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Does CPI disaggregation improve inflation forecast accuracy?

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Abstract

If the consumer price index (CPI), one of the main indicators of inflation, consists of several components, would it be more accurate to forecast them separately? International experience shows that the aggregate of individual forecasts is often more accurate than the forecast of the aggregated index. In this paper, we explore this issue for Russia and test whether the quality of inflation forecasts can be improved by the CPI individual components forecasting.

Using the panel data of Russian regions for the period from 2010 to 2021 we partially confirm the usefulness of a disaggregated approach. Individual modelling of the short-term price dynamics of individual commodity groups is ahead in terms of accuracy of the overall inflation model, including standard benchmark models, but only under certain conditions. First, it is necessary to include the factors of trend inflation in the models, which helps to separate the trend inflation acceleration/deceleration from short-term idiosyncratic fluctuations. Secondly, the models should have the property of inflation convergence to its long-term level, determined by the Bank of Russia's goal. Under these conditions, the disaggregated approach gives a more accurate forecast on short horizons than the aggregated one and a forecast of comparable to non-structural models' accuracy on longer ones.

Additionally, good predictive properties of the “anchored” forecast model were established (the “anchored” forecast is equal to the target inflation rate). The accuracy of this forecast turns out to be higher than the accuracy of standard models and does not deteriorate with an increase in the forecast horizon. This allows us to recommend this model as a simple non-structural benchmark for measuring the quality of inflation forecast models in Russia.

Keywords: price dynamics of CPI components, forecasting, relative prices, trend inflation, idiosyncratic shocks, comparison of forecasting models in panel data

JEL classification: C52, C53, E31, E37.

Contents

1. Introduction

Central banks implementing inflation targeting make monetary policy decisions based on the analysis and forecasting of inflation. There is a rather common practice to complement the analysis of the overall inflation with a study of the price trends for individual goods or commodity groups[1]. The information derived from the analysis of disaggregated price dynamics (supplemented with information on headline inflation) may be useful for various tasks of inflation analysis. It may be used in filtering out the seasonal factor in inflation dynamics (in this way, the Bank of Russia's seasonal adjustment methodology relies on component-by-component smoothing and subsequent aggregation). In the work of (Deryugina et al., 2019), measuring core inflation involves studying the quality of dynamic factor models relying on disaggregated statistics; it is further used for estimating trend inflation and in inflation forecasting. For example, (Fulton and Hubrich, 2021) present a review of US Federal Reserve forecast models and highlight the use of price dynamics of CPI components among the few methods to significantly improve inflation forecasts. This was confirmed by prior research focused on the US, the euro area, and other countries.

This paper is an attempt to verify this thesis as applied to Russian inflation and to ascertain whether information on price dynamics of CPI components contributes to the accuracy of forecasts of headline inflation. To this end, it adjusts the standard approaches brought forward by (Bermingham and D'Agostino, 2014; Faust and Wright, 2013). These approaches consist in building out-of-sample forecasts in pseudo-real time, estimating the expected forecast error, and comparing models by their mean error. The latter is enabled by a formal econometric test procedure presented by (Diebold and Mariano, 1995).

This work discusses the limitations of this approach as applied to Russian data. As far as is known, the construction of pseudo-real time forecasts requires the estimation of the forecasting model on a training subsample with a subsequent check of the forecasts on a test subsample. The assumption that inflationary processes remain homogeneous over a long period of time is critical to ensure the reliability of the comparisons and the appropriate power of the statistical test, but it may be too strong for the case of Russia. On the one hand, the structural and institutional changes of the past (most of all, the transition to inflation targeting in 2014–2015) triggered significant changes in the nature of inflation processes. On the other hand, limiting the training and test subsamples to the post-2015 period would make a strong cut to the comparison base and the results become sensitive to the (possibly accidental) specifics of the recent short period.

To prevent the negative effects of these specifics, two corrections to the methodology are made. First, the variations of models allowing parameters changes, including changes in the unconditional mean, are added to the pool of forecasting models

[1] In the literature, the latter has also come to be known as the *dynamics of relative prices,* the *dynamics of disaggregated components of inflation*, etc. Although these concepts are not identical and their discourse is different, they are used interchangeably in this paper.

being compared. Among these, a ‘naive’ approach to forecasting, which assumes that the Bank of Russia's inflation target is the inflation forecast (4% in annual terms), is considered.

Second, to increase the comparison base, this paper proposes the use of regional-level inflation data to increase the power of the econometric test. Moving from aggregated time series for Russia to a panel of over 80 regions increases the sample size to the point that, in the extreme case and under certain conditions, the forecasts can be compared by accuracy even for a single month’s test sample. This becomes possible when the test of Diebold and Mariano (1995) is replaced with its panel version suggested by Timmermann and Zhu (2019) This work uses the bootstrapped, rather than the classical, version of the final test. This approach demonstrates the importance of price dynamic of CPI components and the verification of the robustness of the conclusions not only for the whole period under review on average, but also for individual, shorter, segments.

Finally, aiming to estimate trend inflation, Stock and Watson (2016) showed that the use of disaggregated statistics provides a more nuanced view of core inflation in comparison to the use of only headline inflation. However, estimates of the same quality can be obtained by analysing a measure of inflation that strips out the volatile components (price changes for energy and food, for the US). This suggests that most of the information in disaggregated statistics – on the basis of which core inflation trends are singled out – can be obtained using an inflation measure net of the volatile components. This paper places special emphasis on testing this hypothesis using Russian data.

It should be noted in connection with this paper’s contribution to the existing Russian and foreign literature that the problem of forecasting Russian inflation has received wide coverage in the domestic literature. In one of the first reviews of forecasting models for Russian inflation, Andreyev (Андреев) (2016) discusses the method of combining forecasts and concludes that forecasts by this method outperform those by individual models. The combined models the author considers include both simple statistical and more complex models. In the context of the topic of this work, it is noteworthy that several disaggregated models are considered, although a dedicated study of this class of models is beyond the scope of the study. Styrin (2019) presents a study of the dynamic averaging of models, and the models covered in the work include multiple linear regressions using a wide range of macroeconomic, survey, and financial variables. The author explores the explanatory value of each indicator from the standpoint of the inflation forecast for various periods. Although price dynamic of CPI components is outside of the scope of the paper, the methodology for comparing forecasting models, including in the context of structural changes in inflationary processes (which the author claims are responsible for a significant share of forecast errors) serves as a reference point for this work. Khabibullin (2019) questions whether the effect of using real sector variables is beneficial for the accuracy of inflation forecasts, while Pavlov (2020) and Baybuza (2018) find that inflation forecasts based on machine learning models are no less accurate than the forecasts of traditional models.

This paper complements the existing studies on Russian inflation forecasting and bridges the gap by exploring forecasting methodology which has been proved valid for different countries. In addition, this paper is one of the first to compare forecasting models for the period that follows the transition to inflation targeting and the period the economy has operated in this mode, including the 2020–2021 period of accelerated inflation. Related problems in forecast comparisons may be the subject of future study.

The paper is structured as follows. Section 2 provides an overview of current discussions in the literature on price dynamic of CPI components in general and its application in forecasting in particular. Section 3 introduces the notation used and describes the methodology for comparing the accuracy of models. Section 4 discusses data on price dynamics of CPI components and outlines their key attributes. Section 5 describes the forecasting models. Section 6 presents the results of the comparison, and Section 7 concludes the study.

2. Literature review

Speaking of the role of price dynamics of CPI components in general forecasting and the treatment of this problem in research, it is necessary to present works that describe disaggregated price dynamics in general, document its value for forecasting, and discuss the sources of this value.

Data on disaggregated price dynamics is a part of the headline inflation calculation. The process of calculating the consumer price index – the most common measure of inflation – consists in collecting the price statistics for individual products, calculating indices for individual commodity groups varying in degree of aggregation (from niche groups of two or three products to the broadest groups such as *food and services*). These disaggregated indices are published by the statistical service (almost) simultaneously with the CPI.

The presentation of disaggregated statistics in the same format as headline inflation reports, at the same frequency and at the same time, makes them convenient to analyse, and it is a low-cost exercise. Unsurprisingly, almost all empirical attributes of inflation (rate, volatility, persistency, degree of price rigidity, average price duration, elasticity in terms of various factors including, most of all, the exchange rate pass through, monetary shock effect, Phillips curve coefficients, relationship to the economic cycle, wages, etc.) are studied not only at the level of headline inflation but also at the disaggregated level.

The study of price dynamics of CPI components has a long history. This concept was introduced to the scientific discourse by Gordon (1975) and Eckstein (1981), who sought to refine estimates of current inflation by stripping out the impact of volatile factors affecting the US economy in those years. Their suggestion that such data should take centre stage spurred on intense discussion in the literature, including on the questions of whether central banks should respond to fluctuations in relative prices and transient and idiosyncratic factors, and of whether the latter should be taken into account in inflation forecasts, etc. This resulted in the emergence of the concepts of core inflation, trend inflation, secondary effects, and so on (for an existing discussion of these problems, see Ida (2020)).

There are contrasting views on price dynamics of CPI components and related issues. On the one hand, the movement of relative prices in disaggregated statistics can be viewed as microstructural noise unrelated to macroeconomic factors, devoid of information about them, and therefore useless for inflation forecasting. Specifically, this assumption (sometimes implicitly) is made in a number of studies including dynamic factor models (Altissimo et al., 2009; Boivin et al., 2009; Mumtaz et al., 2009; Reis and Watson, 2010). In this case, working with disaggregated statistics amounts to nothing more than extracting core inflation, after which no new information can be derived from sectoral statistics in forecasting. However Graeve and Walentin (2015) note that the claim of the irrelevance of sectoral statistics in dynamic factor models is an assumption, rather than a consequence, and so the corresponding conclusion is an artefact of the methodology rather than a reflection of real phenomena.

On the other hand, the dynamics of relative prices can be linked to the direct impact of macroeconomic factors. The assumption that different commodity groups are subject to multiple macroeconomic factors, to different extents, makes the case that price dynamics of CPI components contains information on the effective factors of inflation. In this case, disaggregated price dynamics enables the identification of the contributions of individual factors (which cannot be done by considering only the general movement of inflation) and thereby helps in forecasting (for example, whether the factors have varying persistency).

This view has a long tradition in theoretical models of macroeconomics. Among the best-known models is the Balassa-Samuelson model, in which the dynamics of the relative prices of tradable and non-tradable goods are linked to changes in the real exchange rate and the productivity differential of the economy. The conditional breakdown into tradable and non-tradable goods with known reservations fits well into individual components of the consumer basket. Byrne et al., (2013) и Feldstein, (2017) empirically establish a relationship between price dynamics of CPI components and productivity growth.

Other dichotomies of this kind include a breakdown into domestic and imported goods (which may be differently affected by external sector shocks and may differ in the scale of exchange rate passthrough), as well as the differentiation of durable goods in the consumer basket (theoretically, they may differ in their response to demand-side shocks, including monetary shocks). Erceg and Levin (2006) and Cantelmo and Melina (2018) demonstrate the difference in the dependence of price dynamics in the sectors of durable and non-durable goods (in both SVAR and DSGE models). Attanasio et al. (2022) reveal the particular sensitivity of car prices to macroeconomic shocks in the US. Stock and Watson (2020) identify the components of inflation that are sensitive to fluctuations in economic activity, and they formulate the concept of cyclically sensitive inflation. Osbat et al. (2021) show the difference in exchange rate pass-through across various sectors, and Tallman and Zaman (2017) show the difference in the coefficients of sectoral Phillips curves. Kaufmann and Lein (2011) expose the difference in the response to overall macroeconomic shocks. Among Russian authors who assume heterogeneity of price dynamics across various commodity groups depending on macroeconomic conditions, Eliseev et al. (2021) are the first to build a model with such properties.

Another area in the literature explores the sectoral specifics of the pricing process itself. While the aforementioned studies examine and simulate differences in the cost of or demand for disaggregated groups, the following studies focus on the pricing process itself. Bils and Klenow (2004), Clark (2006) study the relationship between the persistency of price dynamics across sectors and the degree of price rigidity in them. Carlton (1986), Gopinath and Itskhoki (2011) и Leith and Malley (2007) show that price sensitivity to costs is low in high-concentration sectors, Duval et al. (2021) show that price sensitivity to monetary policy shocks is lower in those sectors, and Kato et al. (2021) show that the persistency of price fluctuations is lower.

If price fluctuations in any sector makes an equal correction to the forecast for future changes, this means that price dynamics of CPI components does not contain information relevant to forecasting. At the same time, heterogeneity is almost always significant, which has been confirmed for the US by (Golosov and Lucas Jr., 2007; Imbs et al., 2011; Leith and Malley, 2007).

Finally, empirical work looking at price dynamics of CPI components in the context of forecasting can be highlighted. (Hubrich, 2005; Hendry and Hubrich, 2011; Linder et al., 2013) are among the first authors to find the value of CPI components price dynamics in forecasts for European countries. (Elmer and Maag, 2009; Kaufmann and Lein, 2011) conduct a similar study for Switzerland, (Mumtaz et al., 2009) study the UK, and (Boivin et al., 2009; Faust and Wright, 2013; Fulton and Hubrich, 2021) are among the first authors to study the problem in the case of the US. The list of works is particularly long in the case of developing countries and countries with emerging financial markets. A non-exhaustive list includes similar studies for Mexico, Spain, Poland, Turkey, India, Iran, and a number of African and Latin American countries. Almost all of the works listed incorporate disaggregated price dynamics in forecast models either by moving to indirect forecasts (the dynamics of each component are predicted separately, most often with ARIMA models) or by using (B)VAR and DFM models, which simultaneously account for several components.

Bermingham and D'Agostino (2014), which serve as a reference point for this study, systematise the knowledge available at the time about CPI components price dynamics forecasts and empirically compare inflation forecasting models and the use of disaggregated statistics. They compare aggregated and disaggregated forecasts as well as the different depth of disaggregation. For example, for the USA, they compare the aggregated forecast and forecasts for 3, 15, 50, and 169 components.

The authors are able to provide a snapshot of the pros and cons of deeper disaggregation. On the one hand, a more detailed, disaggregated forecast is expected to be more accurate because it relies on a broader set of data and broader information structures. On the other hand, using disaggregation, one may lose information about the movement of inflation, failing to give a proper account of secondary effects and the correlation between individual components. This compromises the accuracy of forecasts. Therefore, the dependence of the mean errors on the depth of disaggregation can take a U-shaped form: initially, disaggregation reduces the error, but the negative effects eventually predominate. Their consequences can be eliminated by taking into account the influence of the common factors in each model.

The empirical part of the study supports the authors' assumptions for the US and, partially, for the euro area. If autoregressions are used to forecast individual components, disaggregation to the depth of 15 components is optimal for forecast accuracy, while further deepening is counterproductive. Conversely, if each model takes into account the common factor (for example, by means of the first main component of all price increases), even more accurate models can be obtained and the decline in the efficiency of disaggregation can be eliminated. A similar effect is produced with the use of a Bayesian vector autoregression model. It can be assumed that the use of a dynamic factor model could be another alternative.

3. Methodology for comparing predictive accuracy of models

3.1. Notation

Here and elsewhere, the rate of headline inflation at point in time t is denoted by π_t, and the rate of price dynamics of CPI components for the $j-\text{th}$ component is $\pi(j)_t$. Assume that there exist weights w_{jt}, such that at each point in time

$$\pi_t = \sum_j w_{jt}\pi(j)_t.$$

In accordance with Rosstat's methodology for the construction of consumer price indices, the weights for the consumer basket are calculated at the beginning of the year and fixed for the twelve months of the year. In this paper, the possible deviations of the actual data from the above formula are disregarded (they are possible due to rounding and other errors), in part due to their insignificance and in part due to the negative effect of the abovementioned problems only on disaggregated forecasts. If it can be shown that even in this case the latter proves more accurate than the aggregated forecasts, then the ideal scenario of accurate data would most likely yield a correlation of similar quality.

The forecast estimate of inflation at point in time $t+h$, obtained at point in time t with the help of model m is denoted by $\hat{\pi}^m_{t+h|t}$. In this paper, individual comparisons are made for forecasts of various horizons from 1 to 12 months. Once forecasts are obtained for individual CPI components $\hat{\pi}(j)^m_{t+h|t}$, the corresponding aggregated forecast can be calculated as

$$\hat{\pi}^m_{t+h|t} = \sum_j w_{jt+h}\hat{\pi}(j)^m_{t+h|t}.$$

This approach is not wholly consistent with real practice, since the real values of the weights for the year ahead are unknown in advance. However, it is hoped that the alternative approaches will not essentially change the results.

By comparing inflation forecast $\hat{\pi}^m_{t+h|t}$ and the actual inflation rate at the same point in time π_{t+h}, forecast error $e^m_{t+h|t} = \pi_{t+h} - \hat{\pi}^m_{t+h|t}$ can be calculated, for which the same indices are convenient to use. The order of summands does not matter since all the errors are estimated either by absolute value or as squares.

Finally, the depth of disaggregation (the use of 3, 6, 45, or more components) is indicated whenever necessary with index m of the model. For example, $\hat{\pi}^{m-3}_{t+h|t}$, $\hat{\pi}^{m-6}_{t+h|t}$, or $\hat{\pi}^{m-45}_{t+h|t}$.

Whenever regional data are used, region indicator i is the corresponding subscript index: π_{it}, $\pi(j)_{it}$, $\hat{\pi}^{m}_{i,t+h|t}$ and $\hat{\pi}(j)^{m}_{i,t+h|t}$. It should be noted that regional weights w_{jt} may differ from the federal weights. The regional weights are used in this paper in the processing of regional data.

3.2. Standard comparison methodology

Traditionally, the simplest and most direct way to compare the accuracy of forecasts is to calculate the mean errors of out-of-sample forecasts in pseudo-real time and test the equality of the mean errors of the two models. Under this approach, the available data are divided into two parts – a training sample and a test sample. The training subsample is used to estimate the models, which help make a forecast for one or several forecast horizons, which are then compared with the corresponding data of the test subsample. The training sample is then expanded (or shifted) by one period, and the procedure is repeated. By repeating these actions T times, the researcher receives errors $e^{m}_{t+h|t}$, $t = \overline{1,T}$.

Root mean square error $RMSE^{m}_{h}$ and mean absolute error $MASE^{m}_{h}$ are most often used as indicators of the mean error:

$$RMSE^{m}_{h} = \sqrt{\sum\left(e^{m}_{t+h|t}\right)^{2}/T},$$

$$MASE^{m}_{h} = \sum\left|e^{m}_{t+h|t}\right|/T.$$

The root mean square error is used as the basic measure, with the mean absolute error viewed as an auxiliary measure to check robustness. It should be noted here that in no case do the measures produce essentially conflicting results.

The wide range of other mean error measures commonly used in similar studies (e.g., MAPE, Theil Index, etc.) are omitted. This is explained by the intention to use only measures that have matches in formal econometric tests and, specifically, good statistical properties (for example, on finite samples, $RMSE^{m}_{h}$ has a normal distribution, while the Theil Index significantly differs from the normal distribution (for further details, see the work of Franses, 2016)).

Diebold and Mariano (1995) propose the formal procedure for the comparison of two models by the accuracy of their out-of-sample forecasts. Compare model $\times$ and model $\circ$. Once the abovementioned procedure is complete, the researcher has set of errors $e^{\times}_{t+h|t}$, $t = \overline{1,T}$ and set of errors $e^{\circ}_{t+h|t}$, $t = \overline{1,T}$.. To draw a conclusion as to whether the model forecasts are equally accurate in terms of $RMSE$, auxiliary series

$\Delta_{t+h|t}= \left(e^{\times}_{t+h|t}\right)^2 - \left(e^{\circ}_{t+h|t}\right)^2$ is considered. The hypothesis that the model forecasts are equally accurate is formulated as $E\left(\Delta_{t+h|t}\right) = 0$ and can be tested by simple statistical tests. If the hypothesis is rejected in favour of hypothesis $E\left(\Delta_{t+h|t}\right) < 0$, model $\times$ is the more accurate, and vice versa. From a theoretical standpoint, a certain problem may arise from the fact that $\Delta_{t+h|t}$ can rarely be described well by assumption $\Delta_{t+h|t} \sim iid$ and quite often has significant autocorrelation and heteroscedasticity. However, appropriate test corrections help overcome these problems easily.

Going forward, the work is limited to comparisons of models in pairs, since this is sufficient to draw final conclusions on the issue under investigation. Models are most often compared with a benchmark; in other cases, it is clear from the context which pair of models is subject to comparison.

3.3 Use of regional data

The Diebold and Mariano (1995) test is quite demanding in terms of volume of data T and assumes series stationarity $\Delta_{t+h|t}$. If this requirement is violated or the volume of data is small, the test may be insufficiently powerful, failing too often to reject the incorrect null hypothesis and finding both models to be equal in their predictive strength.

Timmermann and Zhu (2019) propose a switch to panel data as a way of increasing the power of the test. This is the method used in this paper, operating with regional inflation data. Access to data for N regions provides, in addition to set of forecasts $\hat{\pi}^m_{t+h|t}$, set of errors $e^m_{t+h|t}$, and pairwise comparison yields set of squared error variances $\Delta_{t+h|t}$; the panel analogues of all these structures: $\hat{\pi}^m_{it+h|t}$, $e^m_{it+h|t}$, $\Delta_{it+h|t}$, $t = \overline{1,T}, i = \overline{1,N}$. In this case, the errors are calculated with slightly modified formulas:

$$RMSE^m_h = \sqrt{\sum\left(e^m_{t+h|t}\right)^2 / NT},$$

$$MASE^m_h = \sum\left|e^m_{t+h|t}\right| / NT.$$

Hypothesis $E\left(\Delta_{it+h|t}\right) = 0$ can also be tested. Importantly, with $\Delta_{it+h|t} \sim iid$, the procedure is almost indistinguishable from the one-region case.

Significant difficulties arise following the recognition of the strong interdependence of individual regions If $corr\left(e^m_{it+h|t}, e^m_{jt+h|t}\right) \gg 0$, as is the case in the data, the dynamics of inflation, inflation surprises, and the forecast errors do not differ significantly from region to region, then the addition of new regions does not bring new information and does not increase the power of the test. Timmermann and Zhu (2019) formalise this important probability as follows:

Let the forecast errors in different regions have a factor structure, that is, there is a small number of factors common to all regions, which are complemented with an idiosyncratic part in each region:

$$e^m_{it+h|t} = \lambda^m_{ih} f_{t,h} + \xi^m_{it+h|t}.$$

$f_{t,h}$ can be interpreted as the common factors of an inflationary surprise. In this case, $corr\left(e^{m}_{it+h|t}, e^{m}_{jt+h|t}\right) \gg 0$ holds. Then,

$$\Delta_{t+h|t} = \left(e^{\times}_{t+h|t}\right)^2 - \left(e^{\circ}_{t+h|t}\right)^2 = \left(\lambda^{\times}_{ih} f_{t,h} + \xi^{\times}_{it+h|t}\right)^2 - \left(\lambda^{\circ}_{ih} f_{t,h} + \xi^{\circ}_{it+h|t}\right)^2.$$

Removing the parentheses and assuming that $E\left(f_{t,h}\xi^{m}_{it+h|t}\right) = 0$ yields

$$\Delta_{t+h|t} = \left[\lambda^{\times}_{ih} f_{t,h}\right]^2 - \left[\lambda^{\circ}_{ih} f_{t,h}\right]^2 + \left(\xi^{\times}_{it+h|t}\right)^2 - \left(\xi^{\circ}_{it+h|t}\right)^2.$$

The expression has a simple interpretation: one forecast may be more accurate than another due to both lower susceptibility to general error factors and a smaller residual error. At the same time, one forecast may be more accurate in one case, while the other is more accurate in another case.

Importantly, in this case, $\Delta_{t+h|t}$ cannot have a normal distribution. The distribution of these statistics depends on the distribution of $f_{t,h}$. In this case, hypothesis $E\left(\Delta_{it+h|t}\right) = 0$ can be tested using a bootstrap procedure. A 'wild bootstrap' is used, randomly selecting blocks of observations and calculating statistics $\overline{\Delta_{t+h|t}} / sd(\Delta_{t+h|t})$ for each case. Further on, in accordance with the bootstrap methodology, the empirical confidence interval for the statistics is found, and it is checked for whether it includes 0. In the positive case, the zero hypothesis is considered accepted, and the accuracy of the models is identical.

4. Data

4.1. CPI and its structure

The study uses data on the movement of components of the consumer price index in Russia and its regions between 01.2002 and 11.2021 in month-on-month growth terms, seasonally adjusted. The seasonal adjustment is based on the methodology of the Bank of Russia.[2] The seasonal adjustment conducted takes all the available information into account, which, to a degree, runs counter to the pseudo-real time methodology (in fact, at the beginning of the period, there is no way of knowing the data as of its end), but this is not an unprecedented technique. This exact procedure is used in a few works (such as the work of Styrin (2019)).

Wherever possible, the calculations use the weights officially published by Rosstat for individual components of the consumer basket. If they are unavailable, they are approximated based on the available information in accordance with the Rosstat methodology.

The composition of the consumer basket changed every year throughout the period under review and in 2022 includes more than 500 individual products and services. Since

[2] Seasonally adjusted indices for Russia are available at http://www.cbr.ru/statistics/ddkp/aipd/.

a uniform consumer basket cannot be formed for certain goods, this level of disaggregation is done without, and the focus is limited to more aggregated product groups. In particular, divisions of the consumer basket into three components (food, non-food, and services), six components (the separation of fruit and vegetables, motor fuel, and housing and utilities services), eighteen components (several more significant and/or volatile groups are distinguished), and forty-five components (the full list is presented in Table 1 in the Appendix) are used. Thereafter, segregated inflation forecasts are made at all three levels of disaggregation.

The pseudo-real time forecast is designed as follows. The entire period up to September 2015 is used as the first training sample. Forecasts are made for periods of one to twelve months. The first forecast for 1 month ahead is made for October 2015. Further on, the training sample is expanded in increments of one month, and the final forecast point falls on December 2021. This means that observations from the transition period follow December 2014 are not included in any of the test samples.

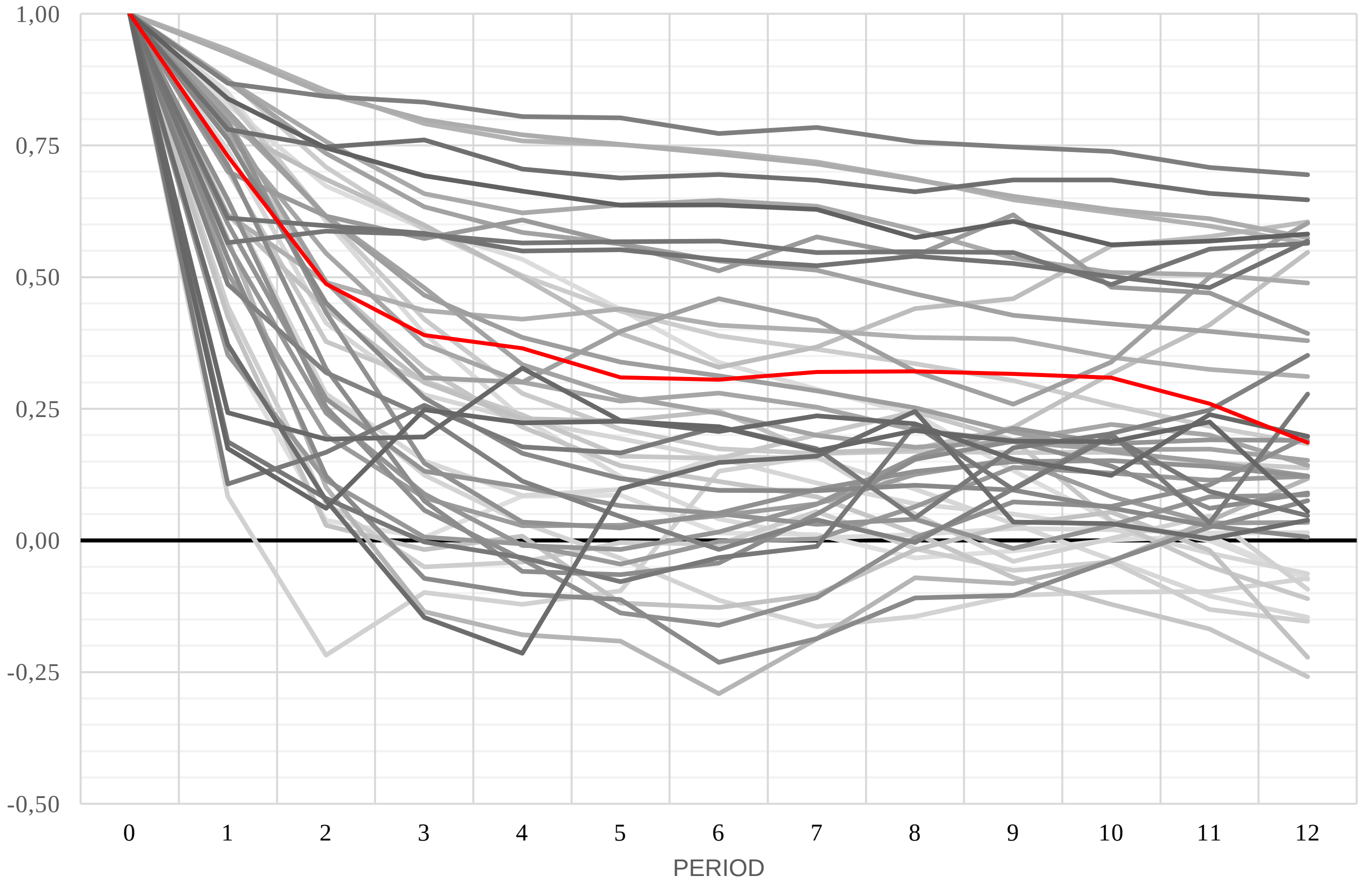
4.2. Specifics of price dynamics of CPI components in Russia

Before moving on to the results of the forecasting models, it is necessary to describe several key properties of the available data. This can be achieved by examining the characteristics of the forty-five-component series and comparing them with the overall inflation dynamics.

First, note that the dynamics of the CPI individual components may differ significantly from those of overall inflation. Table 1 in the Appendix presents descriptive statistics for these components, including the average, standard deviation, first-order autocorrelation, and overall correlation with inflation, for the entire period under review. The individual components of these indicators are clearly marked by manifest differences. In this vein, the average price increase for tobacco products is several times higher than the overall inflation, whereas electronic devices and household appliances are characterised by price decrease in most periods. Several products, including fruit and vegetables, eggs, and sugar, are marked by significant volatility, while certain types of services change little for a long period of time.

From the forecasting perspective, it is essential to characterise the persistency of inflation. As already mentioned in Section 2, the heterogeneity of persistency is a necessary condition for the use of price dynamics of CPI components in forecasts. In the available data, the heterogeneity of persistency is quite obvious: the first-order autocorrelation for 45 components differs in a wide range, while the empirical functions of the autocorrelation (see Figure 1 in the Appendix) show all possible patterns of behaviour – from low-value-added food products (where the autocorrelation rapidly becomes negligible and by the third month is no different from zero) to individual services (where the autocorrelation remains significant throughout the 12 months).

Figure 1. Autocorrelation functions of components of CPI



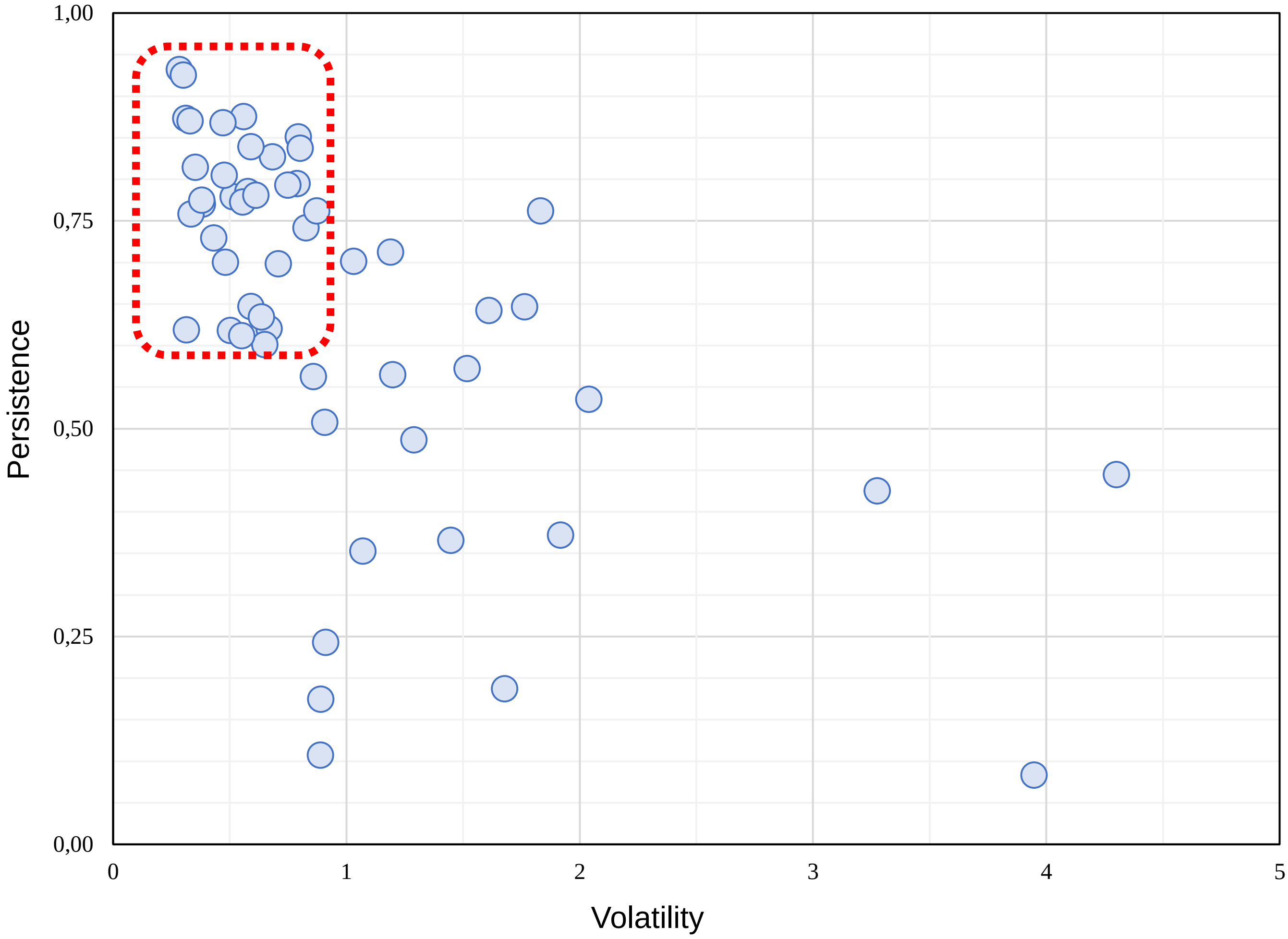
The chart shows the autocorrelation functions of 45 product groups, demonstrating the persistence of the series. The coloured line indicates the autocorrelation of the dynamics of inflation in general.

Source: Rosstat, author's calculations.

Finally, the correlation of components among themselves and with the overall inflation also differs greatly, but for most components it is quite high. This is evidence of the impact of the common factors and possibly signals a drop in the efficiency of disaggregation if the models do not additionally take the common factors into account.

At the same time, everything suggests that price dynamics of CPI components can be successfully used in forecasts. In Figures 2 and 3 (in the Appendix), groups of low-volatility components with high correlations among themselves and with median growth rate, as opposed to volatile components with predominantly idiosyncratic dynamics, are well identified. It is possible that the uniform approach to shocks in these groups gives way to differentiated treatment: attaching more importance to the first groups in the analysis may add accuracy to the forecast.

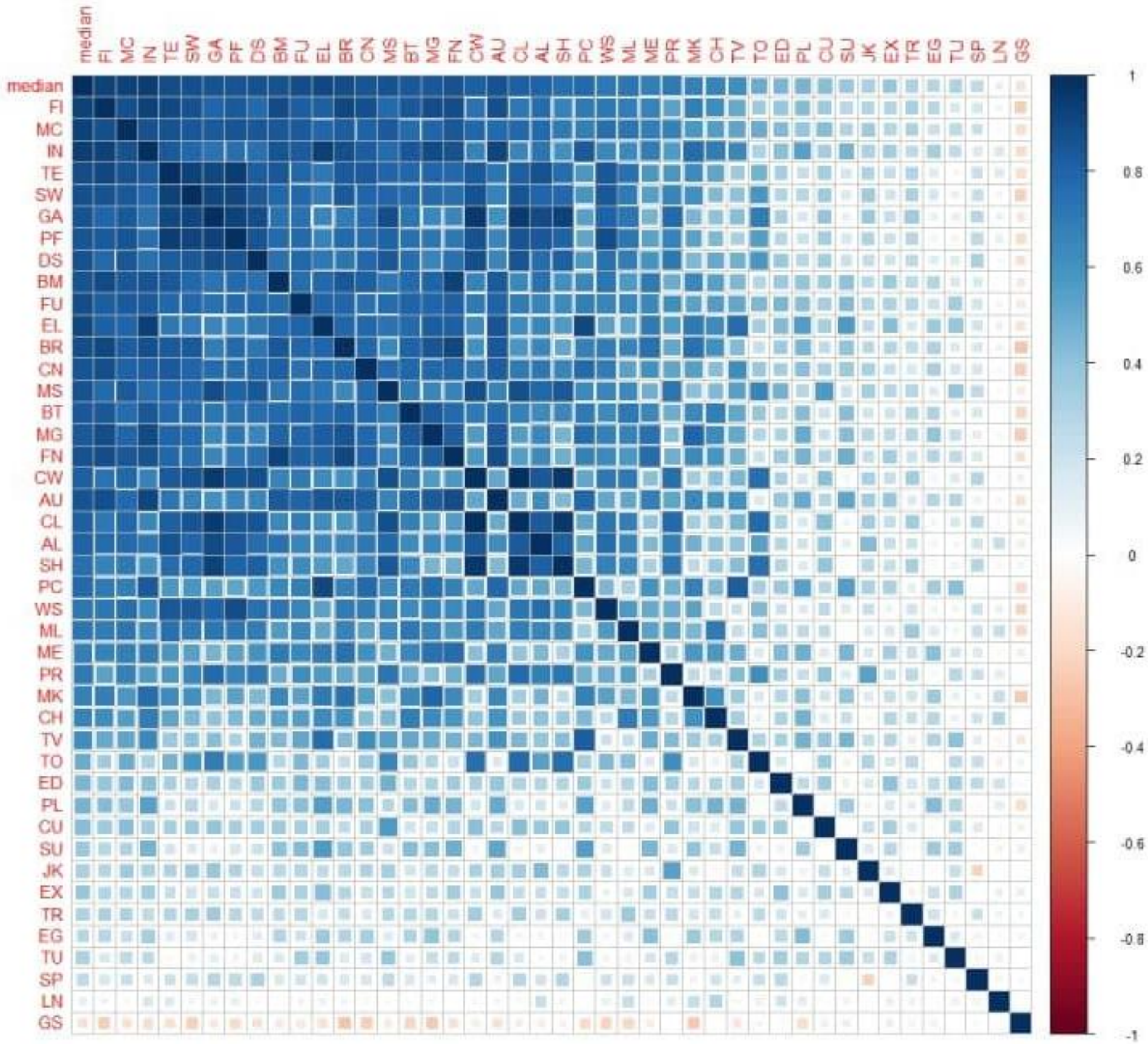
Figure 2. Persistency and volatility of price dynamics of CPI components



The chart shows the product groups. The horizontal axis indicates their volatility as measured by standard deviation. The vertical axis shows their persistency as measured by first-order autocorrelation. The points in the top left corner correspond to the product groups which are most informative for forecasting.

Source: Rosstat, author's calculations.

Figure 3. Correlations between components of CPI



The colours indicate the correlation between respective components of the CPI. The following abbreviations are used:

FI – fish products, MC – public catering, IN – tools, TE – tea and coffee, SW – confectionery, GA – smallware, PF – perfumes and cosmetics, DS – personal services, BM – construction materials, FU – furs, EL – electrical products, BR – bread and baked goods, CN – communication devices, MS – medical services, BT – oil and fats, MG – medical products, FN – furniture, CW – knitwear, AU – cars, CL – clothing, AL – alcoholic beverages, SH – shoes, PC – personal computers, WS – washing products, ML – milk and dairy products, ME – meat products, PR – print media, MK – pasta and cereals, CH – cheese, TV – TV and radio goods, TO – tobacco products, ED – education services, PL – fruit and vegetables, CU – cultural services, SU – sugar, JK – utilities, EX – excursion services, TR – transport services, EG – eggs, TU – outbound tourism services, SP – health resort services, LN – communication, GS – motor fuel.

Source: Rosstat, author's calculations.

5. Models

5.1. Benchmark models

It is quite important to address the problem of choosing a simple model with which it is convenient to compare the other models in their predictive properties. The traditional approach to US inflation has been the random walk model, which assumes inflation over the forecast horizon to be equal to current inflation:

$$\pi_{t+h} = \pi_t + u_{t,h}.$$

The forecast for h periods ahead is calculated as:

$$\hat{\pi}^{RW}_{t+h|t} = \pi_t.$$

A slightly modified version of the random walk model is proposed in the work of Atkeson and Ohanian (2001) Instead of the final value of inflation, the averaged value for several periods is used:

$$\pi_{t+h} = \frac{1}{\tau}\sum_{\tau} \pi_t + u_{t,h}.$$

The forecast for h periods ahead is calculated as:

$$\hat{\pi}^{RW-AO}_{t+h|t} = \frac{1}{\tau}\sum_{\tau} \pi_t.$$

Both models have proved themselves quite well in the analysis of US inflation. The empirical fact is that it is extremely difficult to find a forecasting model for US data with better accuracy than random walk forecasts.

Although it is the standard for US inflation forecasting, the random walk model may not necessarily be a reliable benchmark for other countries. It is arguable that the model owes its outstanding performance to the nature of the US data (the availability of a long history of data, the absence of a stated target for inflation for most of such data, the change of monetary policy regimes, etc.) and therefore may not be universal.

In particular, it may not work in the case of Russian data. For the period after the transition to inflation targeting (from 10.2015 through 11.2021), it is worth considering the simple model which assumes that the inflation forecast is simply equal to the current inflation target. This rule-of-thumb approach is proposed by Diron and Mojon (2005) It reflects the fact that an effective central bank is capable of delivering on its inflation target. If the central bank enjoys confidence, its anchored inflation forecast is consistent with the anchored inflation expectations of households and may well be quite viable.

Anchored forecast model:

$$\pi_{t+h} = \pi_{SS} + u_t,$$

where π_{SS} is the central bank's inflation target. The forecast for h periods ahead is calculated as:

$$\hat{\pi}^{IT}_{t+h|t} = \pi_{SS}.$$

It is apparent that it is quite possible to apply these models to disaggregated components and aggregate the forecast, but also that this does not make sense. Theoretically, the results should be completely identical forecasts, and the disaggregated forecasts would in practice be inferior to the aggregated ones due to rounding errors. Therefore, comparison requires other models.

5.2. One-dimensional models

Following Bermingham and d'Agostino (2011) and most other researchers exploring price dynamics of CPI components forecasting, ARIMA and autoregression models are used as the models for the disaggregated forecasts.

AR model:

$$\pi_{t+h} = \mu + B(L)(\pi_t - \mu) + u_{t,h},$$

where μ and $B(L)$ are the estimated coefficients. The forecast for h periods ahead is calculated as:

$$\hat{\pi}^{AR}_{t+h|t} = \hat{\mu} + \hat{B}(L)(\pi_t - \mu).$$

There are direct and recursive approaches to forecasting based on such models. Under the recursive approach, one model is estimated – the forecast model for one period ahead, and the forecasts for more periods are obtained by substituting the forecasts for the previous periods in the model. Under the direct approach, a separate model is estimated for each forecast horizon. This makes the direct approach akin to the methodology of *local projections* (see (Jordà, 2005)), which has successfully proved itself in empirical research.

In addition to the core version of this model, estimated on expanding training samples, estimates of the same models on rolling samples of 36 months are used. This allows for a certain change to the model parameters, since data spaced more than 36 months away from the forecast are not used to generate it.

5.3. Common factor models

A more compelling argument for or against the use of price dynamics of CPI components may come from the comparison of common factor models. For such comparisons, the models of Bermingham and d'Agostino (2011) and Faust and Wright (2013) are adapted.

Bermingham and d'Agostino (2011) propose complementing *individual component models* with the common factor and obtain Factor-Augmented AR (FAAR):

$$\pi_{t+h} = \mu + B(L)(\pi_t) + \gamma F_t + u_{t,h},$$

where μ, γ and $B(L)$ are the estimated coefficients, and F_t is a measure of the common factors concurrently affecting all or most components of inflation. The forecast for h periods ahead is calculated as:

$$\hat{\pi}_{t+h|t}^{FAAR} = \hat{\mu} + \hat{B}(L)(\pi_t) + \hat{\gamma}F_t.$$

For F_t, Bermingham and d'Agostino (2011) consider the first main component of the cross-section of the prices for individual products. This paper uses the median price growth rate for F_t, and the core consumer price index (CCPI) and the inflation rate free of the prices for fruit and vegetables, motor fuel, and utility services are intended for the robustness test. The results are not fundamentally different.

Faust and Wright (2013) explore the option of using inflation estimates in gaps. To this end, they deduct the level of trend inflation (which they approximate as the long-term inflation expectations of analysts) from the inflation dynamics, separately forecast the dynamics of this difference, and add forecasts for the future difference to the current level of trend inflation (that is, they assume the stability of the latter over the forecast horizon). This approach factors in non-stationarity and produces good results.

This model is adjusted and uses the median price growth rate as the level of trend inflation.

AR-in-gap model:

$$\pi_{t+h} = \gamma\mu_t + B(L)(\pi_t - \gamma\mu_t) + u_{t,h},$$

where $B(L)$ are the estimated coefficients, and μ_t is the median price growth rate. The forecast for h periods ahead is calculated as:

$$\hat{\pi}_{t+h|t}^{gap} = \hat{\gamma}\mu_t + \hat{B}(L)(\pi_t - \hat{\gamma}\mu_t).$$

The latter model is convenient in that it factors in the informed mean, as does the anchored forecast model. This allows an attempt to obtain results that are comparable to the benchmark in accuracy, which is attributable to the fact that it is not biased – its key advantage.

6. Results

Comparison of the accuracy of forecasts on a test sample from October 2015 to November 2021 leads to the following conclusions.

1. Among the benchmark models, the anchored forecast model shows the best results.

The accuracy of the anchored forecast by the RMSE metric is high compared to other models. Standard benchmark models - the random walk model and the autoregressive model - give a large amount of error. It is important to note that with an increase in the forecasting horizon, the quality of forecasts of both RW and AR models deteriorates, while for the “anchored” forecast model it is stable by construction (see Table 2a).

To a certain extent, these results are not unexpected. For the period 2016–2020 the average inflation rate was close to the target of the Bank of Russia. Not surprisingly, during this period, forecasts that exactly matched the target level had good accuracy.

More importantly, other models could not come close to this because they relied only on the previous inflation dynamics, which did not contain information about the transition to the targeting regime, the target level and the corresponding changes in the long-term properties of inflation dynamics. Consequently, the predictions of such models are systematically overestimated. On the contrary, the anchored forecast model produces unbiased forecasts, which turns out to be decisive in terms of accuracy, even despite the obviously primitive modelling of short-term dynamics.

Table 2a. Модели и метрики RMSE точности их прогнозов (часть 1)

Model	1m	3m	6m	9m	12m
«Anchored» forecast	0,2397	0,2397	0,2397	0,2397	0,2397
RW	1,0813**	1,2166***	1,3408***	1,4616***	1,7954***
RW-AO (3 мес)	0,9841	1,0866**	1,1935***	1,3071***	1,7406***
RW-AO (6 мес)	0,9766	1,0548*	1,1579***	1,4318***	1,7384***
RW-AO (12 мес)	1,0395*	1,1817***	1,3897***	1,5739***	1,7206***
RW-AO (36 мес)	1,4261***	1,4758***	1,5508***	1,6207***	1,6714***
AR	1,0353	1,1764***	1,2820***	1,4343***	1,7858***

Note (here and below). Calculation based on regional data. Asterisks indicate significance levels of the Timmermann and Zhu (2019) test. Except for the benchmark, all RMSEs are relative to the benchmark. Significantly less accurate models are highlighted in grey. Blue shading corresponds to models without disaggregation.

At the same time, the goal of the Bank of Russia was explicitly announced, information about it was included in the information set of economic agents and could be considered when making forecasts. If the modelling ensures that the unconditional mean of the forecasts is close to 4% (for example, by constrained parameter estimation), then the accuracy of the forecasts will be comparable to the “anchored” forecast model.

2. For models based only on the dynamics of inflation, disaggregation does not lead to an increase in accuracy.

The accuracy comparison results are presented in Table 2b below. Models of all levels of disaggregation give forecasts comparable in accuracy. On a horizon of 1–3 months, their accuracy is approximately equal to the accuracy of random walk and anchored forecasts, but the quality deteriorates over a longer horizon.

Moving sample estimates provide more accurate estimates if the entire period is used as a comparison, and comparable estimates if limited to only the period after the transition to the targeting regime. All conclusions are supported by the results of both Diebold and Mariano (1995) and Timmermann and Zhu (2019) econometric tests.

Consequently, the mere use of disaggregated statistics does not yield more accurate forecasts. This may be driven by both the absence of useful information in such statistics and the problems that arise when the common factors are ignored. Furthermore, changes in the structural parameters of inflation, in particular in its mean, seem to be a significant barrier to the use of these models. In terms of accuracy, the models based on rolling samples outperform those based on expanding samples, and the anchored forecast model significantly outperforms all the models.

Table 2b. Модели и метрики RMSE точности их прогнозов (часть 2)

Model	1m	3m	6m	9m	12m
AR	1,0353	1,1764***	1,2820***	1,4343***	1,7858***
AR-3	1,0518	1,1807***	1,2974***	1,5413***	1,6597***
AR-6	0,9889	1,224***	1,2974***	1,4729***	1,6928***
AR-18	0,9969	1,2382***	1,2666***	1,4760***	1,7297***
AR-45	1,0178	1,1545***	1,2633***	1,4169***	1,7683***
AR (TVP)	1,0018	1,1063***	1,2591***	1,4581***	1,8523***
AR-3 (TVP)	1,0125	1,1451***	1,3216***	1,3454***	1,8218***
AR-6 (TVP)	1,0089	1,1389***	1,3139***	1,3966***	1,8763***
AR-18 (TVP)	1,0105	1,0877**	1,2726***	1,2379***	1,8586***
AR-45 (TVP)	1,0154	1,0955**	1,2562***	1,2437***	1,7971***
AR (direct)	1,0353	1,2624***	1,3566***	1,3139***	1,5922***
AR-3 (direct)	1,0444	1,2601***	1,2647***	1,3156***	1,5970***
AR-6 (direct)	0,9739	1,2055***	1,1464***	1,3397***	1,4863***
AR-18 (direct)	0,9971	1,2851***	1,4045***	1,2969***	1,5994***
AR-45 (direct)	1,0178	1,2276***	1,3209***	1,2975***	1,4215***

Source: authors' calculations.

3. Inflation factors common to most commodities contribute to the accuracy of forecasts (even when accounted for in the simplest ways)

The results of the models with common factors are shown below in Table 2c. They qualitatively differ from the results discussed above.

First, the models with differing degrees of disaggregation begin to differ, with deeper levels of disaggregation corresponding to more accurate forecasts. Although this difference is negligible in the case of Russian data, the test using regional data indicates that this difference is relevant. This may be due to the low power of the Diebold and Mariano test (1995), while the approach of Timmermann and Zhu (2019) proves to be more sensitive and effective.

Second, the disaggregation models, although, as before, inferior to the benchmark on long horizons, are comparable to it on near-term horizons and outperform the benchmark in some cases. With regard to the comparison of the disaggregated models with their closest peers, the inclusion of the common factors allows them to outperform the disaggregation-free models.

Third, the use of median price growth rate boosts the accuracy of forecasts even without disaggregation. This increase in accuracy in absolute terms is slightly more than the further increase from the use of price dynamics of CPI components. This finding is to some degree aligned with the results of Stock and Watson (2016), who argue that the role of disaggregated price dynamics is limited to stripping out volatile components, but, on the other hand, the finding contradicts them, because there is a tangible increase in accuracy.

Table 2c. Модели и метрики RMSE точности их прогнозов (часть 3)

Model	1m	3m	6m	9m	12m
FAAR	0,9277**	1,0942**	1,2909***	1,2494***	1,6803***
FAAR-3	0,9706*	1,0939**	1,1867***	1,2421***	1,5477***
FAAR-6	0,9622*	1,0564*	1,1847***	1,2948***	1,5478***
FAAR-18	0,8951**	1,0148	1,2404***	1,3748***	1,7553***
FAAR-45	0,8541***	1,0221	1,2517***	1,3975***	1,8954***
AR-in-gap	0,8457***	0,9213**	0,9845	1,0125	1,0056
AR-in-gap-3	0,8532***	0,9217**	0,9702	1,0148	1,0012
AR-in-gap-6	0,8378***	0,9115**	0,9754	0,9867	1,0033
AR-in-gap-18	0,7805***	0,8814***	0,9676*	0,9552	1,0122
AR-in-gap-45	0,7584***	0,8633***	0,9515*	0,9937	0,9987

Source: authors' calculations.

At the same time, the models with changing coefficients are in most cases more accurate than those with constant ones.

4. When considering common factors and fixing the unconditional average at the inflation target, disaggregation significantly improves accuracy over the short term.

Finally, if information about the target level is communicated to the AR-in-gap models and the median price growth rate over the forecast horizon is set at this level, the forecasts of all degrees of disaggregation are not inferior to the benchmark on all horizons and are significantly better on near-term horizons in the case of regional data. The latter results are not unexpected, since the forecast in this model quickly converges to the level of trend inflation, and for this reason, it scarcely differs from the specified inflation target.

As a robustness test for these conclusions, it is worth considering models that include the exchange rate. The latter is reasonably considered one of the few variables that are consistently correlated with inflation changes. In addition, in terms of individual components of the consumer basket, the exchange rate can safely be considered the common factor and an example in the verification of the conclusions about the role of the common factors in the inflation forecast.

The results of the exchange rate models are summarised below. The inclusion of the exchange rate in the model leads to a significant improvement in the accuracy of the forecasts, especially on short horizons. The addition of the exchange rate to the disaggregation models also increases their accuracy compared to the exchange rate models. However, in the comparison of disaggregation models with disaggregation-free models, the inclusion of the rouble exchange rate does not add any new information. In the case of Russian data, these models are invariably comparable in accuracy, and in the case of regional data, substantially improved forecasts are possible only if the disaggregated components and the common factors are included concurrently. This not only supports the conclusions above, but also shows that the impact of the exchange rate is not the only common factor. By itself, it does not produce the same effect as does the inclusion of median price growth rate.

Nor do the results change with respect to the benchmark and the anchored forecast. A *foreign exchange rate and target* model outperforms a *foreign exchange rate* model. A *foreign exchange rate, target, and common factor* model outperforms a target model. Deeper disaggregation significantly increases accuracy, but only on near-term forecast horizons. It seems that, in terms of the effects of the exchange rate, the comparison of models of various degrees of disaggregation, *target* models, and *common factor* models is invariant: the results do not change when the exchange rate is added to or excluded from the models.

In general, the results indicate that the use of price dynamics of CPI components in forecasts may significantly improve their accuracy, but this is possible only after the common factors considered (even in a very simple manner). Absent the latter, model accuracy does not improve. Importantly, to compare forecasts over long periods of time, it is necessary to take into account changes in the parameters of inflationary processes, and a viable strategy to outperform the simple benchmark of the anchored forecast may be communicating information about the unconditional mean to the model.

Conclusion

This work explores the role of price dynamics of CPI components in forecasting headline inflation in Russia. As follows from the literature review and empirical evidence, disaggregated statistics can improve the accuracy of headline inflation forecasts. The results obtained for other countries are only partially confirmed in the case of Russian data.

Ultimately, price dynamics of CPI components can boost the accuracy of inflation forecasts, at least for short-term horizons. However, its inclusion is not the most important step to take. First of all, changing parameters of inflationary processes should be accounted, especially the transition to inflation targeting, and setting the unconditional mean of the inflation level at the inflation target. This approach is a decisive factor in the accuracy of forecasts on horizons of six months and longer.

Only after that disaggregated statistics can be used in forecasting. At the same time, it is necessary to recognise the dynamics of the common factors (for example, exchange rate effects). Without them, the sectoral statistics no longer improve the accuracy.

An indirect but important result of this study is the anchored forecast model supremacy. Even such a simple model sets the bar high for most non-structural models. For this reason, this model can be recommended as a simple benchmark for non-structural inflation forecasting models in Russia.

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Appendix

Table 1. Descriptive statistics of price dynamics of CPI components

	w	$E(\pi_t)$	$\sigma(\pi_t)$	$ACF(\pi_t)$	$corr$
All goods and services	100.0 %	0.68	0.43	0.73	1.00
CPI net of fruit and vegetables, oil products, and utilities	81.0%	0.62	0.38	0.77	0.93
Food products	38.2%	0.70	0.67	0.62	0.89
Food products Food products (excluding fruit and vegetables, and potatoes)	33.7%	0.71	0.52	0.78	0.82
Other goods	2.5%	0.46	1.45	0.37	0.14
Meat products	9.0%	0.68	0.68	0.83	0.54
Fish products	2.1%	0.75	0.79	0.85	0.68
Oil and fats	1.2%	0.79	1.61	0.64	0.42
Milk and dairy products	3.1%	0.79	0.83	0.74	0.41
Cheese	1.3%	0.74	1.77	0.65	0.30
Eggs	0.5%	0.73	3.95	0.08	0.29
Sugar	0.4%	0.67	4.30	0.44	0.41
Confectionery	2.6%	0.72	0.56	0.88	0.65
Tea and coffee	1.1%	0.64	0.80	0.84	0.55
Bread and baked goods	1.5%	0.83	1.03	0.70	0.38
Pasta and cereals	1.2%	0.86	1.83	0.76	0.54
Fruit and vegetables including potatoes	4.4%	0.74	3.28	0.43	0.61
Alcoholic beverages	4.6%	0.63	0.50	0.62	0.39
Public catering	2.5%	0.76	0.58	0.79	0.73
Non-food goods	35.0%	0.55	0.34	0.76	0.76
Non-food goods excluding petroleum products	30.5%	0.55	0.38	0.77	0.74
Other non-foods	3.8%	0.38	1.52	0.57	0.13
Clothes and underwear	4.2%	0.56	0.29	0.93	0.64
Furs	0.3%	0.37	0.32	0.62	0.55
Knitwear	1.0%	0.59	0.30	0.93	0.66
Leather, textile, and combined footwear	1.8%	0.52	0.31	0.87	0.57
Washing and cleaning products	0.8%	0.61	0.56	0.77	0.44
Perfumes and cosmetics	1.6%	0.61	0.48	0.80	0.54
Smallware	0.9%	0.58	0.33	0.87	0.61
Tobacco products	1.4%	1.13	0.79	0.79	0.01
Furniture	1.8%	0.53	0.35	0.81	0.77
Electrical goods and other household appliances	1.3%	0.41	0.91	0.51	0.53
Print media	0.2%	0.79	0.48	0.70	0.46
TV and radio goods	0.4%	0.12	1.07	0.35	0.43
Personal computers	0.5%	-0.05	0.86	0.56	0.40

	w	$E(\pi_t)$	$\sigma(\pi_t)$	$ACF(\pi_t)$	$corr$
Communication devices	0.7%	-0.14	0.65	0.60	0.37
Construction materials	1.0%	0.65	0.75	0.79	0.29
Cars	6.1%	0.49	0.59	0.65	0.54
Tools and equipment	0.1%	0.55	1.19	0.71	0.87
Petroleum products	4.5%	0.79	2.04	0.54	0.11
Medical goods	2.5%	0.59	0.87	0.76	0.54
Services	26.9%	0.89	0.71	0.70	0.63
Services excluding housing and utilities	16.7%	0.76	0.64	0.63	0.65
Other services	2.4%	0.32	1.29	0.49	0.36
Personal services	3.4%	0.76	0.47	0.87	0.61
Passenger transport services	2.1%	0.83	0.89	0.11	0.34
Communication services	2.8%	0.50	1.68	0.19	0.23
Utilities	10.1%	1.23	1.20	0.57	0.47
Education services	2.0%	0.86	0.55	0.61	0.53
Cultural services	0.3%	0.90	0.61	0.78	0.51
Foreign tourism services	1.6%	0.65	1.92	0.37	0.36
Excursion services	0.3%	0.85	0.91	0.24	0.39
Health resort services	0.4%	0.79	0.89	0.17	0.33
Medical services	1.5%	0.91	0.59	0.84	0.53

The columns from left to right show data on the weights of the product groups in the consumer basket, the average historical growth (month-on-month, seasonally adjusted), its standard deviation, the first-order autocorrelation of the same series, and the correlation between the corresponding series and the series for inflation in general.

Table 2. Models and RMSE metrics of their forecast accuracy (10.2015-11.2021)

Model	1 month	3 months	6 months	9 months	12 months
Anchored forecast	0.2397	0.2397	0.2397	0.2397	0.2397
RW	1.0813**	1.2166***	1.3408***	1.4616***	1.7954***
RW-AO (3 months)	0.9841	1.0866**	1.1935***	1.3071***	1.7406***
RW-AO (6 months)	0.9766	1.0548*	1.1579***	1.4318***	1.7384***
RW-AO (12 months)	1.0395*	1.1817***	1.3897***	1.5739***	1.7206***
RW-AO (36 months)	1.4261***	1.4758***	1.5508***	1.6207***	1.6714***
AR	1.0353	1.1764***	1.2820***	1.4343***	1.7858***
AR-3	1.0518	1.1807***	1.2974***	1.5413***	1.6597***
AR-6	0.9889	1.224***	1.2974***	1.4729***	1.6928***
AR-18	0.9969	1.2382***	1.2666***	1.4760***	1.7297***
AR-45	1.0178	1.1545***	1.2633***	1.4169***	1.7683***
AR (TVP)	1.0018	1.1063***	1.2591***	1.4581***	1.8523***
AR-3 (TVP)	1.0125	1.1451***	1.3216***	1.3454***	1.8218***
AR-6 (TVP)	1.0089	1.1389***	1.3139***	1.3966***	1.8763***
AR-18 (TVP)	1.0105	1.0877**	1.2726***	1.2379***	1.8586***
AR-45 (TVP)	1.0154	1.0955**	1.2562***	1.2437***	1.7971***
AR (direct)	1.0353	1.2624***	1.3566***	1.3139***	1.5922***
AR-3 (direct)	1.0444	1.2601***	1.2647***	1.3156***	1.5970***
AR-6 (direct)	0.9739	1.2055***	1.1464***	1.3397***	1.4863***
AR-18 (direct)	0.9971	1.2851***	1.4045***	1.2969***	1.5994***
AR-45 (direct)	1.0178	1.2276***	1.3209***	1.2975***	1.4215***
FAAR	0.9277**	1.0942**	1.2909***	1.2494***	1.6803***
FAAR-3	0.9706*	1.0939**	1.1867***	1.2421***	1.5477***
FAAR-6	0.9622*	1.0564*	1.1847***	1.2948***	1.5478***
FAAR-18	0.8951**	1.0148	1.2404***	1.3748***	1.7553***
FAAR-45	0.8541***	1.0221	1.2517***	1.3975***	1.8954***
AR-in-gap	0.8457***	0.9213**	0.9845	1.0125	1.0056
AR-in-gap-3	0.8532***	0.9217**	0.9702	1.0148	1.0012
AR-in-gap-6	0.8378***	0.9115**	0.9754	0.9867	1.0033
AR-in-gap-18	0.7805***	0.8814***	0.9676*	0.9552	1.0122
AR-in-gap-45	0.7584***	0.8633***	0.9515*	0.9937	0.9987

The calculation is based on regional data. The asterisks indicate the significance levels of the Timmermann and Zhu test (2019). Except for the benchmark, all RMSEs are shown in relation to the benchmark. The models with markedly less accuracy are highlighted in grey. The coloured fill indicates the models without disaggregation.