Monetary Policy and the Yield Curve*

Vladislav Abramov† Konstantin Styrin‡ Alexander Tishin§

April 2022

Abstract

This paper discusses the impact of monetary policy on financial and macroeconomic variables in Russia. We distinguish two types of monetary policy: (1) that causes by changes in the current rates and (2) that causes by any other reason (such as forward guidance, communication, and central bank information). We find that these two types have distinct effects on financial variables. The first type better explains the variation of interest rates for the entire yield curve. In contrast, the second type explains the variation in the exchange rate and market indices. Moreover, we also show that monetary policy transmission from interest rates to inflation takes about one year but this effect is only temporary.

Keywords: monetary policy surprises, high-frequency identification, principal component analysis

JEL Codes: E52, E58, E43, E44

* **Link to the most recent version.** All remaining errors are the authors' responsibility.

†Bank of Russia, abramovvv01@mail.cbr.ru
‡Bank of Russia, styrinka@mail.cbr.ru
§Bank of Russia, tishinav@mail.cbr.ru; corresponding author

1 INTRODUCTION

This paper takes monetary policy seriously. Monetary policy remains the most important tool for achieving price stability, especially when many central banks have adopted the inflation targeting paradigm. While many advanced economies (AEs) are stacked in liquidity traps, unconventional monetary policy has become commonplace and necessary. However, in emerging market economies (EMEs), both interest rates usually are far enough away from the zero lower bound, and inflation is much more volatile. Hence, central banks in EMEs are more actively using their conventional policy tools (e.g., the policy rate) to manage inflation.

Furthermore, there is widespread agreement that monetary policy is not a one-dimensional type of policy; instead, it has different dimensions (Gürkaynak, Sack, and Swanson (2005), Altavilla et al. (2019), and Jarociński and Karadi (2020) and many others). For instance, according to the interest rate expectation theory (Mishkin, 2007), setting a monetary policy rate today influences not only today's short-term money market rates but also expectations about future interest rates in the economy. Furthermore, central banks also try to manage expectations via various types of public communication by giving press conferences after the policy meetings, providing multiple analytical and research publications (e.g., disclosing the expected future path of the key rate, GDP growth trajectories, or mentioning the view of the economic situation and underlying risks in the economy). Therefore, it becomes essential to correctly estimate how different dimensions of monetary policy transmit to the real economy and financial markets.

In this paper, we attempt to assess the monetary policy transmission in Russia. To do it, we assume that monetary policy is multidimensional, namely, it has two separate dimensions. The first one, which we call regular monetary policy (target shock), influences only short rates[1]. The second one, which we call forward guidance

[1]The near part of the yield curve.

monetary policy (path shock), influences long- and medium-term rates[2]. Specifically, we collect the exact date and time of each policy meeting from 2011 and then calculate daily returns for each instrument for a day of a meeting. Then, we apply a principal component analysis (PCA) to this set of daily monetary policy surprises to extract the first two components. Finally, we find a rotation of these components such that the first principal component refers to regular monetary policy and the second to forward guidance monetary policy.

The transmission of Russian monetary policy is not yet profoundly studied. For example, Tishin (2019) applied a high-frequency identification scheme to the Russian economy. Although he used only one high-frequency instrument and identified only one monetary policy shock, he found a price puzzle. Other papers, such as Pestova and Bannikova (2021), got further in research of Russian monetary policy and improved the estimation of monetary policy surprises by exploiting uncovered interest parity. However, they still use a one-dimensional monetary policy measure and still observe a price puzzle.

We fill this gap and find that target and path shocks play a conceptually different role in the transmission of monetary policy. Target shock is more important for the term structure of interest rates. It increases the short rate by almost 1:1. What's more, it also statistically significantly influences long-term rates. In response to 25 basis points (bp.) target shock, 15 years bonds yield increases to 10 bp., which is a bit larger than usually found in similar exercises in the US and EA. However, the role of path shock for interest rates is considerably smaller. 10 bp. path shock influences only medium and long-term interest rates less than their original value (<10 basis points). Additionally, target shock is this shock that explains almost all variance in interest rates.

Moreover, path shock becomes more important for financial variables. For example, in response to the 25 basis points target shock, the exchange rate appreciates by less than 1%, and a stock markets index is insignificant. However, in response to

[2]The far side of the yield curve.

10 basis points path shock, the exchange rate depreciates more than 1%, and the stock markets index decreases. Furthermore, path shock explains much variation in financial variables. Thus, the unconventional policy, such as forward guidance, is not that effective for short-term and long-term rates but has a potent impact on Russia's asset prices and exchange rate dynamics. Our results are robust for different specifications of monetary policy shocks[3]. We additionally estimate our models on a rolling window sub-sample to ensure that our results are not caused by periods of high turbulence or structural breaks.

Our contribution is three-fold. Firstly, we adapt Gürkaynak, Sack, and Swanson (2005) methodology to Russian data: we combine high-frequency data of exchange tradable and Over-the-counter (OTC) instruments. Secondly, the multidimensionality of monetary policy is a novel study for Russia that solves price puzzles that emerged in previous papers. This direction is equally important for academic research and the design and evaluation of monetary policy. Thirdly, we apply our results to both financial and macroeconomic variables while many papers usually studied them separately.

In this paper, we rely on high-frequency monetary policy surprises, pioneered by Kuttner (2001), which have gained tremendous popularity in modern literature. He was the first who disentangled the expected component of policy actions from unanticipated shocks using data from futures markets to estimate the transmission mechanism from the monetary decision to interest rates in the economy. The idea behind basic high-frequency identification (HFI) is to isolate monetary policy shocks within a tight-enough time window around monetary policy decisions (or other monetary policy communication events). By assumption, there is no other systematic news in this time window, except monetary policy event itself. As a substantial advantage of high-frequency data, monetary policy shocks usually bear less endogeneity bias than VAR-based counterparts.

[3]Different instruments that were used to identify monetary policy shocks.

While high-frequency identification has become a standard tool to study monetary policy transmission to the economy, many early studies found puzzling effects of using a one-dimensional measure of monetary policy. Later, however, many researchers have significantly developed the idea of HFI further. The role of information and other shocks that emerged in monetary policy announcements is now widely acknowledged in the literature. There are seminal papers (such as Gürkaynak, Sack, and Swanson (2005), Jarociński and Karadi (2020), Jarocinski (2021), and Swanson (2021)) that provide evidence that policy announcements contain a mix of different monetary policy shocks – a current rate decision, large scale asset purchases, disclosure of Central bank private information, forecasts about the future stance of the economy, etc.

This idea of multidimensionally monetary policy was first carefully examined in Gürkaynak, Sack, and Swanson (2005), where the authors identified two monetary policy shocks and looked at the response of financial variables to these shocks. Later, Swanson (2021) expanded this approach and added the third shock that appeared during the financial crisis in 2007-2008 – large scale asset purchases (LSAP) shock. In both papers, the authors used principal component analysis to identify shocks. We took the same approach in our work and estimated monetary policy surprises from high-frequency data for assets with different maturity in line with Gürkaynak, Sack, and Swanson (2005) (hereafter GSS).

Furthermore, the identification of Jarociński and Karadi (2020) is based on another approach, they used the fact that financial markets react differently to different news. They exploited this observation that assumes that in response to a positive regular monetary policy shock, interest rate increases and the market index decreases, while in response to central bank information shock, both interest rate and market index increase. Another stellar example is Nakamura and Steinsson (2018), which studies the non-neutrality of money, explaining this phenomenon by the fact that FED announcements contain information not only about monetary policy and interest rates but also FED's outlook on the economy. This leads to puzzling responses to forecasts, which contradicts the economic theory. The authors called this the "Fed Information Effect". A similar idea is that the central bank's press-realizes and communication contain information about economic fundamentals studied in Cieslak and Schrimpf (2019). Bauer and Swanson (2020) attempted to explain the "Fed Information Effect" and show that the public and the FED react to the same macroeconomic news. Jarocinski (2021) assuming a non-normal distribution of shocks find that it is possible to identify four conceptually different monetary policy shocks. Besides, regular and LSAP shocks, Jarocinski (2021) divided forward guidance shock into two different components, similar to ideas in Campbell et al. (2012): Delphic and Odyssean forward guidance.

There are many other modern techniques to identify monetary policy shocks. For instance, Miranda-Agrippino and Ricco (2021) studied the role of the information in monetary policy transmission using forecast-based identification. They define a monetary policy shock as an unanticipated change in market instruments unrelated to the central bank's systematic response to its economic forecasts. That means the authors clean up usual monetary policy surprises from any future information summarized in projections. As well as Bachmann, Gödl-Hanisch, and Sims (2021) used central bank information set to identify monetary policy surprises. They exploit the revision in statistical data to extract exogenous variation in monetary policy.

Kaminska, Mumtaz, and Sustek (2021) applied an affine term structure model to high-frequency changes in the yield curve. Gurkaynak, Kisacikoğlu, and Wright (2020) and Bu, Rogers, and Wu (2021) exploited the idea that the volatility of financial instruments is different in the policy announcement period and other periods. Thus, they applied heteroskedasticity-based identification. Another gaining popularity approach is based on machine learning methods. Munday and Brookes (2021) using computational linguistic tools, examined the communication efficiency of the Bank of England. Ter Ellen, Larsen, and Thorsrud (2019) applied a text analysis to Norwegian data and estimated "narrative monetary policy surprises" for Norges Bank. They used both official communication and accompanying media coverage to extract monetary policy surprises. Finally, Gorodnichenko, Pham, and Talavera (2021) studied the influence of press conferences on asset prices. Using computational linguistic techniques, they decompose the tone of answers during the Q&A session after the policing announcement.

Virtually all of the mentioned above papers conclude that to assess the monetary policy's transmission mechanism thoroughly, we need to take into account the multidimensionality of policy.

The incredible depth and liquidity of financial markets in the EU and the US provide researchers with an opportunity to explore different approaches to studying monetary policy Gertler and Karadi (2015), Altavilla et al. (2019), and Leombroni et al. (2021). However, few papers use modern techniques (such as high-frequency identification) to estimate the transmission in emerging economies. Taking into account that financial markets are yet quite well developed in many such countries, there should be no problem in exploring high-frequency data.

We are familiar with a limited number of such papers. Aruoba et al. (2021) use monetary policy surprises as a difference between the actual monetary policy decision and the consensus forecast of Bloomberg experts. Then, they used these surprises in Bayesian Vector Auto Regression to find responses of macroeconomic variables. There are many questions to such an identification scheme, such as noisiness of data, the timing of Bloomberg surveys, etc. Ceballos (2014) also used the consensus forecast from Bloomberg to calculate surprises and study how these surprises affect the yield curve. Surprisingly, only a couple of papers study monetary policy transmission to interest rates in other AEs, except the Euro area and the US. Some rare examples are Kubota, Shintani, et al. (2020) and Nagao, Kondo, and Nakazono (2020), which studied unconventional monetary policy in Japan using high-frequency data. Laséen (2020) and Brubakk et al. (2021) studied the effects of forwarding guidance and central bank information on assets prices and economic activity in Sweden and Norway.

TARGETING INFLATION IN RUSSIA Before going further, we tell a brief history of monetary policy in Russia. Russia has a relatively small history of inflation targeting (IT). Only at the end of 2014 Russia adopt the IT framework and set an aim for inflation close to the target of 4%[4] in the medium term. After that, there are eight policy meetings each year. Gaining initial experience in inflation targeting, the Bank of Russia enhanced the transparency of its monetary policy actions. For instance, now the Bank organizes a press conference on the day of the policy announcement. After ten days, it published a detailed monetary policy report that discusses the decision and provides a careful assessment of the economic outlook for analysts and the general public. Moreover, the Bank of Russia has only recently started publishing a future trajectory of the key rate. All these actions added versatility and transparency to the policy of the Central Bank and are devoted to explaining to the public the whole process, and the motivation behind each monetary policy decision. Thus, the current monetary policy of the Bank has multidimensional facets.

The rest of the paper organized as follows. Section 2 presents our empirical methodology. Section 3 describes data. Section 4 shows the results. Section 5 discusses the policy implications. Section 6 concludes.

2 METHODOLOGY

Our analysis relies on three main steps. First of all, we need to calculate monetary policy surprises from high-frequency data. Then we extract two monetary policy shocks from this set of monetary policy surprises. Finally, we estimate the responses of government securities with different maturities, exchange rates, and stock market indexes in response to these two monetary policy shocks. In this section, we discuss each of these steps in greater detail.

[4] https://www.cbr.ru/eng/dkp/

2.1 *Monetary policy surprises*

Monetary policy surprises are unexpected changes in prices of some tradable and liquid enough instruments around policy meetings or press-conference or during other important events like media interviews. Our paper analyzes only policy meetings days because of two reasons. First, these days are pre-scheduled, and the timing is known in advance. Second, it is hard to justify the (un)importance of other public communication events of the Central Bank Governing Council members, as there is no systematic way in the literature at the time of writing this work to distinguish the wheat from the chaff *a priori*.

It is assumed that the instrument's price right before the meeting captures all available information accessible to the general public. The instrument's price after the meeting captures all new information that becomes available after the decision is released. The change between these two prices reflects a monetary policy surprise. Usually, the 'size' of the window around the monetary policy event is taken as 10 minutes before the meeting and 20 minutes after the meeting (Gürkaynak, Sack, and Swanson (2005), Gertler and Karadi (2015), and Swanson (2021) etc.). However, in our paper, we use a daily window because of observed data limitations. Specifically, we calculate a difference in closing prices a day before a policy meeting and closing prices on the day of the policy meeting.

Let's assume that there are two monetary policy shocks: ϵ_t^{target} (we denote it as regular monetary policy shock or target shock) and ϵ_t^{path} (we denote it as forward guidance monetary policy shock or path shock). Also, we denote $s_{i,t}$ as a monetary policy surprise and $p_{i,t}$ as a closing asset price on the day of the policy meeting. As assets, we use a wide range of instruments (we discuss them in detail in Section 3) that cover all yield curve (both exchange tradable and OTC). Therefore we add a subscript i to notion of monetary policy surprises: $s_{i,t}$ and asset prices $p_{i,t}$. Hence, we have a set of monetary policy surprises containing different information about structural shocks.

Also, subscript t does not denote the 'usual' time dimension but rather the 'monetary policy event' dimension (t changes not month-by-month but meeting-by-meeting).

$$s_{i,t} = \alpha_{i,target}\epsilon_t^{target} + \alpha_{i,path}\epsilon_t^{path} + \zeta_{i,t}, \tag{1}$$

$$cov(\epsilon_t^{target}, \zeta_{i,t}) = 0, \tag{2}$$

$$cov(\epsilon_t^{path}, \zeta_{i,t}) = 0, \tag{3}$$

$$\hat{s}_{i,t} = \frac{p_{i,t} - p_{i,t-1}}{p_{i,t-1}}. \tag{4}$$

With equation (1) we assume that monetary policy surprise is a weighted sum of two structural monetary policy shocks (ϵ_t^{target}, ϵ_t^{path}) with some idiosyncratic error ($\zeta_{i,t}$). Equation (4) indicates our assumption that changes in prices of some assets contain information about monetary policy surprises.

Note that regular monetary policy shock reflects the changes in the current monetary policy stance, i.e., it represents all changes in the current interest rates. Therefore, it influences the short end of the yield curve primarily. The definition of the second shock is a little more open to various interpretations. Formally speaking, the second shock shows us all the rest changes that are not explained by the first shock. In other words, it could be central bank information or a forward guidance policy. Hence, for simplicity, we call these shocks – forward guidance shocks. Thus, these shocks mainly affect the long end of the yield curve.

Usually, it is assumed that this surprise s_t is uncorrelated with all other events (x_t) that may affect monetary policy decision (equation (5)). Also, it should be correlated only with a structural shocks ϵ_t^{target} and ϵ_t^{path} (equations (6) and (7)).

$$\mathbf{E}(s_{i,t}x_t) = 0, \tag{5}$$

$$\mathbf{E}(s_{i,t}\epsilon_t^{target}) \neq 0, \tag{6}$$

$$\mathbf{E}(s_{i,t}\epsilon_t^{path}) \neq 0. \tag{7}$$

It is quite difficult to justify the exclusion restriction assumption (equation (5)) using daily surprises because there are much more events that could have happened than in a 30-minute window. However, we still can think that we estimate a monetary policy surprise because it is highly unlikely that on the same day there are other macroeconomic news will be released. Furthermore, there is also a so-called 'week of silence' before the policy meeting in Russia. It is a week when policymakers neither give interviews nor comment on the upcoming decision. Therefore, we can expect that the market participants have already formed their expectations. Therefore, although we understand that the data is noisier using a daily window setting, it still contains mainly information about monetary policy decisions.

2.2 *Principal Component Analysis*

After obtaining a set of monetary policy surprises, we need to divide it into two components: regular monetary policy shock and forward guidance monetary policy shock. To extract those components, we employ Principal Component Analysis (PCA), similar to Gürkaynak, Sack, and Swanson (2005).

Let's assume that we have N assets and T monetary policy announcements. We can collect it into $T \times N$ matrix X, where each element $x_{i,j}$ represents a daily surprise of asset j on the announcement made in time i. Then to extract k unobserved factor, we employ a factor model,

$$X_t = F_t \Lambda + \varepsilon_t, \tag{8}$$

where F_t is a $T \times k$ matrix contacting k unobserved factors (in our case we assume that $k = 2$ and later we confirm it by formal tests). Λ is $k \times n$ matrix of factor loadings and ε_t is the error term. Note, that the data used in PCA demeaned and standardized before analysis.

The idea of this factor model is the following. We need to identify matrix F, which indicates our k principal components. That means that the model tries to describe data in X by using fewer factors, $k < n$. So, this model reduces the dimensionality of X by estimating new uncorrelated factors that explain a maximum possible fraction of X variance.

Let's denote the first two principal component as $\eta_{1,t}$ and $\eta_{2,t}$. These principal components reflect two monetary policy shocks: regular and forward guidance. However, PCA gives us the only statistical transformation of original data. There is no reason to think that $\eta_{1,t}$ relates to the regular monetary policy shock and $\eta_{2,t}$ corresponds to the forward guidance shock. It means that any PCA decomposition is subject to orthogonal rotation (U): any model of $\tilde{F} = FU$ and $\tilde{\Lambda} = U'\Lambda$ gives us the similar principal components.

Therefore, among all possible rotations of U we need to find the one that would correspond to changes in regular monetary policy and forward guidance. That means that the first principal component, $\eta_{1,t}$, should reflect changes in short-term rates. The second principal component, $\eta_{2,t}$, should correspond to changes in long-term rates (and all other possible information about the future path of interest rates that are above and beyond changes in current interest rates). One way to find a rotation matrix is to make certain restrictions on the matrix $\tilde{\Lambda}$, similar to Gürkaynak, Sack, and Swanson (2005). However, we follow a slightly different approach here that gives us exactly the same results.

To estimate two monetary policy shocks: ϵ_t^{target} and ϵ_t^{path}, we:

1. Arrange monetary policy surprises $s_{i,t}$ in order $i = 1, 2, 3, \ldots N$ by their maturity, so, $s_{1,t}$ is a monetary policy surprise with the shortest maturity (e.g., government security with one month to expire), and $s_{N,t}$ is a monetary policy surprise with the longest maturity, correspondingly. Then, without loss of generality, only regular monetary policy constitutes a surprise $s_{1,t}$. That it, in equation (1) we assume that $\alpha_{1,path} = 0$.

2. Build an OLS projection on the principal component space, running a regression of $s_{1,t}$ on $\eta_{1,t}$ and $\eta_{2,t}$ and taking fitted values $\hat{s}_{1,t}$. By construction, $\hat{s}_{1,t} = \hat{\epsilon}_t^{target}$.

3. Build orthogonal complement to $\hat{s}_{1,t}$, by regressing $\eta_{1,t}$ on $\hat{s}_{1,t}$ and getting residuals as $\hat{\epsilon}_t^{path}$. After this rotation exercise we end up with two rotated principal components $\hat{\epsilon}_t^{target} = z_t^{target}$ and $\hat{\epsilon}_t^{path} = z_t^{path}$, which we use in our main exercise[5].

3 DATA

The most important task in our analysis is to collect all necessary data. In our paper, we use several courses of data. First, the data about each policy meeting is gained from the Bank of Russia. Second, all tradable instruments (such as bonds, stock market index, futures, and exchange rates) are collected from the Moscow Exchange. Third, all over-the-counter (OTC) tradable instruments (interest rate swaps, and forward rate agreements) are collected from Bloomberg. Finally, since it is impossible to obtain intra-day data for OTC Russian market, we use all data on a daily frequency.

POLICY MEETING DATES To calculate monetary policy surprises, we collect information from the beginning of 2008 to the middle of 2021 (2021M7) about the Board Directors' meeting dates. These meetings are crucial to the formation of monetary policy. As a result of these meetings, a decision is made on the policy rate and other tools at the disposal of the Bank of Russia based on the current and projected economic situation. However, we have market data only from 2011, limiting our data sample of policy meeting dates to start from the middle of 2011. Moreover, the Russian financial market was less developed and liquid in the 2000-es than nowadays, which also motivates the choice of sample length.

The Bank of Russia has been targeting inflation since the beginning of 2014; that is why the Bank of Russia increased the transparency and credibility of monetary

[5] We denote estimated values of monetary policy shocks as z_t^j for simplicity

policy. For instance, the Bank now has a pre-scheduled policy meetings date eight times per annum. Before 2014 policy meetings were irregular and without any 'time-consistency'. Our sample has information about the exact date and time of publication (up to one minute) and a full text of each press realize. We have data for 127 entries (policy meetings), but effectively we use this data only after 2011 because of the above-mentioned data limitations.

HIGH-FREQUENCY DATA To extract policy surprises that may reflect the changes in expectations about the current and future strand of monetary policy, we appeal to data that are available on high-frequency. Despite many previous papers, we use daily data to extract monetary policy surprises for several reasons. The main reason is the low liquidity of a government securities market. In contrast to the financial markets of many AEs, the Russian government bonds are traded almost exclusively by big institutional investors, with a relatively small share of private investors, which makes it less agile. As a result, those often clumsy players do not usually get involved in any speculative or high-frequency strategies and may not respond immediately to monetary policy shock. The second reason for using daily data is that there are no tradable instruments in the exchange market, which were closely related to the interest/key rate except government bonds. Therefore, we also have to rely on OTC markets and use several money market instruments for which the underlying assets are the interest or the policy rate.

However, we understand the limitations of this approach. It is harder to justify the exclusion restriction (a monetary policy surprise must be uncorrelated with all other events within the daily window) with the daily data. Therefore, we expect our monetary policy surprises to be noisier than intra-day surprises.

Thus, we use the following set of instruments (full description of data is in Appendix B). First of all, we use data on government securities. We apply here approach proposed by Nelson-Siegel (the construction of the fixed-maturity yield indexes directly from the bond data gave us similar results in general). The idea of this approach is that we use information from individual bonds with different maturities to fit the whole yield curve for a given date and time. In Appendix A we describe Nelson-Siegel methodology in details.

After applying the Nelson-Siegel model (we take an estimated model from the Moscow exchange website), we end up with two sets: (i) parameters of the model (β_0 serves as a long-term factor, β_1 serves as a short-term factor, β_2 serves as a medium-term factor and τ as the exponential decay rate), (ii) a fitted yield curve (from which we can choose any maturity for each date). Although we can obtain fitted values for any maturity, we chose to work with a reasonably detailed (yet compact) set of government bonds yields: 1 month, 3 months, 6 months, 9 months, 1 year, 2 years, 3 years, 5 years, 7 years, 10 years and 15 years.

Regressing monetary policy shocks on a similar set of variables used to construct those shocks in PCA is incorrect since the same information is contained in shocks and our variables of interest. Therefore, we use another set of tradable instruments to construct the yield curve. For the short term rate, we use a 1-month OFZ rate, futures on USD/RUB (Si, 3 months to expiration), futures on RTS (RTS, dollar-valued Russian stock market index, 3 months to expiration), and Moscow Exchange government bond index with less than 1-year duration (RUGBICP1Y, clean price index). Finally, we use interest rate swaps as proxies for the medium and long-term (from 1 year to 10 years) interest rates.

We prove that applying PCA to this set of variables gives us the first two principal components, which, after rotation, will work as our target and path monetary policy shocks. We check this with several methods. Firstly, we run a formal test of Cragg and Donald (1997) to determine the number of factors. The hypothesis (H_0) is: the number of factors equals k versus alternative: the number of factors is greater than k. The results are shown in Table 1 are clearly in favor of rejecting the null for $k = 0$ and $k = 1$. The null, however, is not rejected for $k = 2$, which tells us that the number of factors is at least two. Moreover, using the rule of thumb, we can show that the third eigenvalue becomes less than 1 (which also indicates that it is optimal to use two principal components). Finally, we also show in Figure 1 (bottom right picture) that the first principal component explains about 50% of variation in the original data, while the first and the second components together already explain more than 75%. Adding the third and subsequent components does not significantly improve explained variance's share. All this formal and graphical analysis suggests that there are at least two principal components in the data, which coincides with an economic intuition about the interpretation of these components.

Table 1: Test for a number of components

H_0: number of factors equals	degrees of freedom	Wald statistic	p -value
0	36	51	0.00
1	27	40.11	0.00
2	19	30.14	0.12

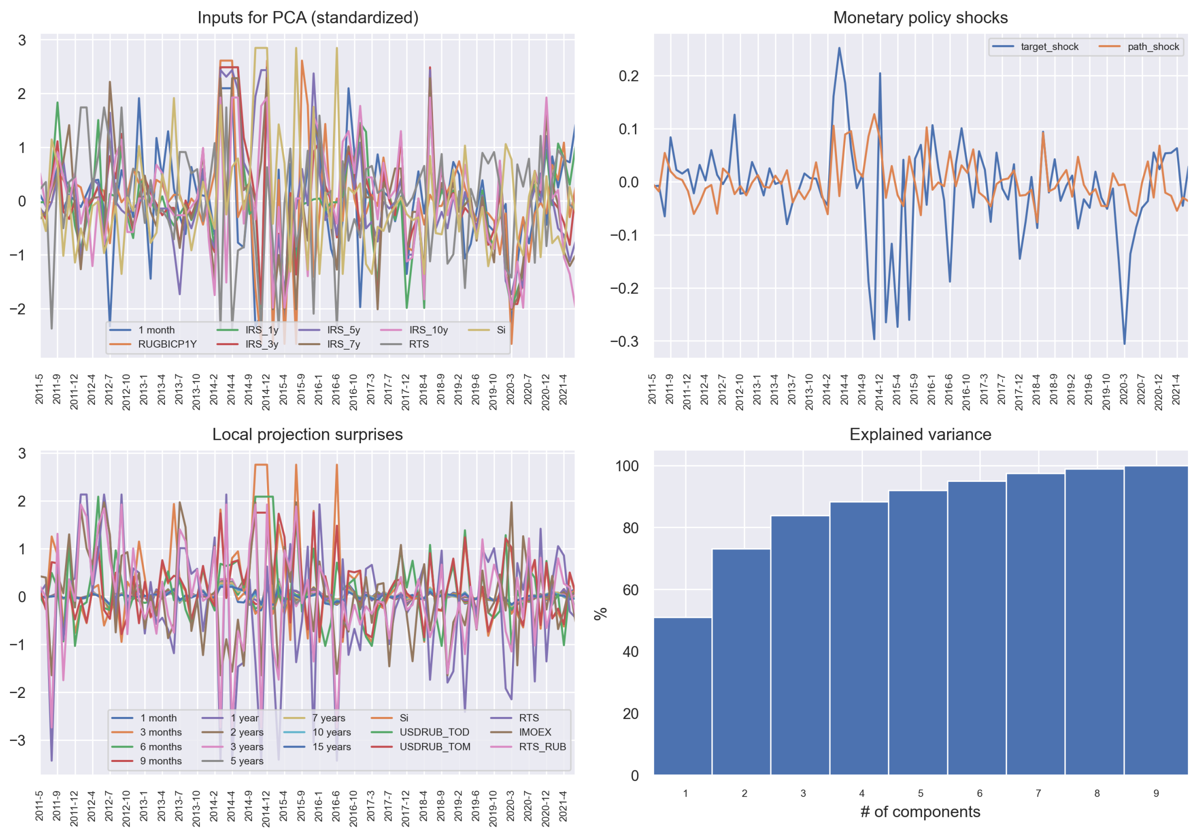

Figure 1: Descriptive figures

Let's graphically present our data. The first row of Figure 1 shows the raw data (surprises that are used as inputs for PCA, upper-left picture) and the extracted and rotated two monetary policy shocks (upper-right picture). The biggest shocks have occurred during the transition and volatile period of 2014-2015 and correspond to several unusually sharp monetary policy tightenings caused by the inflation surge in Russia and subsequent fast reversing of the policy in 2015. Also, there is a large negative target shock at the begging of 2020, corresponding to the policy easing in the COVID-19 period. Note that, path shock is less volatile than a target. Moreover, a positive path shock in June 2018 may be associated with a more negative economic outlook of the Bank of Russia (higher inflation and lower growth) related to the news about the VAT increase in January 2019. Finally, the bottom left picture shows data that is used in the local projection exercise (as Δy_t in equation (9)).

Also, we remove extreme values from the data because they negatively influence the estimation. We apply 5-95 winsorization, replacing extremely low and extremely high values in the data by 5% and 95% percentiles. Figure 1 already utilizes the cleaned data, as the reader can see from small vertical lines (which otherwise would become huge spikes). Winsorization is one of many standard methods to remove outliers. As an alternative, we also check the robustness of our results by employing the 1.5 and 3 interquartile range (IQR) rule and using different instruments for PCA (such as a full set of fitted OFZ values from the Nelson-Siegel model or forward rate agreements). The results remain stable and are available upon request.

As previously mentioned, all inputs to PCA are daily changes on the day of the monetary policy announcement. Interest rates are taken as a simple difference between the closing price on the day of the announcement and the closing price of the previous day. The variables that are not measured as yields or rates are taken as a percentage change over a similar period. Independent variables in local projections regressions (Δy_{t+h}) are changes between period $t+h$ and $t-1$. Indeed, with $h=0$, it is a change in a day of the monetary policy announcement.

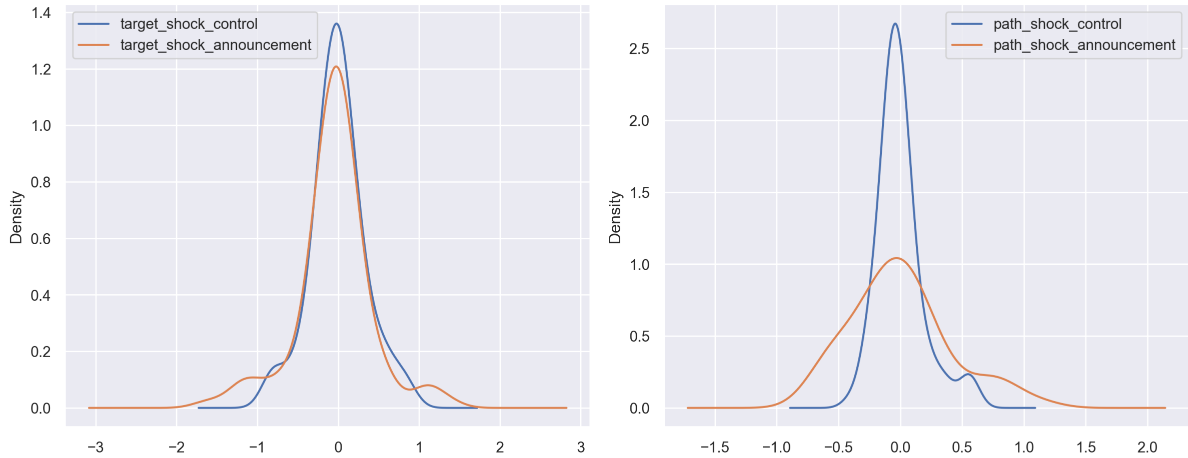

Figure 2: Announcement versus control: 1 week ahead

At the end of Section 4 we also apply a similar analysis to macroeconomic data such as inflation, industrial production, and exchange rates on a monthly frequency. In this case, (Δy_{t+h}) means the changes between each month and monetary policy shocks are aggregated to a monthly frequency.

Nevertheless, the last concern about the identified shocks may be about the background noise, similar concerns appear in Nakamura and Steinsson, 2018; Känzig, 2021. The idea is as follows. Some non-monetary news may affect the prices of our instruments. It is important because we consider daily surprises – larger window than usual 30-minutes surprises.

To address this concern, firstly, we refer to our local projections exercise and advise to consider any other day after day 0 (day of monetary policy announcement). The effects on returns on other days are considerably smaller.

Secondly, we compute our surprises on other days other than a day of monetary policy analysis. We take the same weekday but another week to form this control sample of monetary policy surprises. To check our surprises for background noise we compare densities for surprises computed on actual days of monetary policy announcement and surprises computed for days shifted one week ahead (Figure 2) and one week ago (Figure 3). Other experiments with shifting day of monetary policy surprises are available upon request.

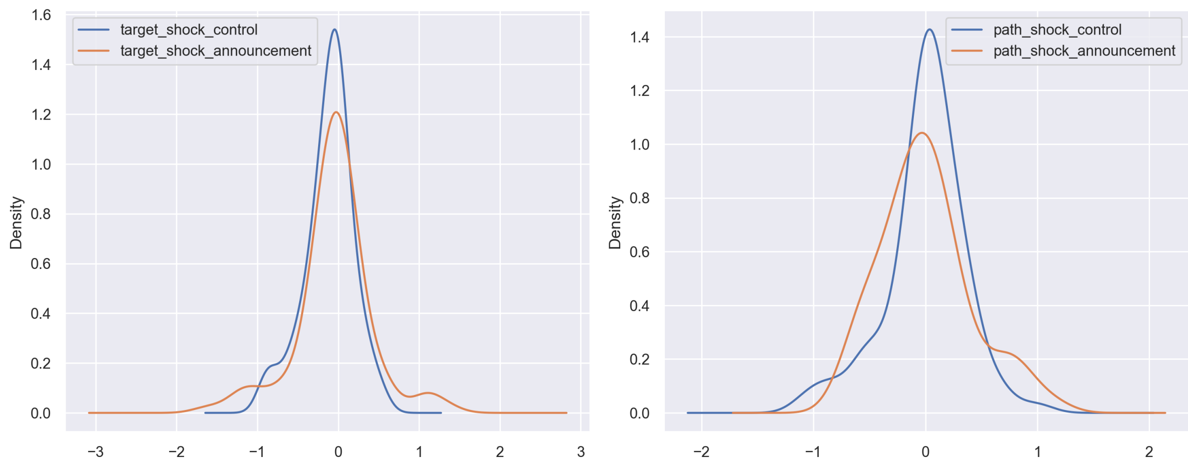

Figure 3: Announcement versus control: 1 week ago

These probability density functions show more variance and fatter tails for both target and path shocks on the days of the monetary policy announcement. It indicates that these days are unique. Moreover, we can also compute the variance and formal test for announcement and control surprises. However, we still need to be cautious because we use a daily window for surprises, therefore, some background noise can bias the results.

Finally, after winsorization, principal component extraction, and factor rotation, we obtain two monetary policy shocks which we use as independent variables in local projections in equation (9). Our dependent variables (Δy_{t+h} in the baseline model are: a set of fitted bonds values (from 1 month to 15 years) and several financial variables: USD/RUB futures, exchange rate (USD/RUB today and tomorrow), IMOEX stock market index, RTS dollar-valued futures on a stock market index. As robustness checks, we also used other independent variables (such as bond indices from Moscow exchanges based on actual (not fitted) yields). The results are available upon request.

4 RESULTS

Our paper is mostly devoted to the effects monetary policy decisions have on financial markets. As financial markets are usually able to process new information relatively fast and are characterized by high frequency and volatility, we start our discussion with the short-term effects of different types of monetary policy on financial variables on a daily basis.

Our main results are obtained from local projections model a-la Jordà (2005). In our work local projections take a simple following form:

$$\Delta y_{t+h} = \beta_0 + \beta_{target} z_t^{target} + \beta_{path} z_t^{path} + u_t. \tag{9}$$

Note, that sub index t denotes dates on monetary policy decisions (not consecutive days). While sub index h means consecutive days. So, Δy_{t+h} is the change between day $t+h$ and $t-1$ of the variable of interest around policy meeting day t.

In our first exercise, we look only at the contemporaneous reaction of financial variables. That is, we set $h = 0$, which means that we are analyzing responses of financial variables *in the day* of the monetary policy announcement.

The results are shown on Figure 4. The first column shows the reaction of a bonds curve (OFZ-curve), and the second column indicates the responses of financial variables (exchange rate and stock market indices). The first row corresponds to target shock; the second row corresponds to forward guidance shock. Finally, the last line shows R^2 in the models with just one or both shocks presented. The target shock is normalized in a way to influence the current interest rate exactly on +25 basis points (in our case, the shortest available interest rate – 1-month bond rate). The path shock is normalized to have a +10 basis points impact on the medium-term rate (in our case – 3 years bond rate).

We believe that 3 years is a horizon for monetary policy conducting[6]. Therefore, we think that changes in the policy rate should be reflected in changes in the short term rates, and changes in forward guidance, different communication, etc., should be focused on medium (and long) term rates.

[6] This horizon was mentioned repeatedly in the speeches of Board of Directors Members.

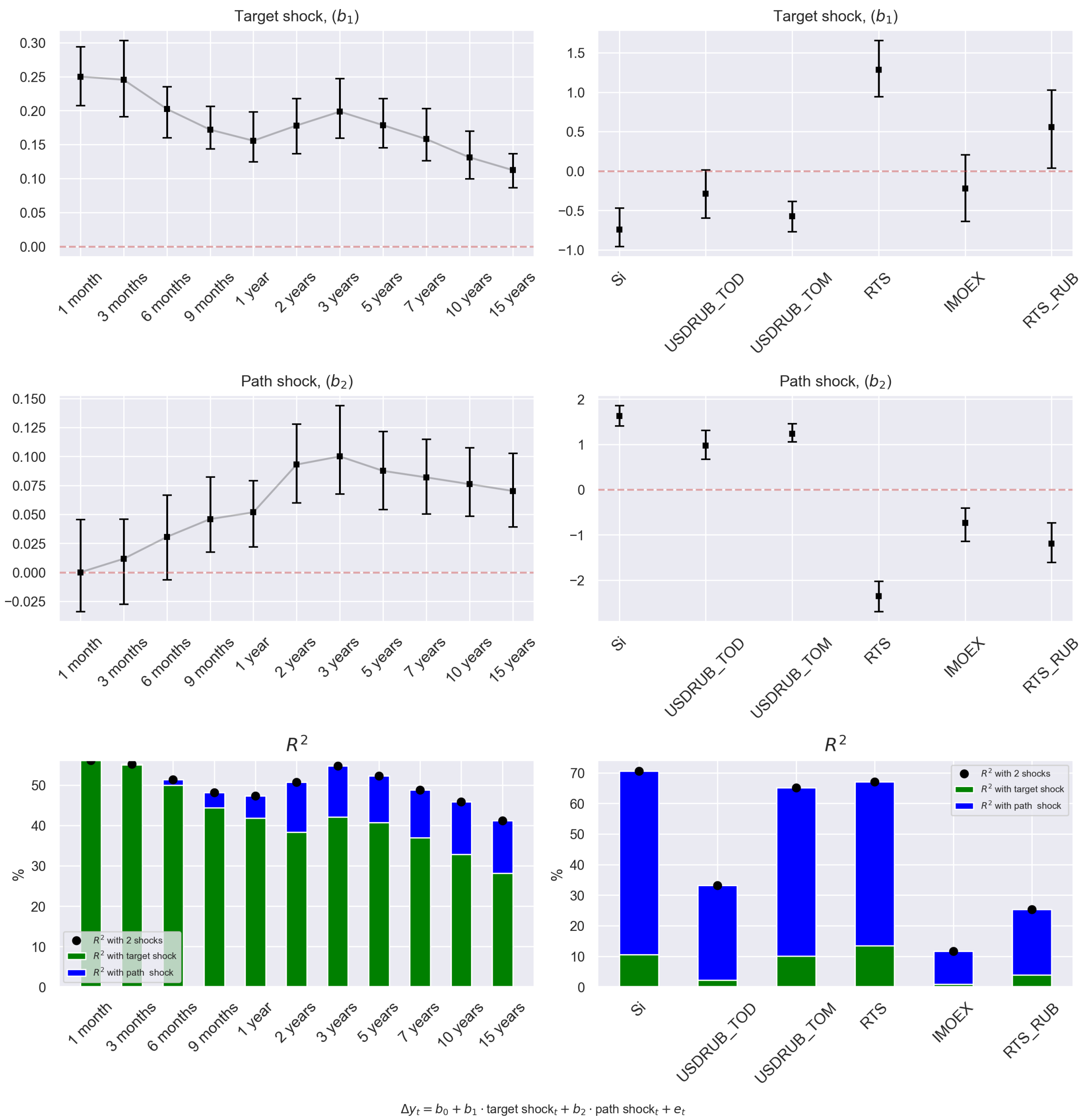

Figure 4: Contemporaneous regressions

The results are somewhat expected. In response to target shock, the highest reaction is for short-term rates. The 3 months bond rate increases almost 1-to-1 (up to 25 basis points). And then, the response generally fades out along the maturity spectrum. Medium-term rates (from 1 year to 5 years) show an increase from +20 to +15 basis points, and the long-term rates (7 years to 15 years) rise from +15 to +10 basis points.

Yet, we also observe some non-monotonic behavior. The reaction decreases for the short-term rates (up to 1 year), rises (from 1 to 3 years), and then declines again. This movement is interesting, and the local maximum coincides with the horizon length of monetary policy. Possible, the markets are more interested in the Bank of Russia's medium-term outlook, which adds to the response in this part of the yield curve. We also note that reaction of long term rates (7-15 years) are statistically significant, even that by constriction, the target shock must explain variation in short term rates in most.

The financial variables also have an expected reaction. In response to monetary policy tightening, exchange rates decrease (the ruble appreciates) by about 0.5%, which corresponds with economic theory. This appreciation is almost the same for USD/RUB futures (Si) and exchange rates with 'today' and 'tomorrow' settlements. The market index (IMOEX) reaction is not statistically significant at the 5% level, while the futures on the USD-denominated stock index (RTS) increases (primarily because of exchange rate appreciation).

In response to path shock (+10 basis points), the reactions of short-term rates are insignificant. Although the reaction increases from 9 months and further, it is still relatively small for all medium and long-term rates. Medium-term rates (2-5 years) increase slightly less than +10 basis points, while long-term rates (7-15 years) increase even less. It looks like the path shock is not very potent for interest rates, which somewhat contradicts the previous literature for the US and Europe.

However, we see a much stronger reaction of financial variables in response to the path shock. All kinds of exchange rates significantly deprecate (from 1% to almost 2%). Stock market indices decrease. IMOEX decreases slightly less than 1%, and RTS (that contains both decreasing index and deprecation of exchange rate) decreases higher than 2%.

Finally, in the last row of Figure 4, there are marginal R^2. These bars show the contribution of each of the shocks in explaining the variation of each variable. The green color corresponds to a contribution of target shock, and the blue color is for path shock. These bars confirm that target shock is more important for interest rate (because most of the variations in the bonds' rates are explained only by target shock).

Path shock, however, is much more important for explaining variation in financial variables.

LOCAL PROJECTIONS While contemporaneous regressions shed light on the current day reaction, it is uncertain how long the effects of monetary policy could last. To answer this question, we re-estimate equation 9 with $h = 0, \ldots, 20$, representing roughly a one-month span of business days ahead.

The results of the exercise are presented in Appendix C. In Figures 5-16 you can find the results of estimation for all bonds curve and financial variables. The left subfigure shows local projections coefficients for target shock, and the right subfigure is for path shock.

Speaking about the long-run (about month) effects of monetary policy on the yield curve, the change in the key rate must work as a level-shifter. Once interest rates are changed, they must remain on a new level until further changes, given all other things are equal. Indeed, we see that after the Bank of Russia announcement ($h = 0$ on figures), the interest rates rise and usually remain at the elevated levels for both target and path shocks and expectedly do not reverse back (at least for short-term rates). For long-term rates (5-15 years), we see a much less prolonged impact of target shock. It raises the long-term rates only during the first weeks after the decision; the effect becomes insignificant after that. However, somewhat in contrast with previous results from the contemporary analysis, a path shock plays an important role during the whole month after the decision.

The stock market index (IMOEX) significantly declines only due to path shock, with the effect lasting less than two weeks. On the other hand, the RTS (USD-denominated futures) increases in response to target shock (but the effect disappears after a couple of days) and significantly and persistently declines after path shock. Exchange rates behave similarly to each other: consistently appreciate in response to target shock, and depreciate in response to path shock.

ROLLING OLS One may notice that our sample of monetary policy events is quite heterogeneous. Indeed, the Russian economy is much more volatile than AEs usually analyzed in the literature. Several big shocks and structural changes, such as a switch in monetary policy regime in 2015, may change monetary policy transmission and introduce some bias in our results. This type of concern, for example, was examined for the US in Paul (2020), where the author exploits the time-varying parameters model and studies monetary policy transmission to asset prices. It turns out that monetary policy effects are not constant in time, and that should be taken into account.

To examine this issue in our data, we estimate the same equation (9) with $h = 0$ on a rolling window. We set the length of the window as 40 monetary policy events (which approximately corresponds to five years of monetary policy). The results are in Appendix D on Figures 17-28. The left sub-figures show estimated coefficients to target shock on a rolling window basis; the middle sub-figures correspond to path shocks, right sub-figure shows marginal R^2 for every window.

This exercise serves as a robustness test. As we see, all coefficients are relatively stable during the whole sample, suggesting a persistent transmission process from policy to the financial market. That also means we do not have significant outliers influencing our main results. One exception is a slight break in coefficients at the end of 2019 – the beginning of 2020, which presumably happened because it is the last period when 2015 still is in the sample. 2015 was a transitional year between two monetary policy regimes, characterized by high-interest rates volatility.

Further, in confirmation of past results, we see that the major part of interest rates variation can still be explained only by target shock during any sub-sample. At the same time, the variation of stock market indices and exchange rates is better explained by path shock.

MACROECONOMIC VARIABLES Finally, it is important to assess not only the reaction of financial markets to monetary policy but also macroeconomic variables. Monetary policy in Russia aims to ensure price stability; thus, the Bank of Russia needs to understand how monetary policy transmits into inflation. The reaction of other macroeconomic variables to monetary policy may also be a subject of interest.

Using similar regression as in equation (9) we estimate the model on a monthly frequency. Now index t denotes a month of the monetary policy announcement, and h shows the number of months after the monetary policy announcement. To aggregate monetary policy surprises from daily to the monthly frequency, we attribute a value of monetary policy surprise to a given month if a monetary policy decision took place in this month, and zero otherwise.

We consider the following set of dependent macroeconomic variables: consumer price index (CPI), industrial production (IP), and exchange rate. The results are presented in Appendix E. On Figures 29-31 you can find the results of estimation. The left subfigures show local projections coefficients to target shock, and the right subfigures correspond to reaction on path shock.

Moreover, we see that these results are counterintuitive if we compare them with the event studies methodology. Previous, the exchange rate depreciates in response to path shock. However, now it appreciates. This result needs further research. The reasons could vary from different samples (in event studies we do not have zero surprises while in monthly data we have) to some control variables for monthly regressions.

As a result, we see that an unexpected rise (tightening) of either of the two types of monetary policy negatively affects CPI. The transmission period from the decision to CPI is about one year. Indeed, 11-12 months after the decision, we see that CPI declines in response to both target and path shocks. Then, CPI quickly recovers to its previous level. It is, to some extend, similar to Gertler and Karadi (2015), but it contradicts Bachmann, Gödl-Hanisch, and Sims (2021) who found that CPI persistently declines.

Finally, we do not observe any significant reaction of industrial production, while the exchange rate reacts only to path shock and appreciates almost immediately after the decision.

To sum up, CPI and exchange rate respond to changes in monetary policy in a usual way. When the Bank of Russia tightens monetary policy unexpectedly, CPI starts to slow down, while the exchange rate appreciates.

5 DISCUSSION

POLICY IMPLICATIONS Our results shed light on the effectiveness of monetary policy in Russia and may be relevant for conducting monetary policy in the future. We find that target shock is important for interest rates, influencing both short-term and long-term rates. Moreover, path shock turns out to be foremost for financial variables such as exchange rate and stock market indices. The transmission period from the decision to inflation is about one year.

This distinct role of target and path shocks requires additional attention from the policy perspective. Based on this analysis, we can conclude that it is important to pay much attention to forward guidance, communication, and other policies that may be connected to path shock. It may require the Bank of Russia to continue developing transparent monetary policy tools. Because for now, the effects of monetary policy on the interest rates primarily go through changes in the key rate. According to the best practices of other central banks, it is not the only option to change market interest rates.

We, however, emphasize that the impact of path shock (even with a similar magnitude as target shock) on interest rates is smaller than expected. Contrary, the effect of path shock on financial markets with a similar magnitude is inadequately high.

We assume that target shock changes have a similar magnitude as an unexpected change in the policy rate, given its high correlation with surprises in the shortest rates. However, we do not know how large a 'typical' path shock is. Based on the data, the volatility of path shock is considerably smaller than that of target shock. Arguably, path shock may have even less influence, given its actual average size. For instance, if, as a result of the monetary policy announcement, path shock changes ten times less than our estimate (1 basis point instead of 10 basis points), then the effects on the long-term rates would be economically negligible.

However, the source of this inactivity of interest rates in response to path shock may come from the public side. As we see that path shock is important for financial variables, meaning that the market participants pay attention to policies other than changes in the key rate. So, the problem may arise in a misunderstanding between the public and the Bank of Russia – market participants may not fully understand the economic outlook or are unsure about the meaning of the current policy agenda of the Bank. Therefore, the inability to adjust the expectations about the long-term rates efficiently and adequately could be the reason why we see only a small impact.

LIMITATIONS Before going to the conclusion, let us point out several important remarks and limitations in our data and results. Russian monetary policy is quite heterogeneous. Inflation expectations are not well anchored. Therefore, any rise in inflation leads to higher inflation expectations. Explanation of the reasons for non-anchored inflation expectations is beyond our paper. Nevertheless, to some extent, it hinders the transmission mechanism from monetary policy to the financial market and real sector.

Available trading data is also limited for Russia. Despite the US, we have only a couple of liquid futures on the Moscow exchange: on the stock market index, on the USD/RUB exchange rate, on Brent oil, and several Russian companies' shares. None of these futures is linked to an interest rate. The same story holds for the Russian bonds market. Bonds often are not liquid enough with a small number of deals inside one day, even if it is a day of the monetary policy announcement.

However, the OTC market is much better. Here commercial banks actively trade with each other using different interest rate swaps and forward rate agreements. Even so, we can not be sure that the prices of these trades reflect unexpected changes in the key rate with high precision. Banks can use the OTC market for different reasons, for hedging their risks, meeting the regulator's requirements, etc. Moreover, Russia's banking sector is somewhat segmented, and these trades on OTC markets are usually between the top-10 largest banks.

Based on data limitations, we conduct our analysis using only daily data, keeping in mind that it is a wide window for high-frequency identification. However, even if our estimates may be noisy, they are still quite consistent on different subsamples, within different approaches to handle outliers and different inputs sets to PCA.

Moreover, our monetary policy announcement database contains only days when a monetary policy decision was made. However, policy communication from the Board of Directors members happens also on other days, through various media interviews, press reports, etc. It is possible and desirable to include days with other significant events in our database to increase the accuracy of estimates.

Additionally, some authors (Campbell et al., 2012; Gürkaynak, Kara, et al., 2021, among others) divide path shock into two distinct components, which are usually called Delphic and Odyssean forward guidance shocks. Both of these shocks influence long-term rates similarly; however, they differ in the reaction of market indices. Delphic Odyssean forward guidance leads to higher market indices, while Odyssean forward guidance leads to lower market indices. To divide our shocks into a more detailed structure, we need some tradable inflation-linked products. They exist in the Russian financial market, but they are relatively new, less liquid, and do not have long price history.

Finally, as we previously mentioned, our sample consists of two periods of different monetary policy regimes. It is important to understand that before 2015 the Bank of Russia did not have an inflation target; thus, we should expect a different type of working transmission mechanism during this period. However, the robustness test on rolling subsamples shows that the results are almost stable during the pre-2015 and post-2015 periods.

6 CONCLUSION

This paper discusses the effects of monetary policy shocks on financial markets and macroeconomic variables. Using high-frequency monetary policy surprises, taken from tradable financial instruments, we construct two orthogonal monetary shocks. The first shock – target shock – is related to changes in the short-term interest rate and could be interpreted as a standard policy rate shock. The second shock – path shock – is related to other aspects of monetary policy, such as forward guidance, communication, central bank information, etc. After, we use these shocks as independent variables in local projection regressions and study the short-term and dynamic effects on financial variables. Moreover, we also aggregate these shocks to a monthly frequency and analyze responses of macroeconomic variables.

As a result, we show that a target shock primarily influences the term spreads and explains the most variation of rates on the entire yield curve. A standard step of monetary policy, 25 basis points, raises short terms rates by 20-25 basis points. Surprisingly, we find an effect on long terms yields too. The target shock leads to an increase of 7-15 years bonds yields by 15-10 basis points. Interestingly, it indicates that market participants adjust their long-term expectations based on changes in the current rates.

However, path shock has a very limited impact on interest rates and mostly influences financial variables: exchange rate and stock market indices. A much less 10 basis point path shock leads to a statistically significant depreciation of the exchange rate (more than 1%) and decreasing of stock market indices (1-1.5%).

Moreover, we also do not observe a price puzzle, which was usually found in the previous papers about Russian monetary policy. Apparently, high-frequency identification and accounting for the multidimensionality of monetary policy do their work in the price puzzle resolution. Our estimates suggest that an inflation reaction happens after about one year after the decision, which coincides with the Bank of Russia's predictions.

We also highlight the important distinction in the impact of these two shocks on variables. It is clear that target and path shocks have different underlying sources, which suggests both additional attention from the policymaker and further research are needed.

REFERENCES

Altavilla, Carlo et al. (2019). "Measuring euro area monetary policy". *Journal of Monetary Economics* 108, pp. 162–179.

Aruoba, Boragan et al. (2021). "Monetary Policy Surprises in Chile: Measurement & Real Effects".

Bachmann, Rüdiger, Isabel Gödl-Hanisch, and Eric R Sims (2021). "Identifying Monetary Policy Shocks Using the Central Bank's Information Set".

Bauer, Michael D and Eric T Swanson (2020). "The Fed's response to economic news explains the" Fed information effect"".

Brubakk, Leif et al. (2021). "The macroeconomic effects of forward communication". *Journal of International Money and Finance*, p. 102536.

Bu, Chunya, John Rogers, and Wenbin Wu (2021). "A unified measure of Fed monetary policy shocks". *Journal of Monetary Economics* 118, pp. 331–349.

Campbell, Jeffrey R et al. (2012). "Macroeconomic effects of federal reserve forward guidance". *Brookings papers on economic activity*, pp. 1–80.

Ceballos, Luis (2014). "The yield curve factors and economic surprises in the Chilean bond market". *Revista de Análisis Económico–Economic Analysis Review* 29.2, pp. 3–24.

Cieslak, Anna and Andreas Schrimpf (2019). "Non-monetary news in central bank communication". *Journal of International Economics* 118, pp. 293–315.

Cragg, John G and Stephen G Donald (1997). "Inferring the rank of a matrix". *Journal of econometrics* 76.1-2, pp. 223–250.

Diebold, Francis X and Canlin Li (2006). "Forecasting the term structure of government bond yields". *Journal of econometrics* 130.2, pp. 337–364.

Gertler, Mark and Peter Karadi (2015). "Monetary policy surprises, credit costs, and economic activity". *American Economic Journal: Macroeconomics* 7.1, pp. 44–76.

Gorodnichenko, Yuriy, Tho Pham, and Oleksandr Talavera (2021). "The voice of monetary policy".

Gurkaynak, Refet S, Burçin Kisacikoğlu, and Jonathan H Wright (2020). "Missing Events in Event Studies: Identifying the Effects of Partially Measured News Surprises". *American Economic Review* 110.12, pp. 3871–3912.

Gürkaynak, Refet S, A Hakan Kara, et al. (2021). "Monetary policy surprises and exchange rate behavior". *Journal of International Economics* 130, p. 103443.

Gürkaynak, Refet S, Brian Sack, and Eric T Swanson (2005). "Do Actions Speak Louder Than Words? The Response of Asset Prices to Monetary Policy Actions and Statements". *International Journal of Central Banking*.

Jarocinski, Marek (2021). "Estimating Fed's Unconventional Policy Shocks".

Jarociński, Marek and Peter Karadi (2020). "Deconstructing monetary policy surprises—the role of information shocks". *American Economic Journal: Macroeconomics* 12.2, pp. 1–43.

Jordà, Òscar (2005). "Estimation and inference of impulse responses by local projections". *American economic review* 95.1, pp. 161–182.

Kaminska, Iryna, Haroon Mumtaz, and Roman Sustek (2021). "Monetary policy surprises and their transmission through term premia and expected interest rates".

Känzig, Diego R (2021). "The macroeconomic effects of oil supply news: Evidence from OPEC announcements". *American Economic Review* 111.4, pp. 1092–1125.

Kubota, Hiroyuki, Mototsugu Shintani, et al. (2020). "High-frequency Identification of Unconventional Monetary Policy Shocks in Japan".

Kuttner, Kenneth N (2001). "Monetary policy surprises and interest rates: Evidence from the Fed funds futures market". *Journal of monetary economics* 47.3, pp. 523–544.

Laséen, Stefan (2020). "Monetary policy surprises, central bank information shocks, and economic activity in a small open economy".

Leombroni, Matteo et al. (2021). "Central bank communication and the yield curve". *Journal of Financial Economics*.

Miranda-Agrippino, Silvia and Giovanni Ricco (2021). "The transmission of monetary policy shocks". *American Economic Journal: Macroeconomics* 13.3, pp. 74–107.

Mishkin, Frederic S (2007). *The economics of money, banking, and financial markets*. Pearson education.

Munday, Tim and James Brookes (2021). "Mark my words: the transmission of central bank communication to the general public via the print media".

Nagao, Ryoya, Yoshihiro Kondo, and Yoshiyuki Nakazono (2020). "The Macroeconomic Effects of Unconventional Monetary Policy: Evidence from Japan". *Available at SSRN 3757802*.

Nakamura, Emi and Jón Steinsson (2018). "High-frequency identification of monetary non-neutrality: the information effect". *The Quarterly Journal of Economics* 133.3, pp. 1283–1330.

Paul, Pascal (2020). "The time-varying effect of monetary policy on asset prices". *Review of Economics and Statistics* 102.4, pp. 690–704.

Pestova, Anna and Viktoria Bannikova (2021). "The effects of monetary shocks on inflation: High-frequency approach." *Voprosy economiki* 6, pp. 47–76.

Swanson, Eric T (2021). "Measuring the effects of Federal Reserve forward guidance and asset purchases on financial markets". *Journal of Monetary Economics* 118, pp. 32–53.

Ter Ellen, Saskia, Vegard H Larsen, and Leif Anders Thorsrud (2019). "Narrative monetary policy surprises and the media".

Tishin, Alexander (2019). "Monetary Policy Surprises in Russia". *Russian Journal of Money and Finance* 78.4, pp. 48–70.

APPENDIX

A NELSON-SIEGEL METHODOLOGY

In this appendix, we briefly describe the Nelson-Siegel model. The idea of this model is as follows. We can consider each day in our sample separately. For each day we have a number of tradable bonds with corresponding maturity date (τ) and yields (y_t). Here sub-index t refers to separate days. Then, we can estimate the following model for each t separately (the following specification is from Diebold and Li, 2006):

$$y_t(\tau) = \beta_{1,t} + \beta_{2,t}\left[\frac{1-\exp(-\lambda\tau)}{\lambda\tau}\right] + \beta_{3,t}\left[\frac{1-\exp(-\lambda\tau)}{\lambda\tau} - \exp(-\lambda\tau)\right] \tag{10}$$

After estimation of equation (10), we end up with parameters of the model (β_0 serves as a long-term factor, β_1 serves as a short-term factor, β_2 serves as a medium-term factor and τ as the exponential decay rate). Note, that these parameters differ for each day (t), meaning that these parameters can fully describe the whole yield curve.

Therefore, for each day (t) we can obtain a fitted yield curve (from which we can choose yields for each date and for any maturity). Although we can obtain fitted values for any maturity, we chose to work with a reasonably detailed (yet compact) set of government bonds yields: 1 month, 3 months, 6 months, 9 months, 1 year, 2 years, 3 years, 5 years, 7 years, 10 years and 15 years.

B DATA

In table 2 you can see the description of data used.

Table 2: Data

Variable	Decription
1 month - 15 years OFZ bonds yields	Fitted values using Nelson-Siegel model, parameters are taken from Moscow exchange.
1 year - 10 years IRS	A vanilla interest rate swap is an agreement between two counterparties to exchange cashflows (fixed vs. floating) in the same currency. This agreement is often used by counterparties to change their fixed cashflows to floating or vice versa. The payments are made during the life of the swap in the frequency that is pre-established by the counterparties.
Si	Futures on USD/RUB with expiration in 3 months
RTS	Futures on dollar-valued Russian stock market index with exparation in 3 months
USDRUB_TOD	Today USD/RUB exchange rate
USDRUB_TOM	Tomorrow USD/RUB exchange rate
IMOEX	Spot value of Russian stock market index
RUGBICP1Y	Bonds index with less than 1 year duration, calculated by Moscow Exchange
CPI	Consumer price index, monthly seasonally adjusted
IP	Industrial production index, monthly seasonally adjusted
Exchange rate	US Dollar/Russian Rouble FX Spot Rate, monthly

C LOCAL PROJECTIONS

This appendix presents the extended results for local projections exercise. Here, we estimate Equation (9) with $h = 0, \dots, 20$, where h means one business day. That means that for each h the dependent variable is cumulative growth of y from t to $t + h$. That is, if $h - 0$, then y is a change from $t = 1$ to t in the current day of announcement.

The left sub-figures in Figures 5-16 show coefficients for target shock (normalized to 25 basis points shortest rate reaction). The right sub-figures show coefficients for path shock (normalized to 10 basis points of 3 years bonds yield).

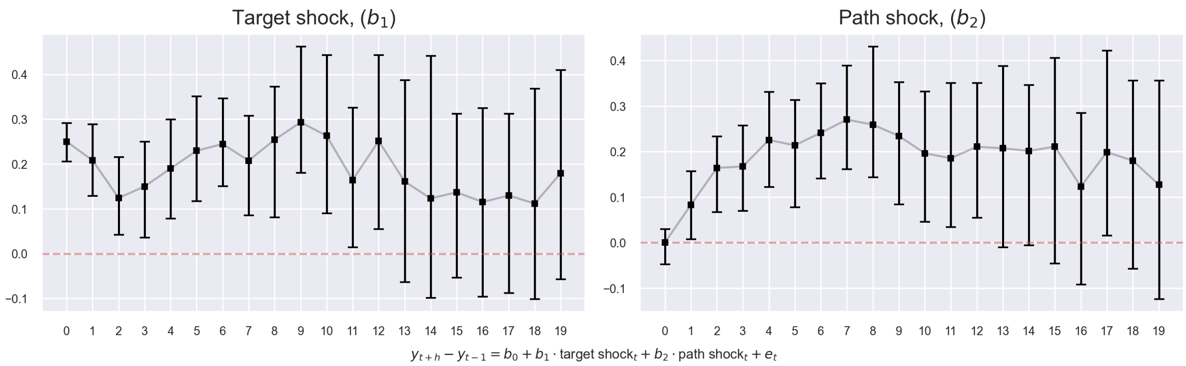

Figure 5: Local projections: 1 month bond rate

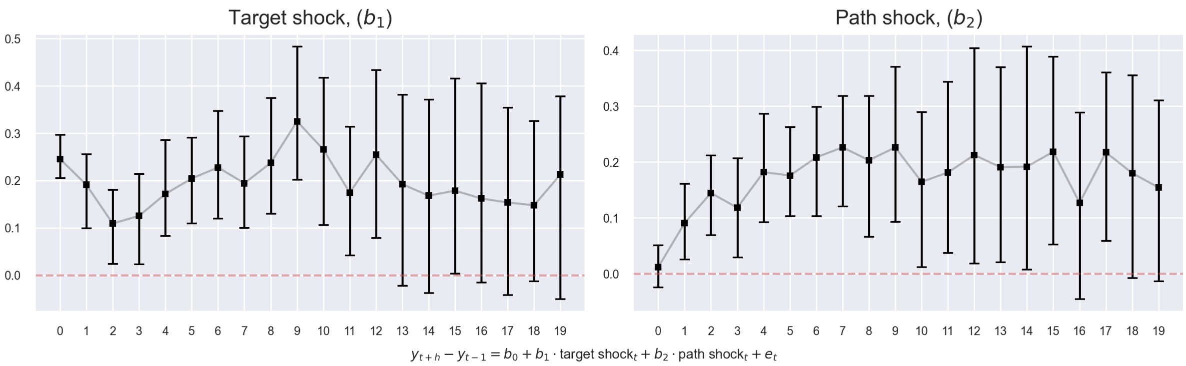

Figure 6: Local projections: 3 months bond rate

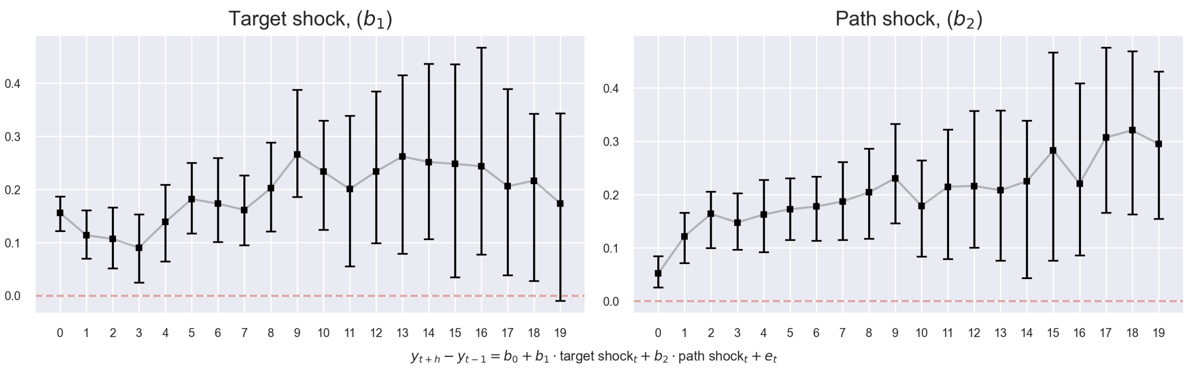

Figure 7: Local projections: 1 year bond rate

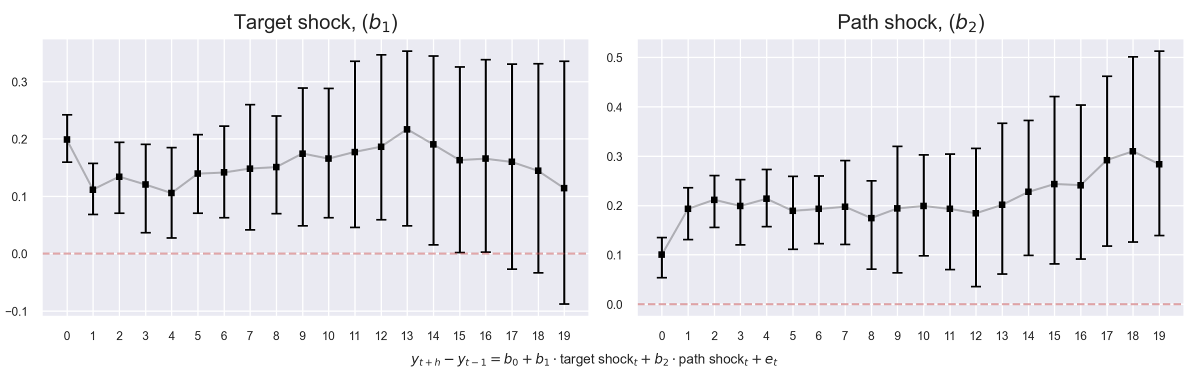

Figure 8: Local projections: 3 years bond rate

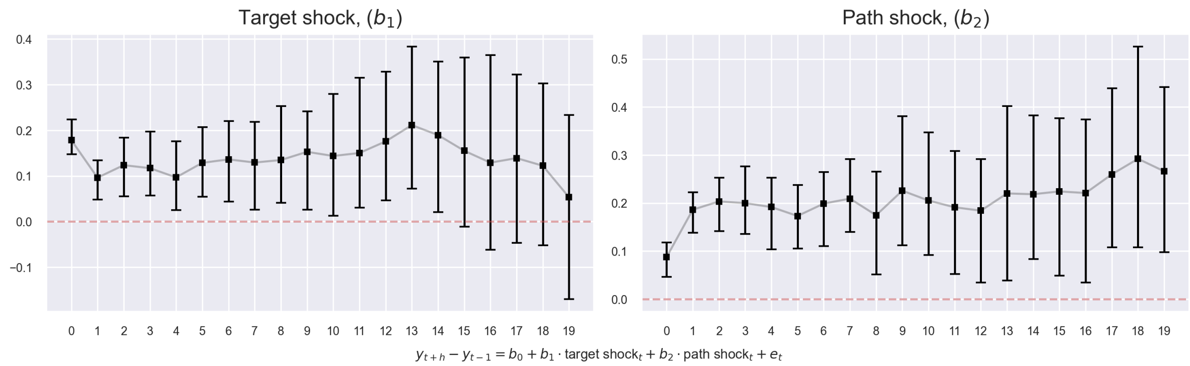

Figure 9: Local projections: 5 years bond rate

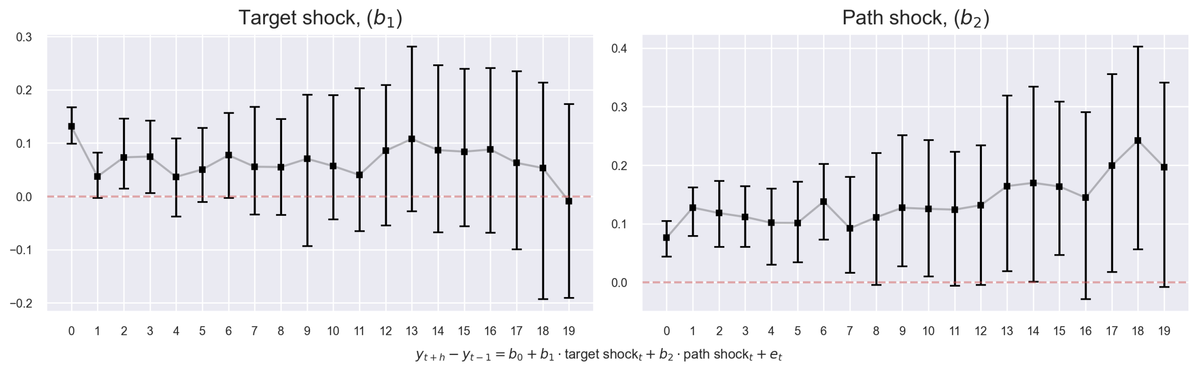

Figure 10: Local projections: 10 years bond rate

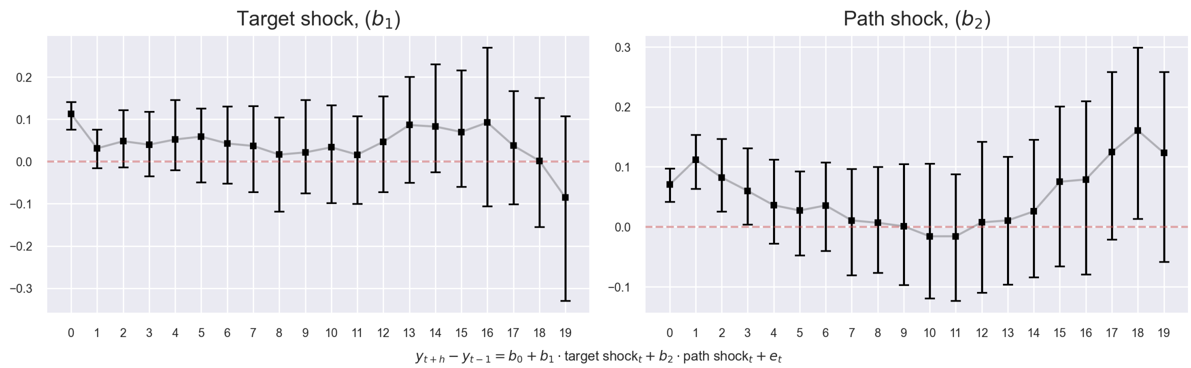

Figure 11: Local projections: 15 years bond rate

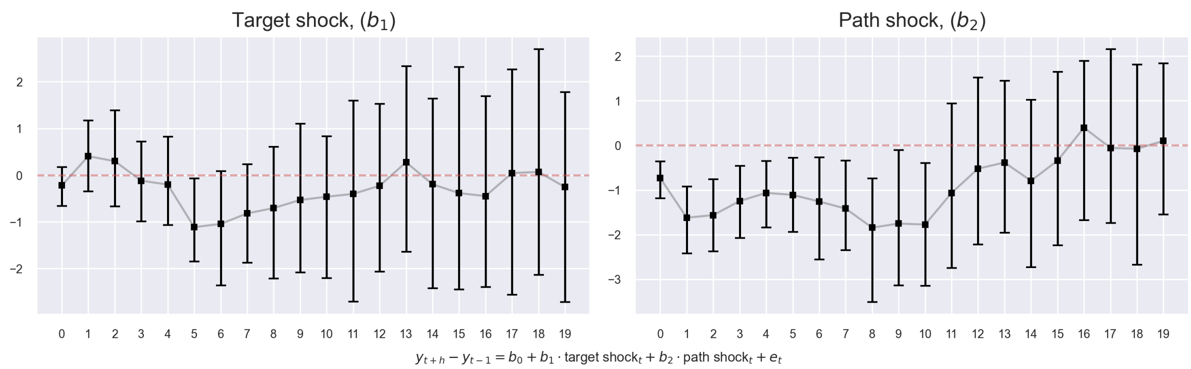

Figure 12: Local projections: IMOEX stock market index

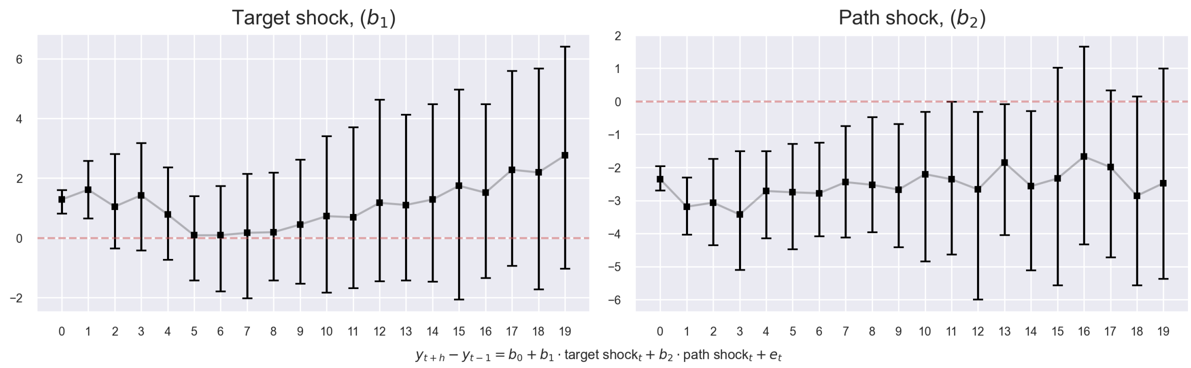

Figure 13: Local projections: RTS futures

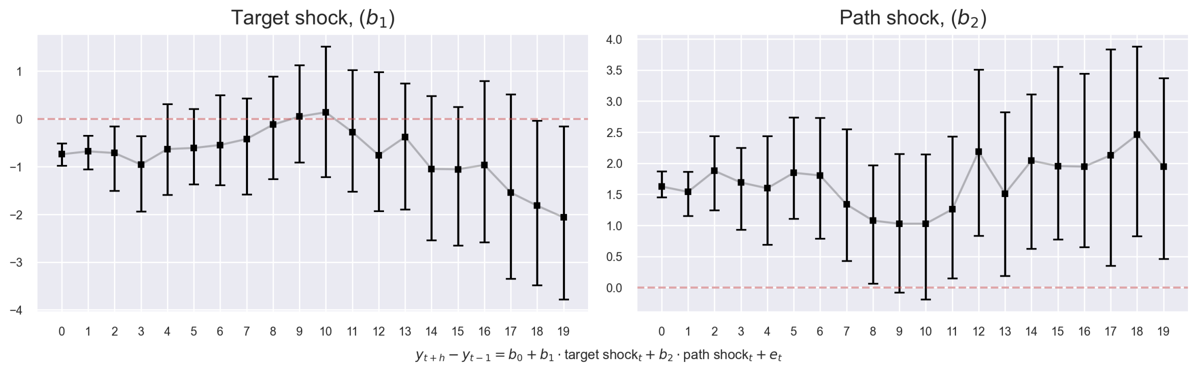

Figure 14: Local projections: USD/RUB futures

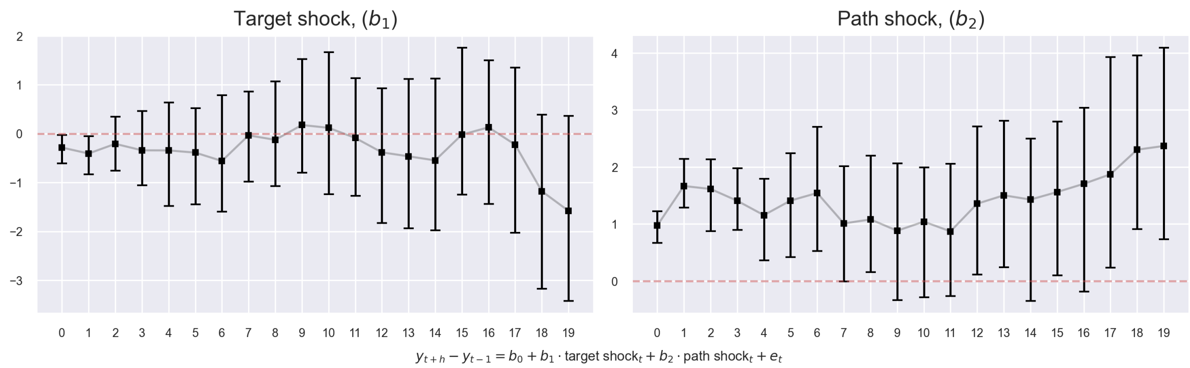

Figure 15: Local projections: USD/RUB today exchange rate

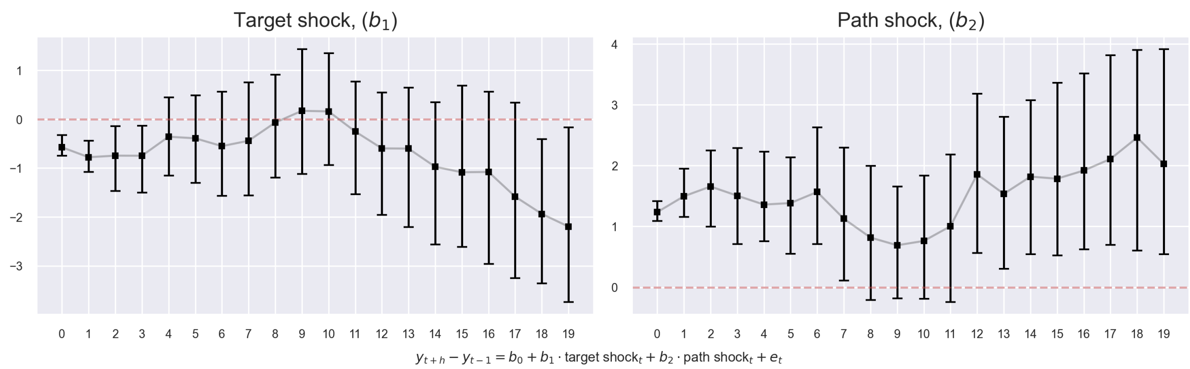

Figure 16: Local projections: USD/RUB tomorrow exchange rate

D ROLLING OLS

This appendix presents the extended results for rolling window subsample analysis. Here, we estimate Equation (9) with $h = 0$ and for each 40 consecutive points (days) in our sample.

The left sub-figures in Figures 17-28 show coefficients for target shock (normalized to 25 basis points shortest rate reaction). The right sub-figures show coefficients for path shock (normalized to 10 basis points of 3 years bonds yield).

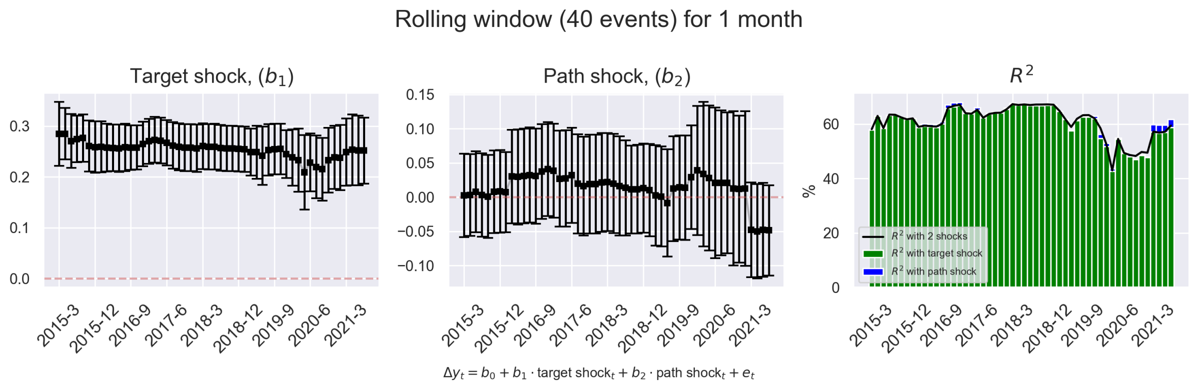

Figure 17: Rolling window: 1 month bond rate

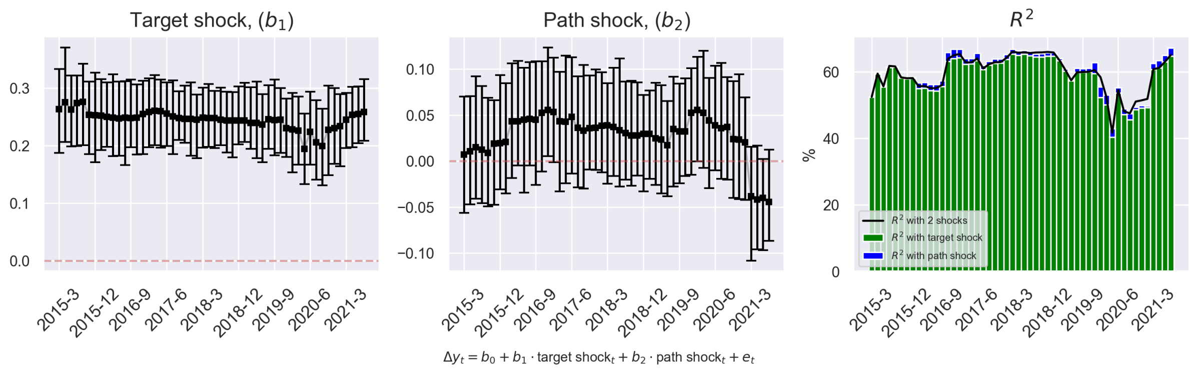

Figure 18: Rolling window: 3 months bond rate

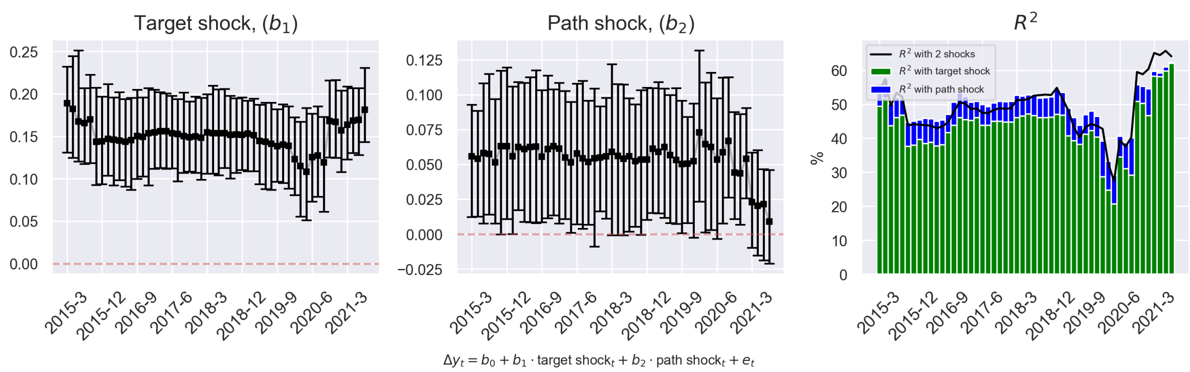

Figure 19: Rolling window: 1 year bond rate

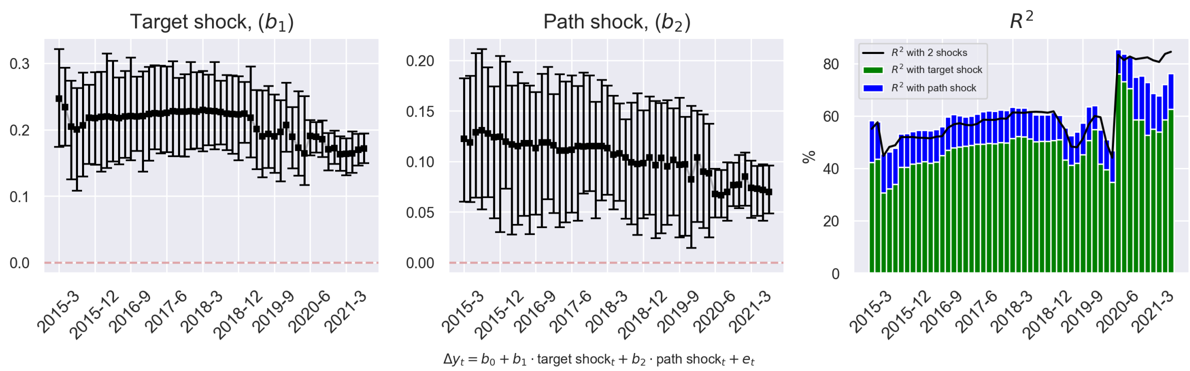

Figure 20: Rolling window: 3 years bond rate

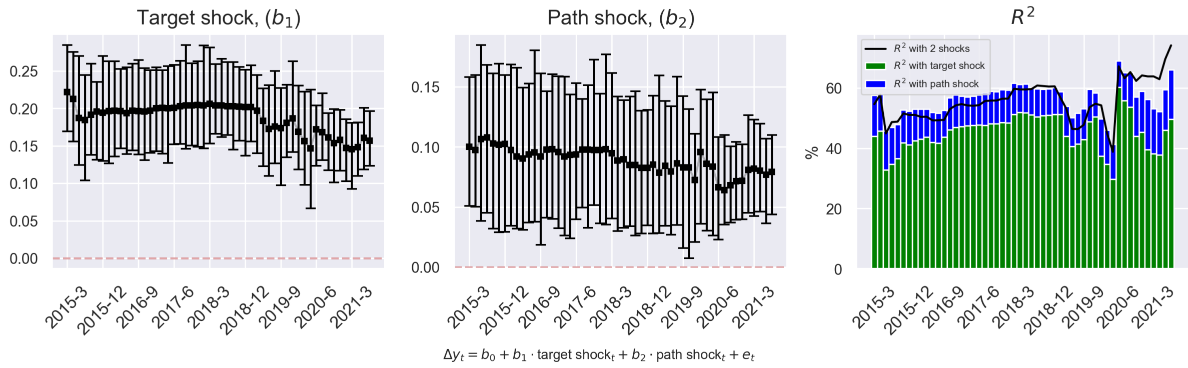

Figure 21: Rolling window: 5 years bond rate

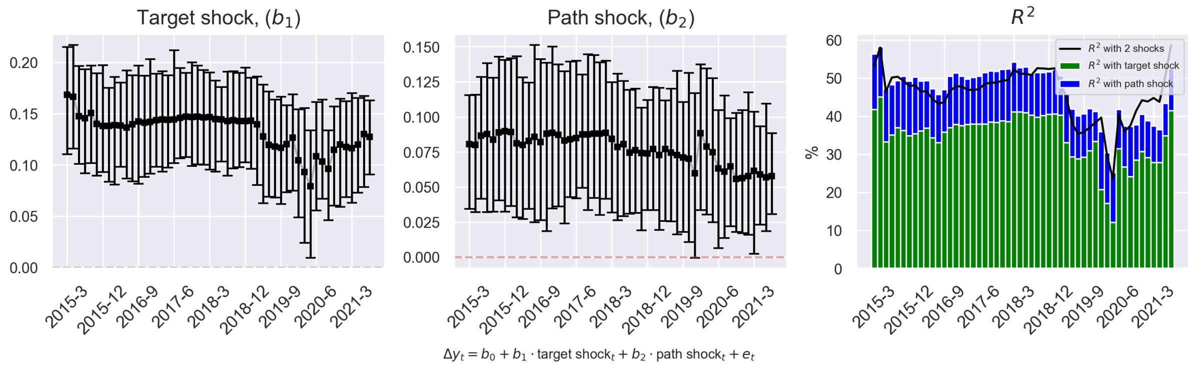

Figure 22: Rolling window: 10 years bond rate

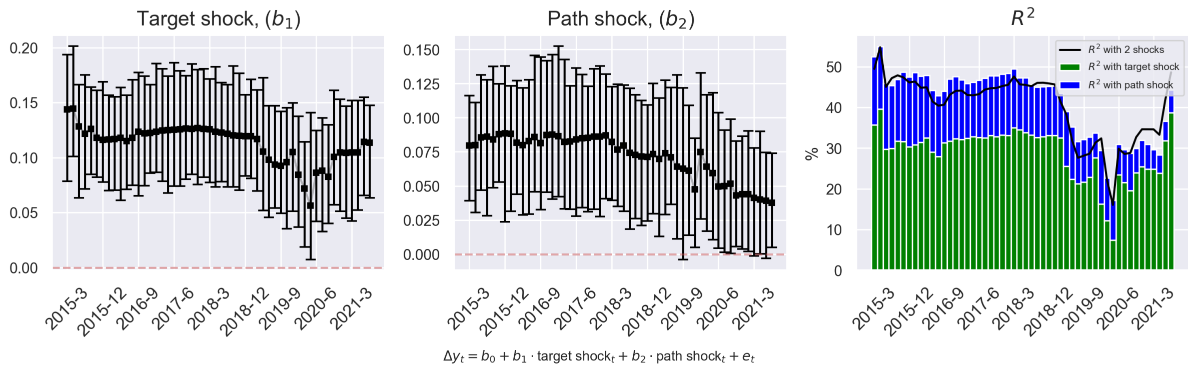

Figure 23: Rolling window: 15 years bond rate

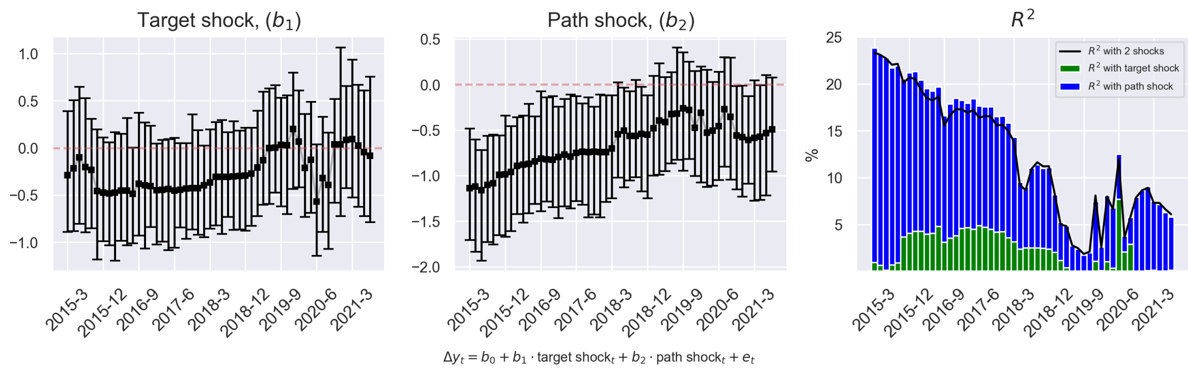

Figure 24: Rolling window: IMOEX stock market index

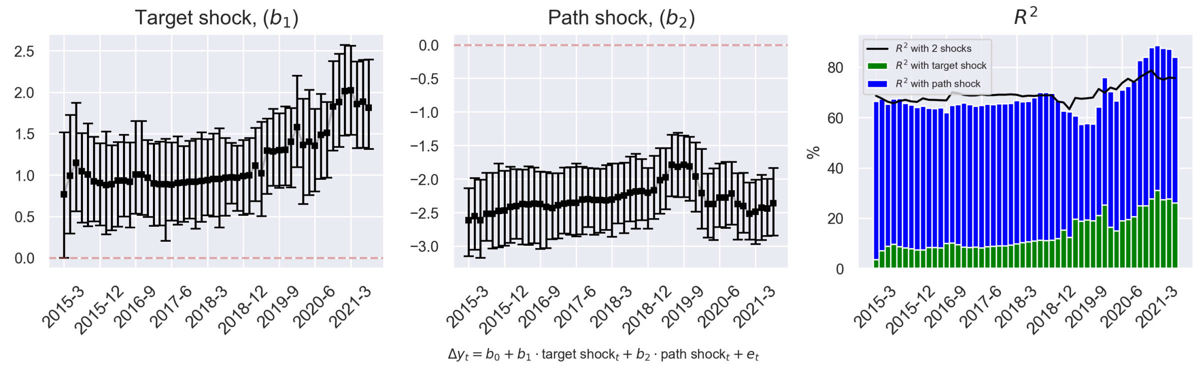

Figure 25: Rolling window: RTS futures

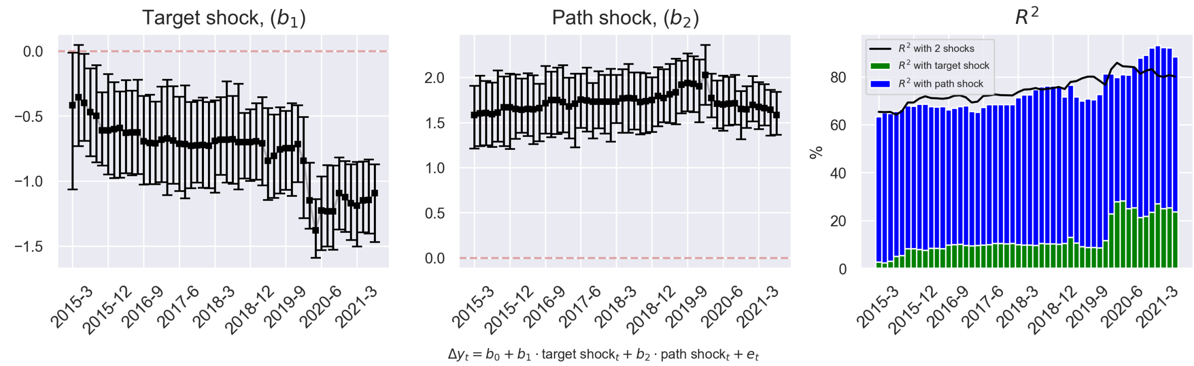

Figure 26: Rolling window: USD/RUB futures

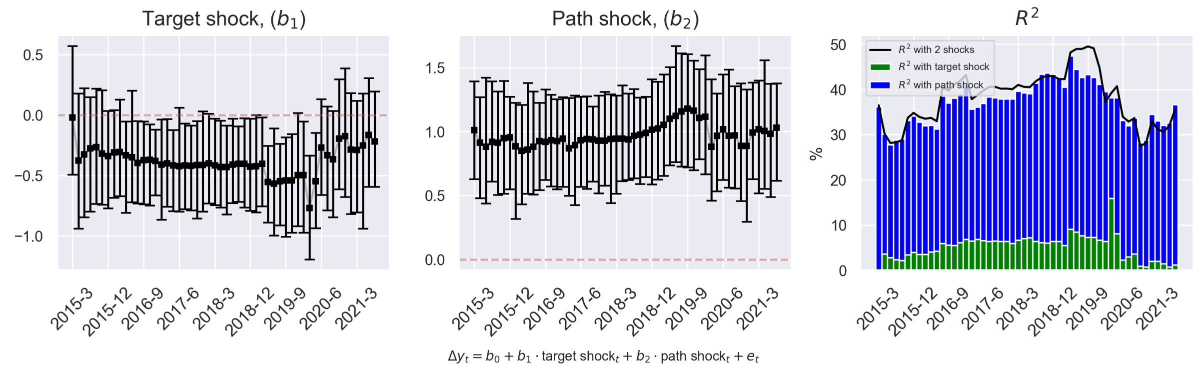

Figure 27: Rolling window: USD/RUB today exchange rate

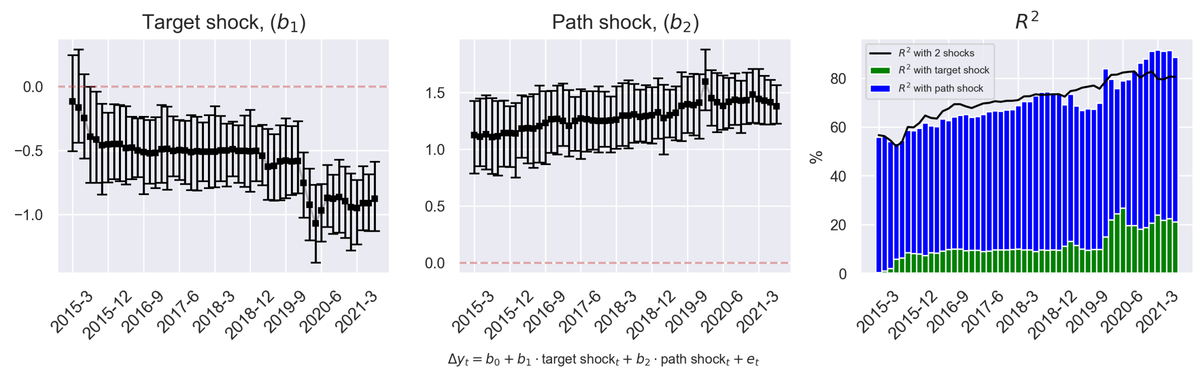

Figure 28: Rolling window: USD/RUB tomorrow exchange rate

E MACROECONOMIC VARIABLES

This appendix presents the extended results for local projections on macroeconomic data. Here, we use monthly data and sum up monetary policy shocks to a monthly frequency. If there are one or more monetary policy announcements in the current month, we attribute the value of corresponding shocks to this month. If there were no monetary policy events, we attribute zero value to our monetary policy shocks this month.

Then, we estimate Equation (9) with $h = 0, \ldots, 20$, where h is a number of months. That means that for each h the dependent variable is the cumulative growth of y from t to $t + h$. That is, if $h = 0$, then δy is a change from $t - 1$ to t in the current month.

The left sub-figures in Figures 29-31 show coefficients for target shock (normalized to 25 basis points shortest rate reaction). The right sub-figures show coefficients for path shock (normalized to 10 basis points of 3 years bonds yield).

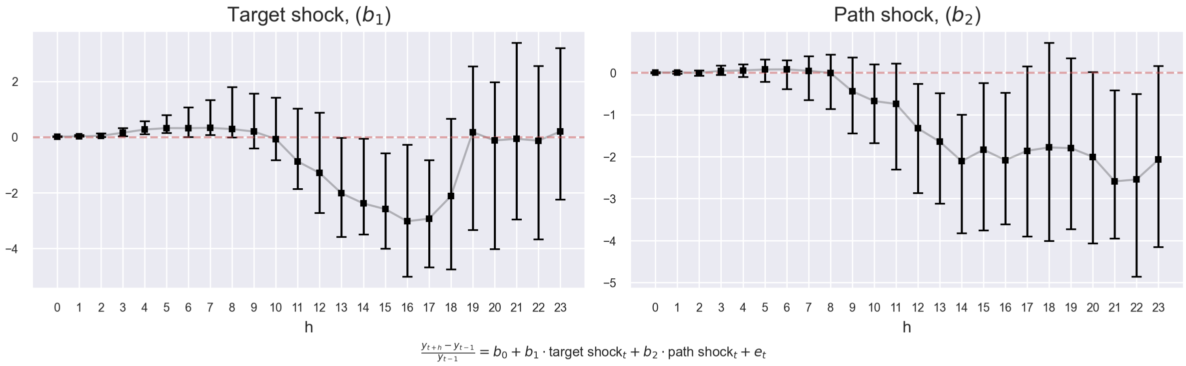

Figure 29: Local projections: CPI

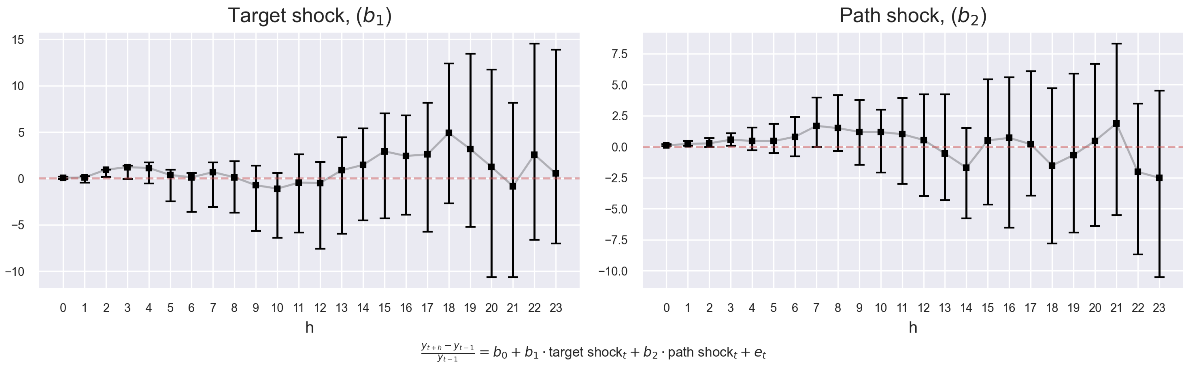

Figure 30: Local projections: Industrial production

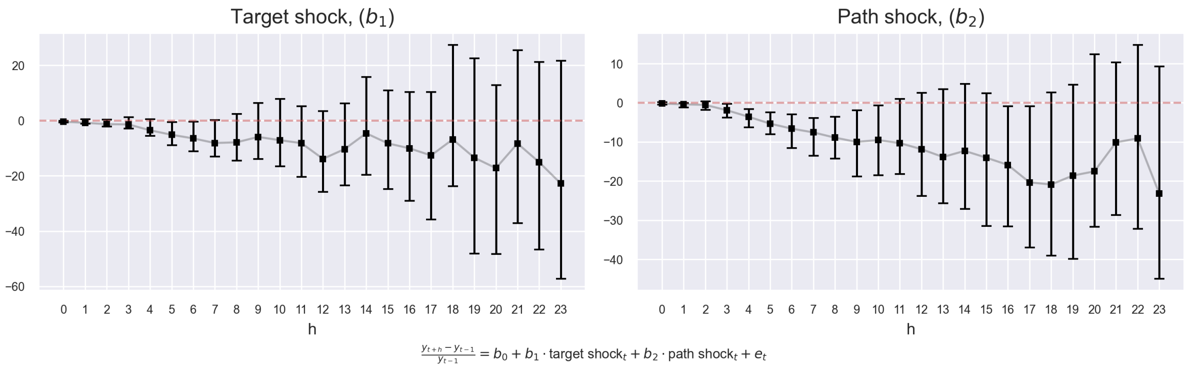

Figure 31: Local projections: Exchange rate