Measuring monetary policy (in)effectiveness in Russia: a structural dynamic factor model approach

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Abstract

In this paper, we estimate the effect of monetary policy shocks on a wide range of Russian macroeconomic indicators using modern structural dynamic factor model approach (SDFM). The main advantage of the DFM over the standard structural vector autoregression models (VARs) is that DFMs allow us to avoid "the curse of the dimensionality" and at the same time include the large number of macroeconomic series into the model. The monetary policy shocks here are identified by means of sign restrictions. 57 monthly time series spanning from 2003 to 2017 are used to estimate the SDFM. The structural model is also re-estimated for the two sub-periods which correspond to the monetary policy shift from the exchange rate targeting to inflation targeting in Russia: January 2003 – June 2008 and January 2010 – February 2017. The results for the whole period indicate the significant negative impact of the contractionary monetary policy shock on the real and financial sectors of the economy. The estimated model for the first period points to the non-significant effect of the restrictive monetary policy shock on market interest rates. That confirms the poor efficiency of interest rate channel of monetary transmission during pre-2008 crisis period. The results for the second period show that the most of responses are surprisingly not significant. That could be explained by the several notions. During that period, the monetary policy conducted by the Bank of Russia was not perfectly homogenous. Indeed, since 2013 the Central Bank has changed the main policy instrument and in 2014 finally moved to the inflation targeting and the floating exchange rate regime. Moreover, we found some evidence that "the price puzzle" might exist in the Russian economy for the considered 2010-2017 period. These results for Russian economy may be interpreted as the evidence that the monetary policy tightening in Russia has a limited ability to restrain inflation.

Key words: dynamic factor model, structural identification, monetary policy shock, sign restrictions.

JEL codes: E31, E42, E43, E51, E58

I Introduction

In recent years the debates about the monetary policy effectiveness became one of the central in economic literature in Russia. During the 2008-2009 crisis, the Central Bank of Russia for the first time began to provide liquidity on a large scale to commercial banks. That measure led to the increase in liabilities of the banks to the Bank of Russia and therefore boosted the importance of the interest rate channel of the monetary transmission mechanism. After that, in the second half of 2013 the Bank of Russia announced that the key interest rate would be considered as the main monetary policy instrument.

The growing attention to the monetary policy debates is also related to the recent switching to the inflation targeting and the abolition of the fixed exchange rate regime. Altogether the decisions made by the Central Bank are discussed in terms of timeliness and compliance with the existing macroeconomic conditions, and there is no consensus what is more effective – the inflation targeting or, for instance, the targeting of monetary aggregates. To make the judgments about the effectiveness of a particular policy measure on the economy, it is viable to know how that measure affects the key macroeconomic variables. Consequently, researchers paid careful attention to the estimation of the effects of monetary disturbances.

The standard approach to identify the nonsystematic component of the monetary policy is to build upon the structural VAR models. There are some papers considering the Russian economy (i.e. Drobyshevskiy, 2008, Vashelyuk et al., 2015, Lomivorotov, 2015, Mallick, Sousa, 2012). However, in recent years the criticism of the VAR models has significantly increased (see Stock, Watson, 2016). The blame of VAR is driven by the fact that the analysis of shocks here is usually based on the assumption that the information set of the central bank is the same as the set of variables used by the researcher (Luciani, 2015). However, it is obvious that the central bank monitors the wider range of economic indicators. As a result, the VAR models with the small number of regressors included could lead to biased results because of the omitted variables problem. From the other hand, the inclusion of the large number of variables may cause the phenomenon known as "the curse of dimensionality". One way to avoid simultaneously both problems is to estimate the dynamic factor models (DFMs). Empirical results from the influential papers show that the impulse response functions (IRFs) could change dramatically if the econometrician considers the wider list of economic indicators (i.e., Forni, Gambetti, 2010). In addition, the DFMs allow estimating the responses of the large number of variables to the structural shocks.

A few papers consider factor models for the Russian economy (Borzykh, 2016; Kreptsev, Seleznev, 2016, Achkasov, 2016). However, all mentioned papers were not primary focused on the identification of the monetary policy shocks. Using structural models, Borzykh (2016) analyzed the bank lending channel of monetary transmission while Kreptsev, Seleznev (2016) estimated the effect of interbank interest rates on nonfinancial corporations lending rates. Achkasov (2016) developed nowcasting and forecasting model of the Russian GDP by means of a reduced-form factor model with a small number of static factors.

We depart from the recent studies in the following ways. We estimate the structural DFM model, while two aforementioned works estimated FAVAR model, i.e. they treat the factors as observables (a questionable assumption). Moreover, in this paper we use modern identification by means of sign restrictions. In contrast, Borzykh, 2016 and Kreptsev, Seleznev, 2016 applied recursive identification scheme, which was recently criticized (see Gertler, Karadi, 2015; Kilian, 2013). Lastly, we estimate the factor model and identify the monetary policy shocks for the whole period from 2003 to 2017 and then repeat the procedure for the two sub-periods: January 2003 – June 2008 and January 2010 – February 2017. The rationale behind this is the following. Before the 2008 crisis the Bank of Russia put more weight on exchange rate management. After the crisis the Central Bank of Russia changed the priority of monetary policy instruments and gradually switched to the floating exchange rate regime. The process finished in the end of 2014. As we show below, the results change dramatically when the models for sub-periods are estimated.

The rest of the paper is organized as follows: the second section is devoted to the theoretical aspects of SDFM, the third section discusses the data and transformations of the data set, the forth presents the estimation and the identification procedure and the empirical results for the Russian economy.

II The theoretical framework of the SDFM

Dynamic factor model

The main assumption underlying the factor models is that fluctuations of the economy are driven by the two components: the common component which is usually interpreted as "macroeconomic" shocks, and the second – idiosyncratic component which influence only one or few variables and might be called "specific" shocks. Idiosyncratic shocks reflect the dynamics in particular economic sector or region.

The dynamic factor model can be written in two forms: static and dynamic. The dynamic form presents the set of observable time series as depending on current and lagged values of unobservable (latent) factors explicitly. The static form expresses the same dynamics implicitly (Stock, Watson, 2016). As soon as the model is written in the static form, the principal component analysis becomes directly applicable to the DFM model.

The standard expression of the static DFM is the following:

$$X_t = \Lambda F_t + e_t \quad (1.1)$$

$$F_t = \Phi(L) F_{t-1} + G\eta_t \quad (1.2)$$

$$\eta_t = H\varepsilon_t \quad (1.3)$$

where X_t – the vector of N time series *(Nx1)*, F_t - the vector of (*rx1*) r static factors, Λ – the factor loading matrix (*Nxr*), e_t *(Nx1)* – the idiosyncratic component, $\Phi(L)$ and G - the matrixes *rxr* и *rxq* respectively, η_t (*qx1*) – dynamic factors in non-structural form, ε_t – (*qx1*) factor innovations in structural representation, *H* – the invertible matrix *(qxq).*

The first step of the estimation is to determine the numbers of static and dynamic factors ($\hat{r}$ and $\hat{q}$) respectively. The whole procedure could be summarized as follows.

1) Use the scree plot and the set of statistical criteria (i.e. Bai, Ng (2002), Ahn et al. (2013), Onatski (2010)) to determine the number of static factors.

2) Find $\hat{r}$ static factors as $\widehat{\mathrm{F}}_{\mathrm{t}} = \widehat{\Lambda}^{\mathrm{T}} \mathrm{X}_{\mathrm{t}}{}^{\mathrm{T}}$, where $\hat{\Lambda}$ is the factor loading matrix determined with the principal component analysis of standardized data set X_{t}. In other words, the matrix $\hat{\Lambda}$ represents the $\hat{r}$ eigenvectors corresponding to the largest eigenvalues of the variance-covariance matrix X_{t}.
3) Estimate the VAR model for $\hat{r}$ static factors and save the residual matrix from the model. The optimal number of lags can be determined by standard information criteria such as BIC or AIC.
4) Use the common statistical criteria to determine the number of dynamic factors $\hat{q}$ suggested by Bai, Ng (2007), Hallin, Liska (2007), Amengual, Watson (2007).
5) Find the matrix $\hat{G}$ by using a spectral decomposition (Forni, Gambetti, 2010):
   $\hat{G} = \mathrm{R} * \mathrm{D}$, where D (qxq) is the diagonal matrix with the elements $\sqrt{\mu_{\mathrm{i}}}$, where $\mu_{\mathrm{i,i=1,..,q}}$- the largest eigenvalues of the variance-covariance matrix of the residuals from (3),
   R (rxq) – the matrix of the corresponding q eigenvectors.
6) Find the $\hat{q}$ dynamic factors as $\hat{\eta}_{\mathrm{t}} = \mathrm{D}^{-1} \mathrm{R}^{T} \widehat{\varepsilon_{t}}$ (Forni et al., 2009).

To estimate the structural impulse response function, one needs to identify the matrix H (or the single column of the matrix H).

Identification procedure

As widely known, there are many alternative methods to identify the monetary policy shocks: recursive identification scheme, long-run restrictions, sign restrictions, the narrative approach, the external instruments method and the identification via the heteroskedasticity.

We are aware of the most advantages and drawbacks of the particular method, and in this paper, we use the sign restrictions for identification of the monetary policy. The reasons for that choice are the following. First, the recursive identification schemes are not used as they assume the short-run restrictions which might be too binding (Barigozzi, 2014) and does not necessarily can be explained by the economic theory. In contrast, the sign restrictions coincide with the theoretical views (Uhlig, 2005). For example, Uhlig (2005) and Mallick and Sousa (2012) identify contractionary monetary policy shock as the one that decreases the prices and monetary aggregates. That coincides even with the basic IS-LM model. Moreover, long-run restrictions are supposed to be too restrictive and need to be further investigated in the context of particular country (Vaschelyuk, 2015).

The implementation of external instruments (see Gertler, Karadi, 2015) is not applicable for the Russian economy as it requires high frequency data, i.e. the daily changes in derivative financial instrument yields around the dates of the Bank of Russia Board of Directors meetings. Unfortunately, such statistics is not available in Russia for a rather long time period (normally, we have data for the last few years as these instruments appeared at the Russian financial market very recently). The identification through the heteroskedasticity, based on the assumption that the variance of only the monetary shock changes while variances of other shocks keep constant also requires data with the same daily frequency as in the external instrument approach (see Wright, 2012).

As for the narrative approach, the main assumption is that the central bank is fully informed about the state of the economy, and this information is enough to identify the monetary policy shock. The difficulty arises there because no one can be sure that obtained narrative time series is exogenous shocks of the monetary policy. This problem was initially highlighted by Cristiano et al. (1999) in the context of systematic and non-systematic components of the monetary policy. Consequently, narrative data could be “imperfect’ measure of the structural shocks (Stock, Watson, 2016). In addition, the common statistical problem is that the information available for the narrative identification might be published only after a long period of time.

With these notions we argue that the sign restrictions approach to the monetary policy shocks identification is the most reliable due to its theoretical background and its feasibility considering financial data scarcity in Russia.

It is worth to notice also that in the sign restrictions approach the point identification cannot be obtained, that is, an econometrician can estimate only the set of identified models. From the one hand, this fact might be considered as a drawback of the inequality restrictions. From the other hand, sometimes the point identification requires highly controversial assumptions (Stock, Watson, 2016).

Let us briefly describe the sign restrictions identification procedure (we follow Fry, Pagan, 2011 in the description). Using Givens transformation, a vector of angles (q(q-1)/2) is drawn from a uniform distribution [0,2π), and the step is repeated n times. These iterations are necessary to estimate the orthogonal rotation matrix Q s.t. QQ’=I. After the rotation matrix is computed, the structural impulse responses are estimated. In case the impulse responses satisfy the initial sign restrictions, then the draws are accepted. If the restrictions do not hold, the draws are denied. When the certain number (specified by a researcher) of draws is accepted, the algorithm stops.

By means of sign restrictions, the set of admissible models could be drawn in a Bayesian or in a frequentist setting. In this paper we apply the frequentist approach as the Bayesian is criticized from the two points of view (Killian, Lutkepohl, 2017; Moon, Schorfheide, 2012). Firstly, despite the fact that sign restrictions give no a priori information over the identified set, the initially flat prior for Q could turn to be highly informative for the inference. The simple examples are provided by Stock, Watson (2016). Secondly, as Moon and Schorfheide (2012) mentioned, Bayesian credible sets can be too narrow from the frequentist perspective. It means that Bayesian sets exclude part of the estimated identified set.

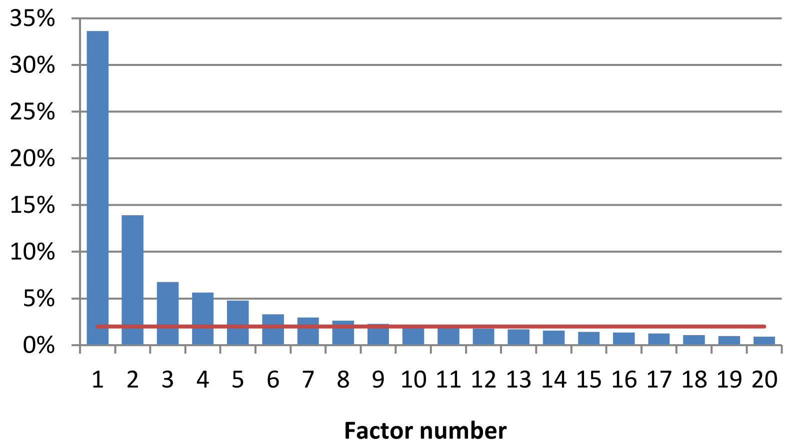
To get confidence bands in the frequentist approach, the bootstrap procedure is used with a large number of draws. Following Barigozzi et al (2014), at each draw we save *p* rotation matrices. From them we select the one rotation matrix that gives the impulse response closest to the median.

III Data transformation and estimation of the number of factors

We take the monthly data set from the paper of Achkasov (2016). We believe that these data are close to the Central Bank’s information set since the Bank of Russia use that set of time series for nowcasting, short-term forecasting and monitoring the current economic conditions. There are 53 time series divided into three groups: 19 real sector time series, 21 financial sector variables and 13 time series reflected the expectations of economic agents. Then we also add four indicators not presented in the initial dataset: key interest rate (managed by the Bank of Russia), monetary base, consumer price index (CPI) and producer price index (PPI). The considered period spans from January 2003 to February 2017. The full list of variables and the description of transformation are presented in the Appendix (Table 1). As suggested in Stock, Watson (2016), the second log differences of prices and money aggregates are taken. For the interest rates, we take the first differences. The variables were seasonally adjusted when it was necessary. All computations were held in R and Matlab.

To estimate the number of static and dynamic factors, we use the set of different criteria. The results of the most tests depend on the assumption about the maximum number of static factors denoted r_{max}. For this purpose, we analyze the scree plot (fig.1) to determine what share of the variance each factor explains. In this paper we assume that factors which explain less than 2% of variance of the dataset are idiosyncratic disturbances or the measurement errors (red line on the fig.1). For the whole period from January 2003 to February 2017 the tenth factor explains slightly more than 2% of variance, so we set the maximum number of factors equal to ten. The eleventh factor explains 1,8% of variance. The total variance explained by ten factors is 78,8%.

Fig.1 Scree plot (the variance explained by i-th factor)



It is common for the researcher who relies on different statistical tests, to receive the ambiguous results (Stock, Watson, 2016). For example, Bai, Ng (2002) information criteria widely known as IC_1, IC_2 suggest 10 and 8 static factors respectively. Ahn et al (2013) and Onatski (2010) show only 2 static factors. To estimate the number of dynamic factors, we use three common tests: Hallin, Liska (2007), Amengual, Watson (2007) and Bai, Ng (2007). Based on the assumption of 10 static factors, the tests suggest {3,5}, {2} and {3,4} dynamic factors respectively. To check the results, we compute the number of dynamic innovations with 8 static factors. The results indicate {4,5}, {2} and {3} dynamic factors respectively. Our basic specification of the model will be constructed under the assumption about $\hat{r} = 10$ and $\hat{q} = 4$ factors.

IV Identification and results

As it was mentioned earlier, we identify the effects monetary policy shock by means of sign restrictions. First of all, we estimate structural impulse response functions for the whole period (January 2003 – February 2017). The initial set of identification restrictions is the following: after the contractionary monetary policy shock the key rate increases while CPI and M2 decrease. We suppose that the restrictions hold for the horizon of 6 months.

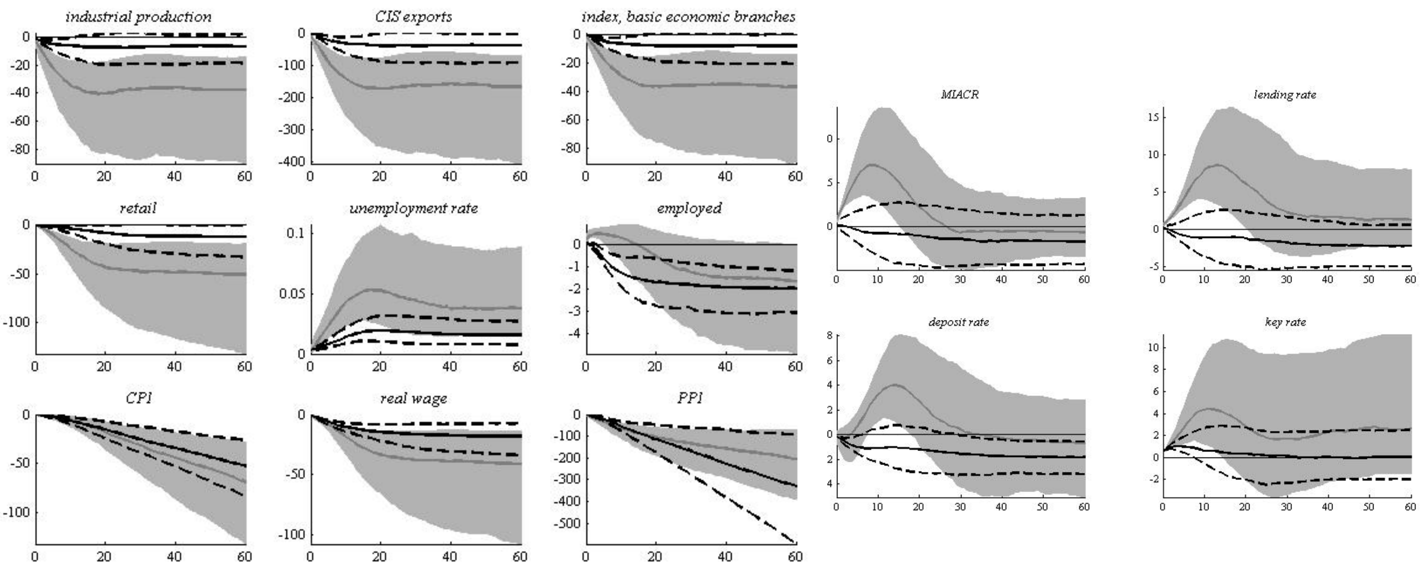
Confidence intervals are computed with 500 bootstrap iterations. At each iteration, we draw 1000 angles to construct the rotation matrix, and then only first 10 matrices satisfying restrictions are selected. Following Fry, Pagan (2011) we choose only one matrix with the closest IRF to the median one to avoid the excessive uncertainty.

The identified shock is normalized so that the key rate increases by 50 basis points. The SIRF for all variables are presented in the Appendix (fig.1., the grey shaded area). The main results are the following.

The contractionary monetary policy shock significantly affects the real sector of Russian economy. To be more precise, the shock reduces the production in all main sectors: manufacturing, mining and electricity, gas and water supply. However, the largest decrease is noticed in the manufacturing sector, while the smallest – in the mining industry. It may be explained by the structural features of the Russian economy as Russia is the commodity exporter. The dynamics of the production in the mining industry is likely influenced by other factors (other than monetary policy shock). Moreover, mining industries in Russia are the largest ones and historically demonstrated the positive dynamics over the considered period and supposed to be highly competitive. In contrast, many industries of manufacturing, for example, manufacturing of textiles, have stagnated since the 1990-ies, so they are the most vulnerable to restrictive policy. The effect of the monetary policy shock on the production reaches the peak after a year and a half.

The negative monetary policy shock also reduces the investments and the agriculture production. The agriculture production in Russia strongly depends on the cost of the debt as Russian agriculture companies have to compete with the cheap imports. The increase in the key rate leads to the increase in the lending rates and, consequently, the cost of the debt for the agriculture producers. The other indicators of the real sector such as the volume of construction and the amount of new housing are also dropped in response to the monetary tightening. Retail turnover which is the proxy variable for consumer spending demonstrates the significant drop in all sub-sectors (food and non-food items).

Fig.2 Impulse response functions to a contractionary monetary policy shock. Grey area – the whole period 2003-2017; dashed line – the period from January 2003 to June 2008



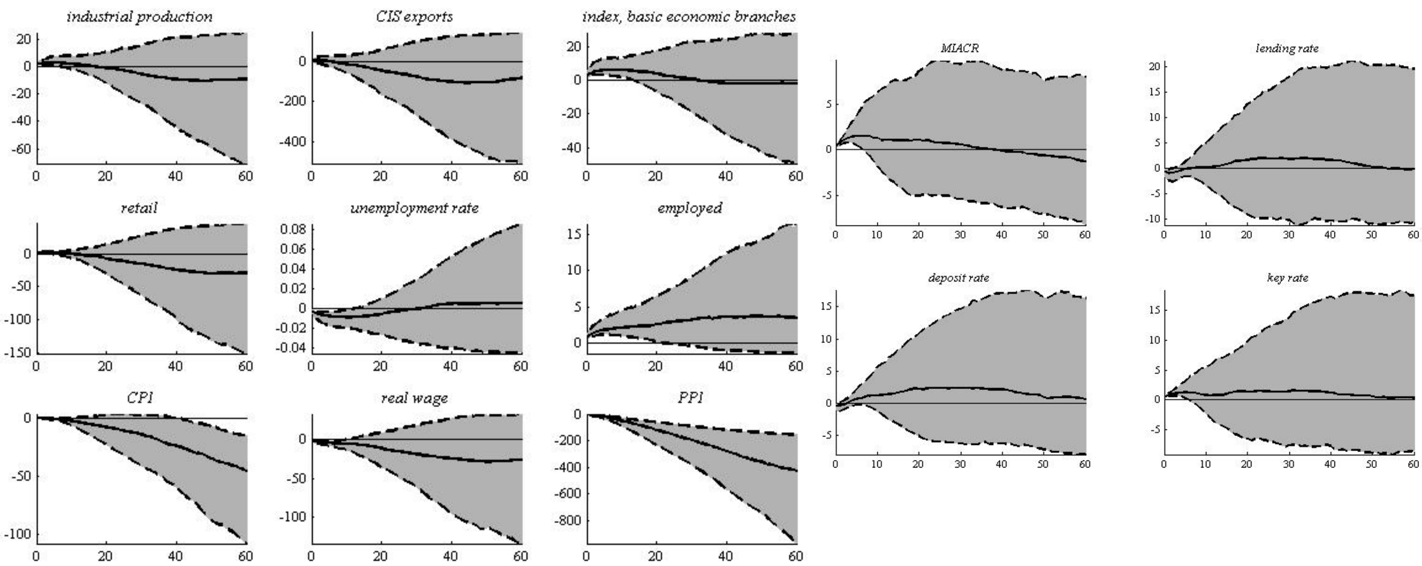
The unemployment rate gradually increases and peaks after around two years. It could be explained by the existence of the labor contracts and the impossibility of employees to shortly lay off employers. The real wages are also decreased what coincides with the economic theory.

The decrease in the producer price index suggests that the “price puzzle” does not exist when the model is estimated for the whole period. The labor force and the capacity utilization also drop what corresponds to the decrease in the production. The share of companies whose financial state is “good” or “normal” falls in response to the contractionary shock.

Then we re-estimate the model for the first sub-period (January 2003 – June 2008). The main result is the following. In contrast to the whole period, the increase in the key rate by 50 basis points does not significantly influence the market interest rates (lending rate, deposit rate and money market rate). It points the poor effectiveness of interest rate channel of monetary transmission mechanism during the pre-crisis period. Before the 2008 crisis, the Central Bank of Russia was mainly focused on the interventions in the foreign exchange market that can be confirmed by the low volatility of the ruble exchange rate (Pestova, 2017). In addition, the Central Bank of Russia did not provide commercial banks with the loans. During that period, the market interest rates were highly volatile (for example, interbank credit rate) and influenced by a number of other factors such as external shocks.

The impulse response of the export to the monetary policy shock is almost non-significant that could be explained by the fixed exchange rate regime during the pre-crisis period. The Central Bank of Russia intervened in the currency market to keep the nominal exchange rate constant what decreases the sensitivity of exports to shocks as the exchange rate directly transmits to the values of export and import.

Fig.3 Impulse response functions to a contractionary monetary policy shock. Period: January 2010 – February 2017. Sign restrictions: key rate goes up, M2 and CPI decrease

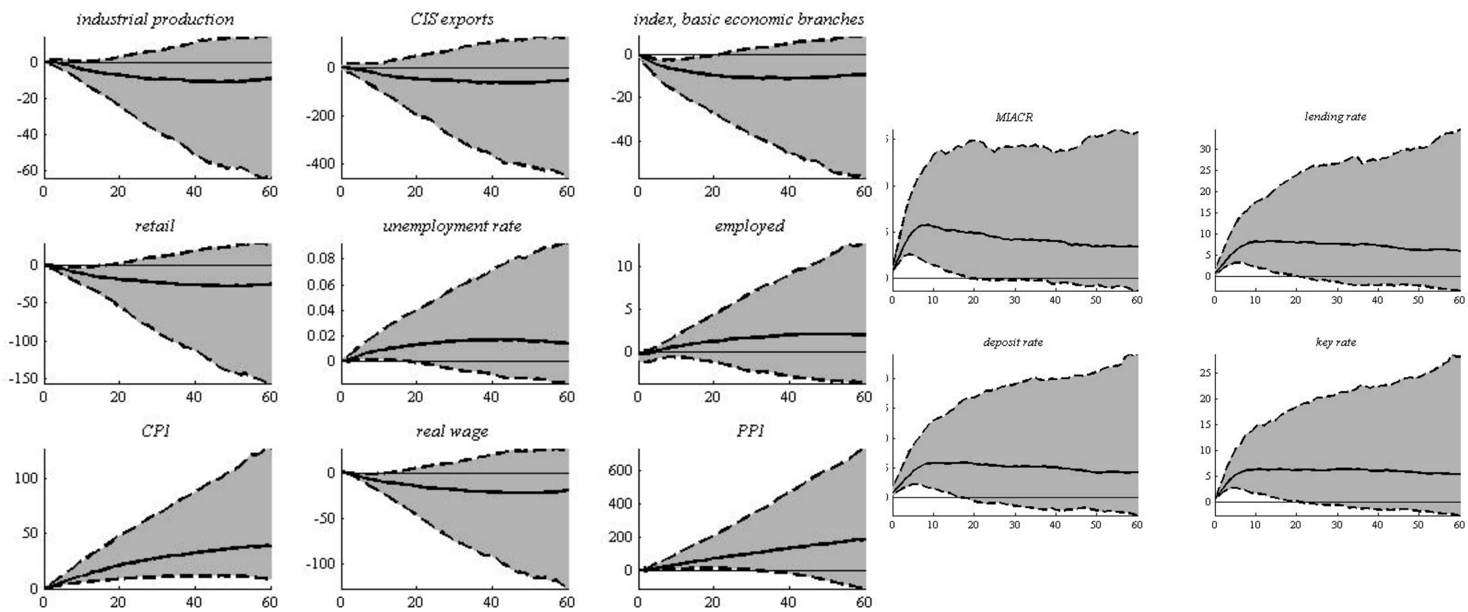


Then we re-estimate the model for the period from January 2010 to February 2017. Compared to the results of previous periods, the SIRFs for the most variables are not significant (figure №3). Below we provide some explanations of these results.

First of all, the period from 2010 to 2015 is characterized by the heterogeneity and instability of the monetary policy. For example, in 2013 the Bank of Russia implemented the reform of the policy instruments: the key interest rate became the main instrument. The Central Bank *gradually* increased the effectiveness of interest rate channel via the narrowing of the symmetric interest rate corridor. In contrast to the first sub-period, the monetary policy shock now significantly influences the market interest rates: the lending and deposits rates and MIACR rate increase in response to the restrictive shock. Again, that result confirms the growing importance of the key rate after the crisis. Moreover, in 2014 the Bank of Russia finally switched to the inflation targeting and floating exchange rate regime. The period of relative homogeneity starts from 2015. However, there are only a few data points available for the estimation. That makes the estimation unreliable on that short period of time.

However, for this period the increase in the production after the contractionary monetary policy shock might be noticed. This result does not correspond with either economic theory. However, we tried to avoid it by changing the initial set of sign restrictions. We re-estimate the model with such restrictions that in response to the monetary policy shock the M2 and the Index of intensity of production for the basic economic industries decreased. The new results suggest that the CPI and PPI increase, i.e. the "price puzzle" arises for that period.

Fig.4. Impulse response functions to a contractionary monetary policy shock. Period – January 2010 – February 2017. Sign restrictions: key rate goes up, M2 and industrial production index decrease



The existence of the "price puzzle" is quite a controversial result. However, there is a theoretical background underlying that phenomenon. The possible explanation of the "price puzzle" in the existing literature is the "cost channel" of monetary policy (Ramey, 2016). The rise in interest rates translates into the increase in inflation through the costs of working capital for firms as they have to borrow from intermediaries to pay the factors of productions.

These results for the Russian economy may be interpreted as the evidence that the Bank of Russia conducting the tightening monetary policy has a limited ability to restrain inflation. Moreover, one more evidence argues in favor of that conclusion over the second period. If we change the sign restrictions so that in response to the monetary policy tightening, the M2, the industrial production index and CPI decrease, we get that there is no rotation matrix with the

SIRF which satisfies the new set of sign restrictions. That points that the output and prices do not move in the same direction after a contractionary monetary policy.

All in all, we found some evidence that "the price puzzle" might exist in the Russian economy for the considered 2010-2017 period. However, the nature of that issue is needed to be further studied for the Russian economy.

Conclusion

In this paper we estimated the structural dynamic factor model with 57 time series to identify the monetary policy shock in Russia for the period from 2003 to 2017 and two sub-periods: 1) January 2003 – June 2008 and 2) January 2010 – February 2017. The identification was implemented by means of sign restrictions. The main results are the following: over the whole period, the contractionary monetary policy shock significantly impacts the real sector of Russian economy. The shock reduces the production in all key sectors: manufacturing, mining and utilities The negative monetary policy shock also influences the investments and the agriculture production, the unemployment rate, the amount of new housing, retail turnover and many other real sector variables.

After the re-estimation of the model for the two sub-periods, some of the results changed. For the first period, the increase in the key rate by 50 basis points does not significantly influence the market interest rates (lending rate, deposit rate and MIACR) that points the poor effectiveness of interest rate channel of monetary transmission mechanism during the pre-crisis period. For the second sub-period, the results confirm the growing significance of the interest rate channel after the crisis as the impulse response functions became significant again.

Most interesting, we find evidence in favor of "price puzzle" for the second period considered. We argue that it likely indicates the limited ability of the Central Bank of Russia to control inflationary processes.

References

1) Achkasov Y., 2016. The model of the GDP estimation in Russia based in the current statistics: the modification of approach. Economic research reports, Bank of Russia, №8 (in Russian).

2) Amengual, D., Watson, M.W., 2007. Consistent estimation of the number of dynamic factors in a large N and T panel. Journal of Business & Economic Statistics, 25, 91–96.

1) Ahn, S.C., Horenstein, A.R., 2013. Eigenvalue ratio test for the number of factors. Econometrica 81, 1203–1227.

2) Bai, J., Ng, S., 2002. Determining the number of factors in approximate factor models. Econometrica 70, 191–221.

3) Bai, J., Ng, S., 2007. Determining the number of primitive shocks in factor models Journal of Business & Economic Statistics, 25, 52–60.

4) Barigozzi, M., Conti A. M. , Luciani M., 2013. Do Euro Area Countries Respond Asymmetrically to the Common Monetary Policy? Oxford Bulletin of Economics and Statistics, Volume 76, Issue 5, p.693-714.

5) Baumeister, C., Hamilton, J.D., 2015. Sign restrictions, structural vector autoregressions, and useful prior information. Econometrica 83, 1963–1999.

6) Borzykh O., 2016. The bank credit channel: estimation of the TVP-FAVAR model. Applied Econometrics, v. 43, p. 96–117.
7) Drobyshevsky S., Trunin P., Kamenskikh M., 2008. Analysis of Transmission Mechanisms of Money and Credit Policy in Russia's Economy. IEPP Research № 116P (in Russian).
8) Forni, M., Gambetti, L., 2010. The dynamic effects of monetary policy: a structural factor model approach. The Journal of Monetary Economics, 57, 203–216.
9) Forni, M., Giannone, D., Lippi, M., Reichlin, L., 2009. Opening the black box: structural factor models with large cross-sections. Econometric Theory 25, 1319–1347.
10) Fry, R., Pagan, A., 2011. Sign restrictions in structural vector autoregressions: a critical review. The Journal of Economic Literature, 49 (4), 938–960.
11) Gertler, M., Karadi, P., 2015. Monetary policy surprises, credit costs, and economic activity. American Economic Journal: Macroeconomics 7 (1), pp. 44–76.
12) Hallin, M., Liska, R., 2007. The generalized dynamic factor model: determining the number of factors. J. Am. Stat. Assoc. 102, 603–617.
13) Killian L., Lutkepohl H. Structural Vector Autoregressive Analysis, Cambridge University Press (forthcoming).
14) Kreptsev D., Seleznev S., 2016. The impact of the interest rates of the money market on credit interest rates. Economic Research of the Bank of Russia, № 9. (in Russian).
15) Luciani M., 2015. Monetary policy and the housing market: a structural factor analysis. Journal Of Applied Econometrics, 30, 199-218.
16) Lomivorotov P.B., 2015. The Bayesian Methods for the analysis of monetary policy in Russian economy. Applied Econometrics, №38 (2).
17) Mallick, Sousa, 2012. Real effects of monetary policy in large emerging economies. Macroeconomic Dynamics, 16 (2), pp. 190–212.
18) Moon H.R., Schorfheide F., 2012. Bayesian and Frequentist Inference In Partially Identified Models. Econometrica, Vol. 80, No. 2 pp. 755-782.
19) Pestova A. A. On the effects of monetary policy in Russia: the role of the space of spanned shocks and the policy regime shifts (forthcoming).
20) Pestova A. A., 2017. Monetary policy regimes in Russia: Guidelines for further quantitative studies. Economic Issues, № 4.
21) Polbin A.V., Trunin P.V., Vaschelyuk N.V., 2015. Macroeconomic effects of the monetary policy shock for Russian Economy. Economic Journal of HSE. №2. C. 169–198 (In Russian).
22) Porshakov, A., Ponomarenko A., Sinyakov A., 2016. Nowcasting and Short-Term Forecasting of Russian GDP with a Dynamic Factor Model. Journal of the New Economic Association, vol. 30(2), p. 60-76 (In Russian).
23) Ramey V., 2016. Macroeconomic shocks and their propagation. In: Handbook of Macroeconomics.
24) Stock J.H., Watson M. W., 2016. Factor Models and Structural Vector Autoregressions in Macroeconomics. In Handbook of Macroeconomics.
25) Wright, J., 2012. What does monetary policy to do long-term interest rates at the zero lower bound? The Economic Journal, 122, F447–F466.
26) Uhlig, H., 2005. What are the effects of monetary policy on output? Results from an agnostic identification procedure. The Journal of Monetary Economics, 52, 381–419.

Appendix

Table A1. The transformation of the dataset

Variable name	Short name	Units	Transformation
Industrial production index	ind production	June 2007=100	3
Industrial production index, mining	ind prod, mining	June 2007=100	3
Industrial production index, manufacturing	ind prod, manuf	June 2007=100	3
Industrial production index, electricity, gas and water supply	ind prod, electr	June 2007=100	3
Agriculture production	Agriculture	June 2007=100	3
Fixed investment	Investment	June 2007=100	3
Freight traffic	Traffic	June 2007=100	3
Volume of constructions	Construction	June 2007=100	3
Total area of living space introduced	Area	June 2007=100	3
Export to CIS countries	CIS export	June 2007=100	3
Export to non-CIS countries	non-CIS export	June 2007=100	3
Retail turnover, non-food items	retail, non-food	June 2007=100	3
Retail turnover, food, beverages and tobacco	retail, food	June 2007=100	3
Retail trade turnover	retail	June 2007=100	3
Unemployment rate	unemp rate	%	2
Labor force, employed	Employed	Mln.	3
Index of intensity of production for the basic economic branches	basic index	June 2007=100	3
Real wage	real wage	June 2007=100	3
Real amount of pensions	Pensions	June 2007=100	3
CPI	Cpi	June 2007=100	4
PPI	Ppi	June 2007=100	4
Diffusion index of finished goods, the share of companies who reported the increase of the indicator	d_finished	%	3
Diffusion index of relative price (produced/purchased), the share of companies who reported the increase of the indicator	d_price	%	3
Diffusion index of purchasing equipment, the share of companies who reported the increase of the indicator	d_equip	%	3
Production capacity, normal level=100	d_capacity	%	2
Labor force utilization, normal level=100	d_labor	%	2
Stock of finished goods, normal level=100	d_stock	%	3
Business acquisition, normal level=100	d_business	%	3

Loans to banks, normal level=100	d_bank_loans	%	3
Share of companies in normal or good financial state	d_fin state	%	3
Share of companies not purchased equipment for two or more months	d_non_pur	%	3
Credit interest rates in next 3 months	credit rates	%	2
Share of companies without debt in current month and next three months	no debt	%	3
Share of companies not intended to borrow a new loan in next 3 months	non borrowing	%	3
MIACR	MIACR	%	2
Lending Rate: Corporate Loans: Up to 1 Year	lend rate	June 2007=100	2
Deposit Rate: Personal Deposits: Up to 1 Year	dep rate	June 2007=100	2
Nominal Effective Rate	NER	June 2007=100	3
Real Effective Rate	RER	June 2007=100	3
RTS Index	RTS	June 2007=100	3
MICEX Index	MICEX	June 2007=100	3
Loans Debt including Non Residents, Corporate: Up to 30	corp loans (30)	June 2007=100	3
Loans Debt incl Non Residents, Corporate: 31 to 90 Days	corp loans (90)	June 2007=100	3
Loans Debt incl Non Residents: Foreign Currency: Corporate: Up to 30 Days	corp loans,f (30)	June 2007=100	3
Loans Debt incl Non Residents: Foreign Currency: Corporate: 31 to 90 Days	corp loans,f (90)	June 2007=100	3
Loans Debt incl Non Residents: Foreign Currency: Corporate: 91 to 180 Days	corp loans,f (181)	June 2007=100	3
Loans Debt incl Non Residents: Foreign Currency: Corporate: 181 Days to 1 Year	corp loans,f (365)	June 2007=100	3
Loans Debt incl Non Residents: RUB: Personal	pers loans	June 2007=100	3
Loans Debt incl Non Residents: Foreign Currency: Personal	pers loans, f	June 2007=100	3
M0	M0	June 2007=100	4
M2	M2	June 2007=100	4
Gas price	gas price	June 2007=100	4
Aluminium price	alum price	June 2007=100	4
PMI USA	pmi usa	June 2007=100	3
Oil Price	oil price	June 2007=100	4
Monetary base	m base	June 2007=100	4
Key rate	key rate	%	2

Note. 1 denotes no transformation, 2 – first differences, 3 - first log differences, 4 – second log differences

Fig.A1 Impulse response functions to a contractionary monetary policy shock. Grey area – the whole period 2003-2017; dashed line – the period from January 2003 to June 2008

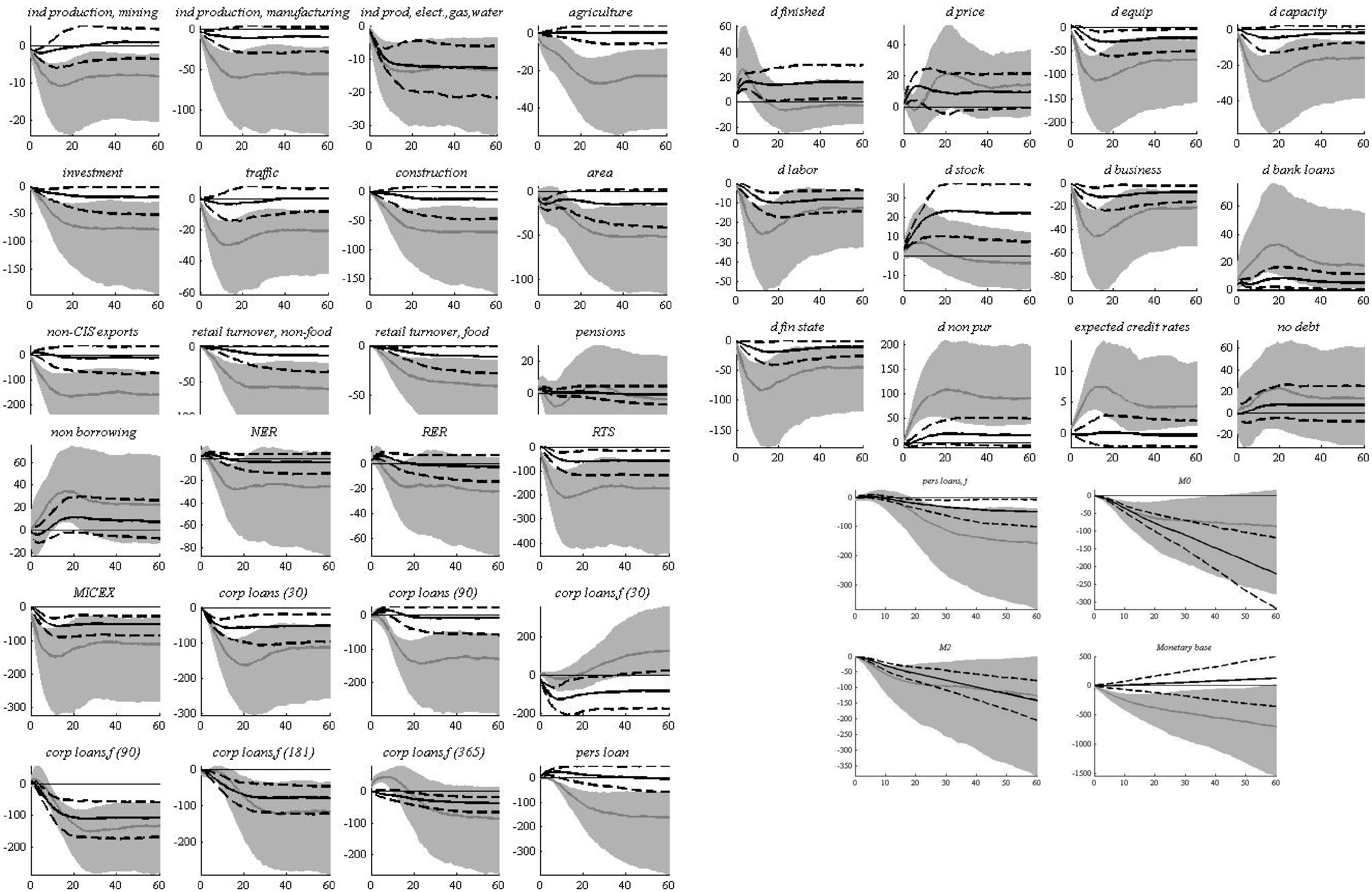


Fig.A2 Impulse response functions to a contractionary monetary policy shock (the period from January 2010 to February 2017). Restrictions: key rate increases, M2 and CPI decrease

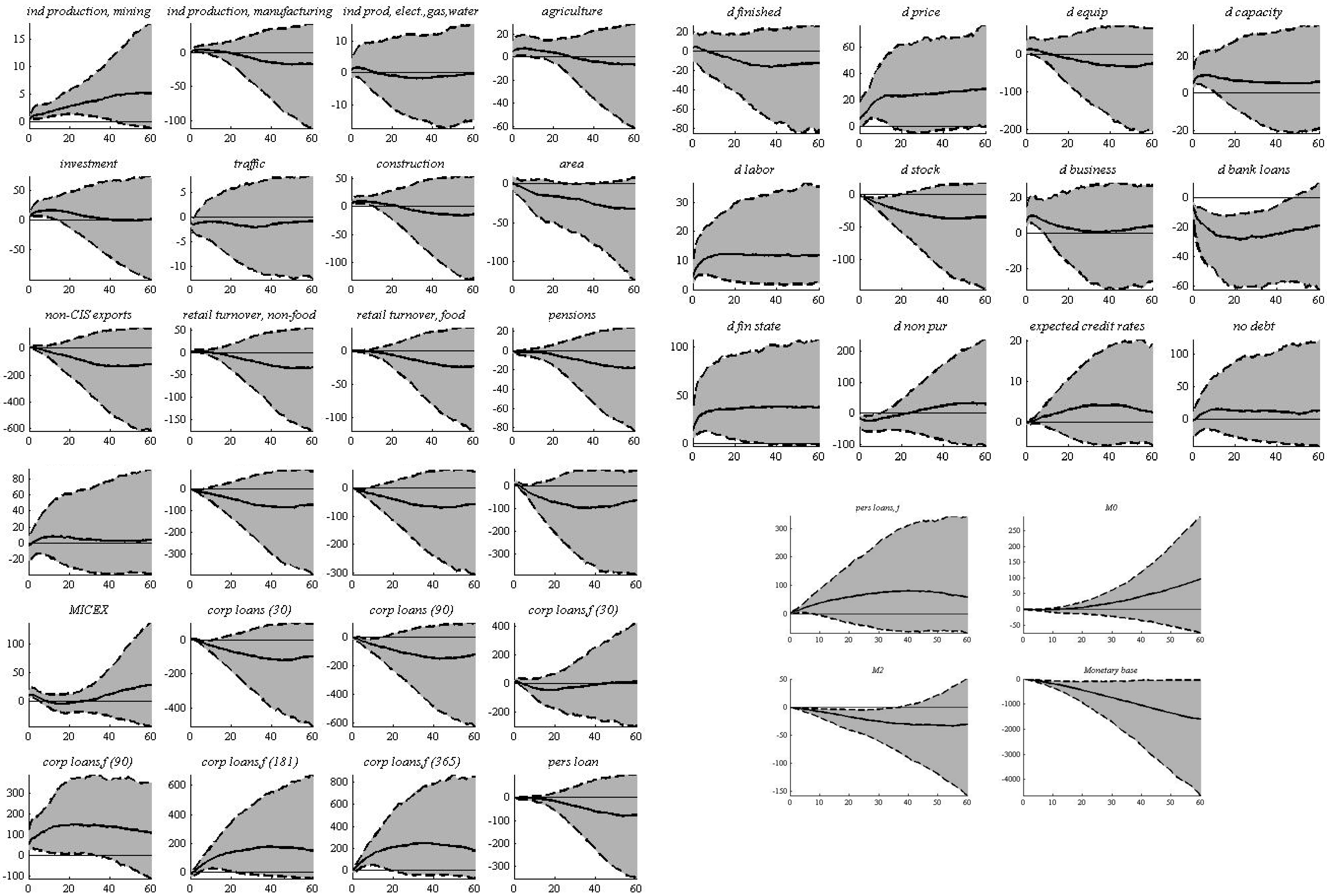


Fig.A3 Impulse response functions to a contractionary monetary policy shock (the period from January 2010 to February 2017). Restrictions: key rate increases, M2 and Index of intensity of production for the basic economic branches decrease