



Bank of Russia



# 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 change in the mean inflation rate). These datasets were used to test the forecasting abilities of alternative underlying inflation indicators (i.e. the 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 reweighting approaches). We also show that a Non-Stationary Dynamic Factor model may be employed for 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

## 1. Introduction

Bank of Russia transitioned to a fully flexible exchange rate and inflation-targeting regime in 2015. Subsequently the inflation rate has declined and fluctuated closely to the target value of 4 percent 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 transition to an inflation-targeting regime and the subsequent disinflation for performance of the underlying inflation measures' used by Deryugina et al. (2018) for Russia. For this purpose, we employ Monte Carlo experiments, which are commonly applied in the analysis of trend/cycle decomposition. There are several reasons in favour of using the artificial datasets to assess the performance of underlying inflation indicators. Firstly, 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 underlying inflation measures' properties, 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 underlying inflation measures' properties from the effects of other developments that affected the historical outcome. In order to generate the artificial datasets, we use a newly developed by Barigozzi et al. (2016a) 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 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

Observed aggregate 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 accurately judge the underlying state of, and 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 underlying inflation. One caveat is that these methods are mostly examined in application to 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 these countries it is not uncommon to attempt bringing the inflation rate to a level that is lower than the observed average (in other words, achieve disinflation). When successful, such policy generates a structural break in the inflation-generating process (for example, mean shift) and affects the performance of underlying inflation measures accordingly. 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).

Our choice of underlying inflation measures is based on Deryugina et al. (2018), who estimate a range of measures underlying inflation in Russia and examine their performance. In this paper we only analyse the measures that were found to perform well historically. The common feature of these methods consists in utilising the cross-section of CPI components (see Table 2 in Annex A) to extract a relevant signal. Accordingly, we use the following approaches.

## 2.1 Unobserved trend models

The benchmark model is the specification proposed by Cristadoro et al. (2005). The model is designed to decompose inflation into two stationary, orthogonal, unobservable components — the common  $\chi_{jt}$  and the idiosyncratic  $\varepsilon_{jt}$ . The common component can be further decomposed into long-term ( $x_{jt}^L$ ) and short-term ( $x_{jt}^S$ ) constituents by identifying low-frequency fluctuations with periodicity above the designated threshold  $h$ :

$$\pi_{jt} = x_{jt}^L + x_{jt}^S + \varepsilon_{jt} \quad (1)$$

The smoothed (long-term) common component can be obtained by summing up the waves with periodicity  $[-\pi/h, \pi/h]$  using spectral decomposition. This long-term component measures underlying inflation and omits idiosyncratic shocks that are not common to all CPI components or short-term fluctuations, which are irrelevant for monetary policy.

The basic model can be written as

$$\pi_{jt} = b_j(L)f_t + \varepsilon_{jt}, \quad (2)$$

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

$$\pi_{jt} = \lambda_j F_t + \varepsilon_{jt}, \quad (3)$$

where  $b_j(L)f_t = \lambda_j F_t$ .

We select the number of dynamic factors 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  $s=12$ .<sup>1</sup>

Our dataset consists of the seasonally adjusted monthly increases in 44 price indicators (CPI and its components). The econometric estimation procedure was replicated in accordance with Cristadoro et al. (2005).

We set  $h=24$  for the benchmark model (*BP-DFM*). We also calculate the indicator based on a dynamic factor model *without* using bandpass filters (*DFM*) and also *solely* on the basis of bandpass filters with  $h=24$  (*BP*).

## 2.2 Exclusion method

In order to calculate the CPI via the exclusion method, certain components which fail to comply with the underlying inflation definition by some criteria, 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 usually excludes CPI components characterised by high 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) of these prices indicates that a change occurs precisely in relative prices.

<sup>1</sup> We found that using a smaller number of lags would worsen the historical properties of the indicator.

Following Lafleche and Armour (2006), we calculated 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 approach to an underlying inflation index on the basis of re-weighting of CPI components is similar 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.

### **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). 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.

We calculated the underlying inflation indicator by discarding the CPI components with the inflation rates below the 25th and above the 75th percentiles of the distribution in a given month.

### **2.5 Domestically generated inflation**

One of the approaches to calculating an underlying inflation indicator is a concept of domestically generated inflation. It is gauged by the measures determined primarily by the growth of domestic costs and the least sensitive to external shocks price indicators. Several measures can be used for this purpose such as service prices, GDP deflator or wages' inflation (see Bank of England 2015 for discussion). Therefore, we have examined the performance of inflation of services' prices, which may be regarded as observed-indicator domestically generated inflation.

### 3. The Non-Stationary Dynamic Factor model and design of the experiments

Modelling permanent disinflation with standard statistical models is not a straightforward task. Firstly, we need a model can identify permanent and transitory shocks. Secondly, we need to jointly model the dynamics of a large set of indicators required for estimation of underlying inflation measures. We therefore set up a Non-Stationary Dynamic Factor model (NSDFM) in the spirit of Barigozzi et al. (2016a):<sup>2</sup>

$$X_t = \chi_t + \xi_t, \quad \chi_t = \Lambda F_t \quad (4)$$

$$S(L)(1-L)F_t = Q(L)u_t, \quad (5)$$

where in (1),  $X_t - N \times T$  is a matrix of de-trended observations decomposed into the sum of two unobservable components:  $\chi_t$  – common component, which is a linear combination of  $r$  factors  $F_t$  with factor loadings  $\Lambda$  and  $\xi_t$  – idiosyncratic component.  $X_t$ ,  $F_t$ , and  $\xi_t$  are assumed to be  $I(1)$ .<sup>3</sup> Factors  $F_t$  are driven by  $q$  common shocks  $u_t$ ,  $d$  of which have temporary fluctuations, while  $\tau$  shocks are permanently effected by common trends.  $S(L)$  and  $Q(L)$  are  $r \times r$  and  $r \times q$  matrix polynomials;  $L$  is lag operator.

The fully-dynamic representation is as follows:

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

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

1. We extract the common factors and their loadings by principal component analysis.

Factor loadings are extracted from  $\Delta X_t = \Lambda \Delta F_t + \Delta \xi_t$ , that is, (1) in first differences.

The common factors are estimated as  $\hat{F}_t = N^{-1} \hat{\Lambda}' X_t$ .

<sup>2</sup> This type of approach is not unprecedented. Originally, Barigozzi et al. (2016a) apply the model to a standard macroeconomic dataset to study the effects of monetary policy shocks and of supply shocks. Meanwhile, similarly to this paper, García-Cintado et al. (2015, 2016) apply an earlier version of the non-stationary DFM model proposed by Bai and Ng (2004) to the cross-section of CPI components. They decompose the observed inflation rate series into a common and an idiosyncratic component, thus allowing identifying presence of a common stochastic trend driving the observed series.

<sup>3</sup> As in Barigozzi et al. (2016a) we assume that  $X_t$ ,  $F_t$ , and  $\xi_t$  are  $I(1)$  even though some of its 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.

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  $\beta$  is estimated by Johansen approach;  $\alpha$  and  $G_1$  are regression coefficients. A VECM can be rewritten as a VAR process  $A(L)F_t = w_t$ . Residuals  $w_t$  are transformed to  $q$  primitive shocks  $u_t$ :  $w_t = Ku_t$ , where  $K$  is denoted as rescaled first  $q$  eigenvectors of the sample covariance matrix of the  $w_t$  (for instance, see Stock and Watson 2005, Bai and Ng 2007, Forni et al. 2009).
3. We choose orthogonal  $q \times q$  identification matrix  $H$  to achieve the conditions under which  $\tau$  common trends are detected among  $q$  common shocks.

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

### 3.1 Design of experiment

Bank of Russia transitioned to a fully flexible exchange rate and inflation-targeting regime in 2015. Subsequently, the inflation rate has declined and fluctuated closely to the target value of 4 percent per annum. Presumably, these developments represent permanent disinflation. The goal of our exercise is to artificially increase the number of disinflation episodes similar to the observed rates available for analysis. Also, we use the artificially created observations to extend the dataset and possibly predict the yet unobserved evolution of the underlying inflation measures' properties. Note that since we are interested in identifying the effect of disinflation on underlying inflation measures, we want to eliminate the impact of 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 aggregate CPI (see Table 2 in Annex A) from February 2002 to September 2014 ( $T = 152$  months):

$$x_{it} = \lambda_i F_t + \xi_{it} \quad i = 1, \dots, N, t = 1, \dots, T, \quad (7)$$

$$A(L)F_t = KHu_t \quad (8)$$

We began 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 ran the simulations until we obtained 100 replications with the following properties:

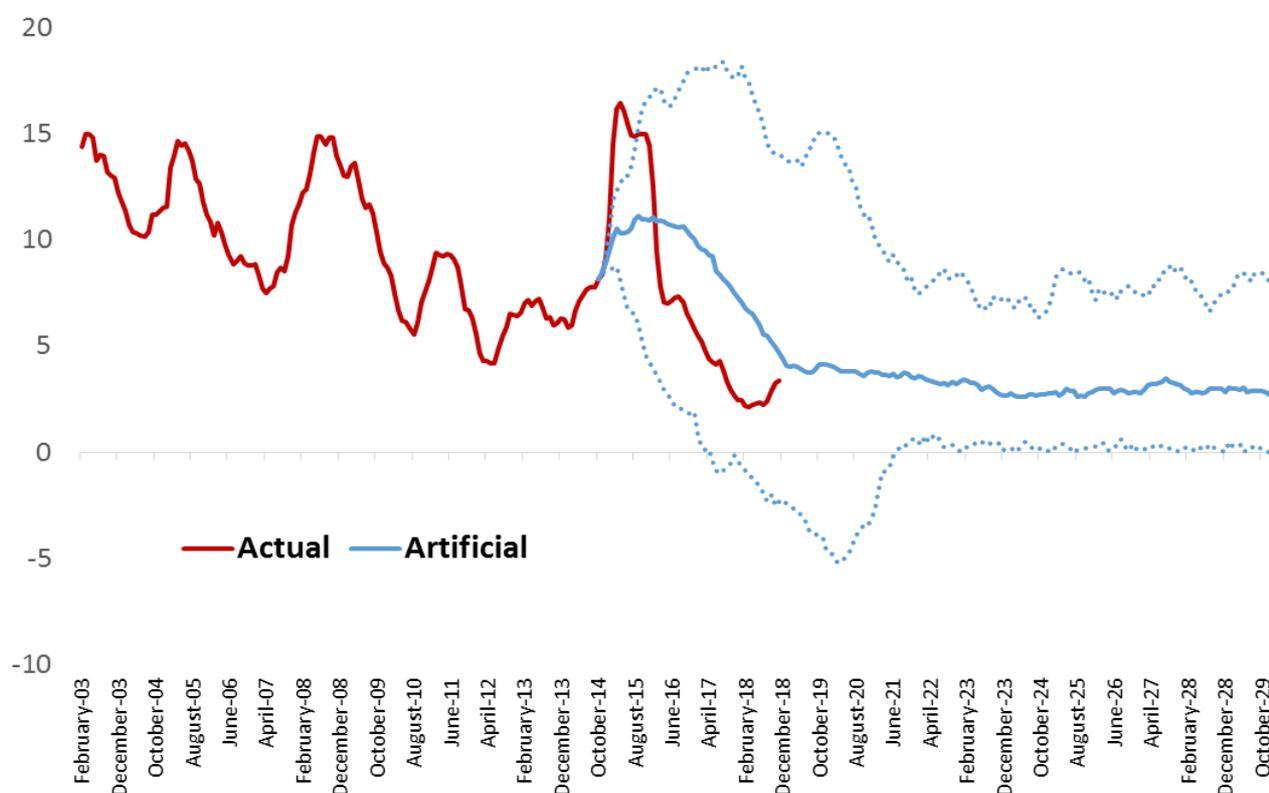
1. During the first 12 months the innovations are driven by  $u_t \sim N(0, \sigma_u^2 * I_q)$ . Over the next 36 months, we introduce a negative drift  $u_t \sim N(-1, \sigma_u^2 * I_q)$  that represents disinflation. In the remaining periods  $u_t \sim N(0, \sigma_u^2 * I_q)$ , where  $\sigma_u^2 = 3$ .<sup>4</sup>
2. We select only those simulations for which the inflation rates of the majority of CPI components (more than 37 of 43 components) are, on average, lower than the actual data (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 aggregate 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 percent to 10 percent band starting from 2021. This 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 obtained artificial CPI growth rates is presented in Figure 1. The obtained artificial datasets represent the disinflation episodes with a magnitude similar to observed instances, but with different short-term dynamics. We use these datasets for Monte Carlo experiments as described in Section 4.2.

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<sup>4</sup> The choice of  $\sigma_u^2 = 3$  allows us to keep variance of the simulated CPI close to the variance of the actual data.

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



## 4. Evaluating the properties of underlying inflation measures

Arguably, the most valuable and clearly defined criterion for assessing the quality of underlying inflation measures is the ability to forecast actual inflation (see, for example, Wynne, 1999; Mankikar and Paisley, 2004; Amstad et al., 2014). 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 forecasting performance of underlying inflation measures during the observed and artificial episodes of disinflation. For that purpose, we calculate our underlying inflation measures (that is, estimate the models, determine the excluded components or the weights for re-weighting, and so on) in pseudo-real time using five-

year-long rolling sub-samples of data.<sup>5</sup> We employ two alternative approaches to evaluate the usefulness of these measures for inflation forecasting.

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

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

where  $\pi_t$  are the annual CPI growth rates, and the  $\pi_t^U$  are annual underlying inflation growth rates.

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

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

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

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

## 4.1 Historical analysis

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

<sup>5</sup> We found that using a recursively expanding time-sample does not improve the performance of the underlying inflation measures.

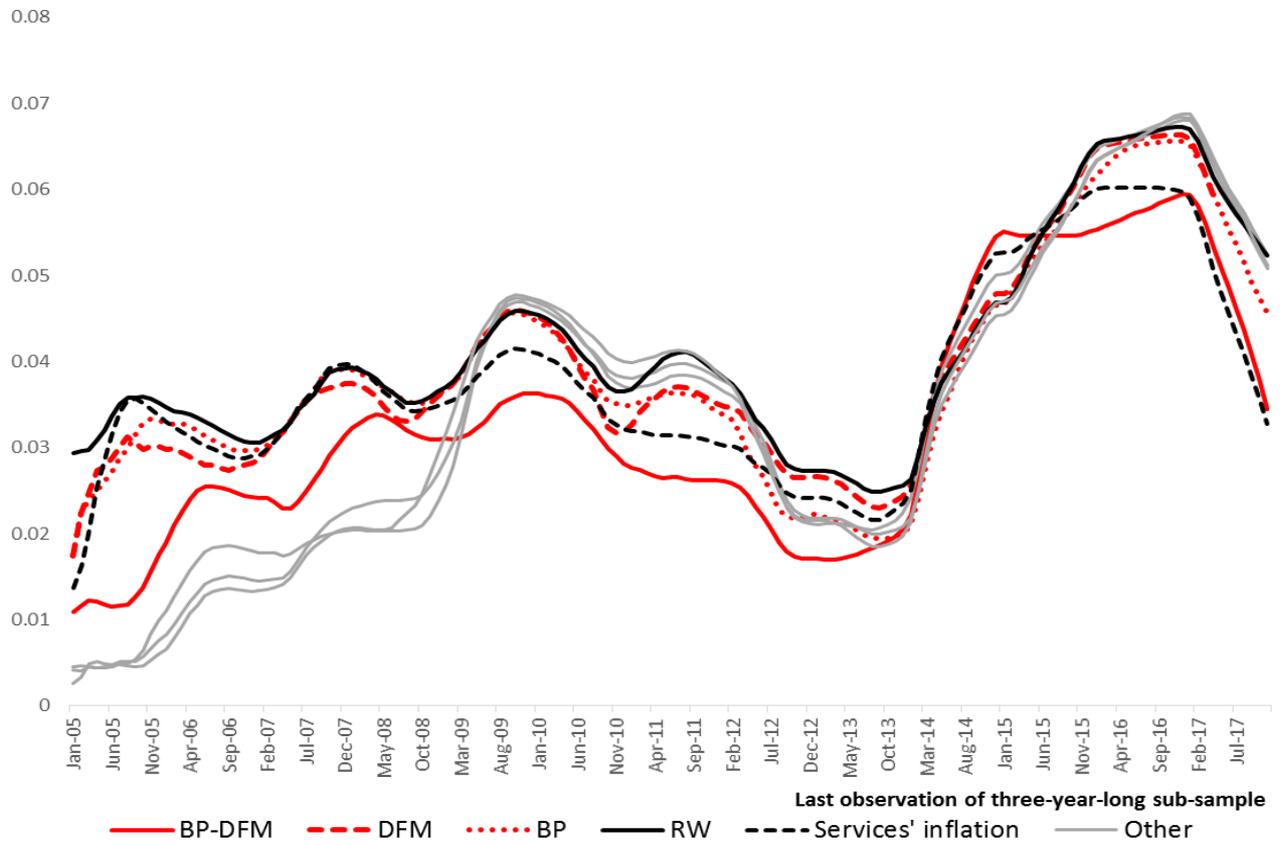
**Table 1.** Cumulative RMSEs over 2005–2018 time sample

Regression-based		Direct	
Measure	RMSE	Measure	RMSE
BP-DFM	0.037	BP-DFM	0.039
Services' inflation	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	Services' inflation	0.049

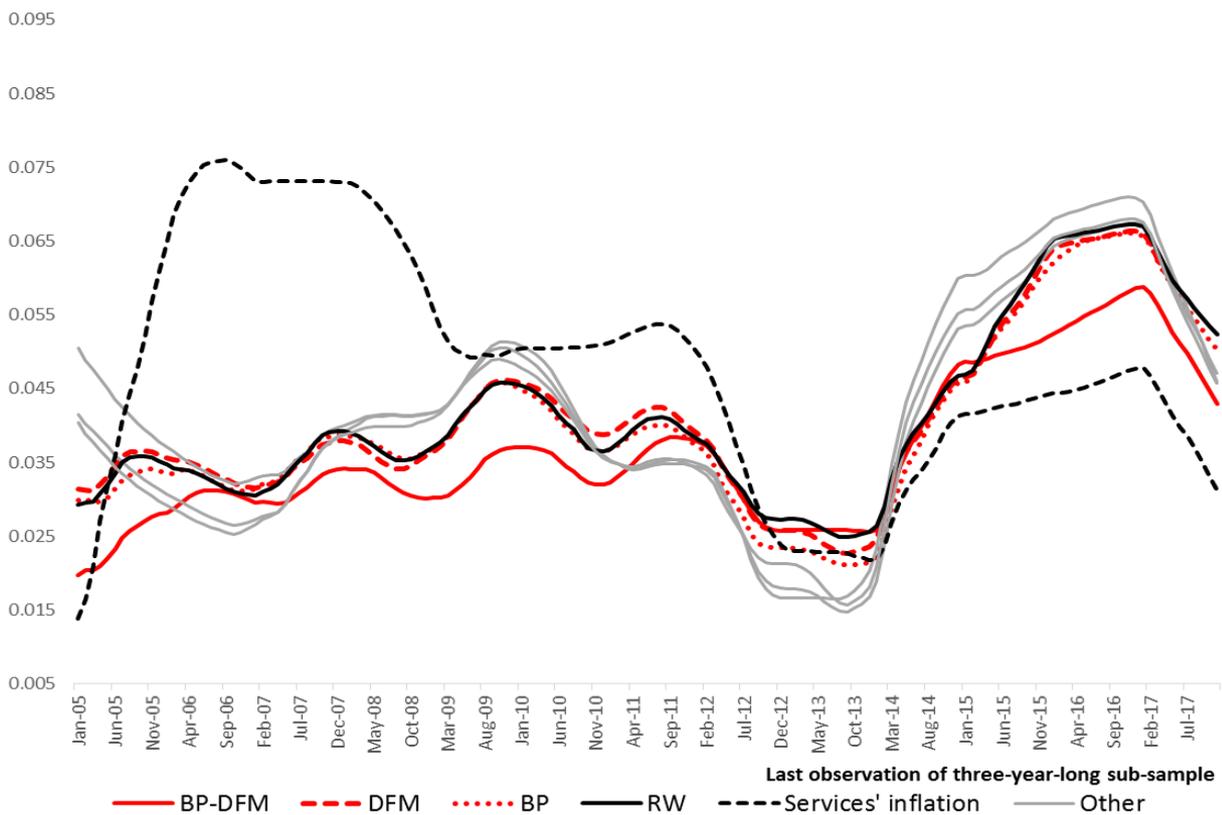
We proceed by examining the changes in the performance of the underlying inflation measures after the disinflation. For this purpose, we calculate the RMSEs over three-year-long rolling sub-samples. The results are reported in Figures 2 and 3.<sup>6</sup> The results indicate that the RMSEs of all measures have deteriorated significantly in the 2014–2016 sub-sample (for all indicators, the errors are significantly higher than the average for 2005–2018). The performance of *BP-DFM*-based measures was still good in relation to the competitors, although the services' inflation indicator outperformed the benchmark.

<sup>6</sup> The performance of measures estimated using exclusion, re-weighting, and trimming approaches proved to be similar. Therefore, for illustrative purposes, the respective RMSEs were labeled 'Other' in Figures 2–5.

**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



Note that, as discussed in Section 3.1, these results are determined not solely by disinflation, but by all of the events that took place in 2015 in Russia (most notably the drop in oil prices and the ensuing ruble depreciation and temporary acceleration of inflation).

## 4.2 Monte Carlo experiments

We proceed by estimating the RMSEs for the datasets extended with artificial observations (generated as described in Section 3.1).<sup>7</sup> The RMSEs are averaged across all datasets.

The results are presented in Figures 4–5. As expected, our exercise predicts that the performance of all measures will deteriorate during disinflation, but not as badly as observed empirically. In fact, for the *BP-DFM*, the highest values of the RMSEs obtained over the artificial sample is still lower than the average error in 2005–2018. We therefore conclude that the deterioration of empirical RMSEs was 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 direct forecasts are predicted to be the worst from the third to the fifth years after disinflation.

As regards the competitor models, the Monte Carlo experiments indicate no clear recommendation for the regression-based exercise. As for direct forecasting, the measures based on exclusion and reweighting methods produced the best direct 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 median errors presented in Figure 6) that accidentally helps to improve the forecasts during disinflation.<sup>8</sup> Contrary to the empirical case, the services' inflation does not outperform the competitors. Arguably, this means that the relatively good historical performance of this indicator was due to its ability to filter out temporary inflationary shocks in early 2015. Another notable finding is that the simpler methods of unobserved trend extraction (*BP* and *DFM*) generally outperform the

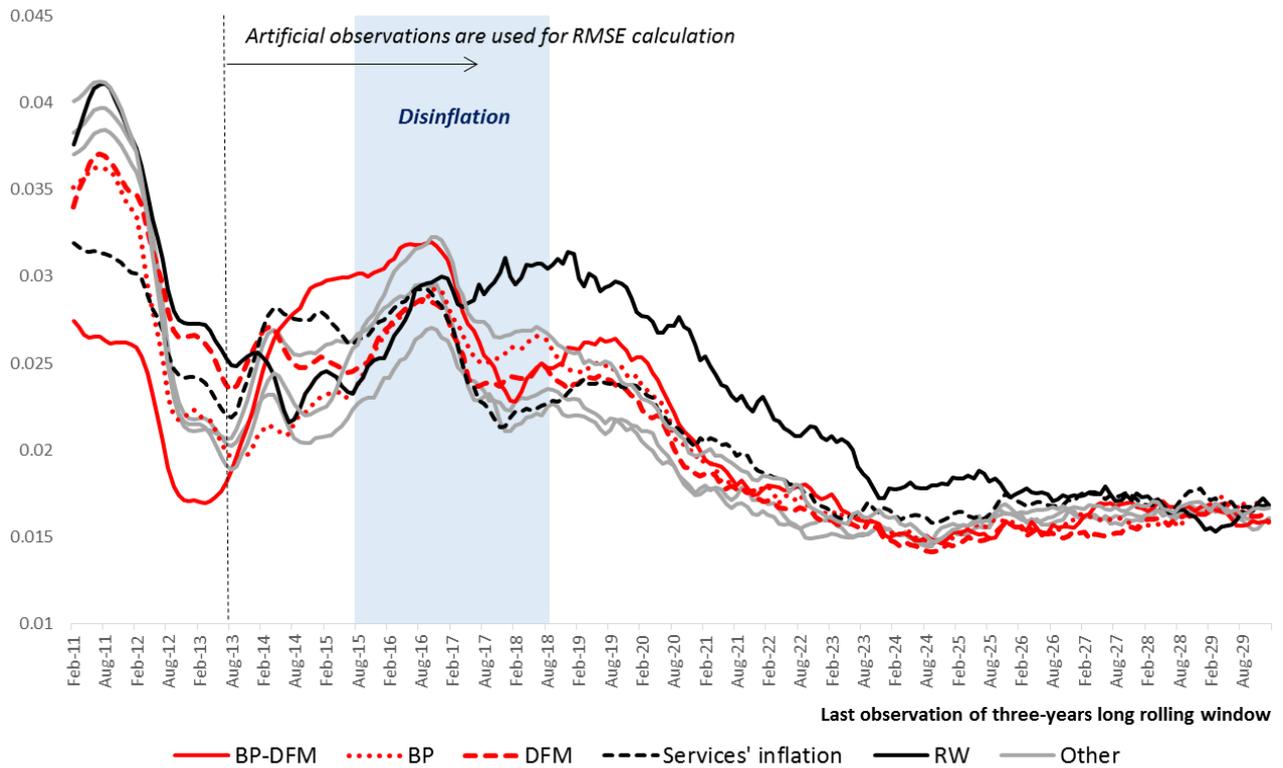
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<sup>7</sup> Admittedly, under this setup, the evolution of the performance of alternative underlying inflation measures over the artificial sample is still, at least partially, determined by historical developments. Therefore, in Annex B, we cross-check our findings using fully artificial datasets.

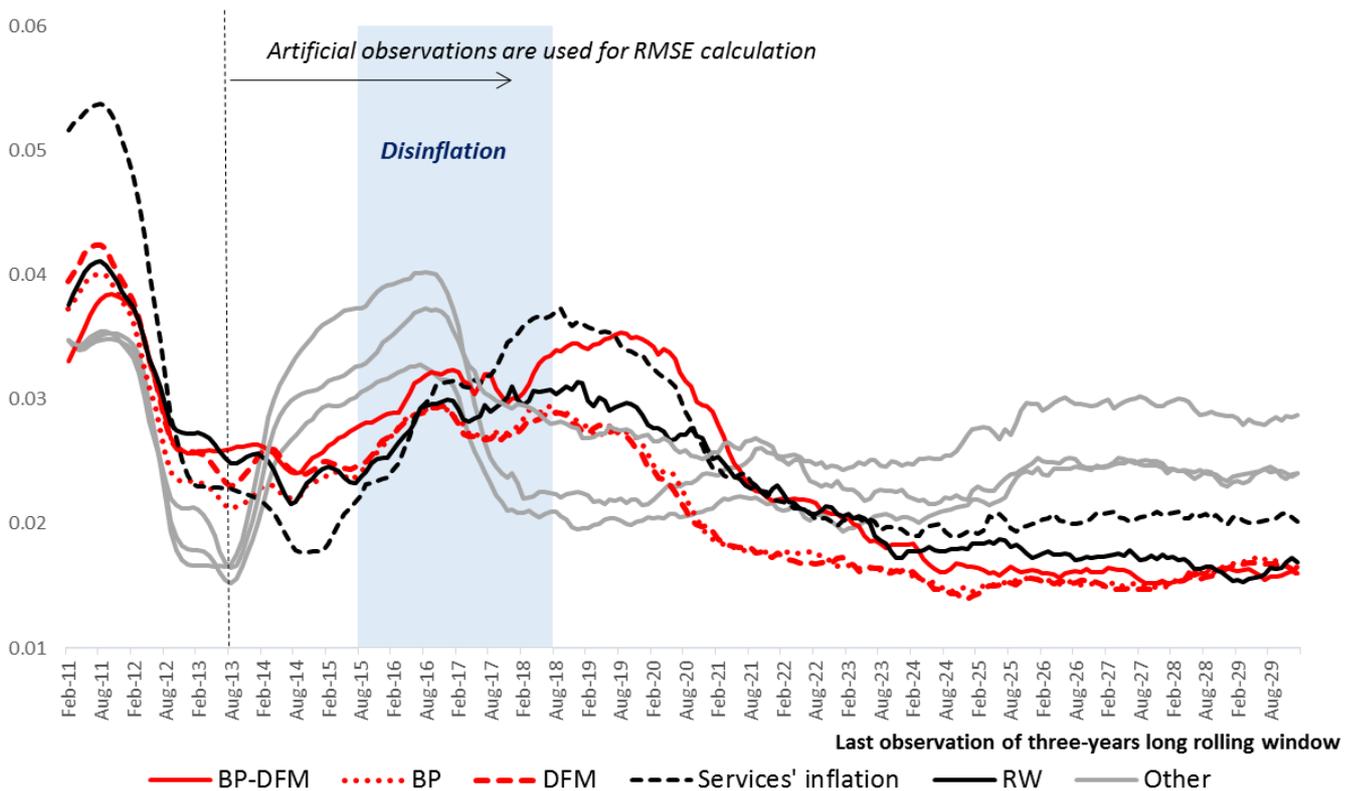
<sup>8</sup> This finding is confirmed by the analysis presented in Annex B. This observation indicates that in Russia, volatile components of CPI, on average, have higher inflation rates.

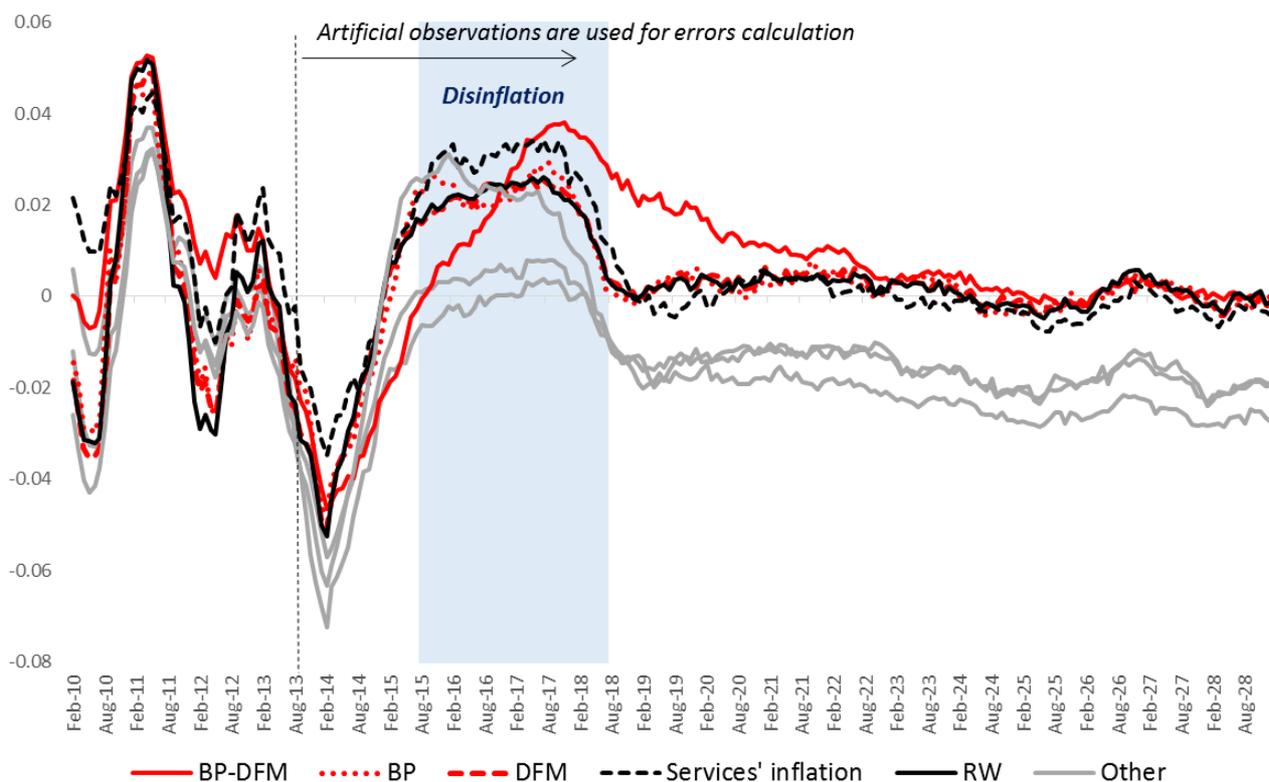
*BP-DFM* on the artificial sample. In six to seven years after the disinflation, the RMSEs of the underlying alternative converge and the *BP-DFM*'s performance improves.

**Figure 4.** RMSEs of regression-based forecasts estimated over three-year-long sub-samples



**Figure 5.** RMSEs of direct forecasts estimated over three-year-long sub-samples



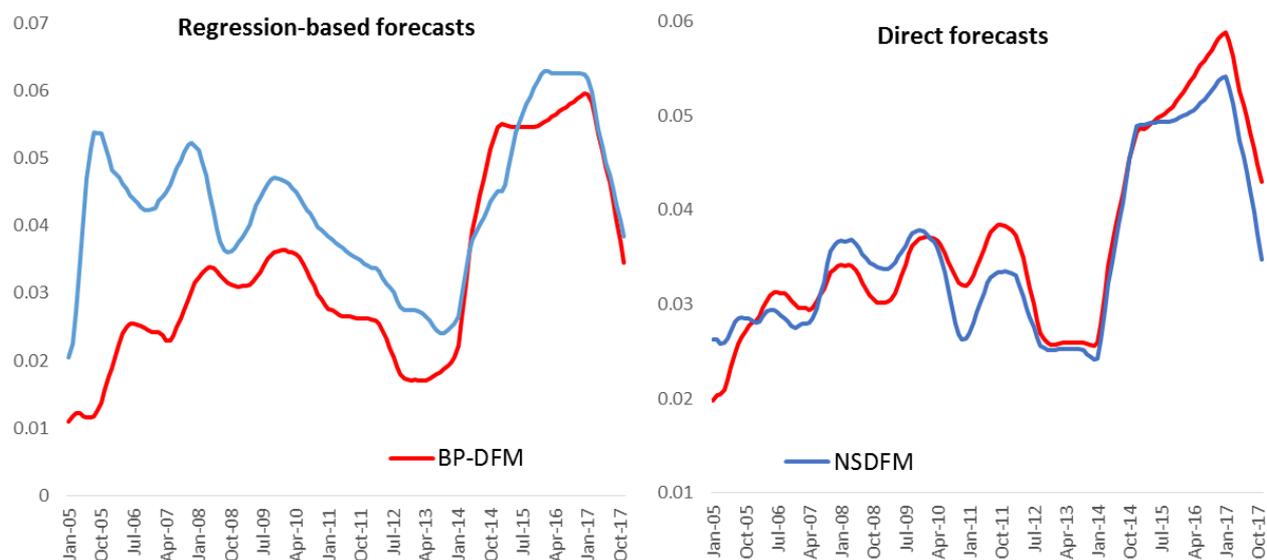
**Figure 6.** Median errors of direct forecasts

## 4.2 NSDFM-based measure of underlying inflation

In the previous sections we have used the NSDFM as a data generator for Monte Carlo analysis, but it may be appropriate to employ this model to estimate underlying inflation when the actual inflation rate is presumably affected by permanent shocks.

We estimate the NSDFM as described in Section 3 for the dataset containing the de-trended indicators of the aggregate CPI and its 43 components over the recursively expanding time sample of 2002–2018 (starting with the first 24 months). For each iteration, we calculate the underlying inflation measure by extracting two common trends ( $\tau$ ) in the aggregate CPI dynamics and add 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 7 in comparison with the benchmark *BP-DFM* measure. The NSDFM-based measure performed as good as (or slightly worse) than *BP-DFM* prior to disinflation and performed 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 7. RMSEs estimated over three-year-long sub-samples**

## 5. Conclusions

Bank of Russia transitioned to a fully flexible exchange rate and inflation-targeting regime in 2015. Subsequently the inflation rate has declined and fluctuated closely to the target value of 4 percent 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 the empirical analysis and confirmed that the ability of 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 temporary rapid acceleration of inflation in early 2015, after 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 exclusion and re-weighting approaches may be the preferable measures of underlying inflation during disinflation.

Alternatively, a more complex Non-Stationary Dynamic Factor model may be employed for extraction of the unobserved trend to be used as an underlying inflation measure.

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## Annex A

**Table 2.** CPI components in the cross-section

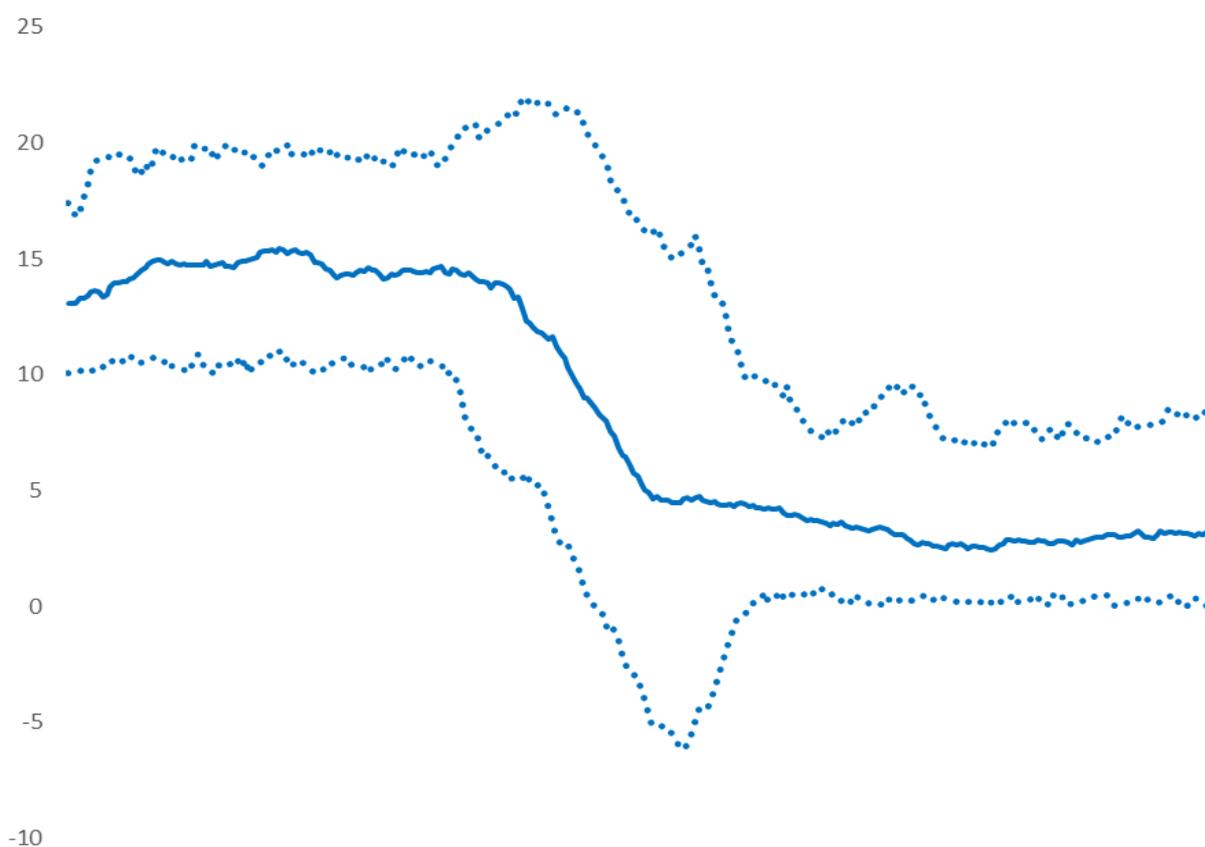
Meat Products
Fish Products
Oils and Fats
Milk and Dairy Products
Cheese
Eggs
Sugar
Confectionery
Tea and Coffee
Bread and Bakery Products
Macaroni and Grain Products
Fruit and Vegetable Products
Alcoholic Beverages
Public Catering
Clothing and Linen
Furs and Fur Goods
Knitted Wear
Footwear
Detergents 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

All data are in monthly growth rates and seasonally adjusted using TRAMO/SEATS.

## Annex B

The results presented in Section 4.2 were obtained using the combined datasets that contained both historical and artificial data. We cross-check our findings by conducting the Monte Carlo experiments over fully artificial datasets. For this purpose, we replace the historical data observed prior to disinflation with a 10-year-long artificial series. The series are generated using the NSDFM model described in Section 3. We select only those simulations where the CPI year-over-year growth rate does not fluctuate outside the 10 percent to 20 percent band. The disinflation and post-disinflation periods are generated as described in Section 3.1. The resulting distribution of CPI inflation rates are presented in Figure 8.

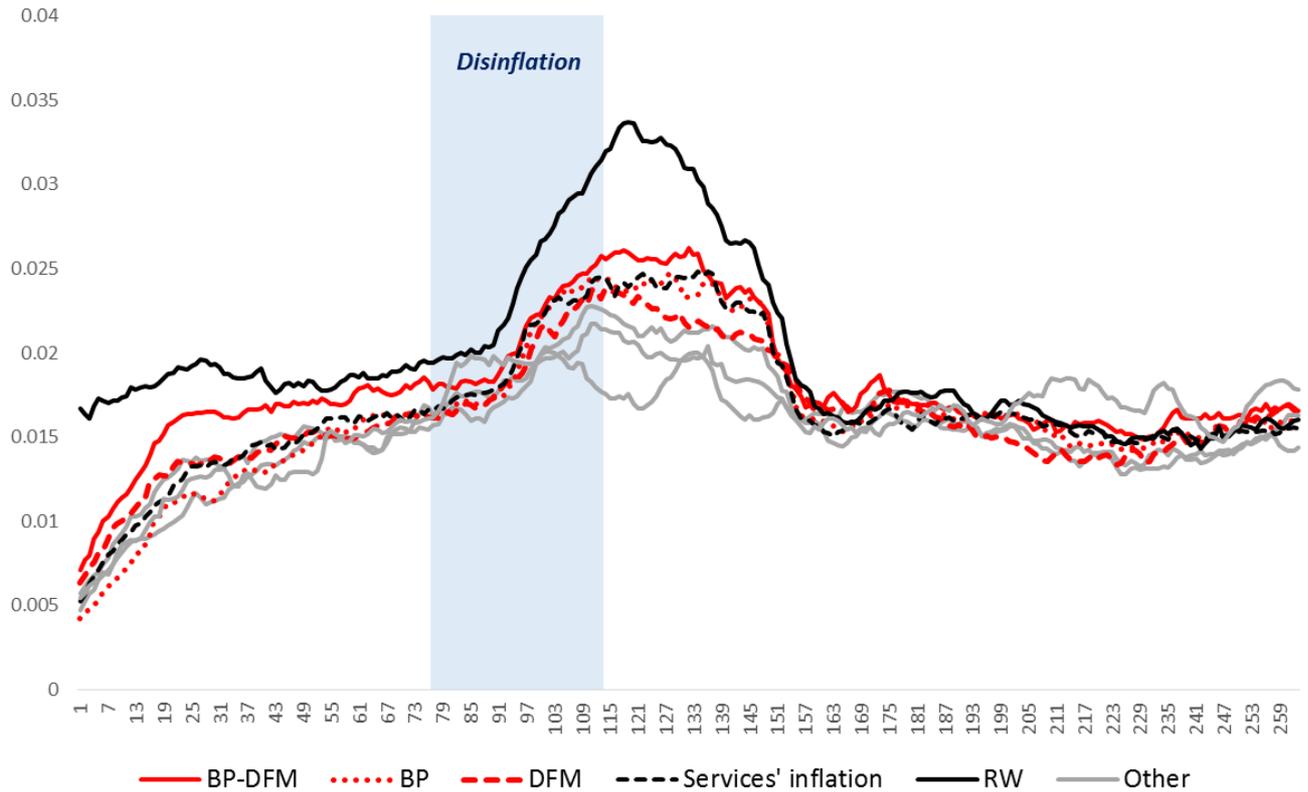
**Figure 8.** Distribution (median, min and max) of artificial year-over-year CPI growth rates (%)



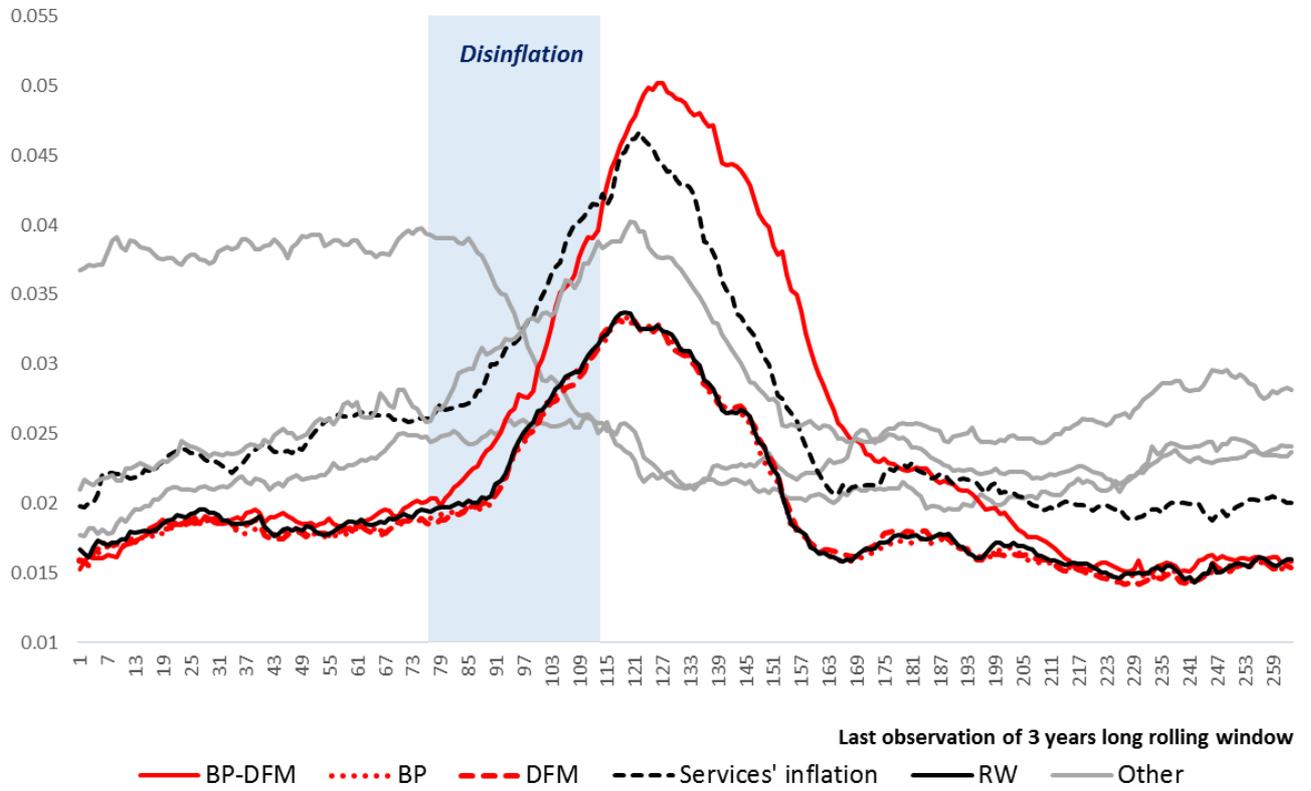
We proceed by conducting the Monte Carlo experiments as described in Section 4.2 and calculate the forecasts' errors for alternative underlying inflation measures (Figures 9–11). The findings reported in Section 4.2 are generally confirmed. The benchmark underlying inflation measure (based on the *BP-DFM* model) is more severely affected by disinflation than

the alternative simpler methods. The simple indicators based on exclusion/re-weighting approaches, as well as simpler unobservable trend models, may be the preferable measures of underlying inflation during disinflation (although the former have systematically biased errors).

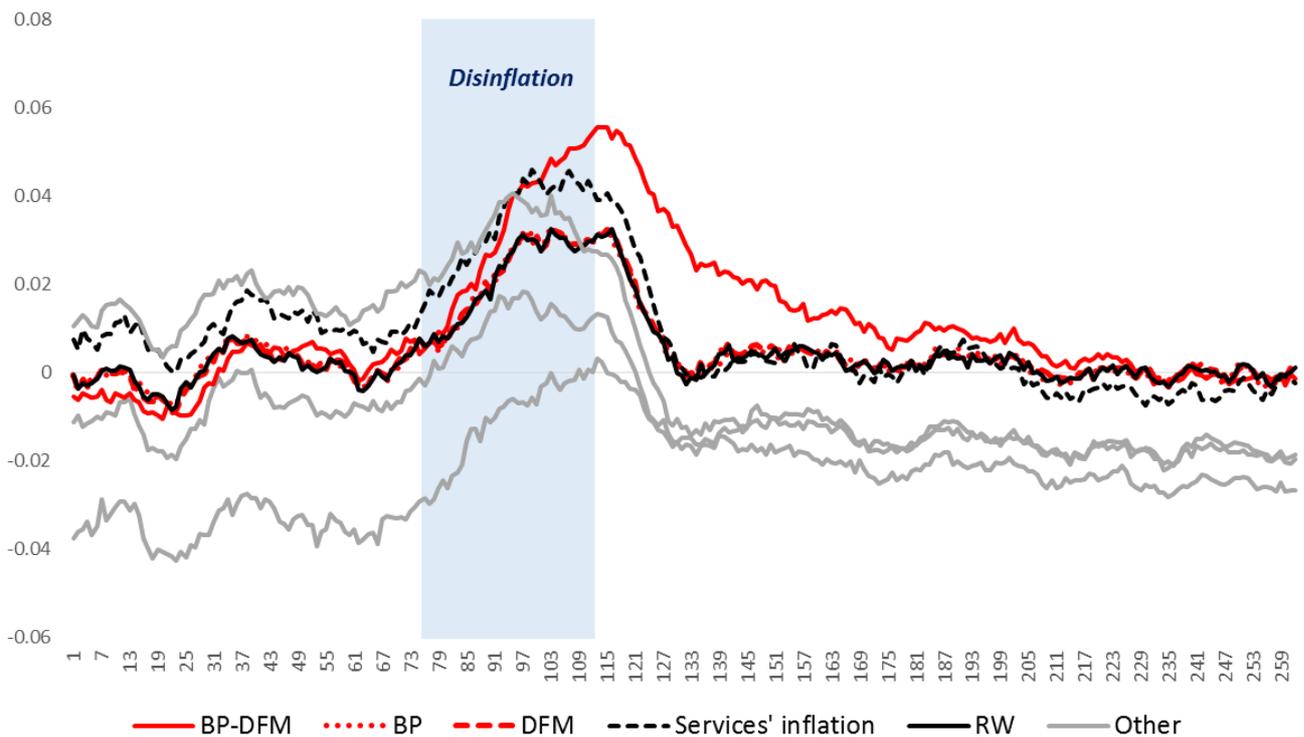
**Figure 9.** RMSEs of regression-based forecasts estimated over three-year-long sub-samples



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



**Figure 11.** Median errors of direct forecasts



## Annex C

We use Bai & Ng (2002) criteria to identify the number of static factors with maximum number of factors  $k_{max}=10$ , and penalty functions  $p1, p2, p3, p4$ .

**Table 3.** Results of Bai & Ng (2002) criteria (number of static factors)

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

$$p1 = \frac{N+T}{NT} \log\left(\frac{NT}{N+T}\right)$$

$$p2 = \frac{N+T}{NT} \log(\min(N, T))$$

$$p3 = \frac{\log(\min(N, T))}{\min(N, T)}$$

$$p4 = (N+T-k) \frac{\log(NT)}{NT}, k=1 \dots k_{max}$$

We apply Hallin and Liška (2007) information criteria to determine the number of common shocks  $q$ , and Barigozzi et al. (2016a) for common trends  $\tau$ , with penalty functions  $pp1, pp2, pp3, pp4$ ; large and small windows are 0.1 and 0.01; the number of replications are 1000.

**Table 4.** Results of Hallin and Liška (2007) criteria (the number of common shocks and its percentage of simulations according with 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

**Table 5.** Results of Barigozzi et al. (2016a) criteria (the number of common trends and its percentage of simulations according with different penalty functions and window sizes)

$\tau$	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

$$pp1 = \left( \sqrt{\frac{M}{T}} + \frac{1}{M^2} + \frac{1}{N} \right) * \log(\min(\sqrt{\frac{T}{M}}, M^2, N))$$

$$pp2 = \left( \min(\sqrt{\frac{T}{M}}, M^2, N) \right)^{(-1/2)}$$

$$pp3 = \left( \min(\sqrt{\frac{T}{M}}, M^2, N) \right)^{(-1)} * \log\left( \min(\sqrt{\frac{T}{M}}, M^2, N) \right)$$

$$pp4 = \left( \min(\sqrt[4]{\frac{T}{M}}, M^2, N) \right)^{(-1)} * \log\left( \min(\sqrt[4]{\frac{T}{M}}, M^2, N) \right),$$

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