The role of “extraordinary” monetary policy shocks*

Sergei Seleznev[†] Alexander Tishin[‡]

This draft: April 2022
First draft: September 2021

Abstract

In this paper, we develop a framework to study the role of “extreme” shocks in Russian data – shocks that have a magnitude of more than four standard deviations. We find that these shocks are the source of biased estimates of the transmission mechanism which leads to a price puzzle. To show it, we develop a monthly DSGE model which we use as a workhorse in simulation exercises. Our focus is on the role of monetary policy shock. We simulate our model under several assumptions about the shocks (whether they come from the shock decomposition of observable variables or simulations). Then we use simulated data from the DSGE model in proxy SVAR to obtain empirical impulse response. Then we compare these responses to the responses estimated from the DSGE model. If monetary policy shock does not contain any peaked shocks, then SVAR impulse responses coincide with DSGE impulse responses. However, if we add a peaked value of monetary policy shock, we immediately observe a price puzzle.

Keywords: external instruments, proxy SVAR, DSGE model, monetary policy shocks

JEL Codes: E52, E58, E47, E65

†Bank of Russia, Research and Forecasting department, SeleznevSM@mail.cbr.ru
‡Bank of Russia, Research and Forecasting department, TishinAV@mail.cbr.ru; corresponding author

1 INTRODUCTION

It is hard to underestimate the importance of monetary policy. Nowadays, about 30 countries have adopted an inflation targeting framework. These countries include both advanced economies (AEs, such as New Zealand, Canada and the UK) and emerging markets (EMEs, such as Chile, Mexico and Russia). Therefore, understating the transmission mechanism is crucial in conducting inflation targeting policy.

One of the main mechanisms works through interest rates, which employ several channels. Raising interest rates for households and businesses influences saving and investment decisions, asset prices, changing the amount of cash and appreciating exchange rate. In total, this monetary policy decision has an impact on aggregate demand with a higher rate dissimulating spending, hence, businesses decrease their prices more in response to lower demand, which leads to lower inflation.

In this paper, we study the transmission of monetary policy with the existence of large (and unexpected) monetary shocks. To do it we employ a DSGE model calibrated to the Russian economy. We define large monetary policy shocks as a shock of extraordinary magnitude (at least larger than 3 standard deviations of a typical monetary shock). We find that a price puzzle, which has been found in the previous papers, evaluating the effectiveness of monetary policy in Russia, could be explained by the transition period at the beginning of inflation targeting. During this period the Russian economy has experienced a large unexpected monetary policy shock as a response to tightening monetary policy from 10.5% to 17%. As an illustration, in Figure 1 we show monetary policy surprises, computed as returns of USD/RUB futures in a 30-minute window around a monetary policy event. We see that the largest surprise occurred in December 2014. Indeed, this "extreme" monetary policy shock is the source of a price puzzle.

The price of prices is documented in numerous works (Bernanke 1990; L. Christiano, M. S. Eichenbaum, and C. Evans 1994; Sims 1992. Until recently, various explanations were offered for the reasons for the appearance of the price puzzle. For example, one

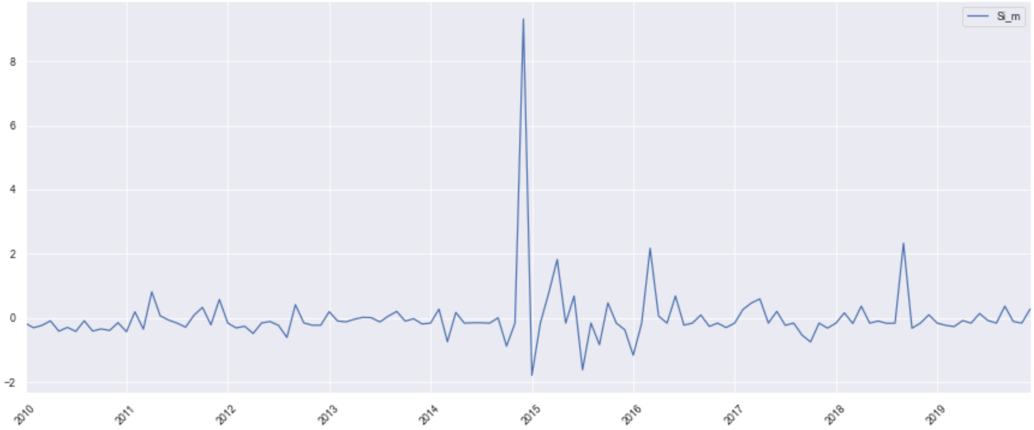


Figure 1: Monetary policy surprises in Russia

of the reasons may be the insufficient reaction of Central Banks to the acceleration of inflation. That is, in response to accelerating inflation, Central banks reacted by increasing the nominal rate, but not so much as to fully compensate for rising inflation (for example, this could be observed in the United States in 1960 and 1970), but in modern economic realities the Central banks of various countries have enough experience in targeting inflation to understand the extent of the impact of monetary policy on the economy.

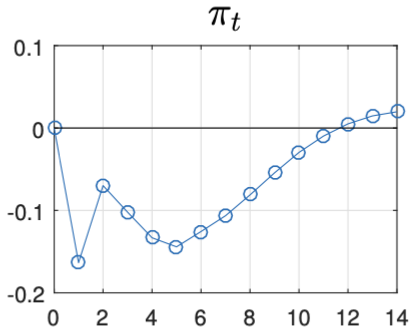
In theoretical macroeconomic models, the transmission mechanism of monetary policy (that is, how the change in nominal rates by the Central Bank is translated into the economy) is described in detail (L. J. Christiano, M. Eichenbaum, and C. L. Evans 1999). While in the previous literature the price puzzle is a well-known result and there were offered plenty of ways to avoid price puzzles. Until recently, some works (for example, Sims 1992) used structural vector autoregressions with Cholesky decomposition to identify monetary policy shocks. The main problem of this was that as a result of evaluating the parameters, it turned out that the shock of monetary policy has a positive effect on inflation (that is, an unexpected tightening of monetary policy leads to an increase in prices). The active use of this model is the reason for the appearance of the price puzzle in many papers.

An alternative identification scheme was proposed by identification using signs Uhlig 2005. Because based on theoretical models, we know how inflation should react to changes in interest rates. In particular, it can be shown that tightening monetary policy does not raise prices for a certain number of periods after the shock. This method avoids the price puzzle. However, the obvious disadvantage of this method is that instead of one specific impulse response function, some set of such functions is obtained that has to be aggregated (most often takes the average or median response). Furthermore, Blanchard and Quah 1988 offered an identification scheme based on long-run restrictions.

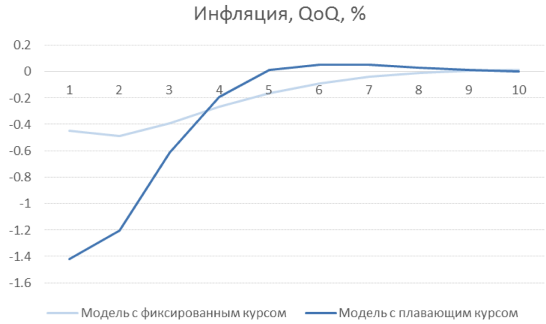
Moreover, recent research on monetary policy employs high-frequency identification of monetary policy shocks. The idea is the following. Authors use external high-frequency data (from stock market exchanges), typically instruments related to interest rates, exchange rates and market indices, to extract monetary policy surprises in a tiny window around monetary policy announcements. This approach confirmed its effectiveness and gained popularity in the monetary policy research (Gertler and Karadi 2015; Swanson 2021; Jarociński and Karadi 2020; Jarocinski 2021; Gürkaynak, Sack, and Swansonc 2005) and proved useful for solving price puzzle, at least for advanced economies.

However, for emerging markets, we often have puzzling results, even if we use high-frequency identification. Policymakers estimate the monetary policy transmission as 3-6 quarters from the decision to inflation. For example, The Bank of Russia quarterly projections model (Orlov 2021) shows that the transmission to inflation reaches a peak 5 quarters after the decision. Other papers build medium-scale DSGE models (Kreptsev and Seleznev 2016; Kreptsev and Seleznev 2017) and arrive to a similar estimate: the effect of monetary policy is significant during the first 5 quarters. See graphical illustration of transition estimates in Figure 2.

Nevertheless, structural and semi-structural models are consistent in estimates while we see significant differences in empirical estimates. For instance, Pestova and Rostova 2020; Tishin 2019 employed high-frequency identification for Russia. The authors found that in response to tightening monetary policy, inflation is increasing employed. It is a classical example of a price puzzle – inflation increases in response to



(a) Orlov 2021



(b) Kreptsev and Seleznev 2016

(c) Kreptsev and Seleznev 2017

Figure 2: Semi-structural and structural estimates of transmission in Russia

unexpected monetary policy shock. Moreover, it contrasts US and EU literature where high-frequency identification solves the price puzzle. This result is counter-intuitive and, thus, in this paper, we show the possible causes of it.

Moreover, our paper touches on the question of the role of high-frequency identified shocks from the perspective of "extreme" shocks. Other papers questioned whether the identified surprises are exogenous and relevant. For instance, a large strand in the literature (Cieslak 2018; Karnaukh 2020; Miranda-Agrippino and Ricco 2021; Sastry 2021; Bauer and Chernov 2021) examined the predictability of monetary policy surprises and documented a large correlation between surprises and public information available before the monetary policy announcement. Another literature (Bauer and Swanson 2021; Ramey 2016) focused on relevance condition – monetary policy surprises should be the part of interest rate changes.

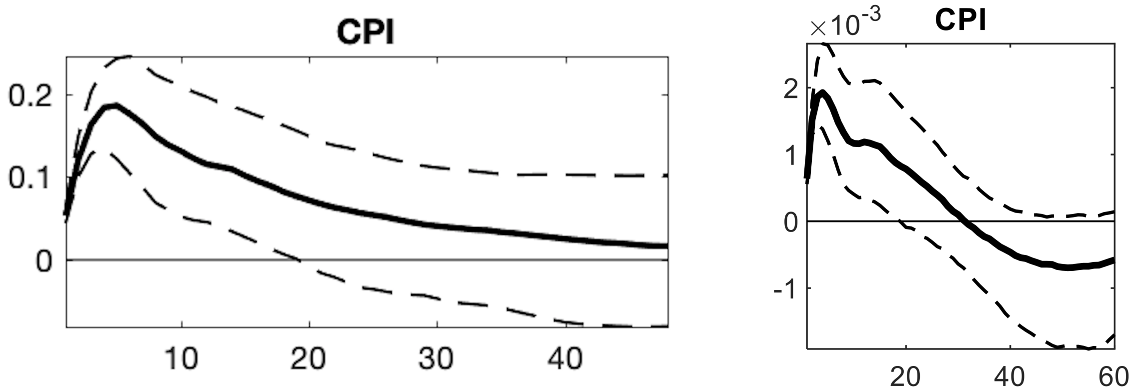
To our knowledge, it is the first paper that studies outliers as an unusually large shock. In some previous papers, such events are removed from the sample and academic literature does not consider the role of such shocks. We focus our attention exactly on the role of unusual monetary policy shocks and how these shocks affect empirical estimates.

We are not the first who re-examines the transmission estimates. There is a meta-study by Balima, Kilama, and Tapsoba 2017. They claim that there is a large discrepancy in findings on the transmission mechanism and its effects on the macroeconomic variables. They try to figure out the reasons for the discrepancies in estimates. They reveal that one of the main reasons – publication selection bias – editors tend to publish papers that are consistent with the common views and statistically significant. What's more important for our paper, the authors also note that different estimates are also caused by characteristics of the study sample, including its structure and composition, the time coverage and so on.

Moreover, we do not doubt the effectiveness of inflation targeting or monetary policy. For instance, there is plenty of literature (Lin and Ye 2009; Walsh 2009) claiming that monetary policy (in the form of inflation targeting) has shown statistically significant results in lowering inflation. In our paper, we aim to show how the bias associated with "extreme" shocks affect the estimation of monetary policy transmission.

In our paper, we illustrate how the empirical estimates may be biased because of large outliers. We claim that the price puzzle, which usually occurs under the Choletsky identification scheme (short-run restrictions), also may appear under high-frequency identification, can have roots in presence of large and unexpected monetary policy shocks. This bias in estimation is primarily due to only monetary policy shocks and is less likely caused by other simultaneously occurring large shocks (i.e. oil prices). This finding is crucial for policymakers because a number of especially empirical estimates may suffer from the presence of such shocks.

The idea of our paper is the following. We use DSGE developed in Kreptsev and Seleznev 2017 and extended in this paper. We use this DSGE model to have an economy in which we know how mechanisms are working. We do not say that this model is the best for the Russian economy, instead, we use it as a workhorse for simulations.



(a) Tishin 2019

(b) Pestova and Rostova 2020

Figure 3: Monetary Policy Surprises in Russia

Then, we conduct several exercises. In each exercise, we estimate two impulse response functions (IRFs): (i) theoretical: IRF that comes from the DSGE model; (ii) empirical IRF that is estimated with structural vector autoregressions using simulated data and shocks without assuming any structure. Later, we compare these impulse responses. The difference is the following. Theoretical impulse responses always behave as prescribed by the DSGE model: in response to tight monetary policy, inflation decreases. However, empirical impulse responses are subject to our manipulations as described below.

In the first exercise, we generate fully artificial data by stimulating the model without any real data. Then we estimate IRFs using this simulated data. The aim of this exercise is to show that in absence of any disturbances in data both types of impulse responses show similar results. In all experiments, we will compare empirical responses to the theoretical ones to see how data can shape results.

In the next exercise, to estimate IRFs in the DSGE model we simulate only monetary policy shock (taken from normal and t- distributions (available by request)) while all other variables and shocks we take from the real data covering the interval from 2006M1 to 2019M12. Then, we replace a monetary policy shock in 2014M12 by 4 (4 times higher than a standard deviation). For both cases (with and without replacement) we compare impulse responses to examine the role of the "extreme" shock.

Finally, we use mixed data in our simulations. Specifically, we again simulate monetary policy shocks on the whole sample but take real data for all other variables only from 2014M12 to 2015M12. While everything outside this period is also simulated. Then, we again replace a monetary policy shock in 2014M12 and also compare the responses. We need these experiments to show that our results are not caused by any other shocks that may happen outside the most turbulent episodes in our sample.

Finally, in two previous paragraphs, we always compare two experiments: with and without a large monetary policy shock. Besides the primary reason - is to show how it shapes the results and how it leads to a price puzzle. There is a secondary reason: in both experiments, all other shocks come from the real data shock decomposition, including oil price shocks. By doing so we show that all other shocks are less likely to cause price puzzles.

2 MODEL

In this section, we describe our theoretical DSGE model which we use as a workhorse in our simulation. As well as, our empirical strategy to estimate impulse responses using simulated data.

2.1 *DSGE model*

We begin with a short describing a DSGE model. For more details about the estimation techniques etc, we refer to Kreptsev and Seleznev 2017. Except for two extensions.

First of all, we extend our model from quarterly data to monthly data. Conceptually, all equations remain the same but observables. We refer reader to Appendix A for the full set of equations. Secondly, we add a correlation between structural shocks. The full specification can be found in Appendix B. The reason to add monthly data and correlations – to make the model more realistic.

The general structure of the model is as follows. The model consists of households, firms, domestic retailers, retailers-importers, retailers-exporters, investment firms, oil exporters, the central bank, the fiscal sector and the external economy. Below we give brief descriptions of each sector and the interactions between them.

Households maximize their utility functions which depend on consumption (with habit formation) and labour subject to budget constraints. Expenditure part of the budget spends on consumption, domestic and foreign bonds. Income comes from labour, domestic and foreign bonds interest payments, and lump-sum transfers (redistribution of taxes and firms profit). Households also face Rottenberg-style quadratic costs on wage changes.

Firms are constructed in a common way. Each firm has a Cobb-Douglass production function and costs on attracting labour and renting capital. Then domestic retailers buy intermediate goods from firms and then sell them to consumer goods packers (households) and investment goods packers (firms) in a market with monopolistic competition. Similarly to domestic retailers, importing retailers maximize discounted profits, however, unlike domestic retailers, they sell goods at their own price and buy goods abroad instead of from firms. Exporting retailers buy goods from manufacturers, as do domestic retailers, but sell them abroad.

For simplicity, the model assumes that all exports of raw materials are exports of oil. We also assume that the real price of oil is exogenous.

The central bank in the model conducts interest rate and currency policy, using the rules for the rate and reserves, which in general may be implicit. The interest rate is set according to the Taylor rule, which focuses on the interest rate of the previous period and the inflation of the current period.

As mentioned above, the fiscal sector in this model is quite simple. Taxes are collected in the form of lump-sum payments from households. These taxes are completely spent on state consumption according to the rule that is set by the autoregressive process. In fact, we assume a balanced budget and the absence of transfers, and the latter is not the key if taxes are perceived as net household payments.

The external economy is defined in the model by the demand for non-primary goods of domestic exports. It is also believed that the external economy is much larger than the domestic one and, as a result, does not respond to its cheeks.

Needless to say, we do not pretend that this model best describes the Russian economy. However, it is only a useful instrument in which we know and understand all the processes and can refer to this model as our workhorse.

2.2 *Empirical model*

In this section, we establish our empirical strategy to estimate impulse responses. Suppose. that we have a vector autoregression (VAR) model in reduced form:

$$Y_t = BY_{t-1} + u_t, \tag{1}$$

where Y_t is a vector of out variables of interest, A is a matrix of coefficients and u_t is an reduced form shock.

Then, we can similar procedure as in Gertler and Karadi 2015. Note, that an reduced form shock can be represented in its structural form:

$$u_t = S\epsilon_t, \tag{2}$$

where ϵ_t is a structural innovations. Then the VAR model in its structural form becomes:

$$AY_t = CY_{t-1} + \epsilon_t, \tag{3}$$

where $A = S^{-1}$ and $C = AB$.

Using equation (3) we potentially can obtain responses of our variables of interest (Y_t) to structural shocks (ϵ_t). However, we need to establish some restrictions to identify elements in S. Usually, it is assumed some contemporaneous impact on variables, but these assumptions are often not realistic. Therefore, we follow Gertler and Karadi 2015 and make use external instruments to identity S.

Assume that we have an instrument z_t, for instance, for monetary policy shock, $\epsilon_t^{MP} \in \epsilon_t$. This instrument should satisfy the following properties:

$$\mathbf{E}(z_t \epsilon_t^{MP}) \neq 0 \tag{4}$$

$$\mathbf{E}(z_t \epsilon_t^{other}) = 0, \tag{5}$$

which means that the instrument z_t should be correlated only with the structural monetary policy shock and should be uncorrelated with all other shocks.

Then, we proceed as follows. We apply two stage estimation to find impulse responses to monetary policy shock. On the first stage we estimate Equation (1) with ordinary least squares and get fitted residuals $\hat{u}_t$. Then we take a residual that corresponds to monetary policy variable, $\hat{u}_t^{MP}$, and regress on z_t:

$$\hat{u}_t^{MP} = \alpha z_t + \psi_t, \tag{6}$$

Taking fitted values of $\hat{u}_t^{MP}$ as $\bar{\hat{u}}_t^{MP}$ we can proceed to the second stage:

$$\hat{u}_t^{other} = \beta \bar{\hat{u}}_t^{MP} + \xi_t, \tag{7}$$

where β corresponds to a (normalized to monetary policy shock) vector in matrix S that indicates the responses of all variables to monetary policy shock.

Given $\hat{\beta}$ we can easily estimate impulse response using Equations (1) and (2) by taking derivative by structural shocks and then iterate.

3 RESULTS

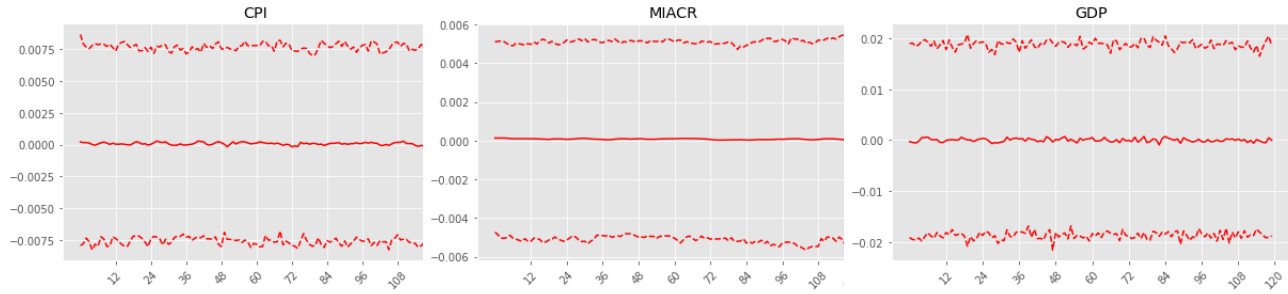
In this section, we present our main results for the following experiments.

First of all, we use an estimated DSGE model, described in Section 2, on Russain data from 2008M1 to 2021M3. All experiments have a similar structure. In each experiment, we simulate the economy under certain conditions, and estimate theoretical (from DSGE) and empirical impulse responses (from SVAR) to monetary policy shock.

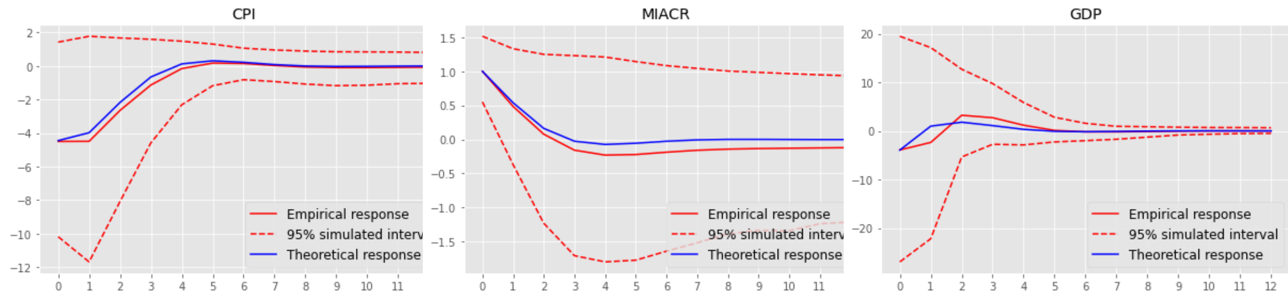
In all charts below we show two responses: the blue line is for theoretical responses and the red line for empirical ones. Theoretical responses are the same for all experiments because they are independent from data and estimated from the structural DSGE model. So, they show how variables should react from the perspective of our DSGE model.

Empirical responses are based on simulated data and estimated from the VAR model where monetary policy innovations are instrumented by simulated monetary policy shock from the DSGE model. So, in this case, VAR "sees" only simulated data and knows nothing about the structure of this data. In each iteration, we estimate such VAR model and take mean responses (red line) and approximate 95% simulated intervals as 2.5% and 97.5% quantities.

The first experiment serves as our baseline. In this case, we just simulate 10 years of "artificial" economy (i.e. such an economy that does not see real Russian data dynamics). In this experiment, all shocks are taken from a standard normal distribution. We need this experiment to show the reader that our DSGE model is correctly specified and without any unusual events, monetary policy shock behaves correspondingly to the theory.



(a) data



(b) impulse responses

Figure 4: "Artificial" model

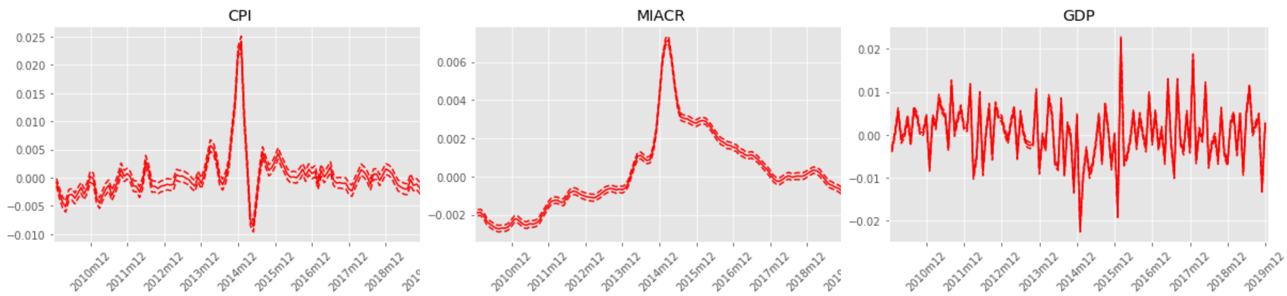
Figure 4 shows the results for simulated economy. Figure 4a presents core simulated variables: consumer price index (CPI), inter-bank interest rate (MIACR) and gross domestic product (GDP). It is not a surprise that all these three lines are at zero because the economy does not affect by any real-world shocks. Therefore, variables are always close to their steady states.

Figure 4b shows the corresponding impulse response functions (IRFs). The blue line represents theoretical (i.e. response from a structural model) impulse response to a monetary policy shock that corresponds to a 1 percentage point increase in nominal interest rate, the solid red line is empirical impulse responses (i.e. responses estimated from the VAR model), a dashed-red line is 95% simulated intervals. According to theory, monetary policy tightening (i.e. increasing interest rate) affects aggregate demand and leads to lower inflation and lower growth rates. In this figure we see that the red and blue lines coincide, meaning that with the VAR model we correctly estimate impulse responses.

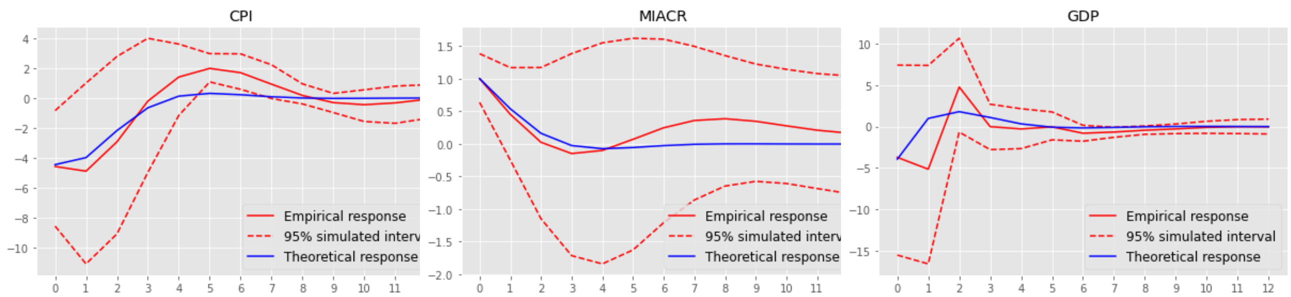
We note an important difference in observed (or we sometimes call them real) monetary policy shocks in opposite to high-frequency monetary policy surprises.

Observed monetary policy shocks are estimated using the DSGE model, so they do not represent any unusual large events while monetary policy surprises are estimated using tradable (usually futures) instruments and surprises represent unexpected changes in, for instance, futures' prices, which may show very large outliers. Furthermore, it is these shocks (estimated shocks from the DSGE model) we use as instruments in empirical exercise.

In the next experiment, we add real (or observed) Russian data into the model. We simulate the DSGE model with all fixed shocks but monetary policy shocks. Monetary policy shocks are taken from a normal distribution. For each simulation we take a vector of variables of interest (CPI, MIACR and GDP) and estimate VAR, taking a mean impulse response. In this case, monetary policy shocks are more or less homogeneous for all periods and because they are taken from one distribution, they do not have any peaks. Figure 5 shows the results for this experiment.



(a) data



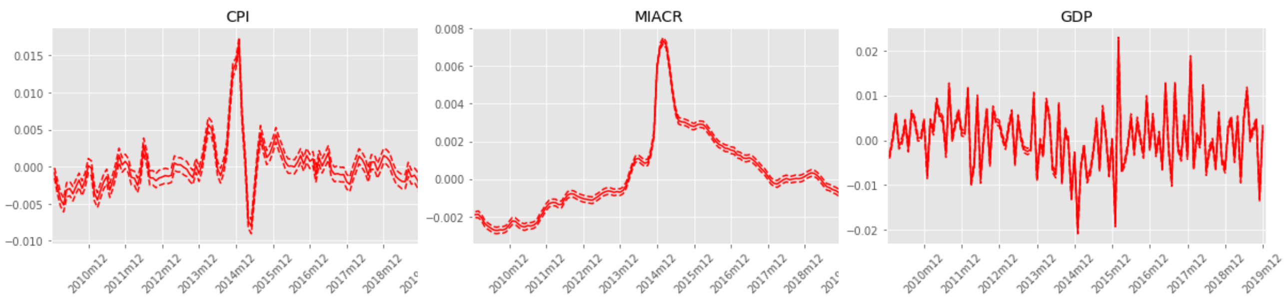
(b) impulse responses

Figure 5: Real shocks with replaced simulated monetary policy shock model

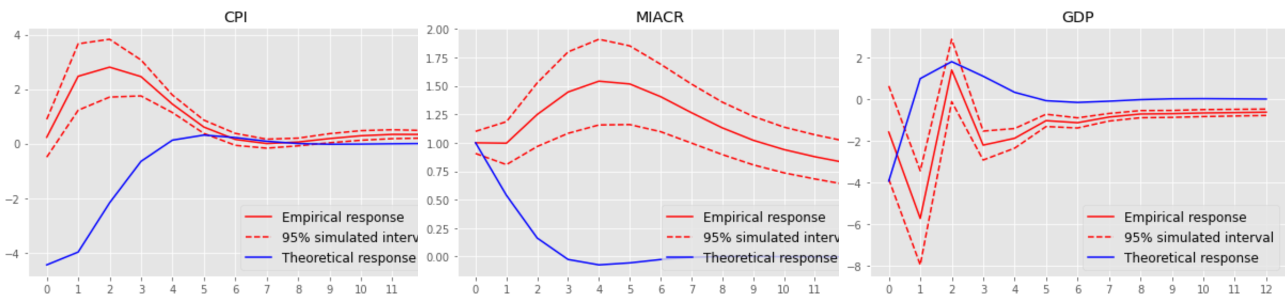
Figure 5a shows the data that used in both DSGE and VAR models: CPI and GDP are in monthly growth rates, MIACR is in levels. All data are in deviation from steady-state.

Figure 5b shows the corresponding impulse responses. We compare the same theoretical responses (which are the same for all experiments) to the empirical responses from the VAR model. Using data from the real economy (except monetary policy shock) gives us slightly different responses. However, these responses are still very close to theoretical ones. So, even if we do not use information from observed monetary policy shocks, we still correctly estimate impulse responses.

Now, let's look if we add a one-time large monetary policy shock. In the next experiment, we use similar settings as in the previous one with one exception. From the high-frequency analysis, we know that in December 2014 there was a large monetary policy surprise. We want to assess the hypothesis that the price prize, found in previous papers (Tishin 2019, Pestova and Rostova 2020), is due to this large surprise. To do it, we synthetically replace a value of monetary policy shock in 2012M12 with a 4 times higher than a typical shock (4 times the standard deviation). In other words, monetary policy shock is still taken from a normal distribution but in December 2014 we increased this shock by 4 times. The results are shown on Figure 6.



(a) data



(b) impulse responses

Figure 6: Real shocks with replaced simulated peaked monetary policy shock model

Figure 6a shows the data that used in both DSGE and VAR models: CPI and GDP are in quarterly growth rates, MIACR is in levels. All data are in deviation from steady-state. We may notice a tiny difference in CPI in December 2014 which is explained by our modification of monetary policy shock in the same month.

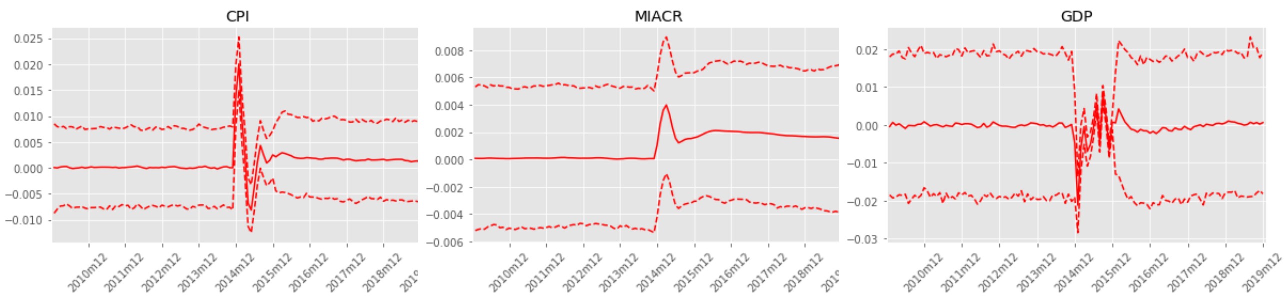
Figure 6b displays the corresponding impulse responses. Indeed, impulse responses clearly demonstrate a price puzzle. In response to tightening monetary policy, inflation rises. It looks counter-intuitive.

This experiment explicitly shows that only a one large monetary policy shock may flip the conclusions. Thus, it may be important to pre-process monetary policy shock in order to find suspicious outliers.

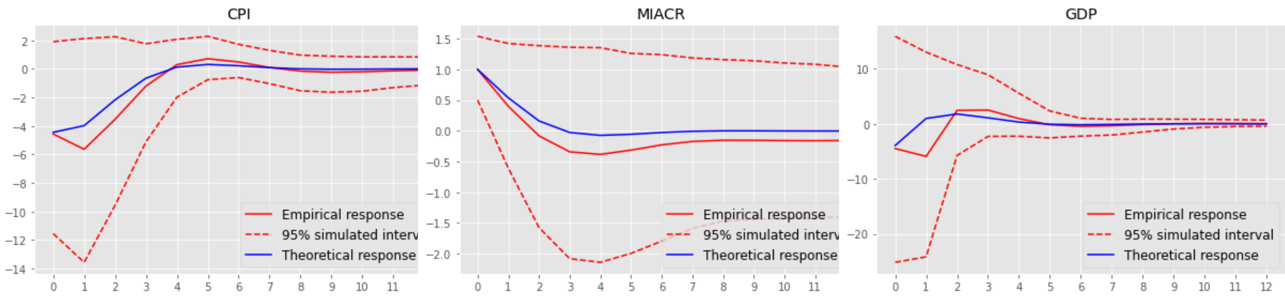
In the next experiment, we combine ideas from the previous experiments and examine, could the transitional period itself cause the price puzzle. To further study the issue, we limit the period when we use estimated shocks (except monetary policy shock) from the DSGE model from 2014m12 to 2015m12. Outside this interval, we set all shocks from a normal distribution (similar to the very first experiment). The idea of this experiment is to isolate the period when the Bank of Russia was charging its monetary paradigm and to ensure that no other events influence our impulse responses. The results are highlighted in Figure 7.

Figure 7a shows the data that used in both DSGE and VAR models: CPI and GDP are in monthly growth rates, MIACR is in levels. All data are in deviation from steady-state. Not surprisingly that these fires are different from ones from the previous experiments. Outside of 2014m12-2015m12 all variables show almost flatlines because all shocks that may drive its volatility are independent and taken from an identical distribution. Inside of 2014m12-2015m12 all shocks but monetary policy are taken from the DSGE model while monetary policy shocks are taken from a normal distribution.

Figure 7b presents the corresponding impulse responses. We see that for this experiment all impulse responses are very close to their theoretical responses. Furthermore,



(a) data



(b) impulse responses

Figure 7: Real shocks for 2014m12-2015m12 with replaced simulated monetary policy shock model

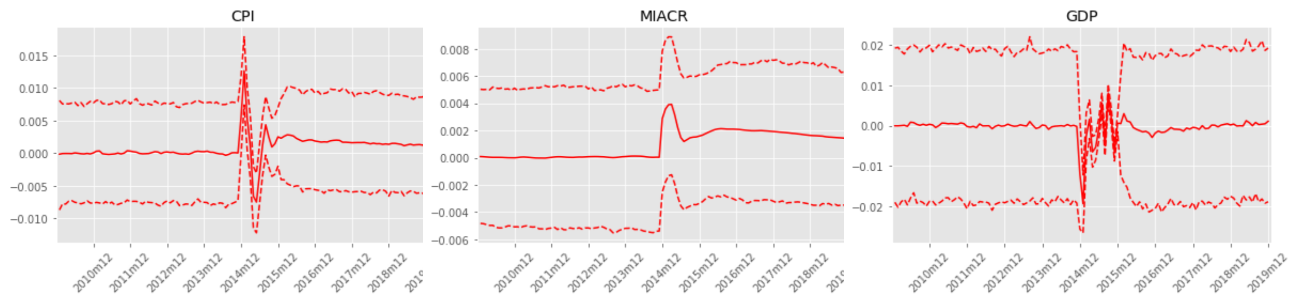
we do not see any price puzzles. The result tells us that if we do not consider monetary policy shock, then no event inside 2014m12-2015m12 triggers the price puzzle.

In the next experiment, we again modify the previous exercise and increase monetary policy shock in 2014m12 by 4. The idea is the same – to check how one unusual shock can change the overall picture. The results are indicated in Figure 8.

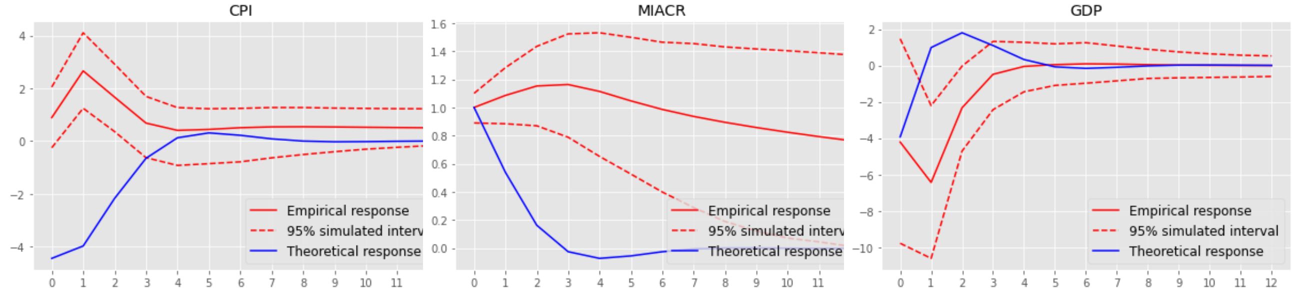
Figure 8a shows the data that used in both DSGE and VAR models: CPI and GDP are in monthly growth rates, MIACR is in levels. All data are in deviation from steady-state. These figures are very similar to the previous exercise except for December 2014, where we add a large shock.

Figure 8b indicates the corresponding impulse responses. Even if we limit our observed data to a 1-year sub-sample, we still see a prize puzzle. Adding only one large shock leads the empirical model to wrong estimates. Indeed, in response to higher interest rates, inflation also increases.

In the conclusion, the reader may ask us, how well our simulated data coincides with the real high-frequency monetary policy shocks? To answer this question, we can compare one of our realisations and the actual shock. Figure 9 compares it. The blue



(a) data



(b) impulse responses

Figure 8: Real shocks for 2014m12-2015m12 with replaced simulated peaked monetary policy shock model

line shows one possible simulation and the red line is for the actual monetary policy shocks. From our perspective, our simulated shocks describe the real dynamics quite accurately.

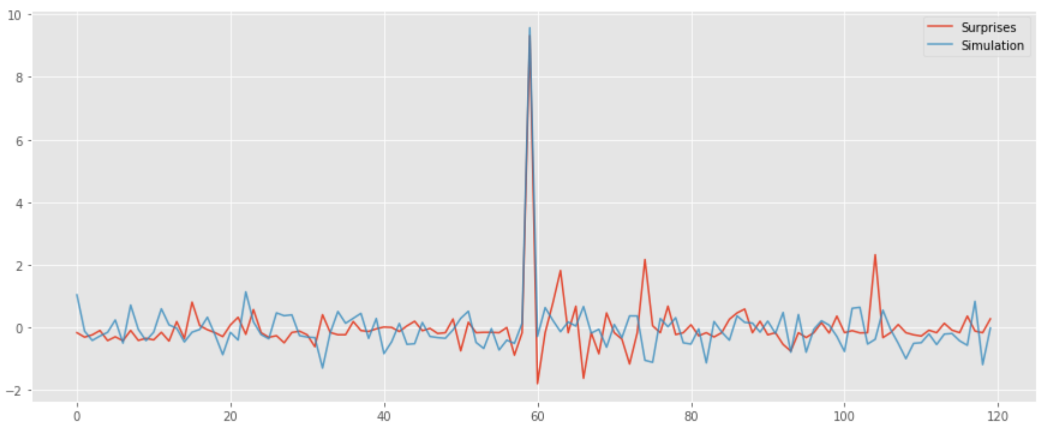


Figure 9: Monetary policy surprises in Russia

4 POLICY IMPLICATIONS

Our paper is crucial for policy implications. First of all, we advise policymakers to pay attention to model tools that they use in their decisions. Do they suffer from "extreme" shocks? As we reviewed in the Introductions section, there are various methods to estimate the transmission mechanism. As we show a couple of these methods may suffer from the problem of "extreme" shocks, leading to price puzzles and incorrect estimates.

On another side, our findings on the role of "extreme" shocks can make policymakers think about the specific announcements (e.g. in December 2014 in Russia). Even if it is an unusual event, which requires immediate action, it is still possible to think about the effects of the Central Bank's decision on the market.

First of all, such "extreme" shocks may tell us about the predictability of the Central Bank. If we observe many large shocks, it may be an indicator that the market often could not predict the actions. However, the Central Banks usually have a number of instruments to form expectations of the market which should be used to address this issue.

Such as, we understand that crises are extremely unpredictable events. Therefore, before such extreme events, Central Banks can form the expectations of the market participants. To do it the Central Bank can use some kind of forward guidance policy to direct the markets' expectations. In combination with written and oral communication, it may be fairly successful to warn the markets about the crisis. Hence, lowering the size of "extreme" shocks.

5 CONCLUSION

In this paper, we shed light on an important topic for both academic research and policymakers. We show, that empirical estimates may be biased because of extraordinary events in the sample.

Indeed, political and financial events in December 2014 caused an unprecedented monetary policy shock. Previous papers did not remove that from their samples, which causes bias in their estimates, which doesn't match the theory. Instead, we show that a large unusual monetary policy shock is the reason for this bias.

We show it using a number of simulation exercises. In which we sequentially add and remove a similar size large shock. By doing so, we show how such a large outlier can shape impulse responses. Actually, without a peaked monetary policy shock, empirical impulse responses behave as predicted by theory – an increase in the interest rate leads to a decrease in inflation. However, adding a peaked shock completely destroys the results – an increase in the interest rate leads to an increase in inflation. It is clearly a price puzzle.

Moreover, we also restrict our sample to ensure that there are no other shocks that may result in the price prize. Nevertheless, we do not find any evidence that a price puzzle may be caused by any other shocks that happened before or after the 2015 year.

In the end, we believe that there is room for improvement. Usually, just removing an "extreme" shock is not enough to obtain statistically significant results. The problem is the same size, using our DSGE model and simulations, it is possible to show how many data points we need to obtain statistically significant estimates.

Moreover, the discussion on the distributions of the shocks is also important. It is crucial to have correct assumptions about how shocks are distributed. The frequentist econometric approach assumes that the Law of Large Numbers works. Furthermore, the estimation of the variance-covariance matrix requires the Central Limit Theorem. If for instance, our shocks have come from distribution without the second or the fourth moments, then asymptotic may not work. Therefore, the role of “extreme” shocks may appear in this content as well. All these issues require further research.

REFERENCES

Balima, Hippolyte W, Eric G Kilama, and René Tapsoba (2017). *Settling the Inflation Targeting Debate: Lights from a Meta-Regression Analysis*. International Monetary Fund.

Bauer, Michael D and Mikhail Chernov (2021). *Interest rate skewness and biased beliefs*. Tech. rep. National Bureau of Economic Research.

Bauer, Michael D and Eric T Swanson (2021). "An Alternative Explanation for the "Fed Information Effect"". In: Federal Reserve Bank of San Francisco.

Bernanke, Ben S (1990). *The federal funds rate and the channels of monetary transnission*.

Blanchard, Olivier J and Danny Quah (1988). *The dynamic effects of aggregate demand and supply disturbances*.

Christiano, Lawrence, Martin S Eichenbaum, and Charles Evans (1994). *The effects of monetary policy shocks: some evidence from the flow of funds*.

Christiano, Lawrence J, Martin Eichenbaum, and Charles L Evans (1999). "Monetary policy shocks: What have we learned and to what end?" *Handbook of macroeconomics* 1, pp. 65–148.

Cieslak, Anna (2018). "Short-rate expectations and unexpected returns in treasury bonds". *The Review of Financial Studies* 31.9, pp. 3265–3306.

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

Gürkaynak, Refet S, Brian Sack, and Eric T Swansonc (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.

Karnaukh, Nina (2020). "Growth forecasts and news about monetary policy". *Fisher College of Business Working Paper* 2020-03, p. 027.

Kreptsev, Dmitry and Sergey Seleznev (2016). "DSGE models of the Russian economy with a small number of equations". *Series of reports on Economic Research No. 12, Bank of Russia*.

— (2017). "DSGE model of the Russian economy with the banking sector". *Series of reports on Economic Research No. 27, Bank of Russia*.

Lin, Shu and Haichun Ye (2009). "Does inflation targeting make a difference in developing countries?" *Journal of Development economics* 89.1, pp. 118–123.

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

Orlov, Andrey (2021). "Quarterly forecast model of Russia".

Pestova, Anna A and Natalia A Rostova (2020). "Economic effects of monetary policy in Russia: What do large datasets tell us?" *Voprosy Ekonomiki* 4, pp. 31–53.

Ramey, Valerie A (2016). "Macroeconomic shocks and their propagation". *Handbook of macroeconomics* 2, pp. 71–162.

Sastry, Karthik (2021). "Disagreement About Monetary Policy". *Available at SSRN 3421723*.

Sims, Christopher A (1992). "Interpreting the macroeconomic time series facts: The effects of monetary policy". *European economic review* 36.5, pp. 975–1000.

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.

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

Uhlig, Harald (2005). "What are the effects of monetary policy on output? Results from an agnostic identification procedure". *Journal of Monetary Economics* 52.2, pp. 381–419.

Walsh, Carl E (2009). "Inflation targeting: what have we learned?" *International Finance* 12.2, pp. 195–233.

APPENDIX

A DSGE: OBSERVABLE EQUATIONS

B DSGE: CORRELATED SHOCKS