russia (BoR) communication is still fairly underinvestigated
- How does BoR monetary policy communication affect stock market?

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# Textual Data

- The initial dataset contained all press service publications in the last decade, published on the BoR website, but importance of the **texts was too heterogenous**
- The sample was narrowed down to the **press releases** on the key rate and the corresponding **press conferences** by the BoR Governor
- Applying an automatic framework to the sample, a tone sentiment was computed for 40 press-conferences and 69 press-releases, covering the period between September 2013 and December 2021

# Textual Data

**Table 1:** Summary statistics for press releases and statements (2010-2022)

| Communication channel | Num of obs. | Mean num of symbols | Min num of symbols | Max num of symbols | Mean num of sententences | Mean num of words |
|---|---|---|---|---|---|---|
| Press releases | 12521 | 1444.9 | 131 | 31075 | 5.3 | 216.8 |
| On the key rate | 111 | 4805.3 | 496 | 10143 | 35.0 | 683.6 |
| Other | 12410 | 1414.8 | 131 | 31075 | 5.0 | 212.6 |
| Statements | 123 | 22649.0 | 192 | 43320 | 192.5 | 3690.4 |
| On the key rate | 41 | 30366.3 | 13700 | 38361 | 281.9 | 5040.3 |
| Other | 82 | 18790.3 | 192 | 43320 | 147.9 | 3015.5 |

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# Style Indicator

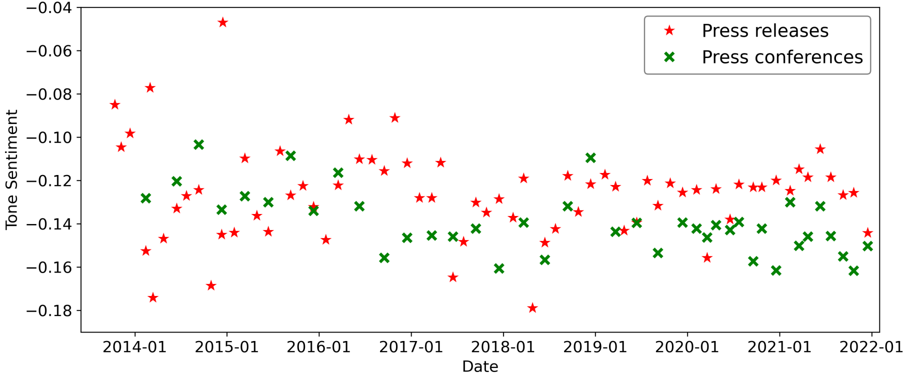
- As summarized in paper by Evstigneeva and Sidorovskiy (2021) and proven in work by Smetanin and Komarov (2021), the state-of-the-art **transformer language models** suggest the highest accuracy score in the sentiment predicting task
- In this study, Dostoevsky model[3] is used for computing a vector of the sentiment probabilities for each text
- **Tone sentiment** reflects net positive sentiment, which ranges from -1 (negative connotations) to 1 (positive connotations):

$$Tone\ Sentiment = Prob(Positive\ Sentiment) - Prob(Negative\ Sentiment)$$

[3] A neural network pre-trained on RuSentiment dataset (Rogers et al. 2018)

# Tone Sentiment Distribution

**Figure 1:** Tone sentiment distribution for the commentary on the key rate



# Market Data

- Daily economic outcomes:
  - Returns on MOEX and RTS indices
  - Returns on gold exchange trade fund (FXGD ETF), which is used as the proxy for immediate reaction of the inflation expectations
- Yearly control variables:
  - General transparency of a regulator's communication under inflation-targeting regimes, suggested by Al-Mashat et al. (2018)
  - Public trust in the Bank of Russia based on a representative all-Russian sample ("INFOM" 2021)

# Empirical Model

$$Outcome_{it} = \alpha_i + \beta_{1i} Tone\ Sentiment_{1t} + \beta_{2i} Tone\ Sentiment_{2t}$$
$$+\gamma_i Rate\ Change_t + \gamma_{1iy} Transparency_y + \gamma_{2iy} Trust_y + \epsilon_{it}$$

- $Tone\ Sentiment_{1t}$ - the sentiment of the press conference by the Governor of the Bank of Russia on the day $t$
- $Tone\ Sentiment_{2t}$ - the sentiment of the press release on the day $t$
- $Rate\ Change_t$ - the absolute change of the key rate on the day $t$

# Results

**Table 2:** Instant effect of tone sentiment, MOEX returns

| | MOEX returns | | | | |
|---|---|---|---|---|---|
| Variable | (1) | (2) | (3) | (4) | (5) |
| Tone Sentiment$_1$ | 0.116 | | 0.124 | 0.298** | 0.296** |
| | (0.0996) | | (0.101) | (0.111) | (0.112) |
| Tone Sentiment$_2$ | | -0.379 | -0.216 | -0.372* | -0.351** |
| | | (0.390) | (0.225) | (0.196) | (0.172) |
| Rate Change | | | -0.0745 | -0.277 | -0.324 |
| | | | (0.374) | (0.356) | (0.335) |
| Transparency | | | | 0.296** | 0.243 |
| | | | | (0.134) | (0.175) |
| Trust | | | | | -1.920 |
| | | | | | (3.166) |
| *Number of obs.* | 40 | 69 | 40 | 40 | 40 |

**Note.** For better interpretability the returns, as the differences between the logs of the open and close prices, are scaled to the basic points. Both tone sentiment variables are normalized to unit variance. Robust standard errors are given in parentheses: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

# Results

**Table 3:** Instant effect of tone sentiment, RTS returns

| | RTS returns | | | | |
|---|---|---|---|---|---|
| Variable | (1) | (2) | (3) | (4) | (5) |
| Tone Sentiment$_1$ | 0.0598 | | 0.0613 | 0.275* | 0.272 |
| | (0.143) | | (0.149) | (0.158) | (0.163) |
| Tone Sentiment$_2$ | | -1.094** | -0.306 | -0.497 | -0.473 |
| | | (0.514) | (0.340) | (0.301) | (0.282) |
| Rate Change | | | -0.400 | -0.649 | -0.704 |
| | | | (0.550) | (0.546) | (0.519) |
| Transparency | | | | 0.364* | 0.302 |
| | | | | (0.206) | (0.282) |
| Trust | | | | | -2.217 |
| | | | | | (4.968) |
| *Number of obs.* | 40 | 69 | 40 | 40 | 40 |

**Note.** For better interpretability the returns, as the differences between the logs of the open and close prices, are scaled to the basic points. Both tone sentiment variables are normalized to unit variance. Robust standard errors are given in parentheses:
*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

# Conclusion

- MOEX returns:
  - 1 std. dev. in the tone sentiment of a press conference **increases** returns by 29.6 basis points
  - 1 std. dev. in the tone sentiment of a press release **decreases** returns by 35.1 basis points
- RTS returns:
  - The magnitude is similar, but the estimates are less stable
- FXGD returns:
  - The effect seems to be insignificant

# Improvements

- Use another model to construct tone sentiment index:
  - RuBERT fine-tuned on Kaggle Russian News Dataset (Smetanin and Komarov 2021)
- Exploit dynamic effects model to test accumulation of the effect
- Apply the analysis to high-frequency data:
  - Effects from tone sentiment of press releases would be separated
- Estimate the bond market reactions, using OFZ indices

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# APPENDIX

**Figure A1:** Dynamics of the key rate

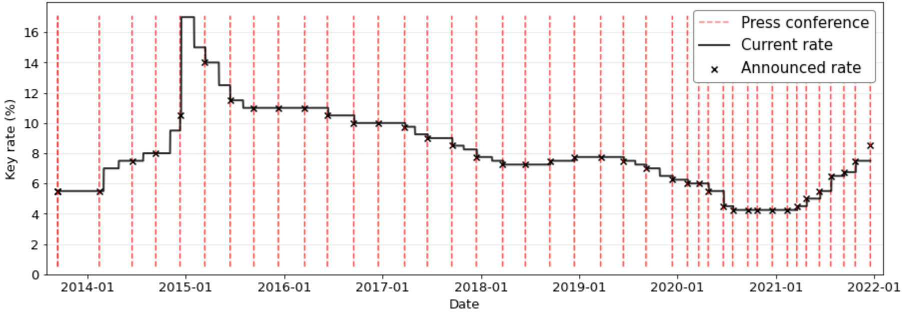


**Figure A2:** Tone sentiment distribution for 2010-2022

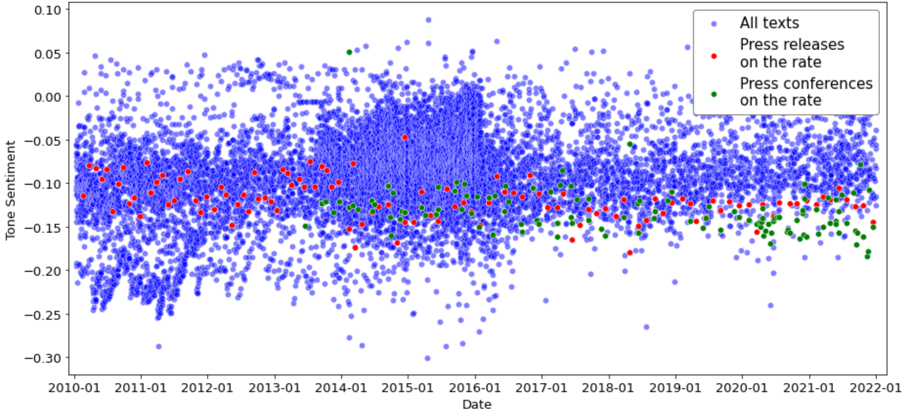
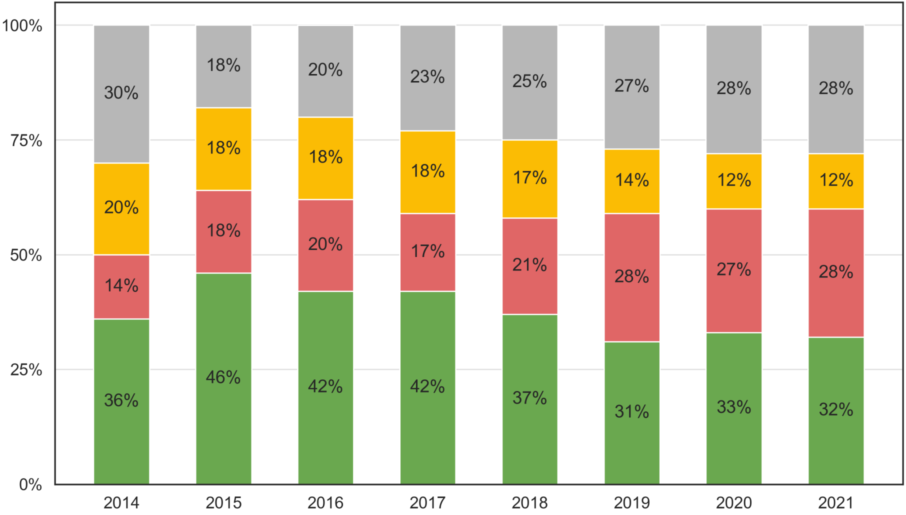


**Figure A3:** FXGD close price (RUB per share)

**Figure A4:** Public trust in Bank of Russia by InFOM (Public Opinion Foundation, Russia, 2021)



# Results

**Table A4:** Instant effect of tone sentiment, FXGD returns

| | FXGD returns | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Tone $\text{Sentiment}_1$ | 0.124 | | 0.128 | 0.154 | 0.154 |
| | (0.318) | | (0.329) | (0.443) | (0.451) |
| Tone $\text{Sentiment}_2$ | | -0.210 | -0.263 | -0.286 | -0.283 |
| | | (0.156) | (0.320) | (0.351) | (0.364) |
| Rate Change | | | -0.263 | -0.292 | -0.298 |
| | | | (0.422) | (0.359) | (0.404) |
| Transparency | | | | 0.0435 | 0.0376 |
| | | | | (0.269) | (0.313) |
| Trust | | | | | -0.214 |
| | | | | | (6.968) |
| *Number of obs.* | 40 | 65 | 40 | 40 | 40 |

**Note.** For better interpretability the returns, as the differences between the logs of the open and close prices, are scaled to the basic points. Both tone sentiment variables are normalized to unit variance. Robust standard errors are given in parentheses:
*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

**Table A2:** Test of the non-linear dependence between the explanatory variables

| | Tone Sentiment$_1$ | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Tone Sentiment$_2$ | 0.0881 | -0.0976 | 16.04 |
| | (0.178) | (2.862) | (33.07) |
| Tone Sentiment$_2^2$ | | -0.695 | 121.0 |
| | | (10.69) | (248.7) |
| Tone Sentiment$_2^3$ | | | 303.1 |
| | | | (618.7) |
| *Number of obs.* | 40 | 40 | 40 |

**Note.** OLS standard errors are given in parentheses: $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.