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Disinflation and Reliability of Underlying Inflation Measures

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Abstract

We estimated a non-Stationary dynamic factor model and used it to generate artificial episodes of disinflation (permanent changes in the mean inflation rate). These datasets were used to test the forecasting abilities of alternative underlying inflation indicators (i.e. measures that capture sustained movements in inflation extracted from information in a disaggregated set of price data). We found that the out of sample forecast errors of the benchmark underlying inflation measures (based on unobserved trend extraction) are more severely affected by disinflation than the alternative simpler methods (based on exclusion or re-weighting approaches). We also show that a non-stationary dynamic factor model may be employed for the extraction of the unobserved trend to be used as an underlying inflation measure.

Keywords: underlying inflation, non-stationary dynamic factor model, Russia

JEL Classification: E31, E32, E52, C32

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1 Introduction

Headline inflation measures can be volatile and 'noisy'. The fluctuations associated with measurement errors and changes in relative prices can make it difficult for policymakers to give an accurate judgement of the underlying state of, and the prospects for, aggregate price level dynamics. Therefore, estimates of 'underlying' ('core') inflation are widely used by academics and central banks, not only as a statistical measure, but also as an analytical tool.

The literature describes different approaches for constructing indicators of underlying inflation, and proposes different criteria for measuring their performance in terms of the desirable empirical properties of the underlying inflation. One caveat is that these methods are mostly examined in advanced economies where the inflation rate is well-anchored around its long-term mean value. This is not the case in emerging market economies. In fact, for many central banks in emerging market countries it is not uncommon to attempt to bring the inflation rate to a level that is lower than the observed average (in other words, to achieve disinflation). When successful, such a policy generates a structural break in the inflation-generating process (for example, a mean shift), and affects the forecasting performance of underlying inflation measures accordingly. Interestingly, Smith (2005) reports changes in the performance of underlying inflation measures after the introduction of inflation-targeting in the advanced economies (see García-Cintado et al. (2015, 2016) and Hałka and Szafrański (2018) for other examples of structural breaks that could affect the inflation-generating process). Obviously, if underlying inflation measures are to continue serving as analytical tools, the evolution of their properties in these circumstances should be examined (or, preferably, predicted).

The Bank of Russia transitioned to a fully flexible exchange rate and inflation-targeting regime in 2015. The inflation rate subsequently declined, and it has fluctuated close to the target value of 4 per cent per annum. Presumably, this disinflation may have caused a structural break in the inflation-generating process and affected the performance of underlying inflation measures. This paper examines the potential implications of this transition and the subsequent disinflation for the performance of the underlying inflation measures in Russia. For this purpose, we employ Monte Carlo experiments, which are commonly applied in the analysis of trend/cycle decomposition (see e.g. Nelson 1988, Basistha 2007, Drehmann and Tsatsaronis 2014 and Gonzalez-Astudillo and Roberts 2016). There are several arguments in favour of using artificial datasets to assess the performance of underlying inflation indicators. First, this approach allows us to generate a large number of disinflation episodes (containing longer post-disinflation series), and to conduct a more reliable evaluation of the properties of the underlying inflation measures, as well as to predict the yet unobserved evolution of these properties. Secondly, by designing the experiments appropriately, we are able to isolate the effect of disinflation on the properties of the underlying inflation measures from the effects of other developments that affected the historical outcome. Naturally, the limitation of this approach is that the design of any Monte Carlo experiment is always somewhat arbitrary. In order to generate the artificial datasets, we use a newly-developed non-stationary dynamic factor model that allows us to introduce appropriate structural breaks in the modelled price developments.

The rest of the paper is structured as follows. In Section 2 we provide a description of the underlying inflation measures. Section 3 presents the non-stationary dynamic factor model and outlines the design of the Monte Carlo experiments. In Section 4, we describe the formal evaluation tests and the results of the empirical and Monte Carlo analyses. Section 5 concludes the paper.

2 Underlying inflation measures

Our choice of underlying inflation measures is based on the paper by Deryugina et al. (2018), in which a range of underlying inflation measures in Russia is estimated and their performance examined. In this paper we only analyse the measures that were found to perform well historically. The common feature of these methods consists in the utilisation of the cross-section of consumer price index (CPI) components (see Table 2 in Appendix A) to extract a relevant signal (Deryugina et al. (2018) found that using larger datasets comprising real and monetary variables does not improve the results sufficiently). This dataset is the most detailed CPI disaggregation available for Russia for a relatively long time sample. Accordingly, we use the following approaches.

2.1 Unobserved trend models

As a benchmark model we choose the approach of Cristadoro et al. (2005). Note that various versions of unobserved trend models, such as the 'pure inflation' model of Reis and Watson (2010), were tested by Deryugina et al. (2018). For brevity we only test the best-performing of these specifications in this paper. In this approach, inflation is decomposed into two stationary, orthogonal, unobservable components – the common χ_{jt} and the idiosyncratic ε_{jt}. Subsequently, the common component can be divided into long-term (or smoothed) and short-term components by applying the band-pass filter:

$$\pi_{jt} = \chi_{jt} + \varepsilon_{jt} = x_{jt}^L + x_{jt}^S + \varepsilon_{jt}, \tag{1}$$

where x_{jt}^L is the smoothed component for the j-th price indicator at time t obtained by summing up the waves with periodicity $[-\pi/h, \pi/h]$ using spectral decomposition, and x_{jt}^S is the short-term component.

The long-term component measures underlying inflation and omits idiosyncratic shocks that are not common to all CPI components and short-term fluctuations, since these are irrelevant for monetary policy.

The common component can be written as

$$\chi_{jt} = b_j(L) f_t, \tag{2}$$

where $f_t = (f_{1t}, ..., f_{qt})'$ is a vector of q dynamic factors, and $b_j(L)$ is a lag operator of order s.
The static representation of the model is

$$\pi_{jt} = \lambda_j F_t + \varepsilon_{jt}, \tag{3}$$

where $b_j(L)f_t = \lambda_j F_t$, $F_t = (f'_t, f'_{t-1}, ..., f'_{t-s})'$ are the static factors, and λj are the factor loadings.
We use a dataset of the 44 seasonally adjusted monthly price indicators (for CPI and its components). The number of dynamic factors is selected 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 $q = 3$ and assume $s = 12$ (we found that using a smaller number of lags worsened the historical properties of the indicator). The underlying inflation is estimated by following Cristadoro et al. (2005)'s three-step procedure.
We set $h = 24$ for the benchmark model (*BP-DFM*).
We also calculate the indicator based on a dynamic factor model *without* using band-pass filters (*DFM*) and also *solely* on the basis of band-pass filters with $h = 24$ (*BP*).

2.2 Exclusion method

Following Lafleche and Armour (2006), we calculate underlying inflation excluding 22 of the most volatile components of CPI, using the weights of the remaining 22 components in the consumer goods basket to construct the aggregate. The volatility of each CPI component is measured by the standard deviation of the monthly inflation rate of this component.

2.3 Re-weighting method

The re-weighting approach to underlying inflation is similar to the exclusion method (see, for example, Macklem (2001)). In this approach the weights of the CPI components are selected in inverse proportion to their historical volatility, calculated in a moving 24-month window. There are no excluded components.

2.4 Trimming method

The trimming method selects only a part of the empirical distribution of the monthly inflation of certain CPI components for the underlying inflation index (normally, the tails of the distributions are cut off; see, for example, Meyer and Venkatu (2012)). We calculate the underlying inflation indicator by discarding the CPI components with inflation rates below the 25^{th} and above the 75^{th} percentiles of the distribution in a given month.

2.5 Domestically generated inflation

We examine the performance of inflation of prices for services, which may be regarded as an observed indicator for domestically generated inflation (see Bank of England (2015) for a discussion). This indicator is the weighted average inflation for all services reported in Table 2 in Appendix A with the exception of 'Other services'. We also tested other domestically generated inflation measures such as nominal unit labour cost and housing price growth rates. For brevity, we only report the performance of the best performing of these, the inflation indicator for services.

3 The non-stationary dynamic factor model and design of the experiments

Modelling permanent disinflation with standard statistical models is not a straightforward task. First, we need a model that can identify permanent and transitory shocks. Secondly, we need to model jointly the dynamics of a large set of indicators required for the estimation of the underlying inflation measures. We therefore set up a non-stationary dynamic factor model (NSDFM) in the spirit of Barigozzi et al. (2016). This type of approach is not unprecedented. See, for example, the paper by García-Cintado et al. (2015, 2016), which applies an earlier version of the NSDFM proposed by Bai and Ng (2004) to the analysis of inflation rates. We set up the model as follows:

$$X_t = \chi_t + \xi_t, \qquad \chi_t = \Lambda F_t \tag{4}$$

$$S(L)(1-L)F_t = Q(L)u_t, \tag{5}$$

where, in (4), X_t is an $N \times T$ matrix of de-trended observations decomposed into the sum of two unobservable components: χ_t the common component, which is a linear combination of r factors F_t with factor loadings Λ, and ξ_t the idiosyncratic component $(t = 1, ..., T)$. X_t, F_t and ξ_t are assumed to be $I(1)$. In the same way as Barigozzi et al. (2016), we assume that X_t, F_t and ξ_t are $I(1)$ even though some of their coordinates may be $I(0)$. For Monte Carlo experiments, we set $\xi_t \sim I(0)$ for simplicity. Setting $\xi_t \sim I(1)$ does not change the results of the exercise.
The factors F_t are driven by q common shocks u_t, d of which have temporary fluctuations, while τ shocks have a permanent effect on common trends. Note that temporary fluctuations do not have a long-run effect on the observed variables. To construct this type of shock we introduce zero restrictions to impulse responses in an infinite horizon. For the permanent shocks there are no restrictions to infinity.
$S(L)$ and $Q(L)$ are $r \times r$ and $r \times q$ matrix polynomials; L is a lag operator.
The fully-dynamic representation is as follows:

$$X_t = \Lambda \left[S(L)(1-L)\right]^{-1} Q(L)u_t + \xi_t. \tag{6}$$

We estimate the model following Barigozzi et al. (2016):

1. We extract the common factors and their loadings by principal component analysis. The factor loadings are extracted from $\Delta X_t = \Lambda \Delta F_t + \Delta \xi_t$, that is, (4) in first differences. The common factors are estimated as $\dot{F}_t = N^{-1}\hat{\Lambda}' X_t$.

2. We then consider a VECM with $c = r - q + d$ cointegration relations for the common factors. $\Delta F_t = \alpha\beta' F_{t-1} + G_1 \Delta F_{t-1} + w_t$, where the matrix of cointegration vectors β is estimated by the Johansen approach, and α and G_1 are regression coefficients. A VECM can be rewritten as a VAR process $A(L)F_t = w_t$. The residuals w_t are transformed to q primitive shocks u_t: $w_t = Ku_t$, where K denotes the rescaled first q eigenvectors of the sample covariance matrix of the w_t (see, for instance, Stock and Watson (2005), Bai and Ng (2007), and Forni et al. (2009)).

3. We choose the orthogonal $q \times q$ identification matrix H to achieve the conditions under which τ common trends are detected among q common shocks.

We set the number of factors $r = 7$, common shocks $q = 4$, and common trends $\tau = 2$ based on the results of different tests for the determination of the number of factors (Bai and Ng (2002, 2007), Hallin and Liška (2007), Barigozzi et al. (2016)) (see Appendix C).

3.1 Design of experiment

The Bank of Russia transitioned to a fully flexible exchange rate and inflation-targeting regime in 2015. The inflation rate subsequently declined, and it has fluctuated close to the target value of 4 per cent per annum. Presumably, these developments represent permanent disinflation. The goal of our exercise is to increase the number of disinflation episodes artificially so that the rates are similar to the observed rates available for analysis. We also use the artificially created observations to extend the dataset and possibly to predict the yet unobserved evolution of the properties of the underlying inflation measures. Note that, since we are interested in identifying the effect of disinflation on the underlying inflation measures, we want to eliminate the impact of the large fluctuations in the inflation rate that happened immediately prior to disinflation in early 2015 (see Figure 1).
For this purpose, we estimate the NSDFM for the 43 components of the headline CPI (see Table 2 in Appendix A) from February 2002 to September 2014 ($T = 152$ months):

$$x_{it} = \lambda_i F_t + \xi_{it} \qquad i = 1, ..., N, t = 1, ..., T, \tag{7}$$

$$A(L)F_t = KHu_t. \tag{8}$$

We begin generating artificial observations in September 2014 using estimated parameters $\hat{\lambda}_i$, $\hat{A}(L)$, $\hat{K}$, $\hat{H}$. The artificial series are 15 years long. We run the simulations until we obtain 100 replications with the following properties:

1. During the first 12 months the innovations are driven by $u_t \sim N(0, \sigma_u^2 \cdot I_q)$. Over the next 36 months, we introduce a negative drift $u_t \sim N(-1, \sigma_u^2 \cdot I_q)$, where $\sigma_u^2 = 3$ (this choice allows us to keep the variance of the simulated CPI close to the variance of the actual data).

2. We select only those simulations for which the inflation rates of the majority of the CPI components (more than 37 of the 43 components) are, on average, lower than the actual rates (the last 10 years of simulations are compared with the last 10 years of actual data). Thus, we only analyse the cases where disinflation occurred across most of the cross-sections.

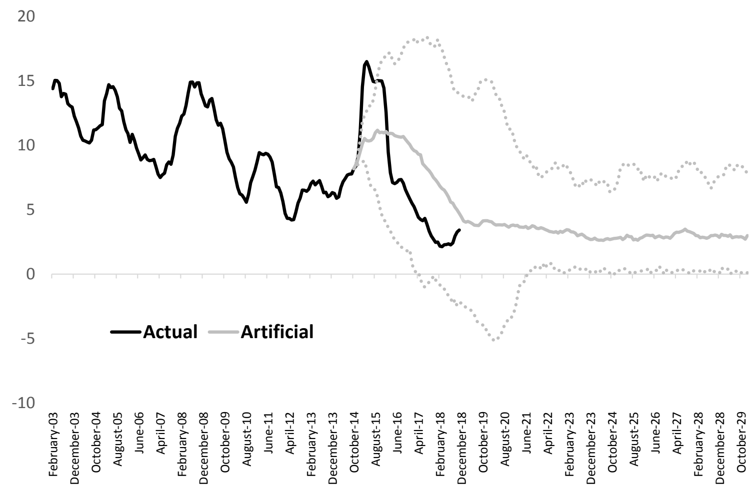
3. We calculate the headline CPI for the simulated component using the respective weights of 2018. We select only those simulations where the CPI year-over-year growth rate does not fluctuate outside the 0 per cent to 10 per cent band, starting from 2021. This prevents the gradual dispersion of CPI inflation rates towards the end of the simulation and represents actual inflation being anchored around the Bank of Russia's target. Each idiosyncratic component is drawn from a normal distribution $\xi_{it} \sim N(0, 1)$ rescaled so that it accounts for a quarter of the total variance.

The distribution of the artificial CPI growth rates obtained is presented in Figure 1. The artificial datasets obtained represent disinflation episodes with a magnitude similar to the observed instances, but with different short-term dynamics. We use these datasets for Monte Carlo experiments as described in Section 4.3.

4 Evaluating the properties of underlying inflation measures

Arguably, the most valuable and clearly defined criterion for assessing the quality of an underlying inflation measure is its ability to forecast actual inflation (see, for example, Wynne (1999), Mankikar and Paisley (2004), Amstad et al. (2014) and Wiesiołek and Kosior (2010)). We choose to assess this property for the 12-month horizon (which is arguably relevant for monetary policy).
We proceed by examining the evolution of the forecasting performance of the underlying inflation measures during the observed and artificial episodes of disinflation. For that purpose, we calculate our underlying inflation measures (that is, we estimate the models, determine the excluded components or the weights for re-weighting, and so on) in pseudo-real time (i.e. we use appropriate time samples but not vintage data or recursive seasonal adjustment) using five-year-long rolling

Figure 1: Actual CPI inflation and distribution (median, min and max) of artificial year-over-year CPI growth rates (%)



sub-samples of data (we found that using a recursively expanding time sample does not improve the performance of the underlying inflation measures). We employ two alternative approaches to evaluate the usefulness of these measures for inflation forecasting.

We use the standard 'regression-based' method (see, for example, Lafleche and Armour (2006)) to assess the forecasting properties of underlying inflation:

$$\pi_{t+12} - \pi_t = \alpha + \beta(\pi_t^U - \pi_t) + u_{t+12}, \tag{9}$$

where π_t are the annual CPI growth rates, the π_t^U are the annual underlying inflation growth rates, and α and β are regression coefficients.

The regression is estimated recursively over the expanding time sample, and 12-month-ahead forecasts are produced using the alternative underlying inflation measures. The results are reported in terms of the root mean squared errors (RMSE) of these forecasts. In addition to testing the set of underlying inflation measures, we estimate the forecast errors using the currently observed CPI rate as a forecast for the CPI rate 12 months ahead (i.e. a random walk process, RW).

An alternative, more demanding, approach implies setting $\alpha = 0$ and $\beta = 1$ in the forecasting equation without estimation – the 'direct' method (which essentially treats the calculated underlying measure as a forecast of the future CPI rate):

$$\pi_{t+12} - \pi_t = (\pi_t^U - \pi_t) + u_{t+12}. \tag{10}$$

We report both measures of forecasting accuracy, but regard the direct forecasts as the primary approach to evaluation.

4.1 Historical analysis

First, we evaluate the historical performance of the underlying inflation measures by estimating the RMSEs over the 2005-2018 time sample. The results obtained using both the 'regression-based' (equation (9)) and the 'direct' (equation (10)) approaches are reported in Table 1. In line with the findings of Deryugina et al. (2018), the *BP-DFM* appears to be the best performing model.

Table 1: Cumulative RMSEs over 2005-2018 time sample

Regression-based		Direct	
Measure	RMSE	Measure	RMSE
BP-DFM	0.037	BP-DFM	0.039
Inflation for services	0.039	BP	0.043
BP	0.041	Trimming	0.043
Re-weighting	0.042	RW	0.043
Trimming	0.042	DFM	0.043
DFM	0.042	Exclusion	0.043
Exclusion	0.042	Re-weighting	0.044
RW	0.043	Inflation for services	0.049

We proceed by examining the changes in the performance of the underlying inflation measures after the disinflation. For this purpose, we calculate the RMSEs over three-year-long rolling sub-samples. The results are reported in Figures 2 and 3. The performance of the measures estimated using the exclusion, re-weighting, and trimming approaches prove to be similar. Therefore, for illustrative purposes, the respective RMSEs are labelled 'Other' in Figures 2–3 and 5–7. The results indicate that the RMSEs of all measures deteriorate significantly in the 2014-2016 sub-sample (for all indicators, the errors are significantly higher than the average for 2005-2018). The performance of the measure based on *BP-DFM* was still good in relation to its competitors, although the inflation for services indicator outperformed the benchmark.

Note that these results are determined not solely by disinflation caused by the adoption of the inflation-targeting regime and the transition to a flexible exchange rate, but by all of the events that took place in 2015 in Russia (most notably the drop in oil prices and the ensuing depreciation of the ruble and temporary acceleration of inflation).

4.2 NSDFM-based measure of underlying inflation

Although the main purpose of the NSDFM is as a data generator for Monte Carlo analysis (Section 4.3), it may be appropriate to employ this model to estimate underlying inflation when the actual inflation rate is presumed to be affected by permanent shocks.

We estimate the NSDFM as described in Section 3 for the dataset containing the detrended indicators of the headline CPI and its 43 components over the time sample of 2002-2018 (starting with the first 24 months). Notably, in this case we use recursively expanding time sample instead of rolling sub-samples as in Section 4.2. For each iteration, we calculate the underlying inflation measure by extracting two common trends (τ) in the headline CPI dynamics and adding the extracted trend during the data transformation. The year-over-year growth rate is calculated as the product of 12 monthly underlying inflation rates.

We test the historical performance of the NSDFM-based measure as described in Section 4.1. The results are presented in Figure 4 in comparison with the benchmark *BP-DFM* measure. The NSDFM-based measure performs as well as (or slightly worse than) the *BP-DFM* prior to disinflation, and it performs better in direct forecasting. Admittedly, these are preliminary results, as we do not have enough data on post-disinflation developments. Nevertheless, we believe that the NSDFM approach may be promising in such circumstances.

Figure 2: RMSEs of regression-based forecasts estimated over three-year-long sub-samples

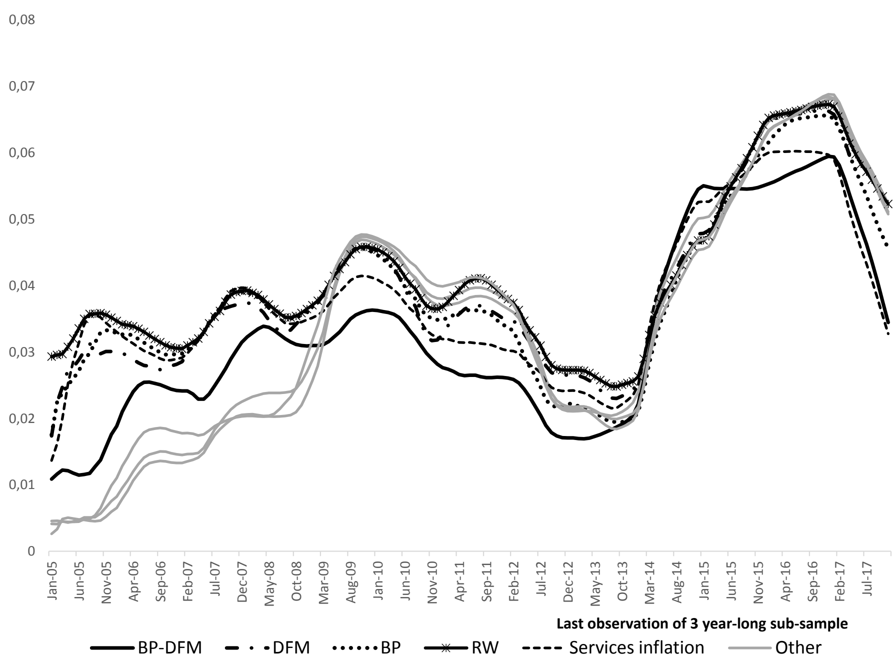


Figure 3: RMSEs of direct forecasts estimated over three-year-long sub-samples

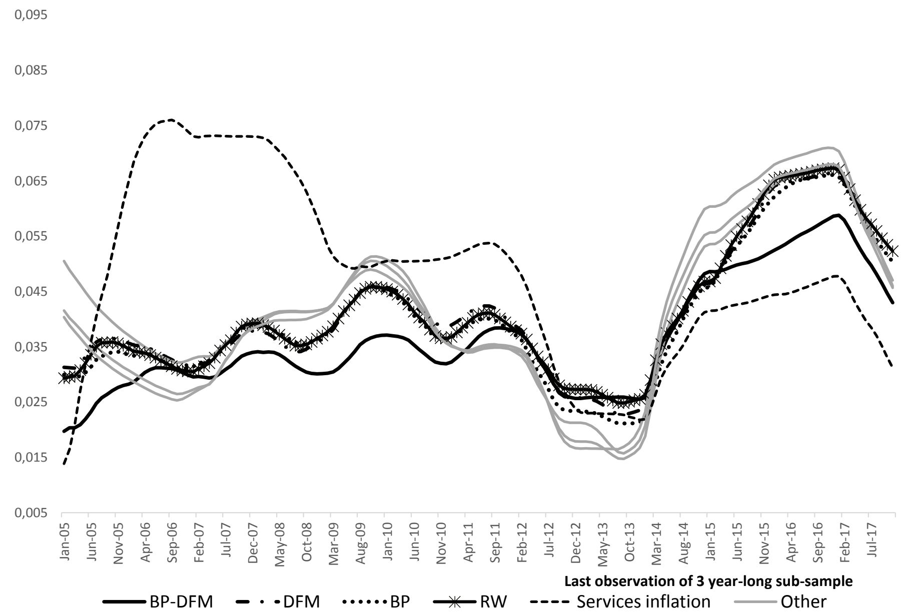
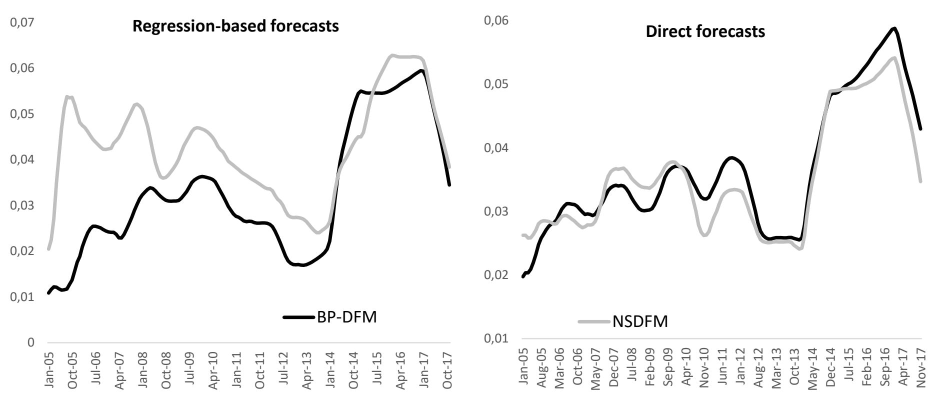


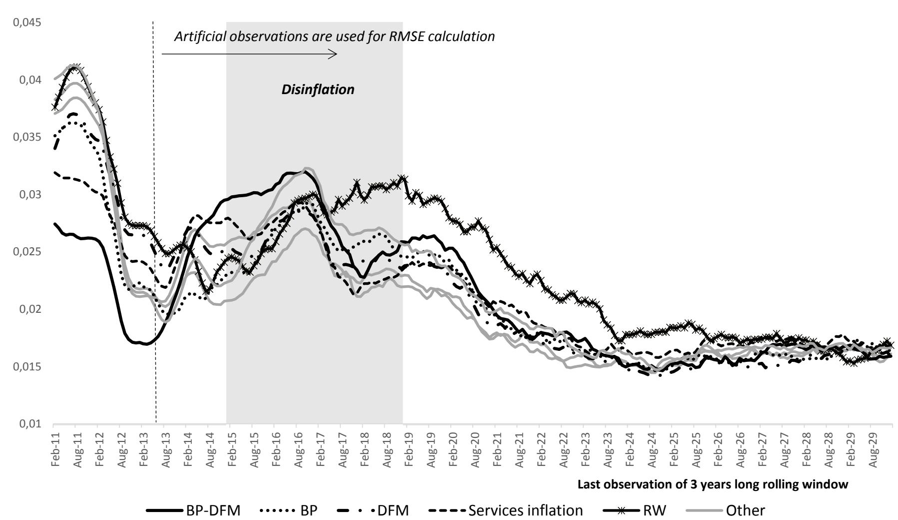
Figure 4: RMSEs estimated over three-year-long sub-samples



4.3 Monte Carlo experiments

We proceed by estimating the RMSEs for the datasets extended with artificial observations (generated as described in Section 3.1). The RMSEs are averaged across all datasets. Admittedly, under this setup, the evolution of the performance of the alternative underlying inflation measures over the artificial sample is still, at least partially, determined by historical developments. Therefore, in Appendix B, we cross-check our findings using fully artificial datasets.
The main results are presented in Figures 5–6. Our exercise predicts that the performance of all measures will deteriorate during disinflation, but not that the deterioration is as bad as we observe empirically. In fact, for the *BP-DFM*, the highest values of the RMSEs obtained for the artificial sample are still lower than the average error in 2005-2018. We therefore conclude that the deterioration of the empirical RMSEs is mostly driven by factors unrelated to disinflation.
Interestingly, and in contrast to the empirical data, the *BP-DFM* is not supposed to remain the best-performing indicator. In fact, the regression-based forecasts obtained with the *BP-DFM* are predicted to be the worst among all the models during the first three years after disinflation, and the direct forecasts are predicted to be the worst from the third to the fifth years after disinflation.

Figure 5: RMSEs of regression-based forecasts estimated over three-year-long subsamples



As regards the competitor models, the Monte Carlo experiments do not provide a clear recommendation for the regression-based exercise. As for direct forecasting, the measures based on the exclusion and re-weighting methods produce the best direct

Figure 6: RMSEs of direct forecasts estimated over three-year-long sub-samples

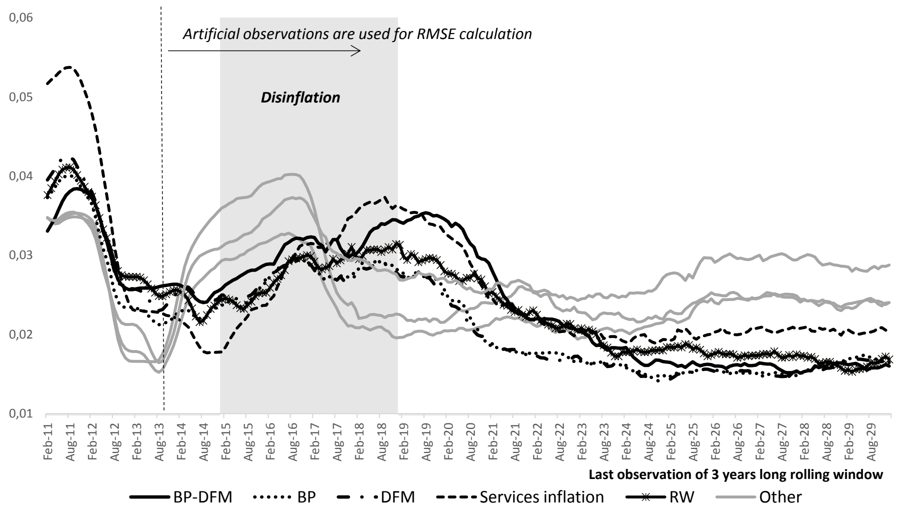
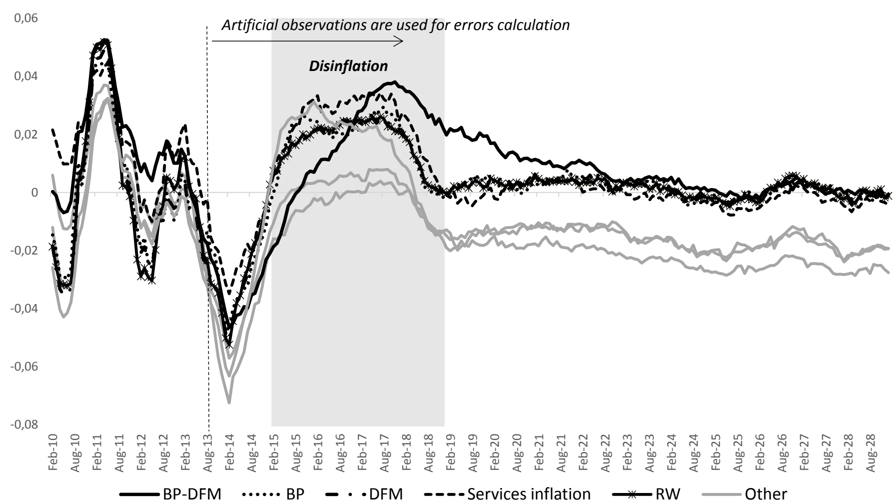


Figure 7: Median errors of direct forecasts



forecasts over the period of three to six years after the disinflation. At least partially, this result may be attributed to the systematic negative bias of the forecasts based on these measures (see the median errors presented in Figure 7), which accidentally helps to improve the forecasts during disinflation. This finding is confirmed by the analysis presented in Appendix B. This observation indicates that, in Russia, the

volatile components of CPI have, on average, higher inflation rates.
In contrast to the empirical case, the inflation for services does not outperform the competitors. Arguably, this means that the relatively good historical performance of this indicator is due to its ability to filter out the temporary inflationary shocks in early 2015. Another notable finding is that the simpler methods of unobserved trend extraction (*BP* and *DFM*) generally outperform the *BP-DFM* on the artificial sample. Six to seven years after the disinflation, the RMSEs of the underlying alternatives converge, and the performance of the *BP-DFM*'s improves.

5 Conclusions

The Bank of Russia transitioned to a fully flexible exchange rate and inflation-targeting regime in 2015. The inflation rate subsequently declined and has fluctuated close to the target value of 4 per cent per annum. Presumably, this disinflation may have caused a structural break in the inflation-generating process and affected the performance of underlying inflation measures.
We conducted empirical analysis and confirmed that the ability of the underlying inflation measures to forecast actual inflation deteriorated after 2015. However, based on the results obtained from the Monte Carlo experiments, we believe that this deterioration was mainly due to a temporary rapid acceleration of inflation in early 2015 after the ruble exchange rate depreciation.
Other findings of the Monte Carlo analysis indicate that the benchmark underlying inflation measures (based on unobserved trend extraction) are more severely affected by disinflation than the alternative simpler methods. The simple indicators based on the exclusion and re-weighting approaches may be preferable for measuring underlying inflation during disinflation.
Alternatively, a more complex non-stationary dynamic factor model may be employed for the extraction of the unobserved trend to be used as an underlying inflation measure.

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A

Table 2: CPI components in the cross-section

Meat Products	Fish Products
Oils and Fats	Milk and Dairy Products
Cheese	Eggs
Sugar	Confectionery
Tea and Coffee	Bread and Bakery Products
Macaroni and Grain Products	Fruit and Vegetable Products
Alcoholic Beverages	Public Catering
Clothing and Linen	Furs and Fur Goods
Knitted Wear	Footwear
Detergents and Cleaners	Perfumes and Cosmetics
Fancy Goods	Tobacco
Furniture	Electrical Goods and Other Household Devices
Publishing and Printing	TV and Radio Merchandise
Computers	Communications Equipment
Construction Materials	Passenger Cars
Gasoline	Medical Goods
Household Services	Passenger Transport Services
Communications Services	Housing and Public Utility Services
Education Services	Culture Organisations Services
Medical Services	Foreign Tourist Services
Other Food Products	Other Non-Food Products
Other Services	

Data source: Russian Federal State Statistics Service (https://www.gks.ru).
All data are in monthly growth rates and seasonally adjusted using TRAMO/SEATS software

B

The results presented in Section 4.3 are obtained using combined datasets that contain both historical and artificial data. We cross-check our findings by conducting Monte Carlo experiments over fully artificial datasets. For this purpose, we replace the historical data observed prior to disinflation with 10-year-long artificial series. The series are generated using the NSDFM model described in Section 3. We select only those simulations where the year-over-year CPI growth rate does not fluctuate outside the 10 per cent to 20 per cent band. The disinflation and post-disinflation periods are generated as described in Section 3.1. The resulting distribution of CPI inflation rates is presented in Figure 8.

Figure 8: Distribution (median, min and max) of artificial year-over-year CPI growth rates (%)

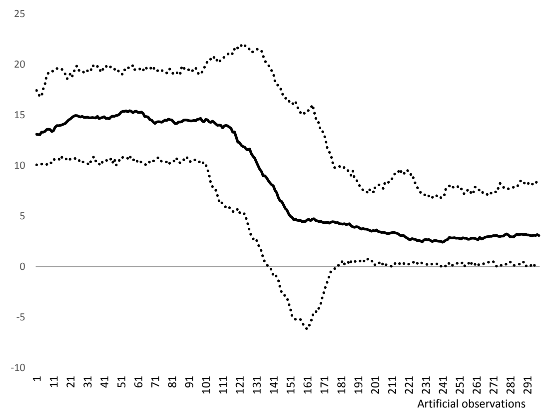
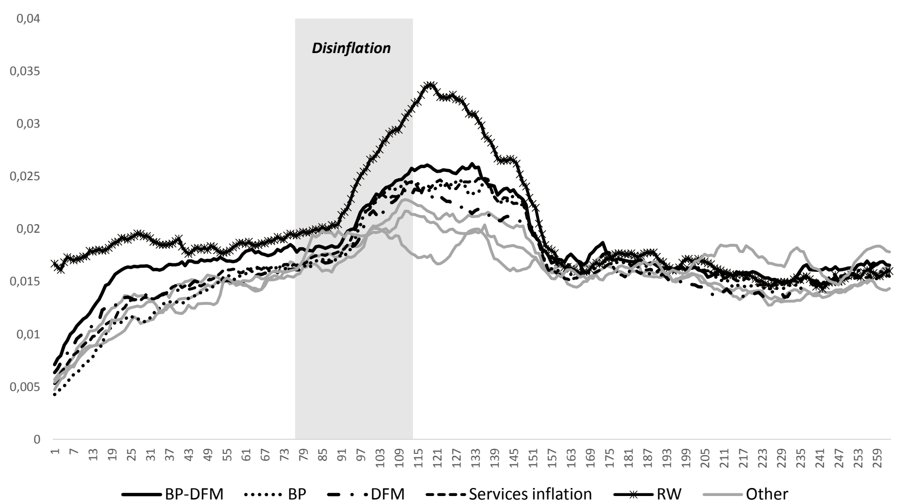


Figure 9: RMSEs of regression-based forecasts estimated over three-year-long subsamples



We proceed by conducting the Monte Carlo experiments as described in Section 4.3 and calculate the errors in the forecasts for the alternative underlying inflation measures (Figures 9–11). The findings reported in Section 4.3 are generally confirmed. The benchmark underlying inflation measure (based on the *BP-DFM* model) is more severely affected by disinflation than the alternative simpler methods. The simple indicators based on the exclusion/re-weighting approaches, as well as the simpler unobservable trend models, may be preferable for measuring underlying inflation during disinflation (although the former have systematically biased errors).

Figure 10: RMSEs of direct forecasts estimated over three-year-long sub-samples

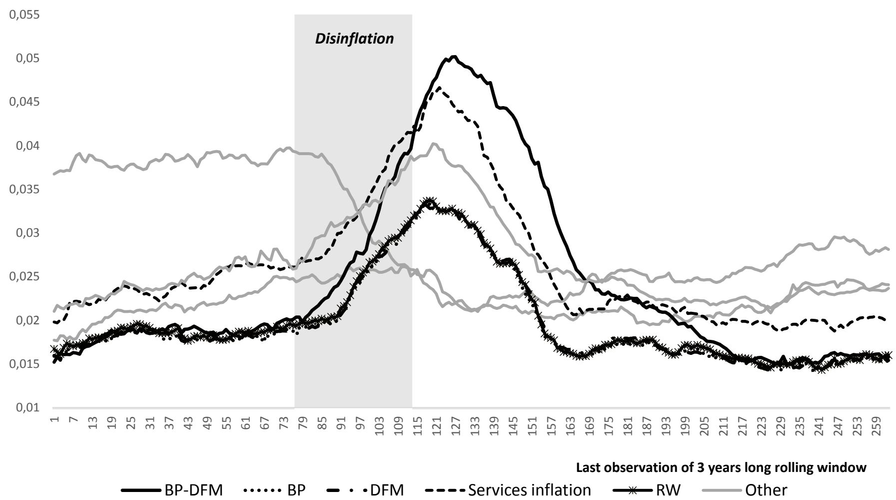
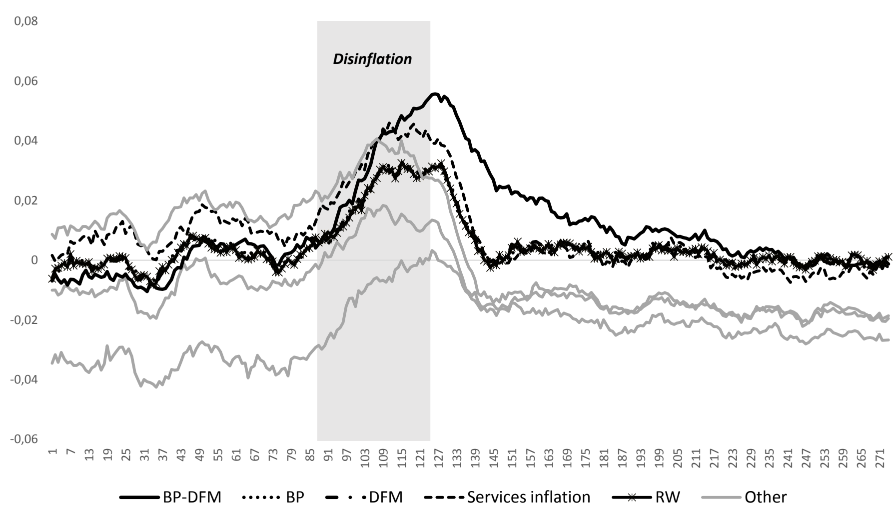


Figure 11: Median errors of direct forecasts



C

We use the criteria proposed by Bai and Ng (2002) to identify the number of static factors, with a maximum number of factors $kmax = 10$ and penalty functions $p1$, $p2$, $p3$, $p4$.

Table 3: Results for the Bai and Ng (2002) criteria (number of static factors)

	IC	PC
$p1$	4	9
$p2$	4	8
$p3$	10	10
$p4$	1	4

$$\begin{aligned} p1 &= \frac{N+T}{NT}\log\left(\frac{NT}{N+T}\right) \\ p2 &= \frac{N+T}{NT}\log\left(\min\{N,T\}\right) \\ p3 &= \frac{\log(\min\{N,T\})}{\min\{N,T\}} \\ p4 &= (N+T-k)\frac{\log(NT)}{NT}, \quad k = 1, ..., kmax. \end{aligned}$$

Table 4: Results for the Hallin and Liška (2007) criteria (the number of common shocks and the percentage of simulations for different penalty functions and window sizes)

q	Large Window				Small Window			
	$pp1$	$pp2$	$pp3$	$pp4$	$pp1$	$pp2$	$pp3$	$pp4$
0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1	100.0	100.0	100.0	100.0	73.7	83.2	80.6	81.3
2	0.0	0.0	0.0	0.0	21.3	16.2	17.9	17.7
3	0.0	0.0	0.0	0.0	5.0	0.6	1.5	1.0

The test results (presented in Tables 3–5) are somewhat inclusive as regards the appropriate number of factors. Therefore we set $r = 7$, as was done by Barigozzi et al. (2016), which is the average value given by the tests. The number of common trends is set to two, which is not ruled out by the tests. We experimented with other

specifications (for instance, $r = 5$, $q = 3$, $\tau = 1$), but this did not affect the main conclusions.
We apply the Hallin and Liška (2007) information criteria to determine the number of common shocks q, and the paper of Barigozzi et al. (2016) for the number of common trends τ, with penalty functions $pp1$, $pp2$, $pp3$, $pp4$, large and small windows of 0.1 and 0.01, and number of replications 1000.

Table 5: Results for the Barigozzi et al. (2016) criteria (the number of common trends and the percentage of simulations for different penalty functions and window sizes)

τ	Large Window				Small Window			
	$pp1$	$pp2$	$pp3$	$pp4$	$pp1$	$pp2$	$pp3$	$pp4$
0	2.8	3.5	1.7	2.5	0.3	0.4	0.3	0.4
1	86.3	88.7	81.0	85.2	35.4	39.6	36.9	37.9
2	10.9	7.8	17.3	12.3	48.0	47.8	48.9	48.7
3	0.0	0.0	0.0	0.0	16.3	12.2	13.9	13.0

$$
\begin{aligned}
pp1 &= \left(\sqrt{\frac{M}{T}} + \frac{1}{M^2} + \frac{1}{N}\right) \cdot \log\left(\min\left\{\sqrt{\frac{T}{M}}, M^2, N\right\}\right) \\
pp2 &= \left(\min\left\{\sqrt{\frac{T}{M}}, M^2, N\right\}\right)^{-1/2} \\
pp3 &= \left(\min\left\{\sqrt{\frac{T}{M}}, M^2, N\right\}\right)^{-1} \cdot \log\left(\min\left\{\sqrt{\frac{T}{M}}, M^2, N\right\}\right) \\
pp4 &= \left(\min\left\{\sqrt[4]{\frac{T}{M}}, M^2, N\right\}\right)^{-1} \cdot \log\left(\min\left\{\sqrt[4]{\frac{T}{M}}, M^2, N\right\}\right),
\end{aligned}
$$

where M is the nearest integer less than or equal to $\sqrt{T}/2$.