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VISIBLE PRICES AND THEIR INFLUENCE ON INFLATION EXPECTATIONS OF RUSSIAN HOUSEHOLDS

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ABSTRACT

A multitude of recent research shows that the inflation expectations of households are far from rational. In making inflation forecasts, people tend to focus on the prices of particular goods and services, which they can observe every day – 'visible prices'. In this paper, we propose a new method for the identification of such items. Our novel 'brute force' algorithm automatically sorts through the full array of prices of goods and services given by Rosstat and constructs consumer baskets. It then selects the best baskets based on their ability to forecast the inflation expectations of Russian households from the FOM Survey. In the end, we get a decomposition of various metrics of inflation expectations for visible prices which also demonstrates good forecasting performance (as compared to the AR(1) process as a benchmark). To ensure robustness, we use an alternative method (optimisation with regularisation) and a variety of metrics of inflation expectations. As a result, we get lists of 'robust visible items' which include not only foodstuffs but mainly durable goods and services. Surprisingly enough, oil and petrol, which are typically labelled 'visible goods' in research, do not fall into this category for Russia.

Keywords: inflation expectations, households, visible prices, visible items, Rosstat, FOM Survey

JEL classification: C43, C82, E31, E37.

CONTENTS

1. INTRODUCTION

Inflation expectations are a key policy variable under the inflation targeting regime. The modern forecasting and policy analysis system (FPAS) of central banks, which is based on the New Keynesian modeling framework focuses on the inflation expectations of households. In particular, structural models assume that these expectations determine the paths of current and future real macroeconomic variables. While DSGE models imply rational expectations, semi-structural models (such as the Bank of Russia's workhorse Quarterly Projection Model, QPM) use hybrid expectations, i.e., a weighted average of the inflation target (the 'rational part') and inflation lag (the 'adaptive part'). However, neither approach is able to account for real-life household expectations, which are far from being rational or even hybrid, as studies have shown. Real households, as opposed to the agents which populate structural macroeconomic models, perceive inflation and make projections differently. Moreover, changes in expectations might not transform into spending and portfolio decisions.

A multitude of recent research shows that individuals make systematic errors when analysing the economic environment. In other words, their perception is subject to cognitive distortions. As a result, people tend to focus on the prices of particular goods and services, which they can observe every day, as they are 'visible prices'. The Bank of Russia has referred to visible prices in its communication, although its list of 'visible items' has changed and there has been no scientific methodology behind it.

In this paper, we study the role of visible prices in the formation of inflation expectations using data from Rosstat and the FOM's household expectations survey. First, we find the items whose prices are most correlated or better statistically linked to household inflation expectations. Second, we employ an automatic selection algorithm to find the optimal consumer baskets composed of the most visible items. To the best of our knowledge, this algorithm has never been used before.

The rest of the paper is organised as follows: Section 2 presents a review of the literature on the subject; Section 3 discusses the data and its properties; Section 4 describes the models used to reveal the list of visible prices; Section 5 presents the estimates of the model and the principal findings; Section 6 tests the robustness of the results; and Section 7 concludes.

2. RELATED LITERATURE

Cognitive distortions and their sources

Since the Rational Expectations Revolution of the 1970s, many attempts have been made to enhance the socio-economic foundations of macroeconomic models. A wide range of experts, from economic psychologists to marketing specialists, have studied the problems of individual decision making. Their results are helpful for the aim of obtaining realistic model assumptions.

Two common sources of cognitive distortions are found in the literature: the information that the individual gets (Armantier et al., 2013) and the individual's perception of this information (Ranyard et al., 2008). The bias may be amplified by the external or socio-economic environment that the individual is influenced by from the outside and by the internal environment or, in other words, the environment that is influenced by the individual themself (Ranyard et al., 2008).

Tversky and Kahneman (1974) are perhaps the first to claim that people tend to pay attention to recent, frequent, sizeable, and positive increases in the prices of the items they often buy. Following this route, Bruine de Bruin et al. (2011) and Armantier et al. (2013) highlight the **consumer purchasing experience**. It is important that, according to Armantier et al. (2013), the wording of the questions in the survey is key: when people are asked about the 'expected growth of prices' ('how fast do prices grow'), they think about their actual consumer experience, while when they are asked about 'expected inflation', they refer to what they have seen on TV, heard on the radio, or read in newspapers or on social media. Researchers examine the following indicators to characterise the consumer purchasing experience: purchase frequency, share of goods in total income, and share of goods in the consumer basket. General price changes (inflation) are also observed by consumers and thus can be added this list (Armantier et al., 2013). The second channel is **information from external sources** not related to personal experience. People get information from the media and from official statistical releases. The mass media tends to interpret economic news in a biased way. For example, they often exaggerate negative news or underplay positive but predictable outcomes. Lamla and Lein (2008) point out two ways that the mass media affect household inflation expectations. First, the number of the reports about inflation in the media matters: a greater number of messages or articles makes consumers' inflation forecasts closer to a rational forecast. In addition, the quality of the messages and the manner the information is presented to the individual play a role: the wording of the message may reduce the forecasting accuracy of consumers. In their study of the role of information channels and life experience in the formation of German household inflation expectations, Conrad et al. (2022) find that the information channels are influenced by their socioeconomic characteristics. The authors suppose that households obtain their information about inflation mainly from the media, while their own ‘economic models’ are shaped on the back of their life experience.

Evstigneeva and Karpov (2023) note that the inflation expectations of Russian households are mainly impacted by recent news, especially by negative news. They find that there are three topics which exert the most considerable influence on household inflation expectations: news about the economic situation, about the ruble exchange rate, and about inflation itself. When respondents make statements concerning future inflation, they refer to the general macroeconomic outlook. When asked about past inflation, they rely on news about price dynamics as well as on the living standards in the country. According to the authors, negative news on the economic situation in Russia serves well as a predictor of future medium-term (12 months ahead) household inflation expectations. The authors’ results are in line with the literature on the anchoring of inflation expectations, which finds a significant negative correlation between inflation expectations and the economic outlook (Reiche and Meyler 2022), and with the evidence from the Russian survey of inflation expectations (FOM Survey).

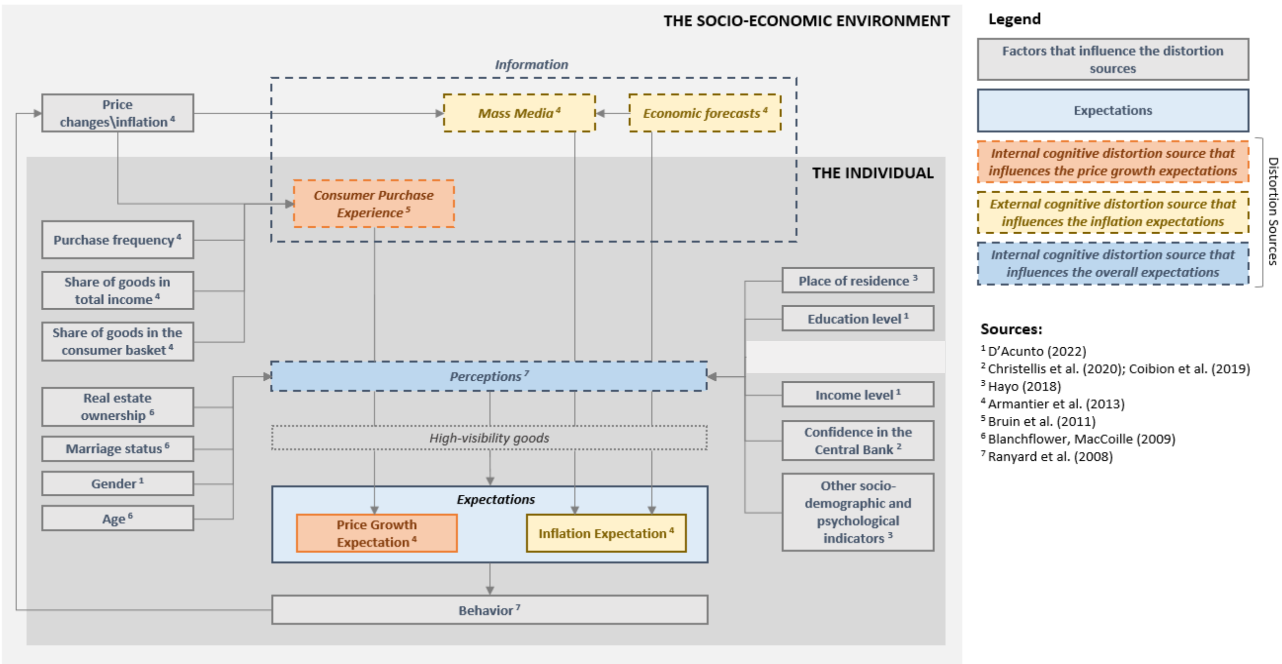
Even if the information consumed by an individual is unbiased, distortions may still emerge as a result of the ‘processing’ of this information or, in other words, in the process of perception (Ranyard et al., 2008). After the information is consumed by households, their thinking process comes into play. Along with socio-demographic and psychological factors such as gender (D’Acunto, 2022), age (Blanchflower and MacCoille, 2009), marital status (Blanch-flower and MacCoille, 2009), real estate ownership (Blanchflower and MacCoille, 2009), place of residence (Hayo, 2018), level of education, race, and income level (D’Acunto, 2022), confidence in the central bank also plays a role (Coibion et al., 2019; Christellis et al., 2020). Researchers document that the perception bias of households tends to persist over time. For instance, Abildgren and Kuchler (2021) study microdata from the EU-Harmonised Consumer Expectations Survey as regards Danish respondents. They find that those who have participated in the survey more than once retain a biased view of macroeconomic developments. Hence, perception bias might be linked to personal socio-demographic characteristics. Angelico et al. (2019) find a discrepancy between the inflation expectations of rich and poor households. According to the authors, the higher inflation expectations of the poor are the result of their different shopping experience and media information. Poor respondents give weight to frequent and salient price fluctuations. Rumler et al. (2019) also highlight the importance of confidence in the central bank and the level of literacy. They note that households with relatively higher levels of inflation literacy tend to have lower and more accurate short-term and long-term inflation expectations. At the same time, such households are less certain about their inflation expectations than people with lower levels of inflation literacy.

Zhemkov and Kuznetsova (2019) study verbal interventions as a factor in the high-frequency inflation expectations of the financial markets in Russia and show that one of the most critical factors that impacts inflation expectations is the communication policy of the central bank and the messages of government officials. They conclude that verbal interventions in the form of statements about the decreasing budget deficit and a future drop in inflation contributed to the decline of inflation expectations in July 2015–December 2016.

Evstigneeva, Shchadilova, and Sidorovskiy (2022) study the nature of Bank of Russia monetary policy shocks (‘monetary policy surprises’). The authors find that professional forecasters make virtually no mistakes in their key rate projections if central bank officials conduct verbal interventions before a decision. Thus, in Russia, monetary policy communication has a meaningful impact on expectations, at least on those of professional forecasters.

The process of the formation of inflation expectations is summarised in Figure 1.

Figure 1.Mechanism of formation of household inflation expectations



Source: compiled by the authors.

To sum up, there are multiple distortions of the signals coming from the general price level and other macroeconomic variables to people’s inflation expectations, and they can be studied in a number of possible ways, depending on the data available. In this paper, we concentrate on the role of the consumer experience – in other words, on the prices of particular goods and services, the dynamics of which households can observe every day. These are ‘visible prices’.

Visible prices

The dynamics of the prices of highly visible items can explain and may be useful for projections of household inflation expectations. Goods or services can be considered highly visible if they meet the following criteria:

a. the good or service is often mentioned in the news

b. the good or service accounts for a significant share of consumption or total income

c. the good or service has close statistical links with inflation expectations

There is much literature devoted to the identification of highly visible goods. Such research usually employs market-based and survey-based approaches, descriptive statistics, and multivariate regressions. Clark and Davig (2008) report that shocks to food prices have a significant and persistent impact on long-run inflation expectations in the United States. The impact of energy prices, however, is found to be insignificant. The authors highlight the high volatility of energy prices but describe their effect as 'temporary' and, hence, as having negligible weight on price changes. At the same time, food prices prove to be more persistent, to say nothing about their larger share in the consumer price inflation basket. Matytsin (2011) also finds that foodstuffs are highly visible goods. The author develops and implements a mechanism for calculating cross-group price indices for the food purchases of different income groups, taking into account the cross-group price dynamics in each year. Weber et al. (2019) show that people form their inflation expectations mostly relying on the prices of grocery products, which they can observe on a daily basis. D'Acunto et al. (2022) turn to the underlying process of the formation of inflation expectations and also highlight the importance of changes in the price of groceries for the formation of household inflation expectations. Cavallo et al. (2014) underline supermarket products as a source in the formation of household inflation expectations. Angelico et al. (2019) also refer to grocery prices.

A number of authors claim that oil prices also tend to be visible. Conflitti et al. (2017) conclude that changes in oil prices had a statistically significant impact on long-term inflation expectations in the euro area after the beginning of the financial crisis. The link between oil prices and long-term inflation expectations is not direct, but rather stems from underlying factors: continued unfavourable economic conditions and the possible decoupling of long-term inflation expectations from price stability. Kilian and Zhou (2021) also find that oil and petrol prices shift households' one-year inflation expectations. According to their estimates, on average, petrol price shocks account for about one third of the variation in these expectations. Moreover, they claim that the cumulative rise of these expectations in the US following the Global Financial Crisis (2009–2013) can be almost entirely explained by unexpectedly rising petrol prices. Consequently, to their mind, this finding can significantly improve the fit of the Phillips curve for the US for the corresponding period. Coibion and Gorodnichenko (2013) also identify oil as a visible item. Its fluctuations, in their view, may explain the changes in the inflation expectations of US households in 2009–2011. Campos et al. (2022) highlight that consumers seem to focus on the prices they see most often, such as the prices of food or new cars.

Thus, researchers tend to identify the following groups of items as highly visible:

- oil and oil products
- grocery products (food)
- cars

The latest research on Russian data shows that the list of visible goods in Russia may be wider. Grishchenko et al (2022) use correlation analysis and find that, in addition to several food products (curd and herring), the most visible goods include various types of cigarettes and tobacco and healthcare items (aspirin, bandages, corvalolum, metamizole sodium). Overall, household expectations in Russia seem to be unanchored and sensible to exchange rate movements and lagged inflation.

In this paper, we propose a scientifically grounded method to identify visible prices.

3. DATA

To account for the role of visible prices in the formation of inflation expectations, we use both actual and survey data on consumer prices and survey data on the inflation expectations of Russian households. The actual data are taken from official statistics (Rosstat). The survey data are from the survey of inflation expectations conducted by the Public Opinion Foundation (FOM).

3.1. Rosstat

Russia's official statistical agency (Rosstat) issues public releases on the dynamics of the prices of 824 categories and groups of items on a monthly basis. To ensure comparability with the data on expectations, we use indices of monthly series starting from 30 April 2014 (30.04.2014 = 100) to December 2021. We start by considering the full range of 824 indices and then filter out data with multiple omissions and group items and generalised categories. We also get from Rosstat the weights of the goods and services included in the consumer basket used for the calculation of official inflation (consumer price index, CPI) by Rosstat. We use these weights later, in the first step of our automatic selection algorithm (see Section 4.2.).

In the end, we get a dataset consisting of 80 series of price indices (big and medium categories which amount to 74% of the average consumer basket, according to the weights calculated by Rosstat).

3.2. FOM Survey

In a joint project by the Bank of Russia, the Public Opinion Foundation (FOM), and the National Agency for Financial Research (NAFI), FOM has been conducting surveys of household inflation expectations and consumer sentiment on a monthly basis since April 2014. On the whole, the methodology conforms to that of the Michigan Survey of consumers and of similar projects by other central banks, but it also takes the socio-cultural specifics of Russia into account.

The sample is representative of the adult Russian population. Each survey consists of the answers of about 2000 respondents from 55 constituent entities of the Russian Federation. Personal interviews are conducted face-to-face at respondents' places of residence. However, it is not a panel survey, and new respondents are asked each time. The questionnaire includes the following blocks:

- questions on the assessment of actual inflation and inflation expectations at different time horizons (monthly, quarterly, annual, three-year)
- questions aimed at assessing consumer sentiment, which are used to calculate the consumer sentiment index
- questions about saving and credit behaviour
- questions about the use of financial instruments and specific features of financial behaviour

The results of the survey are widely used in the monetary policy communication of the Bank of Russia.

For the purposes of our study, we use four metrics of inflation expectations:

1a, 1b) Expected inflation stemming from the ‘Balance of answers’, short- and medium-term (hereinafter ‘BoA EI ST’ and ‘BoA EI MT’): a qualitative estimate of future inflation in 1 month and in 12 months, the difference between the shares of those who expect that ‘prices will grow faster than now’ and those who expect that ‘prices will grow slower’ OR ‘prices will remain the same’ OR ‘prices will decrease’. We exclude respondents who struggle to give any answer from the estimation of the metric.

2) ‘Direct estimate’ or ‘median expected inflation’ (hereinafter ‘Median EI’): the annual inflation (quantitative indicator, measured in %, YoY) people expect in one year’s time.

3) ‘Observable inflation’ (hereinafter ‘OI’): people’s opinion about current annual inflation (quantitative indicator, measured in %, YoY).

Notably, the second indicator (1b) is closely linked to respondents’ consumer experience (since they are asked about the medium-term growth of prices, not inflation per se) while the rest are representative of the impact of the media (but might be loosely connected to consumer decisions) – see Section 2 for details. Additionally, as Slobodyan has demonstrated, median EI and OI are so highly correlated that they may be generated by the same data-generating process (Slobodyan 2019).

4. MODELS

There are many ways to model consumers' cognitive distortions and their impact on household inflation expectations, and the dynamics of inflation expectations can be decomposed in various ways, depending on the set of factors. As we demonstrate in Section 2, if the relevant data are available, researchers may test the link between inflation expectations and a number of socio-demographic characteristics, macroeconomics variables (including lagged inflation and the inflation target), economic news, or visible prices.

When inflation expectations are regressed on a number of factors, the endogeneity problem arises and the omitted variable bias must be overcome. Hence, it is meaningful to search for the best predictors and not for factors (in other words, to solve the problem of forecasting rather than the best fit). Machine learning and factor methods are also suboptimal in our view, since their results are hard to explain in terms of economic intuition. Nevertheless, they may, with other methods, participate in a 'horse race' aimed at obtaining the model with best forecasting performance.

The advantage of decomposing household inflation expectations on the impact of visible prices is that these variables are observable and present in monetary policy communication and are therefore easy to interpret. These prices may not only be used by consumers in the formation of inflation expectations but also have a more pronounced impact on their economic decisions (in other words, negative news may make consumers more anxious but only moderately affect their decisions). In order to estimate the impact of news correctly, the researcher must conduct a controlled experiment. To the best of our knowledge, none has ever been carried out for Russia.

All in all, given that the dynamics of the prices of highly visible goods are reflected in people's consumer experience, in the news background, or in their perception of information, in this paper, we consider price indices of baskets of highly visible goods as predictors of inflation expectations.

To derive the list of the most highly visible goods and services, we use two groups of methods. The manual selection methods aim at identifying the items which meet the criteria given in Section 2. Automatic selection is an algorithm which sorts the candidate items and puts them together in baskets automatically using the criterion of their ability to explain or predict the dynamics of prices or inflation expectations. In all cases, we use inflation expectations from the FOM survey as dependent variables.

4.1. Manual selection

We use two different approaches to manual selection.

The first relies on the assumption of a 'single data-generating process', i.e., that information about inflation expectations and highly visible prices should be generated by the same source. Namely, we explore the relationship between FOM inflation expectations (BoA EI ST, BoA EI MT, and Median IE) and the prices of goods and services which are mentioned by the respondents as having 'risen significantly during the last month'.[1] We look at either correlations or OLS linear regressions. The advantage of this method is that the respondents are asked about their own shopping experience. Hence, the outcomes – both inflation expectations and visible prices – are influenced by the same list of other factors, internal or external in nature. The weakness of the method is that both inflation expectations and visible prices may reflect not actions but people's intentions or inner emotions about price developments. Additionally, the set of candidate visible items in the FOM survey is far from full and includes only large categories. Finally, the estimates of several weights may be below zero, which complicates the interpretation of the results.

The second approach ('intention-action'), partly implemented by Grishchenko et al (2022), is based on the notion that visible prices are usually more volatile and make up a substantial share of the actual consumer basket. We begin with the construction of a list of candidate items using information on the prices of the candidate items from Rosstat statistics. To reduce their number, we also take into account the items most frequently mentioned in Bank of Russia statements and in interviews with officials. We then select the most visible items by looking at the correlations between prices of the candidate items and FOM inflation expectations (BoA EI MT and Median EI). In doing so, we explore the link between people's intentions (inflation expectations from FOM) and the results of consumer actions (actual prices from Rosstat). This approach lets us study much wider range of candidate items (more than 700 categories). However, it lacks scientific justification.

On the whole, manual selection approaches can produce only illustrative results. To upgrade both approaches, we proceed to more formal automatic selection methods.

[1] In Russian: 'По Вашим наблюдениям, на какие основные продукты, товары и услуги, перечисленные на карточке, цены за последний месяц выросли очень сильно? (Карточка, любое число ответов.)'

4.2. Automatic selection

We use a two-step algorithm to identify visible goods and services.

The first step involves a search for the best baskets of potentially visible items in Rosstat's data on actual prices assuming fixed actual weights for the items in each basket. The fixed-weight method can be interpreted as the 'second-best' option. The reason is that, owing to bounded rationality, people may fail to remember the precise frequency of purchases of visible items or their exact share in each household's consumer basket. Hence, in the process of the formation of inflation expectations, they refer not to actual weights (as reported by Rosstat) but to implied weights for the visible items.

In the second step, we evaluate these implied weights. We give up the assumption of fixed weights and let them adjust (at the same time, the list of items is now regarded as given). In the end, we get baskets in which both the items and their weights are optimal.

Step 1: Optimal basket selection (actual weights)

Our aim is to select the best baskets based on their power in predicting inflation expectations, using RMSE as a criterion. The best basket's price index is the one with the lowest RMSE as compared with the benchmark forecasting model, the AR(1) process for inflation expectations (for each basket, we calculate the value of the criterion as the share of the RMSE of the AR(1) model). We assume in this step that the weights of the items in the basket are fixed and are taken from Rosstat (see Section 3.1.).

Initially, we create baskets of the 4 major categories of goods and services which are included in the monthly CPI by Rosstat.[2] We get the new weights for the items in the basket by normalising their initial actual weights. The index of each basket j is calculated using the formula:

$$P_{basket,j} = k_{1,j}P_{1,j} + k_{2,j}P_{2,j} + \cdots + k_{n,j}P_{n,j} \tag{1}$$

where $P_{i,j}$ is the (monthly) price of the i-th item ($i = 1\ldots4$) in the basket, $k_{i,j}$ is the normalised weight of the i-th item in the basket, and n is the number of items in the basket.

The new weights are calculated the following way:

[2] The low number of candidate items is explained by the limited computing capabilities of the software. We hope to increase it in later versions of the paper. Nevertheless, the number cannot be much higher because the data are also limited: the first observation is April 2014, the last is January 2022, and a number of values are omitted.

$$k_{i,j} = \frac{w_{j,i}}{w_{j,1} + \cdots + w_{j,i} + \cdots + w_{j,n}} \quad (2)$$

where $w_{j,i}$ is the initial weight of the *i*-th item in the CPI consumer basket reported by Rosstat.

After that, we regress each type of inflation expectations (short- and longer-term 'balance of answers', 'direct estimate', and 'observable inflation') on the price index of each basket:

$$\pi_j^e = \beta_0 + \beta_1 P_{basket,j} \quad (3)$$

where π_j^e is a metric of inflation expectations from the FOM survey.

Note that we do not include macroeconomic variables as regressors in (3). The reason is that we do not aim to find the best model for forecasting inflation expectations. Rather, our goal is to obtain the best decompositions of inflation expectations for visible items with 'good' forecasting ability (the baskets should outperform the benchmark AR(1) process).

For each regression, the training sample consists of 80% of observations. The selection of the best models is made based on their forecasting performance on the rest of the sample (20%) as compared with the AR(1) process.

Having obtained a 'rating' of the best baskets, we search for the 10 most frequent items in 5,000, 10,000, or 50,000 baskets. The frequency of each item is calculated in the following way:

$$f_{item} = \frac{N_{item}}{N_{baskets}} \quad (4)$$

where N_{item} is the number of baskets which include the item and $N_{baskets}$ is the total number of baskets (5,000, 10,000, or 50,000).

At the end of the first step, we get baskets consisting of (maximum) 10 visible items each.

Step 2. Optimal basket selection (implied weights)

In the second step, we assume that actual item weights given by Rosstat are no longer applicable for the calculation of inflation expectations. In other words, we suppose that people take into account not Rosstat's de facto item weights but 'implied' weights, the values of which might be affected by personal consumer experience and news. To find these implied weights, we propose two approaches to the construction of an optimisation procedure.

1) Grid search

Having found the best baskets for each type of inflation expectations in step 1, we further optimise the weights in baskets consisting of 5 of the most frequent items using grid search.[3] For each combination of weights, we construct an index for the respective basket:

$$P_{basket,j} = l_{1,j}P_{1,j} + l_{2,j}P_{2,j} + \cdots + l_{i,j}P_{i,j} \tag{5}$$

where $l_{i,j}$ are weights calculated using grid search implying $l_{i,j} \in [0,1]$ with a step size of 0.005.

Then, inflation expectations are regressed on each basket's index (the specification is identical to (3)) on the training sample (80% of the whole sample). After that, RMSE is calculated for each regression, and the best combination of $l_{i,j}$ is selected on the basis of the RMSE criterion (smallest RMSE), calculated for test sample (20% of the whole sample).

This method yields the best results in terms of forecasting performance but may explain the tendencies in the training sample worse than the direct optimisation method (see below). In other words, it may increase the weights of the items which are more successful in the test sample which, in turn, may occur by chance. Also, this method is computationally demanding (we can get estimates for baskets consisting of no more than 5 parameters) and requires a lot of memory space. The results of the method might be suboptimal if the optimum is between the nodes of the grid.

2) Direct optimisation

[3] The low number of items is explained by the limited computing capabilities of the software. We hope to increase it in later versions of the paper.

In this method, the coefficients for the most frequent items (up to 16) found in step 1 are calculated directly by OLS estimation of the parameters in a (single) regression on the training sample (80% of the whole sample), with the restriction that $\gamma_{i,j} \geq 0$:

$$\pi_j^e = \gamma_{0,j} + \gamma_{1,j} P_{1,j} + \gamma_{2,j} P_{2,j} + \cdots + \gamma_{\square,j} P_{i,j} \tag{6}$$

Next, the values of $\gamma_{i,j}$ are normalised (converted into weights $\omega_{i,j} = \frac{\gamma_{i,j}}{\sum \gamma_{i,j}}$).

$$P_{basket,j} = \omega_{1,j} P_{1,j} + \omega_{2,j} P_{2,j} + \cdots + \omega_{i,j} P_{i,j} \tag{7}$$

Then, inflation expectations are regressed on each basket's index (the specification is identical to (3)) on the training sample (80% of the whole sample). After that, for the coefficients obtained for this regression, RMSE is calculated for testing sample (the remaining 20% of the sample).

This method more accurately explains the trends in the training sample than grid search. At the same time, it is suboptimal in terms of forecasting.

All in all, the methods complement one another. If an item is significant according to both methods, then we are more confident in labelling it as 'visible'.

5. RESULTS

This section presents the main results of the paper.

5.1. Manual selection

The ‘intentions’ of households revealed from the correlation of inflation expectations with the candidate items and the corresponding regressions show that the list of candidate items is highly heterogeneous.

Single data-generating process approach

The correlations between BoA EI inflation expectations and the candidate items are rather weak, especially when it comes to medium-term expectations (BoA EI MT). The highest correlation is between BoA EI ST and the prices of meat and poultry (0.8), while the correlation between the prices of fish and seafood, eggs, milk and dairy products, cheese and sausages, and pasta and BoA EI ST amounts to 0.6.

The list of items whose correlation coefficient with the expected inflation metric (Median EI) is 0.7 or higher include most food categories which people usually look at when making purchases in grocery stores: fish and seafood, cheese and sausages, meat and poultry, cereals and pasta, pastries, fruits and vegetables, tea and coffee, juice and carbonated beverages, and medicines and drugs. The list of correlations exceeding 0.8 is shorter, but it still includes fish and seafood, cheese and sausages, tea and coffee, pastries, and juice and carbonated beverages. The full table of correlations can be found in the Appendix.

It is interesting that the correlations of the candidate items with two distinct metrics of inflation expectations, Median EI and OI, are very close for all items mentioned in the survey (the discrepancies do not exceed 0.1–0.2, while the correlations of the items with Median EI are nearly always higher than their correlations with OI). Notably, the correlation between the two metrics is even higher, reaching the level of 0.89 (!). We can draw two conclusions from these facts: either (a) in Russia, inflation very much depends on its lags or, as Slobodyan notes, (b) in Russia, the time series for observed inflation and median expected inflation are created by the same data-generating process and the statistical differences between the two time series are insignificant (Slobodyan 2019). In other words, (b) means that people do not forecast inflation at all, rather, they think that tomorrow’s inflation will not differ from today’s.

The regression of inflation expectations ('Median EI') on the full list of candidates yields a somewhat different 'short-list' of items with statistically significant coefficients. These items are: fish and seafood products, cheese and sausages, bread and bakery products, milk and dairy products, clothing, footwear, and leather goods (see the Appendix for summary of regression results).

A comparison is provided in the table in the Appendix.

It is noteworthy that the results obtained refer mainly to households' perceptions and not to their consumer experience: the correlation between BoA EI MT (which is most representative of the link between consumer experience and inflation expectations) is weak, while the other metrics refer to the impact of the media. The items in the table may therefore be interpreted as visible items only with caution.

On the whole, the table shows the items that people mention most frequently. But are their perceptions translated into their actions? Put another way: do actual purchases of such items contribute to inflation expectations, or are there any signs that people avoid buying such items and replace them with similar substitutes?

Intention-action approach

The correlations revealed between BoA EI MT and the candidate items are also relatively low. As for the link between BoA EI ST and the candidate items, only meat, poultry and sulfacetamide (an anti-bacterial medicine) can be included in the list of visible items (their correlations are 0.4, 0.4, and 0.5, respectively). This points to the low effectiveness of this method as a tool for identifying visible items.

The correlations of the candidate items with expected inflation (Median EI) indicate that the prices of the following items are most noticeable to consumers: medicines (aspirin, bandages, corvalolum, metamizole sodium), tobacco and cigarettes, fish (herring), and dairy products (curd). This, in general, goes in line with the results of the first approach. The summarised results are presented in the Appendix.

Surprisingly, neither approach identifies petrol or oil, the price of rent, or municipal fees as visible goods. Petrol and oil are perhaps not identified owing to the fact that petrol prices in Russia are regulated and not volatile. At the same time, the absence of petroleum is more surprising given the commodity-driven nature of the Russian economy and the link between global oil prices, the exchange rate, and inflation. The absence of vegetable prices is quite surprising as well but can be explained. While intensively consumed by Russians, vegetables are either rather cheap, or they might be grown by people themselves, in their gardens or at their dachas.

To summarise, the results obtained from the use of manual selection approaches should be regarded as preliminary and interpreted with caution. Mainly, they show which prices are most noticeable to households, but this is not necessarily linked to the consumer experience. In general, these manual selection methods are too weak to accurately identify which items can be regarded 'visible' for Russian households.

5.2. Automatic selection

First, we report the table containing the best 10 baskets in terms of model RMSE as a share of the AR(1) model's RMSE (the winners of the 'horse race') for all four metrics of inflation expectations (see the Appendix). However, these results are very preliminary, since each of these baskets may have 'won' only accidentally. To make the results more robust, we also calculate the frequencies of each item in the best baskets (5,000, 10,000, or 50,000) using formula (4) (also see the Appendix). The lists of items are relatively stable irrespective of the number of best baskets (5,000, 10,000, or 50,000). At the same time, they contain services and durable goods and are more heterogeneous compared to the results of the manual selection methods.

For the short-term balance of answers (BoA EI ST) metric, the visible items are: cars and car tyres, poultry and pork, and rent (they are present in all lists, for 5,000, 10,000, and 50,000 best baskets). With a degree of certainty, we may add furniture and firewood, home repair and maintenance, repair of vehicles, and funeral services to the list of visible items.

For the medium-term indicator (BoA EI MT), the list of visible items consists of clothes, footwear, haberdashery, home repair and maintenance, urban passenger transport, and educational services.

For expected inflation (Median EI), cars and car tyres, furniture, meat and poultry products, and rent also fall into the list of visible items. Beer, confectionery, clothes, and educational services are also visible, but to a lesser extent.

Finally, for observed inflation (OI), again, cars, furniture, and meat products can be deemed visible. Other items selected include a number of intersections with the results of the manual search: bread and bakery, flour confectionery, and fish and seafood. Interestingly, petrol can be identified as a visible item only for OI.

After selecting the best baskets consisting of the most frequent items, we let the items' weights vary and get the following results from the second step (see the Appendix).

The results of the grid search method are the following. For BoA EI ST, the list of visible items contains only car tyres, cars, furniture, rent, and repair of houses. For BoA EI MT, the visible items are footwear and clothes, repair and maintenance of houses, and hot water supply and maintenance. For Median EI, the prices of beer, meat and poultry, sausages, female clothes, cars and car tyres, furniture, and public catering can be considered visible. For OI, surprisingly enough again, the visible items are fish and seafood, beer, flour confectionery, and repair and maintenance of houses.

As compared with the grid search, the list of visible items returned by direct optimisation is somewhat shifted towards services: public catering, repair and maintenance of houses, and urban public transport.

The most significant visible items (detected by both methods) are: for BoA ST – repair and maintenance of houses; for BoA MT – male and children's footwear; for Median EI – public catering and car tyres; for OI – flour confectionery.

The procedure of the second step does not improve the forecasting results of the baskets obtained in the first step, but it still shows that the forecasting performance of 'robust baskets' is, generally, still better than the benchmark. For BoA EI ST and BoA EI MT, the optimisation of the weights makes the results for the robust baskets comparable with the baskets which win the 'horse race'.

Table 1. Model performance, shares of RMSE of respective AR (1) models

	Fixed weights (average RMSE for best 10 baskets)	**Implied weights – grid search (RMSE for robust baskets)**	**Implied weights – direct optimization (RMSE for robust baskets)**
Balance of answers, 1M	58%	66%	81%
Balance of answers, 1Y	73%	76%	79%
Median EI	18%	121%	85%
Observed inflation	11%	33%	84%

Source: authors' calculations.

6. ROBUSTNESS CHECKS

For the manual selection algorithms, robustness is ensured by the use of four different metrics for inflation expectations and two empirical methods (correlations and OLS regressions).

To check the robustness of the automatic selection algorithm, we employ a different method for searching for visible items: direct optimisation with restrictions. Generally, it looks similar to the way we optimise the weights in step two of our main automatic search algorithm, but now we apply it from the very beginning and to the whole sample. To decrease the number of optimised parameters, we use regularisation (adding the sum of the absolute values of the parameters to the optimised function, in addition to the standard restrictions on the weights – the sum of the parameters should be one, and every parameter should be greater than zero). In effect, we try to find a few parameters that ensure the best fit of the baskets of visible items for various metrics of inflation expectations under the assumption of implied weights (as in step two of the main algorithm). Before estimation, we take the second differences of the variables to avoid spurious regressions. To take into account the lagging nature of inflation expectations and timing of respondents' receipt of information, we use lags of the regressors instead of their current values.

We also check the results of the main 'brute force' method using other estimators of inflation expectations (month-on-month, MoM, values instead of year-on-year, YoY).

Our calculations show that the lists of visible items remains relatively stable (for details, see the Appendix).

7. DISCUSSION AND CONCLUSIONS

Trends in household inflation expectations and professional forecasters' inflation expectations do diverge. This can be explained by the following considerations (Grishchenko et al 2022): people do not have enough stimuli and proficiency to forecast inflation with a high degree of accuracy, while their opinions about how high inflation is do not directly translate into future prices. As opposed to professional forecasters' inflation expectations, those of households remained unanchored in Russia. This paper attempts to discover the nature of household inflation expectations by revealing their key drivers under the assumption that the 'structure of consumption' matters.

The derivation of the list of visible items is the first step in understanding how households form their inflation expectations. After these items are known, the causal relationship can be studied. Although it is not the only way to decompose inflation expectations, given the specifics of the available data, this is one of the best methods of revealing the key drivers of inflation expectations.

We do not include macroeconomic factors in our regressions (though it may potentially improve the forecasting performance of the models) since we do not aim to get the best forecasts of inflation expectations. Likewise, we do not intend to forecast the 'trend inflation index' (Deryugina et al. 2015) of other metrics of underlying inflation using the prices of the visible items identified. Rather, our goal is to obtain the best decompositions of inflation expectations for visible items with 'good' forecasting ability (in terms of predictions of inflation expectations).

To obtain the lists of 'visible items', we use two types of methods, manual and automatic selection, which produce similar but somewhat different results. The divergence can be explained by the different initial ranges of the prices. In the 'single data-generating process' approach, the visible prices are filtered out of a list of 34 aggregated categories which lack a number of important items (such as cars). On the contrary, in the 'intention-action' approach, the initial list of items consists of 30 disaggregated categories which also do not include rarely purchased items, which are seldom mentioned in the news. Consequently, the list of 'visible items' derived in the process of manual selection may be biased towards food, drinks, and other everyday products.

The automatic selection approach also has drawbacks. The data on inflation expectations and prices are obtained from different sources, so they suffer from a lack of integrity. Nevertheless, this method sorts the items in a systematic way based on a more convincing criterion – RMSE (as a % of the RMSE of the benchmark AR(1) model). As a result, this method extends our knowledge of visible prices in the sense that, contrary to the existing literature, the list consists mainly of services and durable goods: cars and car tyres, furniture, clothes, footwear, haberdashery, rent, home repair and maintenance, urban passenger transport, and educational services. This means that the inflation expectations of households might be more resistant to fluctuations in the prices of food products and other highly volatile items.

For future research, one of the next steps might be an exploration of the link between household's inflation expectations and their actions (consumer and financial behaviour). Unfortunately, the existing data on inflation expectations in Russia do not allow the possibility, leading to the need for an effort to construct new waves of surveys with embedded economic experiments.

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Appendix

Table 1. Visible items (single data-generating process approach)

#	**Correlations with BoA EI ST (0.6 or higher)**	**Correlations with Median EI (0.8 or higher)**	**OLS regression (items with statistically significant coefficients)**
1	meat and poultry	*fish and seafood*	*fish and seafood*
2	*cheese and sausages*	*cheese and sausages*	*cheese and sausages*
3	*fish and seafood*	*tea and coffee*	*milk and dairy products*
4	*milk and dairy products*	*confectionery*	*pasta*
5	*pasta*	juice and carbonated beverages	*tea and coffee*
6	eggs		*confectionery*
7			bread and bakery products
8			clothing, footwear and leather goods
9			fruit and vegetables
10			alcoholic beverages
11			household chemicals
12			tobacco and cigarettes
13			Internet and mobile services

Source: authors' calculations.

Table 2. Correlations (single data-generating process approach, observed inflation, median inflation expectations, prices of items mentioned in FOM)

(All respondents, n = 2000)

Items	Median IE	OI
Bread and bakery	0.47	0.36
Meat and poultry	0.77	0.62
Fish and seafood	0.88	0.86
Eggs	0.55	0.41
Milk and dairy products	0.65	0.48
Cheese and sausages	0.85	0.76
Vegetable oil	0.60	0.59
Sugar, salt	0.68	0.63
Pasta	0.72	0.63
Fruit and vegetables	0.71	0.72
Juice and carbonated beverages	0.82	0.78
Alcoholic beverages	0.64	0.47
Tea, coffee	0.84	0.91
Confectionery	0.87	0.88
Household chemicals	0.68	0.77
Clothing, footwear and leather goods	0.61	0.67
Electronics and appliances	0.56	0.60
Furniture	0.55	0.52
Construction materials	0.51	0.46
Medicines	0.76	0.82
Children's goods	0.70	0.70
Gasoline	-0.15	-0.30
Tobacco and cigarettes	0.54	0.37
Perfumes and cosmetics	0.63	0.65
Printed materials (newspapers, magazines, etc)	0.47	0.38
Housing and communal services	0.29	0.22
Medical services	0.51	0.51
Passenger transport services	0.36	0.35
Tourist services	0.54	0.54
Café and restaurants	0.52	0.52
Home services	0.62	0.63
Internet and mobile services	-0.27	-0.25
Educational services	0.07	0.04
Services of cultural institutions (museums, cinema, theatres, etc)	0.24	0.21
Else	0.62	0.55
None	-0.50	-0.34
It's difficult to say	-0.79	-0.68
OI	0.89	1.00
Median IE	1.00	0.89

Source: authors' calculations based on FOM survey.
Note: OI is labelled as INF_OBS, and Median EI is labelled as IE.

Table 3. Summary of OLS Regression, significant coefficients (single data-generation process approach, observed inflation, median inflation expectations, prices of items mentioned in FOM)

(All respondents, n = 2000)

	Median IE		OI	
	coefficient	p-value	coefficient	p-value
Bread and bakery	-0.0985	0.042	-0.2129	0.002
Fish and seafood	0.1558	0.01		
Milk and dairy products	0.0878	0.046	0.1545	0.012
Cheese and sausages	-0.1358	0.027		
Pasta			-0.1035	0.007
Fruit and vegetables			-0.1008	0.016
Alcoholic beverages			-0.2863	0.003
Tea, coffee			0.2854	0.004
Confectionery			0.4426	0.001
Household chemicals			0.5503	0.000
Clothing, footwear and leather goods	0.14	0.025		
Electronics and appliances			-0.4044	0.004
Construction materials	0.1377	0.004	0.3116	0.000
Tobacco and cigarettes	-0.1468	0.025	-0.1962	0.029
Printed materials (newspapers, magazines, etc)			-0.7877	0.002
Passenger transport services			0.1806	0.023
Internet and mobile services	-0.1518	0.057	-0.3064	0.006
Other	0.3827	0.001	0.4557	0.003
None	-0.1768	0.005	-0.1772	0.039
It's difficult to say	-0.1607	0.048	-0.0595	0.588

Source: authors' calculations

Table 4. Visible items (intention-action approach)

#	Correlations with BoA EI ST (0.4 or higher)	Correlations with Median EI (0.5 or higher)
1	meat and poultry	milk and dairy products (curd)
2	*medicines* (sulfacetamide)	fish (herring)
3		tobacco and cigarettes
4		*medicines* (aspirin, bandage, corvalolum, metamizole sodium)

Source: authors' calculations.

Table 5. Correlations of various types of FOM inflation expectations with lags of actual prices of candidate items (intention-action approach)

	INFLATION_FOM_OBS	INFLATION_YOY	IE_FOM_MED_MR	IE_FOM_BAL_MR	IE_FOM_BAL_SR
P_ASPIRIN(-1)	0,6	0,7	0,5	-0,2	0,4
P_BANDAGE(-1)	0,6	0,6	0,5	-0,2	0,3
P_BEEF(-1)	0,4	0,5	0,4	-0,2	0,3
P_BEET(-1)	0,1	0,1	0,1	-0,1	0,0
P_BUCKWHEAT(-1)	0,1	0,3	0,3	0,3	0,5
P_CABBAGE(-1)	0,0	0,1	0,1	0,0	0,2
P_CARROT(-1)	0,1	0,1	0,1	-0,1	0,1
P_CHICKEN(-1)	-0,1	-0,1	0,0	0,3	0,3
P_CORVALOLUM(-1)	0,5	0,5	0,5	-0,3	0,3
P_CURD(-1)	0,6	0,5	0,5	-0,4	0,3
P_EGGS(-1)	0,0	0,1	0,1	0,3	0,4
P_FISH(-1)	0,4	0,5	0,4	-0,1	0,4
P_FISH_FILLET(-1)	0,4	0,5	0,4	-0,1	0,4
P_GRAPE(-1)	0,1	0,1	0,2	0,0	0,2
P_HERRING(-1)	0,7	0,7	0,7	-0,2	0,5
P_LEMON(-1)	0,2	0,2	0,2	-0,2	-0,1
P_MEAT(-1)	0,3	0,4	0,3	0,0	0,4
P_METAMIZOLE_SODIUM(-1)	0,7	0,7	0,6	-0,4	0,3
P_MILK(-1)	0,5	0,4	0,5	-0,2	0,4
P_MUNICIPAL_RENT(-1)	0,4	0,4	0,3	-0,2	0,2
P_MUTTON(-1)	0,1	0,1	0,0	0,0	-0,1
P_OATMEAL(-1)	0,4	0,4	0,5	0,1	0,4
P_ONION(-1)	0,1	0,1	0,1	0,0	0,1
P_ORANGE(-1)	0,1	0,2	0,1	0,1	0,1
P_PORK(-1)	0,0	0,1	0,0	0,0	0,0
P_POTATOES(-1)	0,0	0,0	0,1	0,0	0,1
P_RENT_FLAT1(-1)	0,0	0,1	0,0	0,1	0,1
P_RENT_FLAT2(-1)	0,0	0,1	0,0	0,2	0,1
P_REPAIR_HOUSE(-1)	0,1	0,1	0,1	0,0	0,1
P_SEMOLINA(-1)	0,3	0,4	0,4	0,1	0,4
P_SIGARETTES_FILTER_RUS(-1)	0,8	0,8	0,7	-0,5	0,4
P_SIGARETTES_IMPORT(-1)	0,7	0,7	0,6	-0,6	0,2
P_SUGAR(-1)	0,2	0,2	0,3	0,3	0,5
P_SULFACETAMIDE(-1)	0,3	0,4	0,3	0,2	0,4
P_SUNFLOWER_OIL(-1)	0,4	0,5	0,5	0,0	0,5
P_TOBACCO(-1)	0,8	0,8	0,7	-0,5	0,4
P_VEGETABLES(-1)	0,0	0,1	0,1	0,2	0,4
P_VERMICELLI(-1)	0,5	0,6	0,5	-0,1	0,4
P_WHEAT(-1)	-0,1	0,0	-0,1	0,3	0,1

Sources: Rosstat, FOM, authors' calculations

Notes. High correlation numbers (more than 0.5) are highlighted in red. In the columns: OI, actual YoY inflation, Median EI, BoA EI MT, and BoA EI ST.

Notation: P_X(-1) – lagged price of an item X

Table 6. Candidate items, best 10 baskets (automatic selection approach, actual weights)

#	BoA EI ST	BoA EI MT	Median EI	OI
Average RMSE* of best baskets	58%	72%	18%	11%
1	['Flour', 'Fur and fur products', 'Passenger car tyres', 'Rent']	['Female footwear', 'Swimming classes']	['Beer', 'Male footwear', 'Pipeline gas', 'Used imported passenger car']	['Fish and seafood', 'Furniture', 'Hot water supply', 'Urban passenger transport']
2	['Flour', 'Pipeline gas', 'Passenger car tyres', 'Rent']	['Champagne', 'Female footwear', 'Swimming classes']	['Beer', 'Pipeline gas', 'Urban passenger transport', 'Used imported passenger car']	['Fish and seafood', 'Furniture', 'Pipeline gas', 'Urban passenger transport']
3	['Flour', 'Non-alcoholic beverages', 'Passenger car tyres', 'Rent']	['Female footwear']	['Beer', 'Pipeline gas', 'Children's footwear', 'Used imported passenger car']	['Fish and seafood', 'Furniture', 'Hairdressing services', 'Urban passenger transport']
4	['Pasta', 'Passenger car tyres', 'Rent', 'General physical training classes']	['Champagne', 'Female footwear']	['Smoked meat and poultry', 'Female footwear', 'Pipeline gas', 'Used imported passenger car']	['Fish and seafood', 'Furniture', 'Children's footwear', 'Urban passenger transport']
5	['Flour', 'Passenger car tyres', 'Rent', 'Electricity']	['Female footwear', 'Dry-cleaning', 'Swimming classes']	['Female footwear', 'Pipeline gas', 'Used imported passenger car', 'Funeral services']	['Fish and seafood', 'Furniture', 'Male footwear', 'Urban passenger transport']

6	['Flour', 'Sports shoes', 'Passenger car tyres', 'Rent']	['Fur and fur products', 'Female footwear', 'Swimming classes']	['Beer', 'Knitted outwear', 'Pipeline gas', 'Used imported passenger car']	['Canned vegetables', 'Female footwear', 'Furniture', 'Urban passenger transport']
7	['Flour', 'Ice-cream', 'Passenger car tyres', 'Rent']	['Champagne', 'Female footwear', 'Dry-cleaning', 'Swimming classes']	['Smoked meat and poultry', 'Beer', 'Cold water supply and sanitation', 'Used imported passenger car']	['Beer', 'Furniture', 'Pipeline gas', 'Hairdressing service']
8	['Flour', 'Bedding', 'Passenger car tyres', 'Rent']	['Female footwear', 'Dry-cleaning']	['Female clothes', 'Pipeline gas', 'Repair and maintenance of vehicles', 'Used imported passenger car']	['Cognac', 'Male clothes', 'Furniture', 'Pipeline gas']
9	['Repair and maintenance of vehicles', 'New domestically produced passenger car', 'Passenger car tyres', 'General physical training classes']	['Fur and fur products', 'Female footwear']	['Urban passenger transport', 'Used imported passenger car', 'Car tyres', 'Maintenance and repair of housing']	['Urban passenger transport', 'Used imported passenger car', 'Fresh-cut flowers', 'Maintenance and repair of houses']
10	['Flour', 'Vodka', 'New domestically produced passenger car', 'Passenger car tyres']	['Champagne', 'Female footwear', 'Dry-cleaning']	['Beer', 'Ice-cream', 'Male footwear', 'Used imported passenger car']	['Fish and seafood', 'Sneakers and sport footwear', 'Furniture', 'Urban passenger transport']

Source: authors’ calculations.

Note. *Model RMSE is given in % of RMSE of respective AR(1) model.

Table 7. Shares of visible items in consumer basket

(automatic selection approach, implied weights, grid search, BoA EI ST)

	5000	**10000**	**50000**
Car tyres	25%	25%	18%
New domestically produced passenger car	35%		45%
Rent		38%	
Repair and maintenance of houses	38%	3%	
Used imported passenger car	3%	35%	25%
Furniture			13%

Source: authors' calculations.

Table 8. Shares of visible item in consumer basket

(automatic selection approach, implied weights, grid search, BoA EI MT)

	5000	**10000**	**50000**
Female footwear	13%	15%	20%
Female clothes	50%	53%	78%
Male footwear	3%	3%	
Children's footwear	13%	30%	
Hot water supply and maintenance	23%		
Repair and maintenance of houses			3%

Source: authors' calculations.

Table 9. Shares of visible items in consumer basket

(automatic selection approach, implied weights, grid search, Median EI)

	5000	**10000**	**50000**
Used imported passenger car	43%	38%	83%
Female clothes	28%		
Beer	8%		
Meat and poultry sausages	18%	10%	
Public catering	5%	33%	
Furniture		15%	
New domestically produced passenger car		5%	10%
Car tyres			7%

Source: authors' calculations.

Table 10. Shares of visible items in consumer basket

(automatic selection approach, implied weights, grid search, OI)

	5000	10000	50000
Beer	2%	2%	
Fish and seafood	98%	98%	98%
Flour confectionery			2%

Source: authors' calculations.

Table 11. Shares of visible items in consumer basket

(automatic selection approach, implied weights, direct optimisation)

	BoA ST	BoA MT	Median IE	OI
Flour confectionery				29%
Pork	15%			
Children's footwear		17%		
Male footwear		16%		
Gasoline AI-92				4%
Passenger car tyres			9%	
Used imported passenger car				44%
Educational services		8%		
Public catering			23%	23%
Repair and maintenance of houses	85%		47%	
Urban public transport		60%	21%	

Source: authors' calculations.

Table 12. Visible items (robustness check, optimisation with regularisation)

	BoA 1M	BoA 1Y	Median	Observed
Poultry	16%			
Fish and seafood				5%
Eggs			2%	3%
Sugar	3%			
Coffee			8%	
Vegetables			1%	2%
Vodka	45%	56%	35%	
Public catering			8%	15%
Knitted outwear			7%	
Cold water supply and sanitation			16%	
Housing services			2%	
Urban passenger transport				11%
Used imported passenger car			4%	35%
New domestically produced passenger car			6%	8%
AI-95 petrol	36%	44%	7%	
Repair and maintenance of houses				21%
Recreation services			4%	

Source: authors' calculations.