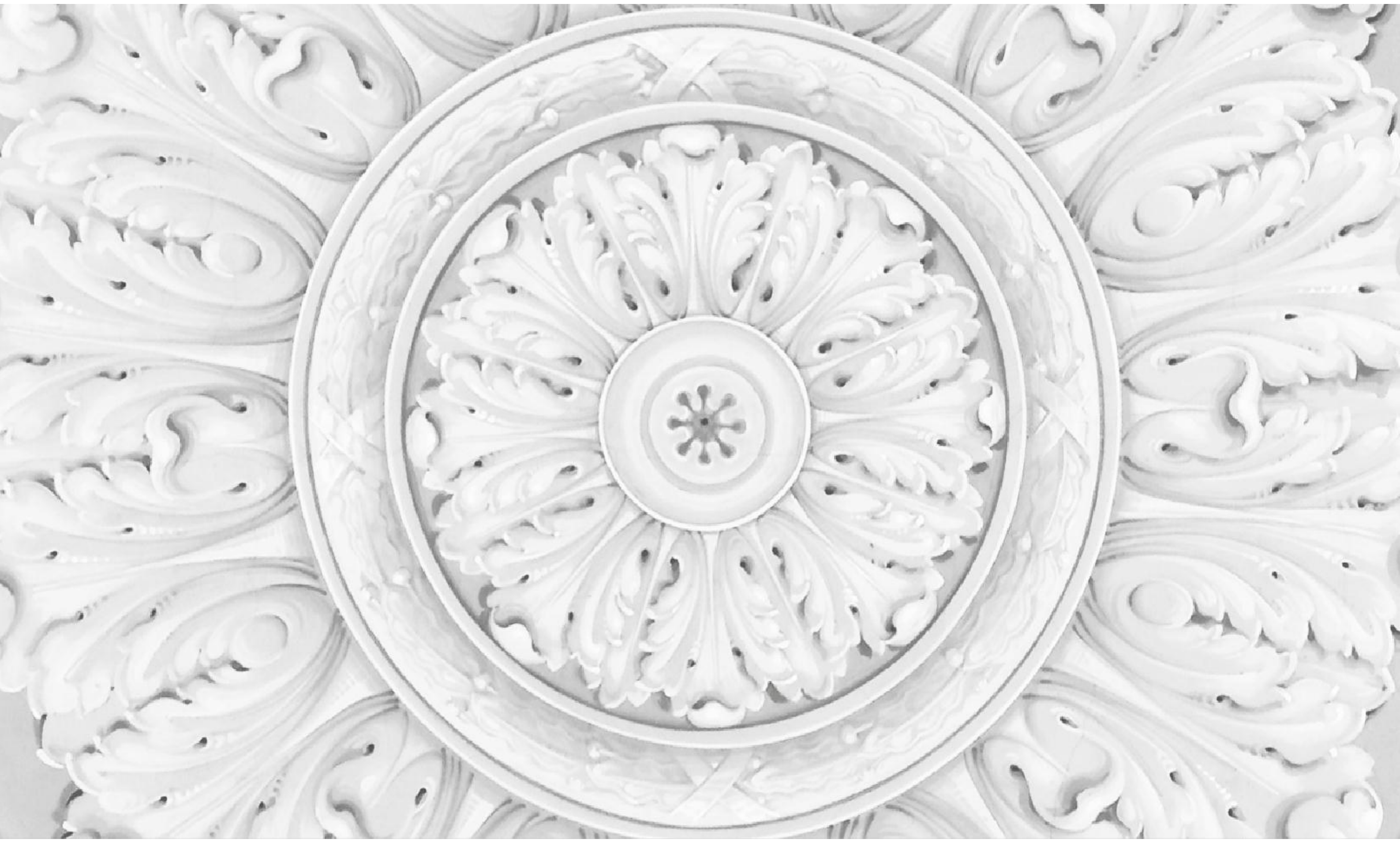
Bank of Russia
Central Bank of the Russian Federation



WORKING PAPER SERIES

Elena Deryugina
Alexey Ponomarenko
Andrey Sinyakov
Konstantin Sorokin

Evaluating the underlying inflation measures for Russia

No. 4 / March 2015

Elena Deryugina
Bank of Russia. Email: DeryuginaEB@cbr.ru

Alexey Ponomarenko
Bank of Russia. Email: PonomarenkoAA@cbr.ru

Andrey Sinyakov
Bank of Russia. Email: SinyakovAA@cbr.ru

Konstantin Sorokin
NRU-HSE. Email: constantine.sorokin@gmail.com

Acknowledgements

The authors would like to express their gratitude to Andrey Dementiev and to the participants in a joint scientific workshop held by the Laboratory for Inflation Problems and Economic Growth Research and the Laboratory for Macroeconomic Analysis at the National Research University of the Higher School of Economics (NRU-HSE) for valuable remarks and comments. All errors and omissions are those of the authors. The views expressed in this paper are solely those of the authors and do not necessarily represent the official position of the Bank of Russia.

Postal address	12 Neglinnaya Street, Moscow, 107016 Russia
Telephone	+7 495 771-91-00, +7 495 621-64-65 (fax)
Internet	www.cbr.ru

Abstract

Underlying inflation indicators can be useful for the monetary policy of the inflation targeting central bank when inflation indicators help separate a change in relative prices from true inflation, as well as when they allow assessing medium-term inflation risks. We apply various methods frequently used in practice to calculate 20 underlying inflation indicators for Russia in the pseudo-real time. We apply three types of tests to these measuring instruments: tests for economic content and the ability to forecast future inflation, as well as a set of technical tests. We find that inflation indicators calculated on the basis of dynamic factor models emerge as the best performing candidates. The dynamics of the obtained range of underlying inflation measures in 2014 compared with headline inflation indicates that the accelerated growth in consumer prices was not fully reflected in underlying inflation dynamics.

Keywords: Underlying inflation, core inflation, monetary inflation, dynamic factor model, Russia
JEL Classification: E31, E32, E52, C32

CONTENTS

INTRODUCTION

Since 2015, the Bank of Russia has adopted inflation targeting as its monetary policy mechanism, which targets a 4% medium-term inflation rate based on the consumer price index measured by the Federal State Statistics Service (Rosstat)[1]. The monetary policy lag[2] makes it impossible to control inflation within the lag horizon. That is why, as noted by Svensson (1997), in practice, central banks have to target future medium-term inflation and assess any price shocks from the viewpoint of the effects of these shocks on future inflation[3]. The Bank of Russia is no exception in this case and, as it monitors price changes, it has to answer the following question: what does this price change mean for inflation in the medium term? In other words, the central bank seeks to identify the factors of observed inflation and make an inflation forecast (to take into account the effect of price shocks observed, and also price changes expected in the future). Specifically, the central bank should determine whether a change in the consumer price index that has been measured reflects a change in relative prices and, consequently, how long the relative price change will have its effect on future inflation and other macroeconomic variables, or whether the CPI change reflects a change in the overall price level and how in this case the central bank perceives inflation fundamentals in the medium term.

Underlying inflation measures applied by central banks are intended to help find answers to the above questions. An ideal measure of underlying inflation[4] represents a part of average inflation (measured by the CPI), which reflects the inflationary trend (medium-term inflation expectations, a change in absolute rather than relative prices, and the dynamics of monetary aggregates). In other words, a measure of underlying inflation necessary (ideal) for monetary policy decisions should help identify headline inflation shocks relevant for monetary policy (a change in relative prices versus a change in absolute prices) and is designed to inform about the dynamics of future headline inflation (measured by the CPI) or about current medium-term inflation expectations. For example, a larger spread between headline and underlying inflation amid stable underlying inflation does not necessarily require the interference of a central bank owing to the fact that this deviation may reflect a change in relative prices that has nothing in common with inflation.

[1] "The monetary policy goal is to lower inflation to 4% in 2017 and keep it close to this level." The Guidelines for the Single State Monetary Policy in 2015 and for 2016 and 2017, Bank of Russia, 2014.

[2] The time interval between the use of a central bank instrument (in the case of the Bank of Russia, a change in the key interest rate) and inflation response. In literature, a monetary policy lag is estimated to range from six months to two years for output and from twelve months to three years for inflation, see, for example, Mohanty (2012), Gruen, et al. (1997), Duguay (1994).

[3] As a result of this practice of choosing the target, a central bank is not responsible for inflation's failure to reach the target due to the fact that price shocks may occur in the future and the central bank may turn out to be unable to influence them immediately. At the same time, the projected inflation rate in excess of the central bank's medium-term target creates grounds for a current change in the key rate to a level, which will suffice to make the central bank's inflation forecast comply with the target.

[4] See a review of underlying inflation definitions at Wynne (2008) and the criticism of their use in practice at Bullard (2011).

See, for example, Reis and Watson (2010), Nessen and Soderstrom (2001). The underlying inflation growth, on the contrary, signals an increase in medium-term inflation risks and may indicate the need for monetary policy interference[5].

Different approaches are described in literature towards constructing underlying inflation not only and not so much as a statistical measure but as an analytical instrument: Amstad et al. (2014), Meyer et al. (2014), Bilke and Stracca (2008), Wynne (2008, 1999), Lafleche and Armour (2006), Aucremanne and Wouters (1999). Dementiev and Bessonov (2012) and Tsyplakov (2004) estimate underlying inflation measures for Russia. Considering that underlying inflation is not an observable characteristic and there is a great number of approaches towards measuring it (that is, statistical and econometric techniques allow for the realisation of the basic features of underlying inflation by more than one method), a task that emerges is to test which of the underlying inflation measures is the best from the viewpoint of the criteria reflecting the underlying inflation definition. These tests are given in Amstad et al. (2014), Mankikar and Paisley (2004) and Silver (2006). In practice, it may turn out that some underlying inflation measures demonstrate good properties by some criteria and bad properties by other criteria set to underlying inflation. For example, some measures, which clean inflation well from extreme price changes (from changes in relative prices, for example, the trimmed weighted mean) may turn out to be excessively stable and providing little information about the future inflation dynamics[6]. This occurs when strong changes in certain CPI components reflect an incipient inflationary trend, which may be falsely perceived as a change in relative prices; see Mankikar and Paisley (2004).

That is why, for practical purposes, the above researches that tested underlying inflation measures recommend to use a whole spectrum of underlying inflation indicators. With this approach, the probability of a monetary policy error is only reduced and confidence in a central bank's decisions grows when the range of underlying inflation measurements is quite narrow, while in cases when the range of assessments is wide enough, monetary policy makers get an opportunity to analyse the causes of the mixed dynamics of indicators.

[5] It is important to note that in this case there is no substitution of the CPI targeting for underlying inflation targeting. As was noted above, a central bank normally chooses medium-term headline inflation (the CPI) as its target. A current deviation of headline inflation from underlying inflation with the latter staying stable at the target level, if such deviation is actually related to a change in relative prices (that is, a underlying inflation measure is adequate), is temporary and therefore poses no threat for the headline inflation target in the medium term. Of course, it should be noted that a necessary condition in this case is the required level of confidence in a central bank's policy, which allows the central bank not to interfere in the event of temporary inflation shocks. For details about changes in relative prices and inflation, see, for example, Fisher (1981).

[6] It is also important to take into account the fact that various structural changes in the policy of a central bank or other parameters of the economy can change the dynamics of underlying inflation, which, however, may not be reflected in its measurements due to the invariable parameterisation of the models used (the Lucas Critique). This critique is also applicable to underlying inflation measures used in practice. This problem is partly resolved through a real-time valuation of the parameters of models (revaluation).

In this article, we present calculations of underlying inflation measures used by central banks in practice and/or proposed in scientific literature for Russia. We then apply a number of tests reflecting the underlying inflation definition to obtained measures, in an attempt to find the best performing indicator or build a range of underlying inflation indicators that most of all comply with its definition. Basing on the results we propose a range of underlying inflation measures for practical use.

The remainder of this article consists of two parts. In the first part, we calculate underlying inflation measures with the description of data and the algorithm used in our calculations, in particular, with reliance on a review given in Dementiev and Bessonov (2012). We calculate 20 underlying inflation indicators based on the methods of exclusion, weight change and trimming of the distribution of monthly price changes, and also with reliance on dynamic factor models. We also consider Rosstat's core CPI measure. In the second part, we describe tests and their results, make a selection of underlying inflation indicators most of all complying with the underlying inflation definition, which has been given. We divide tests into technical, prognostic and substantive economic evaluation procedures. We demonstrate the practical value of the use of underlying inflation indicators we have obtained, providing the example of the inflation dynamics analysis over the past decade in Russia. In the end, we give the conclusions of our research.

1. UNDERLYING INFLATION MEASURES

The basic task in the calculation of underlying inflation indicators in the practice of central banks is to clean inflation dynamics from changes in relative prices and inflation changes that do not deliver information useful for understanding future inflation. The expedience of this procedure arises due to the following theoretical considerations.

The importance of separating relative prices and inflation is noted, for example, in Reis and Watson (2010) and Fisher (1981). Theoretically, one-off changes in relative prices do not affect inflation in the medium term and, therefore, do not require response from monetary authorities, see Nessen and Soderstrom (2001); for criticism in the event of an oil price shock, see Plante (2012) and Bullard (2011). The arguments in favour of a central bank's non-interference are based, first of all, on the substitution effect and, secondly, on the specifics of CPI dynamics in case of relative price adjustment to a new equilibrium or one-off events.

Substitution effect. Theoretically, the substitution of one commodity with another upon a change in relative prices can fully eliminate the effect on measured inflation[7]. In practice, prices are, first of all, rigid. The prices of some goods may change quicker than the prices of other goods in response to a change in relative prices, which limits the substitution effect, extending it over time. Secondly, not all goods and services are included in the CPI calculation and, therefore, it is not always possible to take into account the substitution effect on measured inflation. Thirdly, the specifics of inflation measurement limit the recognition of the substitution effect and intensify the effect of relative prices on the observed inflation rates: thus, consumer goods basket weights are measured with a lag and are normally fixed for a calendar year. As a result, a change in relative prices is reflected after all in the change of observed (statistically measured) inflation. In this case, it is important for a central bank, first of all, to identify changes in relative prices in observed inflation and, secondly, to assess how long they may have their effect on inflation and whether long-term effects may be observed (for example, a change in inflation expectations or wage indexation)[8].

Specifics of CPI dynamics when relative prices change. In case of a change in equilibrium relative prices, the adjustment to a new equilibrium amid price rigidity may take place with accelerating and subsequently slowing inflation for these goods. This will be arithmetically reflected in

[7] Even if the market of this particular commodity registers a shift in the demand curve rather than a shift in the supply curve, for example, due to a change in consumer taste preferences. In this case, both the price and the volume of sales (a weight in the consumer goods basket) grow. Meanwhile, the demand for other goods will contract and, consequently, their prices (or price inflation) should also be expected to fall. This factor also has a balancing effect on inflation in the event of demand shocks.

[8] Central banks with a well-adjusted function of response to inflation shocks and the experience of inflation targeting have greater possibilities not to respond to relative price shocks as the latter do not influence long-term inflation (inflation expectations) precisely for the reason that if such influence could be seen, everyone would understand that a central bank would interfere and tighten its monetary policy.

the dynamics of the headline consumer price index, which will first grow at an accelerated pace and subsequently at a slower pace, i.e. inflation will slow down.

Apart from a change in relative prices, there are *one-off changes in the general price level*, such as a rise in taxes or excise duties. For monetary policy, only their side effects are important as they may influence the medium-term inflationary trend.

Presumably, underlying inflation indicators should be cleaned precisely from such price fluctuations.

All our calculations are conducted in the pseudo-real time. Where underlying inflation measures are calculated in the pseudo-real time, this means that in our underlying inflation calculations for any month we use only real-time information available to the researcher during that month. The pseudo-real time format aims to obtain such a measure of underlying inflation, which a central bank would have calculated in the past. Precisely that level of underlying inflation (with parameterisation of models based on information available as of that time) communicated information important for the central bank to take monetary policy decisions.

We deal with monthly statistics compiled by Rosstat or the Bank of Russia from January 2002 to December 2014. A monthly calculation is designed to ensure an effective analysis of inflation dynamics based on underlying inflation indicators. We deal with Rosstat's CPI (and the underlying inflation index) as price indicators, and also use 43 CPI components of the highest aggregation level, which in total yield 100% of the consumer goods basket for CPI calculations (the list is given in Appendix 1). As there are no data before 2006 on CPI components of the lower aggregation level, we have decided to deal only with the most aggregated CPI categories. In particular, we consider such aggregated categories as 'other foodstuffs', 'other non-food products' and 'other services' as a CPI separate individual category, despite their heterogeneous nature. Seasonal smoothing is made in the TRAMO/SEATS programme of the Bank of Spain.

Further on, we describe 20 indicators of underlying inflation, which we used[9]. Out of this number, we calculated eight indicators as part of the exclusion method, one indicator pursuant to the re-weighing method, four indicators within the framework of the trimming method and seven indicators based on dynamic factor models and models with unobserved trend. We also added to this selection Rosstat's core CPI calculated by the exclusion method. The dynamics of all calculated underlying inflation indicators (recursive and final evaluations) are given in Appendix 2.

[9] In the original version of the article, we considered 40 indicators of underlying inflation but eventually limited the calculation to 20 indicators owing to their visual similarity, which was confirmed by subsequent formal tests.

1.1 Exclusion method

The first approach is called the method of exclusion. In order to calculate the CPI certain components, which fail to comply with the underlying inflation definition by some criteria (for example, the test for the relative or absolute nature of inflation), are excluded from the consumer goods basket. The weights of the CPI components remaining in the basket are adjusted to represent a total of 100% of a new basket, while the weighted average value calculated from the components' indices will represent the underlying inflation index.

The underlying inflation calculation usially excludes CPI components characterised by strong historical volatility (such as energy or fuel prices), the expressly seasonal nature (such as vegetable and fruit prices) or administered nature (such as alcohol prices or the prices of certain social services). The volatility (seasonal or administered nature) of these prices serves as an indication that a change occurs precisely in relative prices[10].

We calculated the following underlying inflations for subsequent tests:

1. Standard and widely used 'CPIs net of vegetables and fruits, energy and administered prices (namely, housing and utility charges)' – an analogue of the US underlying CPI representing 84% of the CPI in Russia; 'Non-food goods excluding energy and fuel' representing 33% of the CPI. Rosstat's core CPI representing 80.5% of the CPI (December 2014) was also included in this group.

2. The CPI net of eight most volatile components (Lafleche and Armour (2006)), where volatility is measured by the standard deviation of the monthly inflation of certain CPI components in the moving 24-month window. Appendix 3 presents CPI components (the most volatile ones) that are most frequently excluded from the calculation of the underlying inflation index for Russia under the methodology of the Bank of Canada.

3. In addition to the exclusion of some components, we calculated underlying inflation without 50% and 75% of the most volatile components by their weights in the consumer goods basket. As before, we used the standard deviation of monthly inflation in the moving 24-month window as a measure of volatility.

4. The inflation indicators representing 50% of the CPI basket characterised by the lowest sensitivity concurrently (on the average) of three types of shocks that are frequently the source of a change in relative prices: world oil price shocks, world food price shocks and exchange rate shocks. The sensitivity of certain CPI components to the above shocks was determined within the framework of a structural VAR model with short-term limitations for the impulse response func-

[10] This approach to the exclusion of relative prices is criticised in literature, for example, in Bullard (2011). In particular, it is noted that energy price inflation changed permanently in the 2000s due to the growing demand in Asian countries and therefore the exclusion of fuel prices from underlying inflation systematically understates the trend inflation as inflation retains components, which experienced downward pressure from demand due to the growth in the share of expenditures on fuel in the budget of US households. That is why the exclusion of energy prices from the US underlying CPI is not justified.

tions. See Davis (2012), Fukac (2011) and Bicchal (2010). For criticism, see Lenza (2011). Additional sensitivity check was held using the Local Projection Method, see Jorda (2005) and Caselli and Roitman (2014). A detailed description of the algorithm of calculations and their results, namely, the most frequently excluded CPI components, are given in Appendix 4.

5. The selection of the components representing 50% of the CPI based on their ability to forecast future inflation (12 months ahead). The calculation is made for data representing 'month on the corresponding month of the previous year'. A similar index is given in Bilke and Stracca (2008). This approach boils down to the following: considering that a change in relative prices should not be reflected in future inflation, the components exposed to a frequent change in relative prices (whose inflation reflects a change in relative prices) should be characterised by poor forecasting capacity for future headline inflation. The algorithm of this calculation is described in Appendix 5.

1.2 Re-weighing CPI weights

The approach of building the underlying inflation index on the basis of re-weighing the CPI weights is a technique close to the exclusion method. See, for example, Macklem (2001). This approach uses weights inversely proportional to the historical volatility of the monthly inflation of certain CPI components where volatility is calculated in the moving 24-month window.

1.3 Underlying inflation measures based on trimming method

The truncation method selects only a part of the empirical distribution of the monthly inflation of certain CPI components for the underlying inflation index (where the frequencies of components distribution are set by their weights in the consumer goods basket). Normally, the tails of distribution are cut off. Then the median has to be found in the selected distribution of monthly inflation, which will be accepted as a measure of underlying monthly inflation, see, for example, Meyer and Venkatu (2014). The first specific feature of this approach is that the basket's components are changed every month for the calculation of the underlying CPI, which makes it difficult to analyse the dynamics of this index. The second specific feature is that the trimming is conducted not for volatilities as was the case above in the exclusion method but for the levels of monthly inflation. The third distinctive feature is that the calculation in the pseudo-real time and the final calculation always coincide as the index is constructed using only information on the consumer price dynamics in a given month.

The trimmed distribution, like the exclusion method, aims at cutting off those price changes in the CPI, which may be related to changes in relative prices, see, for example, the theoretical model in Bryan and Cecchetti (1993).

We have calculated four underlying inflation indicators using this approach.

The first question, which arises when we apply this approach, is as follows: which thresholds to choose? And should this thresholds be symmetrical?

Following the work by Meyer and Venkatu (2014), we calculated optimal thresholds for Russian data. Let 'alfa' denote the lower threshold level, i.e. trimming of the components with the lowest price growth over a month and 'beta' – the upper threshold level for CPI components with the highest price growth over a month. Trimming levels were selected using a 24-month centered moving average of monthly inflation and future monthly inflation (in 24 months). We looked for an optimal threshold level using both a full sample (2002-2014) and the post-crisis sample (2010-2014).

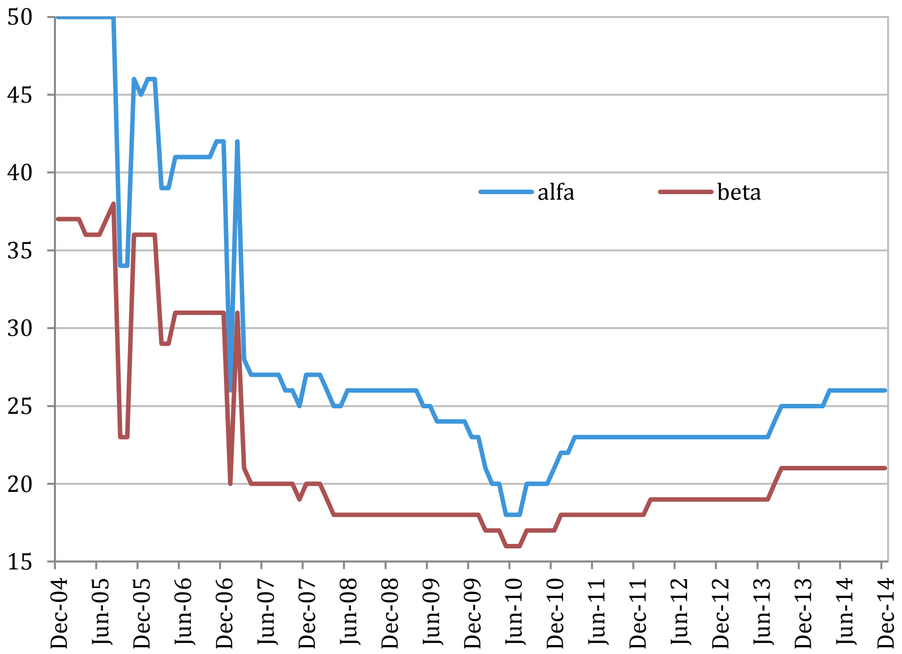
As a comparison criterion we chose the Root Mean Squared Error (RMSE) of deviation for the designated 'alfa' and 'beta' underlying inflation indicators from the comparison base in the data sample under review (the full sample or the sample only from 2010).

The RMSE distribution for various 'alfa' and 'beta' levels calculated for two data samples is given in Appendix 6. The RMSE minimum equalled 2.1 percentage points in terms of annual inflation in the full sample (alfa=25%, beta=21%) and 1.7 percentage points in the sample beginning in 2010 (alfa=24%, beta =22%) for 24-months moving average as the criterion of optimality.

Having obtained optimal thresholds, we calculated two measures of underlying inflation: one each for two optimality criteria: the centered 24-month moving average and future monthly inflation in 24 months. Appendix 6 gives CPI components that were most frequently excluded from the inflation calculation.

Considering that we calculated underlying inflation measures in the pseudo-real time, we should look for optimal thresholds also in the pseudo-real time. This means that we need to apply optimal thresholds criteria to the data available in the past at each moment of time rather than to the final data samples. With reliance on this monthly re-optimisation, we calculated the super-optimal trimmed measure of underlying inflation for the cases of a less strong smoothing of price dynamics (the moving 12-month window) or a stronger smoothing (the 24-month window). Specifically, as Chart 1 shows, in later case the optimal thresholds were observed to decrease significantly before the crisis. This implicitly reflects the circumstance that the contribution by the relative price change to the price dynamics was seen to decline (the contribution by monetary inflation was growing).

Figure 1. Optimal higher ('alfa', blue line) and lower ('beta', red line) thresholds in pseudo-real time with 24-month moving average as an optimality criterion



Source: Rosstat, authors' calculations

We additionally calculated the trimmed inflation indicator where future annual inflation (in 12 months) served as an optimality criterion.

Along with optimal trimmed measures, we calculated the standard underlying inflation indicator as a weighted median (instead of the average as represented by the CPI). The weighted median calculation is designed to reflect a more correct measure of the inflation distribution center in case of the latter's asymmetry.

1.4 Underlying inflation measures based on dynamic factor models

1.4.1 Standard model

Dynamic factor models use information contained in a wide set of indicators and are designed to decompose inflation into two stationary, orthogonal unobservable components – the common χ_{jt} and the idiosyncratic ε_{jt}:

$\pi_{jt} = \chi_{jt} + \varepsilon_{jt}$,

where the common component is driven by a small number of common factors (shocks).

In turn, the common component can be decomposed into the long-term (x_{jt}^{L}) and short-term (x_{jt}^{S}) constituents by identifying low-frequency fluctuations with the periodicity above the designated threshold h (Cristadoro et al. (2005)):

$\pi_{jt} = x_{jt}^{L} + x_{jt}^{S} + \varepsilon_{jt}$

The smoothed (long-term) common component can be obtained by summing up the waves with the periodicity [−π/h, π/h] using the spectral decomposition. This long-term component will measure underlying inflation. This measure will not contain idiosyncratic shocks, which are not common for all CPI components, or short-term fluctuations, which are not relevant for monetary policy. We make calculations for two alternative threshold periods h=12 and h=24, and also calculate the indicator based on a dynamic factor model without using band-pass filters.

The model can be generally presented as follows:

$\pi_{jt} = b_j(L)f_t + \varepsilon_{jt}$,

where: $f_t = (f_{1t}, \ldots, f_{qt})'$ is vector of q dynamic factors and $b_j(L)$ is lag operator of order s. If $F_t = (f'_t, f'_{t-1}, \ldots, f'_{t-s})'$, then the static representation of the model is

$$\pi_{jt} = \lambda_j F_t + \varepsilon_{jt},$$

where: $b_j(L)f_t = \lambda_j F_t$. Therefore, the model with q dynamic factors contains r = q(s + 1) static factors. We select the number of dynamic factors in a way to ensure that each subsequent factor increases the share of variance, explained by the common component, by no less than 10% (Forni et al. (2000)). As a result, we use q=3. We assume that s=2 (correspondingly, r=9).

1.4.2 'Pure' inflation model

The 'pure' inflation concept (Reis and Watson (2010)) can be considered as an alternative approach to the specification of a dynamic factor model. It is assumed under this approach that the price growth is decomposed into three components:

$$\pi_t = v_t + \rho_t + \varepsilon_t$$

'Pure' inflation (v) reflecting price growth under the impact of monetary factors should both be present in the dynamics of all goods and services and be equiproportional. This growth should be separated from changes in relative prices (ρ_t) and idiosyncratic fluctuations (ε_t).

We used the same set of data, which we applied to standard dynamic factor models. The econometric procedure was replicated in accordance with Reis and Watson (2010). The model used three common factors and two lags in autoregressive models.

1.4.3 'Monetary' inflation model

We use the monetary approach to underlying inflation measurement as another alternative model (for details, see Deryugina and Ponomarenko (2013)). We formulate the dynamic factor model in a state-space representation (for details, see Stock and Watson (2011)):

$$X_{it} = a_i F_t + v_{it}$$

$$F_t = \mu + \sum_{j=1}^{L} D_j F_{t-j} + e_t$$

$e_t = R\,u_t$

The 'measurement' equations represent the dependence of the set of price and monetary variables (X_{it}) on static unobservable factors (F_t) (for details, see Appendix 7). The explained part

($a_i F_t$) represents the common component, while the unexplained part (v_{it}) is the idiosyncratic component. The 'transition' equations represent a VAR model of static factors. Structural shocks (u_t) can be subsequently derived from the residuals of the VAR model (e_t). Therefore, similar to structural VAR models, we can calculate impulse response functions related to these shocks and historical decompositions for static factors (and, correspondingly, for observable indicators). We estimate the model using Bayesian methods as proposed in Blake and Mumtaz (2012). The number of static factors and their lags is selected using the same criterion, which was applied for standard models. As a result, the number of static factors (F_t) equalled 2 and the number of lags also L=2.

The structural interpretation of dynamic factor models is rare but hardly unprecedented (Forni et al. 2009, Forni and Gambetti 2010). We believe that the analysis of the macroeconomic properties of structural shocks can be useful for identifying the part of inflation, which we can consider as underlying inflation. For this purpose, we decompose the residuals e_t into independent shocks u_t with the help of the principal components approach[11] (Forni et al. 2009). The function of impulse responses to one of the two identified shocks (see Appendix 7) is considered as economically substantive. A monetary shock leads to the instant acceleration of the monetary indicators' growth, which persists during the next five quarters. The accelerated growth of price indicators begins later and reaches its peak in six to eight quarters (four quarters for real estate prices) and ends in ten to twelve quarters. These dynamics are in line with theoretical concepts about the lag nature of relationship between the rates of growth in money supply and inflation (see, for example, Nicoletti-Altimari (2001)). At the same time, impulse responses to the second structural shock do not possess such properties.

On these grounds, we exclude both the idiosyncratic part (v_t) and fluctuations caused by 'non-monetary' structural shocks from a underlying inflation measure.

2. Assessing the properties of underlying inflation measures

There is a set of criteria that can be used to assess the relevance of alternative underlying inflation measures. In principle, these tests can be divided into three broad categories (see, for example, Wynne (1999)).

2.1 Technical properties

The first category of criteria helps assess the technical properties of underlying inflation measures:

[11] The use of the Cholesky decomposition for this purpose does not lead to any considerable change in the results.

- **Volatility**. We measure volatility as the average absolute deviation of the annual inflation growth rate from the average value on the moving 25-month period.
- **Bias.** We measure the cumulative deviation of underlying inflation from actual inflation for the period of 2003-2014.
- **Stability of real-time estimates**. We measure the deviation of ex-post estimates of annual underlying inflation rates from real-time recursive estimates.

The results we obtained were not determinative on the whole for assessing the quality of underlying inflation measures. The results are presented in Appendix 8.

2.2 Forward-looking properties

The most wide-spread criterion for assessing the quality of underlying inflation measures is their ability to forecast actual inflation. We use the standard model (see, for example, Lafleche and Armour (2006)) for assessing this property on the 12-month horizon as a temporary horizon relevant for monetary policy:

$$(\pi_{t+12} - \pi_t) = \alpha + \beta\,(\pi^U_t - \pi_t) + u_{t+12} \tag{1}$$

where π_t is annual CPI growth rates and π^U_t is annual underlying inflation growth rates. We use recursive estimates of underlying inflation rates to take into account the model's possible instability. The model is estimated[12] using the sample from July 2006 to September 2014. We use R^2 as an indicator of the model's fit. We also conduct the Wald test for $\alpha=0$ and $\beta=1$. In this test is passed, we can say that the current level of underlying inflation is a good benchmark for expected actual inflation[13].

We also conduct a test for the exogeneity of the future value of underlying inflation relative to current actual inflation. If this test is not passed, it may be presumed that the model's latest estimations are unstable or this may evidence that fluctuations relevant for further dynamics of other inflation components were erroneously excluded from the underlying indicator. For this purpose, we assess the equation of the following type:

$$(\pi^U_{t+12} - \pi^U_t) = \delta + \gamma\,(\pi^U_t - \pi_t) + \varepsilon_{t+12} \tag{2}$$

[12] The significance of the coefficients in equations (1) and (2) was estimated with Newey-West adjustment.
[13] This type of test is conventionally used as the main criteria of the forward-looking properties. We found, however, that in case of Russia this tested is easily passed by most of models including those with very low goodness of fit. We therefore augment our analysis by examining R^2.

The test results are presented in Table 1. In terms of R^2 of equation (1), three underlying inflation indicators based on DFM took five out of seven first places, and also passed the Wald test and the exogeneity test (with the exception of 'pure' inflation).

Table 1. Results of assessing forward-looking properties of underlying inflation measures

Measure	***R^2 of equation (1)***	Measures that passed Wald test ($\alpha=0$ and $\beta=1$ in equation (1)) at 5% level of significance	Measures that passed exogeneity test (t-statistics < 1.96 for γ in equation (2))
DFM ('monetary' inflation)	0.44	*	*
Band-pass filter (frequency > 12 months)	0.41		*
DFM (frequency > 12 months)	0.33	*	*
DFM (frequency > 24 months)	0.32	*	*
DFM (all frequencies)	0.22	*	*
CPI ex. 75% of most volatile components	0.22	*	
DFM ('pure' inflation)	0.14	*	
CPI ex. 50% of most volatile components	0.14	*	
Band-pass filter (frequency > 24 months)	0.11	*	*
Non-food products CPI ex. gasoline	0.08		
CPI ex. 50% of worst forecasters of future inflation	0.05	*	*
Optimal trimmed-mean CPI, optimality criterion: future inflation	0.05	*	*
Optimal trimmed-mean CPI, optimality criterion: MA	0.04	*	*
CPI ex. vegetables and fruits, gasoline, utilities	0.04	*	*
Volatility weighted CPI	0.03	*	
CPI ex. 50% of most sensitive components to shocks in SVAR	0.03	*	*
Core CPI (Rosstat)	0.03	*	
CPI ex. 8 most volatile components	0.02	*	
CPI ex. 50% of most sensitive components to shocks in LPM	0.01	*	*
Weighted median	0.01	*	
"Super-optimal" trimmed-mean CPI	0.01	*	*

2.3 Economic relevance of underlying inflation measures

Correlation with fundamental indicators are another category of properties that measures of underlying inflation should presumably possess compared with actual inflation. This primarily relates to the factors reflecting aggregate demand. Specifically, Bryan and Cechetti (1993) test the relationship of underlying inflation measures with money supply, while Andrle et al. (2013) and Khan et al. (2013) test it with business cycle indicators.

In order to test this property, we estimate the standard equation (Filardo et al. (2014)):

$$\pi_t = \mu + \sum_{j=1}^{L} \Theta_j X_{t-j} + e_t \,, \tag{3}$$

where π is annual underlying inflation growth rates, X is the vector of explanatory variables (annual broad money supply growth rates and output gap[14]). The estimation was conducted using the quarterly data for the period of 2002-2014. The number of lags equals L=4. We used R^2 as an indicator of correlation.

Apart from aggregate demand indicators, the relationship of underlying inflation measures with secondary effects (i.e. a change in inflation expectations, wage indexing) that follow price growth can characterise their macroeconomic content. Thus, we can assume that irrelevant inflation fluctuations will not be reflected in the growth of nominal variables. Correspondingly, inflation measures net of such fluctuations will possess better characteristics as an explanatory factor for wage dynamics. In order to test this property, we estimate the standard equation (Zhang and Law (2010)):

$$w_t = \mu + \lambda \pi_{t-1} + \sum_{j=1}^{L} \Theta_j X_{t-j} + \sum_{j=1}^{L} \Omega_j w_{t-j} + e_t \tag{4}$$

where w represents the quarterly rate of growth in the average nominal wage, π is the annual underlying inflation growth rate, X is the vector of other explanatory variables (unemployment and quarterly productivity growth[15]). The estimation was made using the quarterly data for the period of 2002 to 2014. The number of lags equals L=4. The informative nature of the inflation indicator for wage dynamics is characterised by the significance of the (positive) coefficient λ.

The test results are given in Table 2. Most underlying inflation measures exceed the CPI in terms of R2 in equation (3), while the three best measures are indicators based on dynamic factor models. Two of them proved to be statistically significant as explanatory indicators for nominal wage dynamics.

[14] Based on the HP-filter.
[15] The ratio of real GDP to the number of employed.

Table 2. Results of assessing economic relevance of underlying inflation measures

Measure	***R^2 of equation (3)***
DFM (frequency > 24 months) *	0.80
DFM ('monetary' inflation) *	0.79
DFM (frequency > 12 months)	0.77
CPI ex. 75% of most volatile components *	0.76
Optimal trimmed-mean CPI, optimality criterion: future inflation	0.76
Optimal trimmed-mean CPI, optimality criterion: MA	0.75
CPI ex. 50% of most sensitive components to shocks in SVAR	0.74
Rosstat's Core CPI	0.73
Weighted median	0.72
"Super-optimal" trimmed-mean CPI	0.7
CPI ex. vegetables and fruits, gasoline, utilities	0.68
DFM (all frequencies)	0.68
CPI ex. 50% of most volatile components	0.67
Volatility weighted CPI	0.67
CPI ex. 8 most volatile components	0.64
CPI (for reference)	0.61
Band-pass filter (frequency > 24 months)	0.60
Band-pass filter (frequency > 12 months)	0.60
Non-food products CPI ex. gasoline	0.58
CPI ex. 50% of most sensitive components to shocks in LPM	0.56
DFM ("Pure" inflation)	0.48
CPI ex. 50% of worst forecasters of future inflation	0.34

* - indicators, for which t-statistics > 1.96 for λ in equation (4)

2.4 Overall assessment

The test results allow us to conclude that underlying inflation measures calculated on the basis of dynamic factor models (except for the 'pure' inflation indicator and indicator calculated with the help of the standard model without application of band-pass filter) possess the necessary properties in all aspects that have relation to the requirements set for underlying inflation measures. None of the other indicators (including Rosstat's core CPI) possesses the balance of properties required for obtaining satisfactory results in many-sided estimations. In this regard, we deem it expedient to use this methodology for the purposes of monetary policy. We develop a range of three indicators (Chart 2): indicators based on the standard dynamic factor model (with the frequency thresholds of 12 and 24 months), and also 'monetary' inflation (recursive estimates of this range with their medians are given in Chart 3).

We can assert that the fluctuations of the range we have obtained are economically interpretable and represent the main macroeconomic developments in the Russian economy in the past decade. In particular, we can see in the period preceding the crisis of 2008-2009 a clearly expressed disinflation phase in 2003-2005 amid the growing demand for money during this period (de-dollarisation) that gave way to the accelerated price growth in 2006-2008, which is consistent with the idea of the economy's overheating in the pre-crisis period. We can also note that underlying inflation measures during this period would have been more substantive benchmarks for monetary policy than observed CPI and core CPI (their growth continued to slow down rapidly up until the second half of 2007, which implied no need for monetary tightening). In the post-crisis period, the dynamics of underlying inflation measures could also be considered as informative for the purposes of monetary policy. Specifically, underlying inflation was observed to slow down along with the actual CPI in the period after the 2009 recession, reflecting the impact of aggregate demand fundamentals, whereas in the period of 2010-2012 underlying inflation growth rates were stable enough, despite sharp changes in the CPI growth. Considering that these fluctuations were related to one-off short-term factors (the drought in 2010 and the changed procedure for indexing administered prices in 2012), the underlying inflation indices net of these factors were more relevant for the purposes of monetary policy during this period as well. Their dynamics indicate some recovery in the price growth rates in 2010-2011, which coincides with the period of recovery in economic activity, and the subsequent inflation slowdown in 2012-2013. In 2014, the underlying inflation measure stood at 8.5% (measured by median of the range). In January 2015, it slightly exceeded the level of 10%. A sharp deviation of headline inflation from underlying inflation observed since September 2014 reflects the impact of temporary factors on inflation from the viewpoint of the model, for example, factors related to one-off adjustment of prices for imported goods due to the ruble's depreciation and the adjustment of prices for foodstuffs due to the imposition of food counter-sanctions in Russia in the summer of 2014. The large upward revisions of trend inflation level in 2013-2014 in February represent high uncertainty associated with the obtained estimates in conditions of increased volatility of inflation in early 2015.

Figure 2. Range of underlying inflation measures based on dynamic factor models (annual growth rates, %)

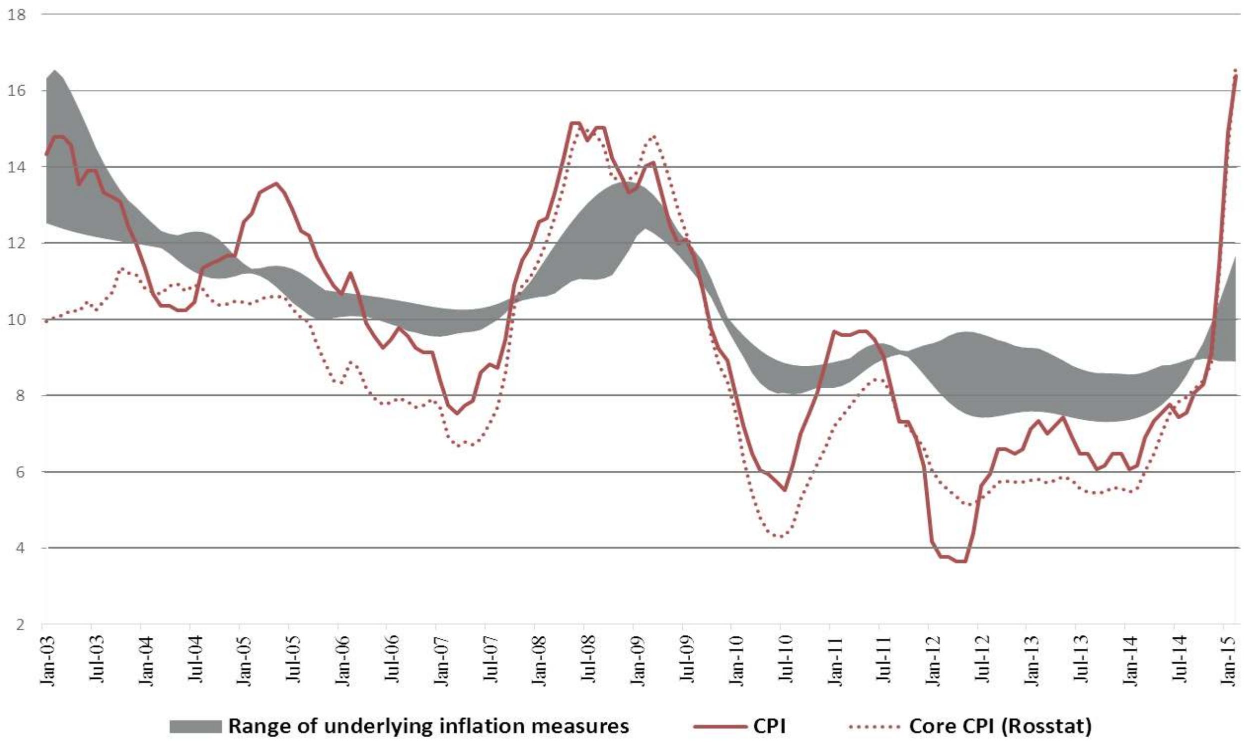
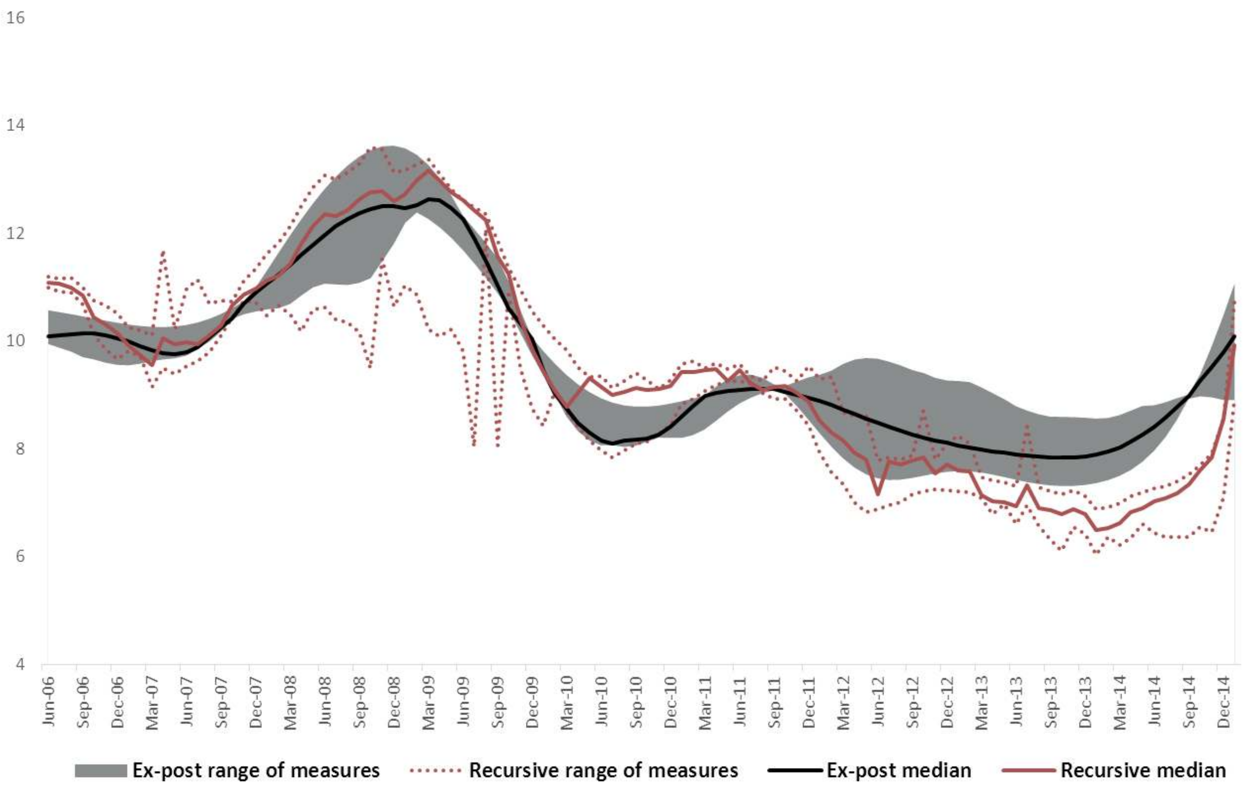


Figure 3. Range and their medians of underlying inflation measures based on dynamic factor models (annual growth rates, %): final estimate and calculation in pseudo-real time



CONCLUSIONS

An underlying inflation measure, i.e. an inflation indicator net of shocks irrelevant for monetary policy, is a key indicator for a central bank whose main task is to maintain price stability. On the one hand, the use of this indicator can help reveal inflation risks and, on the other hand, make monetary policy more balanced, preventing mechanistic response to materialised price changes irrespective of their nature. At the same time, there is no generally accepted method in practice for determining shocks irrelevant for monetary policy. Instead, there are several methodologies making it possible to calculate underlying inflation and some criteria (which are not mutually exclusive but are not necessarily interrelated) that can be used to make an implicit estimation of properties of the indicators obtained. Such work was done as part of this research.

We calculated 20 underlying inflation measures, using four alternative approaches: the methods of exclusion, re-weighing, truncation and estimation of an unobservable trend on the basis of dynamic factor models. We assessed the obtained indices with the help of tests characterizing three aspects of their properties: technical properties, the prognostic capacity and economic content. We came to the conclusion that underlying inflation measures calculated with the help of dynamic factor models demonstrate the best results proceeding from formal tests. In particular, these indicators remained stable in the period of price shocks in 2010 and 2012 but reflected larger inflationary pressure in 2007-2008 and its decrease in 2009. As a result, these indicators remained informative in all the periods with regard to future inflation dynamics in the medium term and were closely related with aggregate demand fluctuations. We believe these indicators possess the necessary properties for their use for the purposes of monetary policy.

REFERENCES

1. Andrle, M., Bruha, J., Solmaz, S. (2013) Inflation and Output Comovement in the Euro Area: Love at Second Sight? IMF Working Paper 13/192

2. Amstad, M., Potter, S. M., Rich, R. (2014) The FRBNY staff Underlying Inflation Gauge: UIG, BIS Working Papers 453

3. Aucremanne, L., Wouters, R. (1999) A Structural VAR approach to Underlying Inflation and Its Relevance for Monetary Policy, In Measures of Underlying Inflation and Their Role in the Conduct of Monetary Policy. Proceedings of the workshop of Central Bank Model Builders held at the BIS on 18–19 February 1999.

4. Bicchal, M. (2010) Monetary Policy and Inflation in India, Artha Vijnana, Vol. 53

5. Bilke, L., Stracca, L. (2008) A Persistence-Weighted Measure of Underlying Inflation in The Euro Area, European Central Bank Working Paper Series 905

6. Blake, A., Mumtaz, H. (2012) Applied Bayesian econometrics for central bankers, CCBS Technical Handbook No. 4, Bank of England

7. Bryan, M. F., Cecchetti, S.G. (1993) Measuring Underlying Inflation, NBER Working Paper 4303

8. Bullard, J. (2011) Measuring Inflation: the Underlying is Rotten, Federal Reserve Bank of St. Louis Review, July/August, 93(4), pp. 223-33

9. Caselli, F., Roitman, A. (2014) Exchange Rate Path-Through in Emerging Markets, IMF, mimeo

10. Cristadoro, R., Forni, M., Reichlin, L.,Veronese, G. (2005) A underlying inflation indicator for the euro area, Journal of Money, Credit and Banking, Vol. 37, Issue 3, pp. 539-560.

11. Davis, J. S. (2012) The Effect of Commodity Price Shocks on Underlying Inflation: The Role of Central Bank Credibility, The Federal Reserve Bank of Dallas Globalization and Monetary Policy Institute Working Papers 134

12. Dementiev, A., Bessonov, I. (2012) Underlying Inflation Indices in Russia, HSE Economic Journal, No. 1

13. Deryugina E., Ponomarenko A. (2013) Money-based inflation risk indicator for Russia: A structural dynamic factor model approach, Bank of England, CCBS Joint Research Paper No. 3

14. Duguay, P. (1994) Empirical evidence on the strength of the monetary transmission mechanism in Canada: An aggregate approach, Journal of Monetary Economics, Volume 33, Issue 1, February, pp. 39–61

15. Fisher, S. (1981) Relative Shocks, Relative Price Variability, and Inflation, Brooking Papers on Economic Activity, 2

16. Forni, M., Gambetti, L. (2010) The dynamic effects of monetary policy: A structural factor model approach. Journal of Monetary Economics 57, 203–216

17. 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

18. Forni, M., Hallin, M., Lippi, M., Reichlin, L. (2000) The generalized dynamic factor model: identification and estimation, The Review of Economics and Statistics 82, 540–554.

19. Fukac, M. (2011) Have Rising Oil Prices Become a Greater Treat to Price Stability? Federal Reserve Bank of Kansas City Economic Review, No. 4

20. Filardo, A., Genber, H., Hofmann, D. (2014) Monetary analysis and the global financial cycle: an Asian central bank perspective, BIS Working Papers 463

21. Giannone, D., Matheson, T.D. (2007) A New Underlying Inflation Indicator for New Zealand, nternational Journal of Central Banking, December, pp. 145-180

22. Gruen, D., Romalis, J., Chandra, N. (1997) The Lags of Monetary Policy, Reserve Bank of Australia, Research Discussion Paper 9702

23. Jordà, Ò. (2005) Estimation and Inference of Impulse Responses by Local Projections, American Economic Review, 95(1): 161-182.

24. Khan, M., Morel, L., Soubrin, P. (2013) The Common Component of CPI: An Alternative Measure of Underlying Inflation for Canada, Bank of Canada Working Paper 35

25. Lafleche, T., Armour, J. (2006) Evaluating Measures of Underlying inflation, Bank of Canada Review, Summer

26. Lenza, M. (2011) Revisiting the Information Content of Underlying inflation, European Central Bank Research Bulletin, No. 14

27. Macklem, T. (2001) A New Measure of Underlying Inflation, Bank of Canada Review, Autumn

28. Mankikar, A., Paisley, J. (2004) Underlying Inflation: A Critical Guide, Bank of England Working Paper Series 242

29. Marques, C., Neves, P., Sarmento, L. (2003) Evaluating Underlying Inflation Indicators, Economic Modelling, Vol. 20

30. Meyer, B., Venkatu, G. (2012) Trimmed mean Inflation Statistics: Just hit the one in the middle, Federal Reserve Bank of Cleveland Working Paper Series 12-17R

31. Mohatny, D. (2012) Evidence of Interest Rate Channel of Monetary Policy Transmission in India, RBI Working Paper Series

32. Nessen, M., Soderstrom, U. (2001) Underlying Inflation and Monetary Policy, International Finance 4(3), pp. 401–39

33. Nicoletti-Altimari, S. (2001) Does money lead inflation in the euro area? European Central Bank Working Paper Series 63

34. Plante, M. (2012) How should Monetary Policy Respond to Changes in Relative Price of Oil? Considering Supply and Demand Shocks, Federal Reserve Bank of Dallas Working Paper Series 1202

35. Reis, R., Watson, M. (2010) Relative Good's Prices, Pure Inflation, and the Phillips Correlation, American Economic Journal: Macroeconomics, 2(3): 128-57

36. Silver, M. (2006) Underlying Inflation Measures and Statistical Issues in Choosing Among Them, IMF Working Paper 06/97

37. Stock, J.H., Watson, M. (2011) Dynamic Factor Models. Oxford Handbook of Forecasting, Michael P. Clements and David F. Hendry (eds), Oxford University Press, Oxford

38. Svensson, L. (1997) Inflation Forecast Targeting: Implementing and Monitoring Inflation Targets, European Economic Review, 41(6), pp. 1111-1146

39. Tsyplakov, A. (2004) Constructing Underlying Inflation Index for Russia, EERC WP, 2004

40. Wynne, M. (1999) Underlying Inflation: A Review of Some Conceptual Issues, European Central Bank Working Paper Series 5

41. Wynne, M. (2008) Underlying Inflation: A Review of Some Conceptual Issues, Federal Reserve Bank of St. Louis Review, May/June, part 2

42. Zhang, W., Law, D. (2010) What Drives China's Food-Price Inflation and How does It Affect the Aggregate Inflation? Hong Kong Monetary Authority Working Paper 6

APPENDIX 1

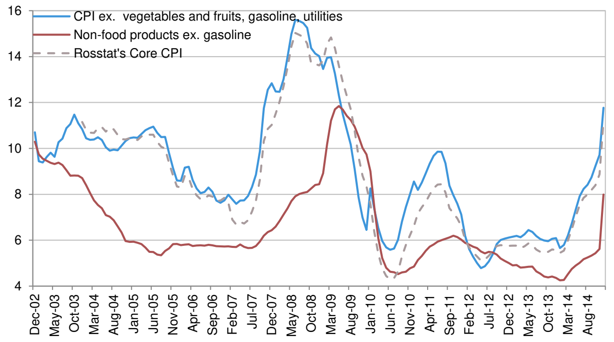
List of 43 components of Rosstat's CPI (with weights as of December 2014)

Rank	Component	Share in CPI, 2014
1	Meat and Poultry	10.1
2	Fish and edible sea products	2.0
3	Butter	1.1
4	Milk and dairy products	2.9
5	Cheese	1.1
6	Eggs	0.4
7	Sugar	0.5
8	Confectionery	2.5
9	Tea and coffee	0.9
10	Bread and bakery products	1.7
11	Pasta products	0.7
12	Vegetables and fruits	3.4
13	Alcoholic beverages	5.5
14	Food in restuarants	2.5
15	Clothing	5.1
16	Fur products	0.7
17	Knitwear	1.2
18	Footwear	2.2
19	Detergents	0.8
20	Perfumery	1.4
21	Haberdashery	0.9
22	Tobacco products	1.1
23	Furniture	2.2
24	Electrical appliances	1.5
25	Press prints	0.4
26	TV and radio sets	0.6
27	Personal computers	0.6
28	Phones	0.6
29	Building materials	1.3
30	Passenger cars	7.3
31	Gasoline	3.3
32	Medicine	2.0
33	Personal services	2.9
34	Passenger transport services	2.7
35	Communication services	2.7
36	Housing and public utilities services	8.9
37	Education	2.3
38	Cultural organizations services	0.4
39	Sanatoria, resorts and health care services	2.3
40	Medicine services	1.5
41	Other food products	2.2
42	Other non-food products	3.8
43	Other services	1.9
	Total:	**100.0**

Source: Rosstat

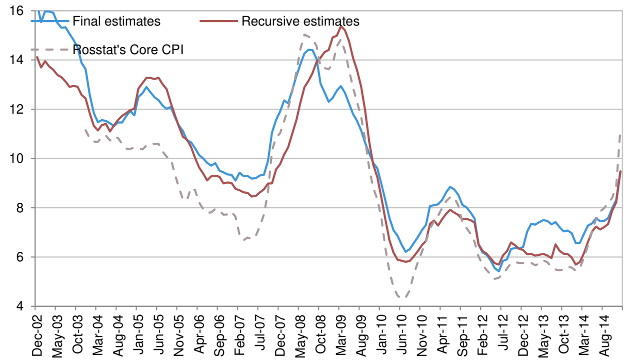
APPENDIX 2

CPI ex. vegetables and fruits, gasoline, utilities; non-food products CPI ex. gasoline and Rosstat's Core CPI, %YoY

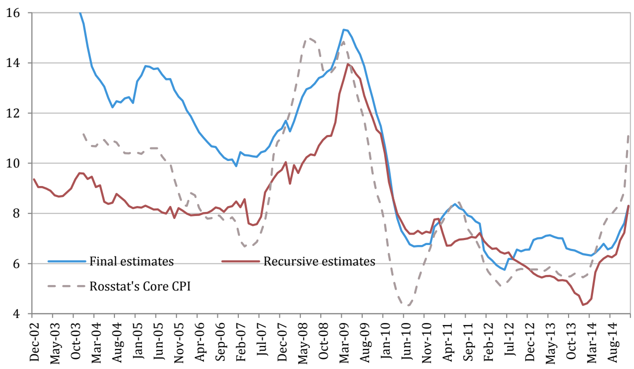


Source: Rosstat, authors' calculations

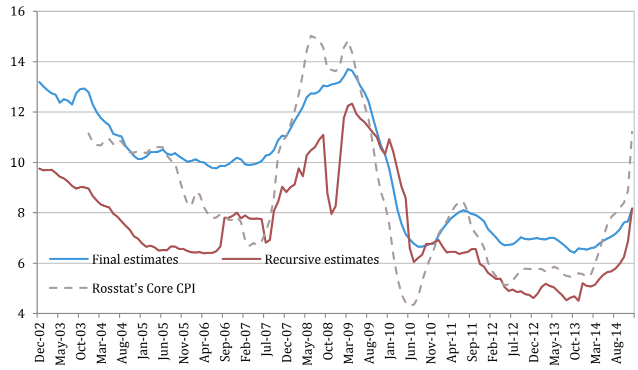
CPI ex. 8 most volatile components and Rosstat's Core CPI, final and recursive estimates, %YoY



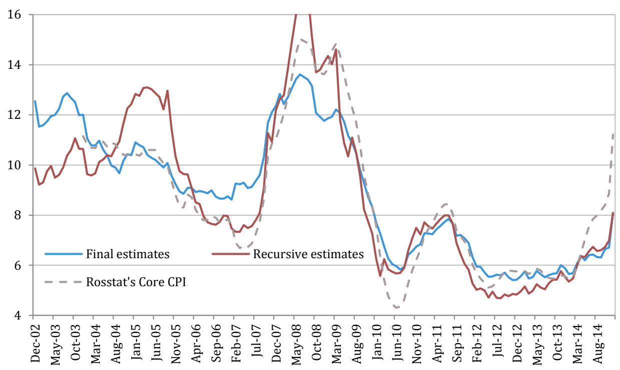
CPI ex. 50% of most volatile components and Rosstat's Core CPI, final and recursive estimates, %YoY



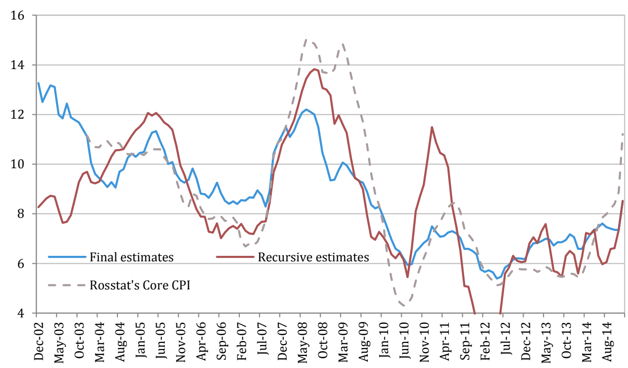
CPI ex. 75% of most volatile components and Rosstat's Core CPI, final and recursive estimates, %YoY



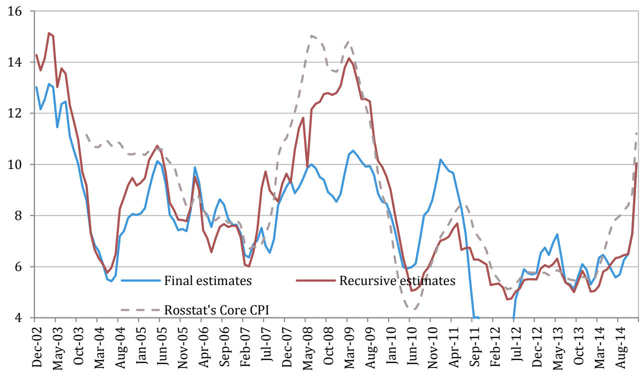
CPI ex. 50% of most sensitive components to shocks in SVAR and Rosstat's Core CPI, final and recursive estimates, %YoY



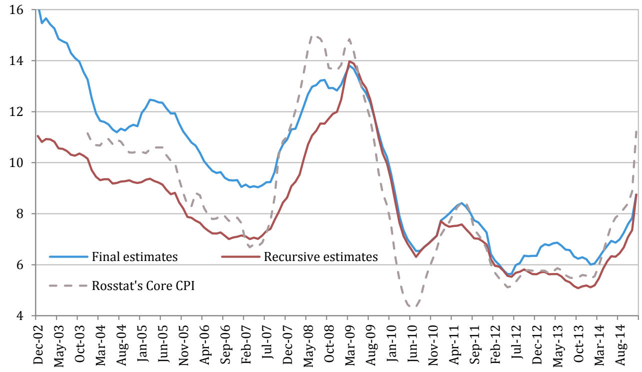
CPI ex. 50% of most sensitive components to shocks in LPM and Rosstat's Core CPI, final and recursive estimates, %YoY



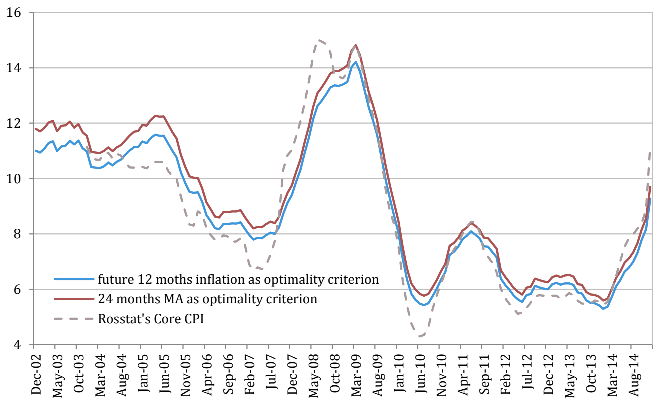
CPI ex. 50% of worst forecasters of future inflation and Rosstat's Core CPI, final and recursive estimates, %YoY



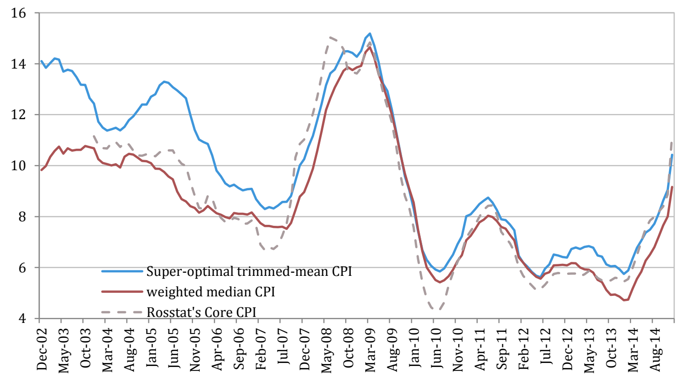
CPI reweighted by volatility and Rosstat's Core CPI, final and recursive estimates, %YoY



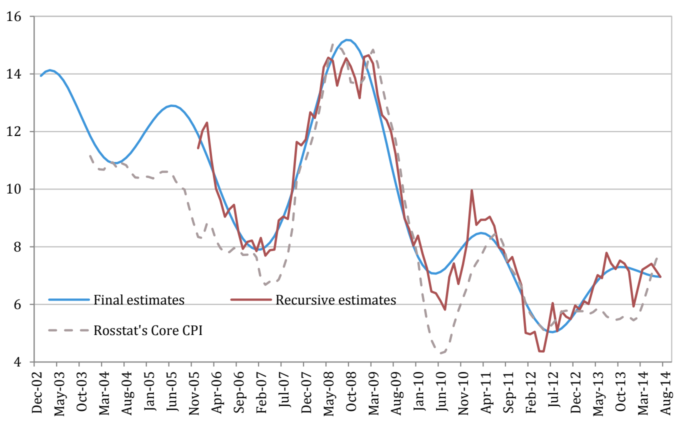
Optimal trimmed-mean CPIs and Rosstat's Core CPI, %YoY



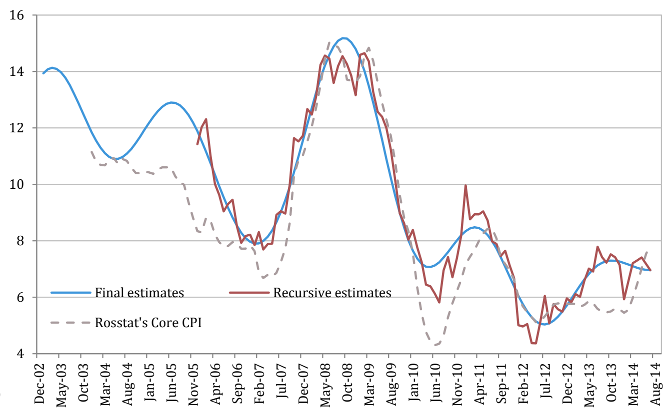
"Super-optimal" trimmed-mean CPI, wiighted median CPI and Rosstat's Core CPI, %YoY



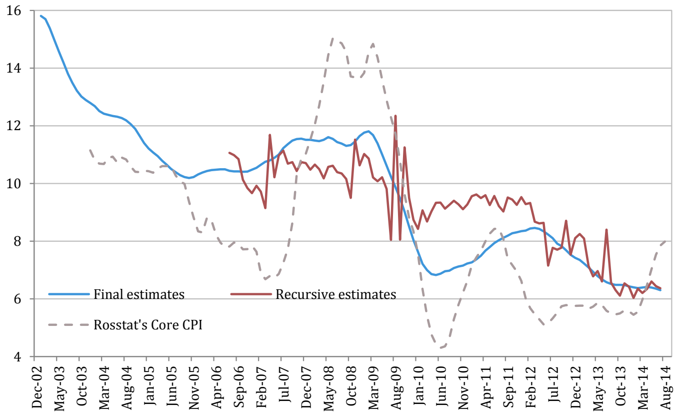
Band-pass filter (frequency > 24 months), %YoY



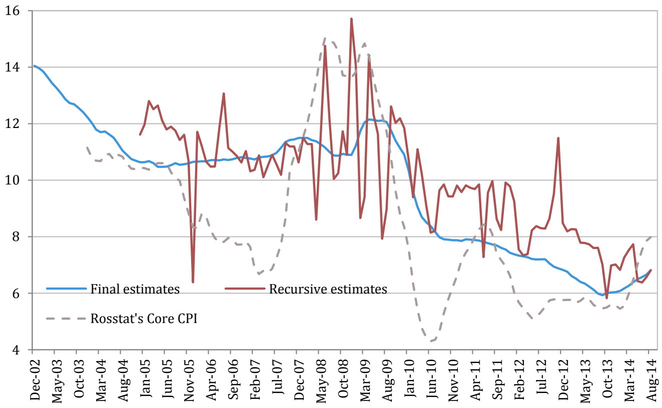
Band-pass filter (frequency > 12 months), %YoY



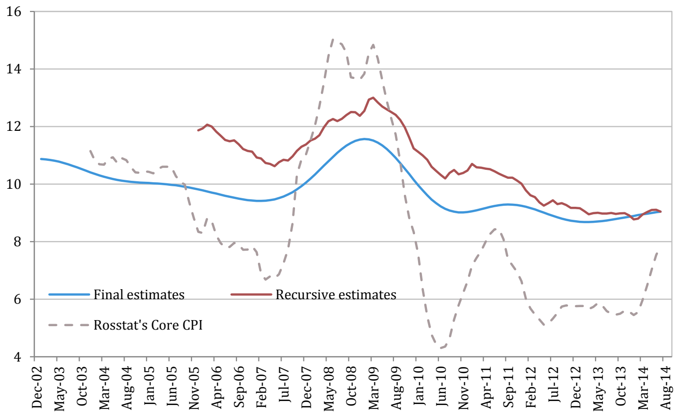
DFM ('monetary' inflation), %YoY



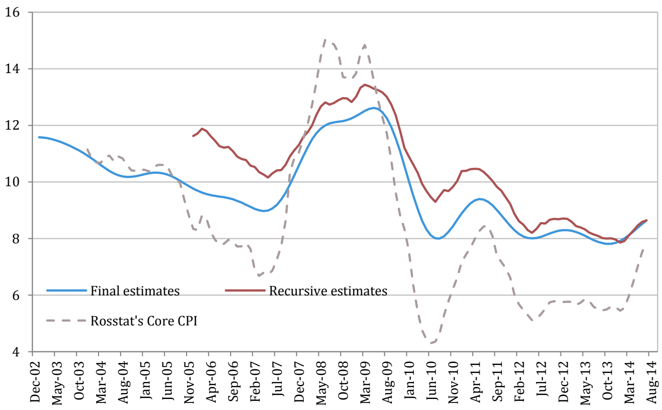
DFM ('pure' inflation), %YoY



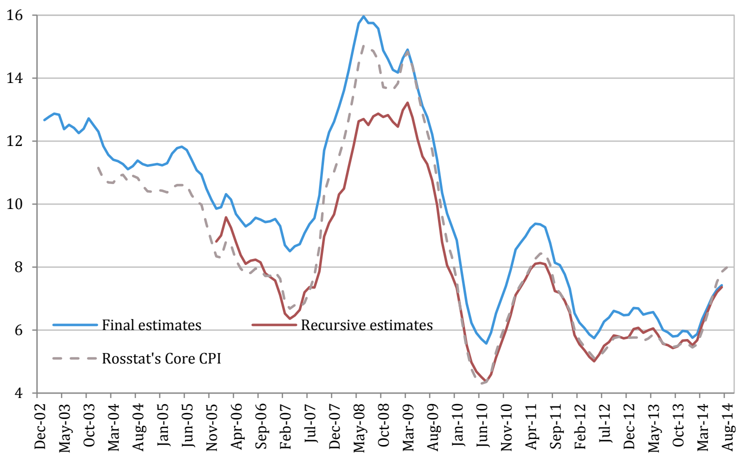
DFM (frequency > 24 months), %YoY



DFM (frequency > 12 months), %YoY



DFM (all frequencies), %YoY



APPENDIX 3

CPI components most frequently excluded from underlying CPI calculation based on Lafleche and Armour (2006) method in moving 24-month window. Percentage of all 132 samples

Eggs	100
Sugar	100
Vegetables and fruits	100
Gasoline	99
Cheese	87
Pasta products	61
Communication services	54
Butter	46
Other services	45
Milk and dairy products	27
Passenger transport services	19
Other food products	19
Medicine	11
Bread and bakery products	10
Meat and Poultry	7
Alcoholic beverages	4
Phones	3
Tea and coffee	3
TV and radio sets	3
Fish and edible sea products	1
Personal computers	1
Housing and public utilities services	1
remaining components...	0

It follows from Table that historically the CPI components with the most unstable monthly inflation include eggs, sugar, vegetables and fruit, petrol, cheese, communications services, pasta and cereals – all these components were included in the underlying inflation index calculation in less than 50% of cases.

APPENDIX 4

Algorithm description: exclusion of CPI components on the basis of their sensitivity to shocks reflecting a change in relative prices.

In order to derive an underlying inflation measure by excluding 25% (50%, 75%) of the consumer goods basket especially sensitive to three shocks (the world prices of Brent crude, world food prices measured by the IMF index and the ruble exchange rate against the dual-currency basket), we analysed a structural VAR model with short-term limitations. In addition, we estimated the impact of the said variables on the dynamics of certain CPI components with the help of the Local Projection Method, see Jorda (2005) and Caselli and Roitman (2014).

In order to derive a measure of underlying inflation insensitive to shocks, we applied the following algorithm to the expanding sample of the pseudo-real data from 2006 (the sample for the original estimation of the model is limited to 2002-2005):

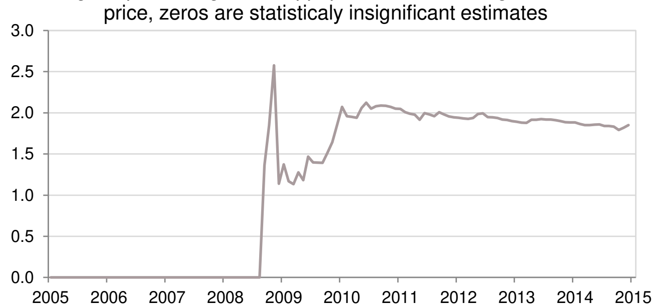
1. For each CPI component (out of 43 components), we analysed a structural VAR model using monthly data with two exogenous variables (a monthly change in oil prices and the IMF index of agricultural prices) and four endogenous variables. For endogenous variables, we selected the exchange rate, one CPI component, one variable of the real sector of the economy (the basic industries index, the industrial production index, the Rosstat index of business sentiment) and one variable as a policy instrument (the monetary base, the interbank money market interest rate). The problem with the estimation of the structural VAR model in this form is that it does not take into account the interaction of the CPI components (we cannot include all the 43 components into the model simultaneously due to the limited number of the degrees of freedom). This gives rise to another problem – a monetary policy instrument in the structural model responds to inflation of a single CPI component rather than to headline inflation. That is why monetary policy shocks, as well as exchange rate shocks, may be identified incorrectly.

2. We applied the Cholesky decomposition to the estimated VAR model to derive structural shocks and assess the functions of impulse response. In another case, at this stage we assessed the Local Project Model as in Jorda (2005) or Caselli and Roitman (2014).

3. The functions of impulse response to shocks by each of the three variables were tested for statistical significance (at the 10% level of significance). Statistically insignificant impulse response functions were assumed as equalling zero. The charts given below show the dynamics of responses by some CPI components to the shocks of oil prices,

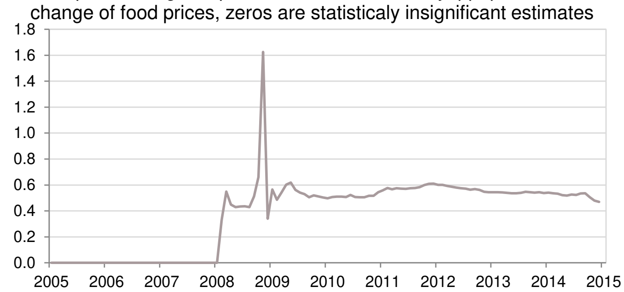
agricultural prices and the exchange rate. The brown line indicates the dynamics of the peak response to a shock (one standard deviation of a standardised shock, i.e. a shock with unit variance) with the consistent addition of one observation (one month) to the model and the model's revaluation.

2002-2005 and then expanding window estimates of oil prices pass through to prices of gasoline, pp. per 1 st. dev. change of Brent oil price, zeros are statisticaly insignificant estimates



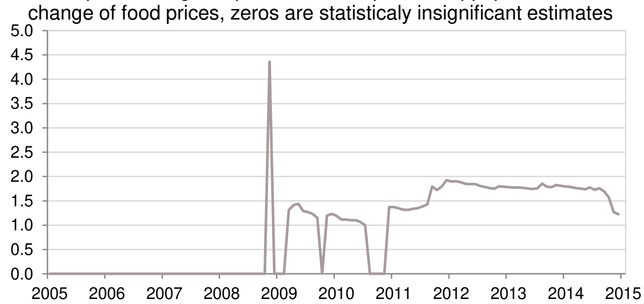
Source: Rosstat, IMF, Bloomberg, author's calculations

2002-2005 and then expanding window estimates of IMF Food price Index pass through to prices of bread and bakery, pp. per 1 st, dev. change of food prices, zeros are statisticaly insignificant estimates



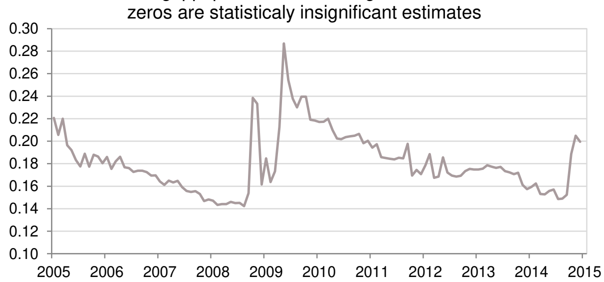
Source: Rosstat, IMF, Bloomberg, authors'calculations

2002-2005 and then expanding window estimates of IMF Food price Index pass through to prices of Pasta products, pp. per 1 st, dev. change of food prices, zeros are statisticaly insignificant estimates



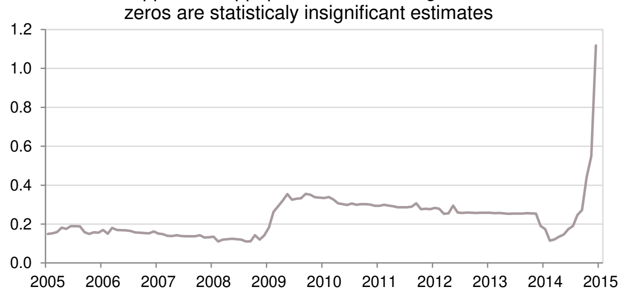
Source: Rosstat, IMF, Bloomberg, authors'calculations

2002-2005 and then expanding window estimates of ERPT to prices of clothing, pp. per 1 st. dev. change of RUR/USD, zeros are statisticaly insignificant estimates



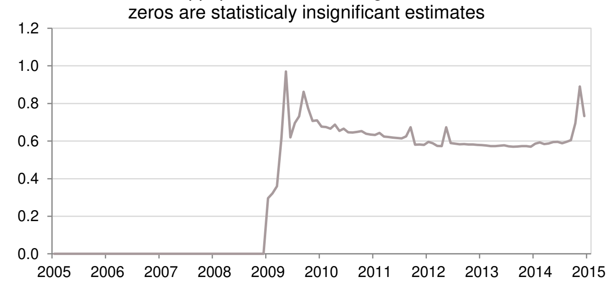
Source: Rosstat, IMF, Bloomberg, authors' calculations

2002-2005 and then expanding window estimates of ERPT to prices of electrical appliances, pp. per 1 st. dev. change of RUR/USD, zeros are statisticaly insignificant estimates



Source: Rosstat, IMF, Bloomberg, author's calculations

2002-2005 and then expanding window estimates of ERPT to prices of medicine, pp. per 1 st. dev. change of RUR/USD, zeros are statisticaly insignificant estimates



Source: Rosstat, IMF, Bloomberg, authors' calculations

4. The estimates of the impulse response functions are comparable with each other for all the three shocks (these are the responses to the shock of random value with the zero mathematical expectation and unit variance) and can therefore be summed up. We calculated the averaged response to the three shocks by each of the 43 CPI components.

5. Considering that inflation of CPI components has different variance, we were expected to preliminarily take into account the volatility of CPI components to range them by their sensitivity to shocks and so we divided the averaged response by the standard devia-

tion of each of the components (the standard deviations, like the responses, were calculated in the pseudo-real time).

6. Having got a distribution of 43 measures of sensitivity to shocks (for each of the CPI sub-indices), we constructed their empirical distribution, using the weights of the CPI components in the consumer goods basket (which make up a total of 100%) as frequencies.

7. We used this distribution to choose the 25% (50% and 75%) quantiles, which we excluded from the index of inflation insensitive to shocks and calculated a new monthly inflation index after re-weighing.

8. Either a whole number of components or the exact quantiles of distribution can be chosen. In the latter case, small deviations from the exact quantile values are possible in recovering the historical values of shock-insensitive inflation for each designated parameterisation of the VAR model, considering that Rosstat changes weights from year to year. We used the selected components or the monthly inflation values we calculated to recover underlying inflation values in year-on-year terms.

For further tests, we selected two measures of inflation insensitive to the shocks of relative prices:

- one indicator for a structural VAR model: 50% of the CPI least of all sensitive to shocks,
- one indicator based on the Local Projection Model with the 50% CPI.

Table 3 gives the list of the most frequently excluded CPI components (for the calculation of 50% of the consumer goods basket least of all sensitive to three relative price shocks in a structural VAR model).

Table 3. Most frequently excluded CPI components, % of all pseudo-real time samples, i.e. the share of all parameterisations of the VAR model for determining sensitivity to shocks (overall, 120 observations from January 2005).

Meat and Poultry	100
Fish and edible sea products	100
Butter	100
Sugar	100
Tea and coffee	100
Bread and bakery products	100
Pasta products	100
Vegetables and fruits	100
Tobacco products	100
Electrical appliances	100
TV and radio sets	100
Personal computers	100
Phones	100
Gasoline	100
Medicine	100
Housing and public utilities services	100
Other food products	100
Other services	100
Confectionery	89
Furniture	73
Perfumery	43
Milk and dairy products	0
all remaining products and services...	0

APPENDIX 5

Exclusion of CPI components based on their ability to forecast future inflation

In this case, underlying inflation is determined as the part of the CPI, those components that can predict future inflation on the medium-term horizon in the best way. Beginning with estimates in the sample of 2003-2004, we analysed the following equation for each of the CPI's 43 components:

$$\pi_{t+12} - \pi_t = \alpha + \beta\left(\pi_t^i - \pi_t\right) + \varepsilon_{t+12},$$

where π_t indicates % of YoY inflation measured by the CPI in month t; π_{t+12} shows % of YoY inflation measured by the CPI in month t+12, π_t^i is % of YoY inflation of the CPI i-component in month t; ε_{t+12} is the iid random variable.

1. In order to analyse the prognostic properties of certain CPI components, we assessed the above regression using an expanding data sample (beginning with the first estimate based on the sample for 2003-2004).

2. Having obtained coefficient estimates, we constructed out-of-sample forecasts in the pseudo-real time. This means that we had a possibility, while living in January 2006, to compare our forecast made in January 2005 for January 2006 with the fact (inflation in January 2006).

3. Having estimated such a pseudo-real out-of-sample forecast for January 2006, we could calculate the average squared error of the forecast or the RMSE (equal to a square error in the case of one observation).

4. Further on, we ranged all of the CPI's 43 components by the increase of their RMSE and constructed their empirical distribution with the frequencies corresponding to the weights of the components in the CPI.

5. Having derived the empirical distribution, we selected separate quantiles for a new index composed of the components with the best prognostic capacity representing X% of the consumer goods basket (where X% is the distribution quantile).

6. In February 2006, we observed the second out-of-sample forecast in the pseudo-real time (it was made in February 2005 based on the forecasting model parameterisation available at that moment). While averaging out two errors of the out-of-sample forecast (for January-February 2006), we repeated steps 4-5 of the algorithm.

As a result, we calculated an underlying inflation indicator representing 50% of the CPI and composed of the best predictors.

APPENDIX 6

Figure 4. RMSE distribution for various truncation levels below ('alfa') and above ('beta'). Calculation based on the full sample for 24-month centered moving average as an optimality criterion

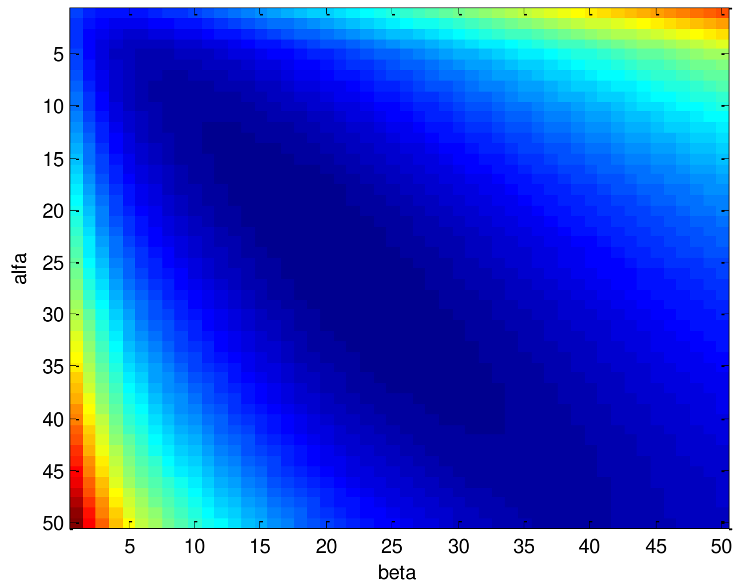
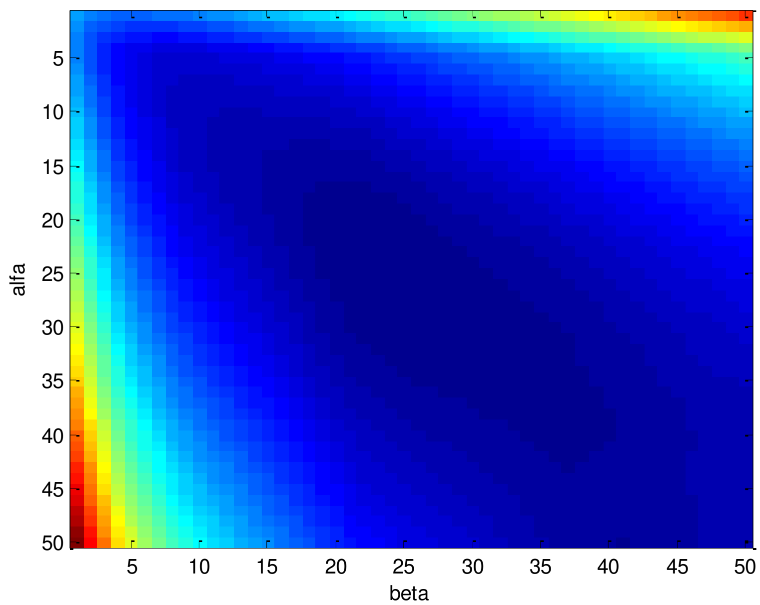


Figure 5. RMSE distribution for various truncation levels below ('alfa') and above ('beta'). Calculation based on the sample from 2010 for 24-month centered moving average as an optimality criterion



The optimal truncation level is almost symmetric and equals 20-25%. After the crisis, the optimal truncation shifted only slightly towards higher levels (both 'alfa' and 'beta').

Table 4. Occurrence frequency of certain CPI components in underlying inflation based on the truncation method (24-month centered moving average of the full sample as a comparison base), a percentage of the number of all 156 monthly inflation observations from 2003.

Phones	6
Eggs	10
Personal computers	10
Sugar	11
Vegetables and fruits	11
TV and radio sets	13
Cheese	24
Gasoline	24
Communication services	24
Pasta products	31
Electrical appliances	31
Tobacco products	34
Other services	36
Bread and bakery products	42
Butter	44
Passenger transport services	51
Passenger cars	51
Medicine	51
Milk and dairy products	52
Housing and public utilities services	52
Sanatoria, resorts and health care services	53
Cultural organizations services	56
Fish and edible sea products	57
Other food products	58
Tea and coffee	63
Detergents	63
Fur products	64
Medicine services	65
Building materials	68
Education	68
Meat and Poultry	71
Other non-food products	73
Perfumery	74
Press prints	76
Alcoholic beverages	80
Personal services	81
Confectionery	82
Food in restuarants	82
Footwear	85
Haberdashery	88
Furniture	88
Knitwear	93
Clothing	97

APPENDIX 7

Table 5. Variables used in 'monetary' dynamic factor model

Monetary indicators	***Price indicators***
M1, households	CPI
M1, corporates	Core CPI
Household term deposits in rubles	Non-food prices
Non-financial organisations' term deposits in rubles	Food prices
Divisia M2	Service prices
M2Y	Fixed capital investment deflator
	Housing prices (primary market)
	Housing prices (secondary market)

Figure 6. Impulse response functions to first ('monetary') structural shock

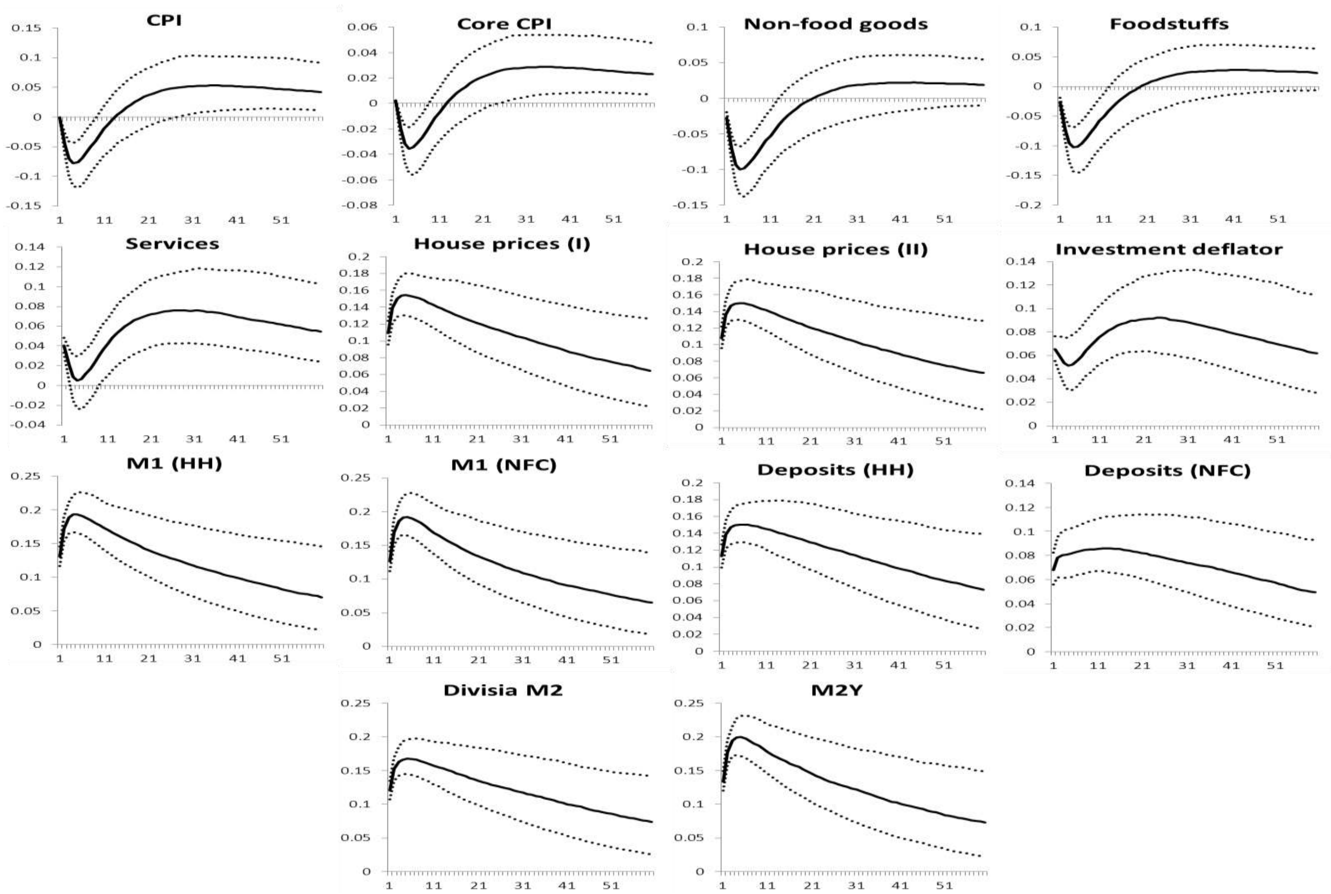
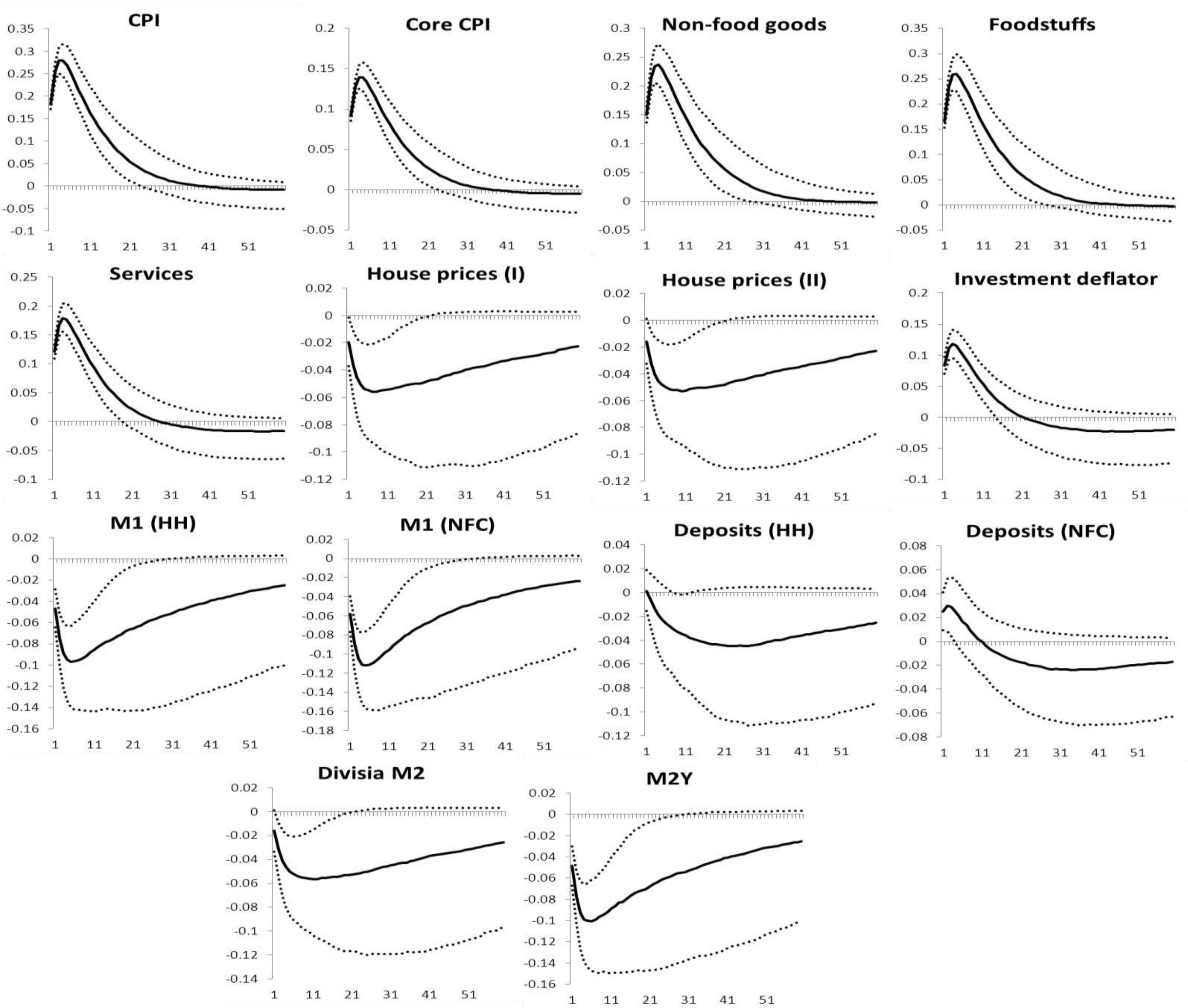


Figure 7. Impulse response functions to second structural shock



APPENDIX 8

Table 6. Average absolute deviation of annual inflation growth rate from average level in moving 25-month period (p.p.)

Indicator	***Volatility***
DFM (frequency > 24 months)	0.2
DFM (‘monetary’ inflation)	0.3
DFM (frequency > 12 months)	0.4
DFM (‘pure’ inflation)	0.4
Inflation excluding 75% of most volatile components	0.5
Non-food goods excluding energy and fuel	0.6
Shock-insensitive 50% CPI in LPM	0.6
Shock-insensitive 50% CPI in SVAR	0.6
Volatility-weighted inflation	0.7
Weighted median	0.8
Optimal trimmed inflation, criterion: future inflation	0.8
Inflation excluding 50% of most volatile components	0.8
Exclusion of eight most volatile components	0.8
Optimal trimmed inflation, criterion: moving average	0.8
DFM (all frequencies)	0.9
‘Super-optimal’ trimmed inflation	0.9
CPI excluding vegetables and fruit, energy and housing and utility services	1.0
Band-pass filter (frequency > 24 months)	1.0
Band-pass filter (frequency > 12 months)	1.3
50% CPI of best future inflation predictors	1.3

Table 7. Cumulative deviation of underlying inflation from actual inflation in 2003-2014 (%)

Indicator	***Deviation***
Inflation excluding 50% of most volatile components	5.9
DFM (frequency > 24 months)	2.1
DFM (frequency > 12 months)	1.8
Exclusion of eight most volatile components	0.9
Band-pass filter (frequency > 24 months)	0.8
DFM (all frequencies)	0.4
Band-pass filter (frequency > 12 months)	0.2
DFM (‘pure’ inflation)	-0.2
‘Super-optimal’ trimmed inflation	-0.5
Volatility-weighted inflation	-1.6
Inflation excluding 75% of most volatile components	-2.3
DFM (‘monetary’ inflation)	-3.0
Optimal trimmed inflation, criterion: moving average	-4.8
CPI excluding vegetables and fruit, energy and housing and utility services	-5.2
Optimal trimmed inflation, criterion: future inflation	-9.1
Shock-insensitive 50% CPI in SVAR	-9.4
Shock-insensitive 50% CPI in LPM	-11.4
Weighted median	-11.8
50% CPI of best future inflation predictors	-20.5
Non-food goods excluding energy and fuel	-29.1

Table 8. Deviation of final estimates of annual underlying inflation growth rates from real-time recursive estimates (p.p.)

Indicator	***Deviation***
Optimal trimmed inflation, criterion: moving average	0.0
Optimal trimmed inflation, criterion: future inflation	0.0
Weighted median	0.0
‘Super-optimal’ trimmed inflation	0.0
Non-food goods excluding energy and fuel	0.0
CPI excluding vegetables and fruit, energy and housing and utility services	0.0
Band-pass filter (frequency > 12 months)	0.2
DFM (frequency > 12 months)	0.4
DFM (frequency > 24 months)	0.5
Band-pass filter (frequency > 24 months)	0.5
Shock-insensitive 50% CPI in SVAR	0.9
Exclusion of eight most volatile components	0.9
DFM (‘monetary’ inflation)	0.9
Volatility-weighted inflation	0.9
Shock-insensitive 50% CPI in LPM	1.2
DFM (all frequencies)	1.2
Inflation excluding 50% of most volatile components	1.3
50% CPI of best future inflation predictors	1.5
DFM (‘pure’ inflation)	1.6
Inflation excluding 75% of most volatile components	1.7