



What information is important for households' inflation expectations: evidence from a randomized controlled trial

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ABSTRACT

In theory, the anchoring of household inflation expectations contributes a lot to the success of inflation targeting, since inflation expectations may significantly influence consumer and financial decisions.

In this paper, we estimate the causal relationship between information and the inflation expectations of Russian households using a randomized controlled trial (RCT) approach applied to the data of the 6th wave of the Survey of Consumer Finance (2024). To the best of our knowledge, this is the first study of this kind based on Russian data.

According to our estimates, direct, quantitative estimates of future inflation are more sensitive to incoming information. Respondents react most strongly to the treatment about growth in the money supply in the previous year, adjusting their inflation expectations upwards. At the same time, as opposed to research based on data from other countries, we find no relationship between information about inflation in the past year or about the central bank's target and its success in inflation targeting, on the one hand, and household inflation expectations, on the other. This means that monetary policy should react more strongly to pro-inflationary shocks to achieve the target. Actions, not words, matter the most.

Keywords: inflation expectations, randomized controlled trial (RCT), Household Survey of Consumer Finances, central bank communication policy.

JEL Codes: C83, C93, D84, E31

1. INTRODUCTION

Theoretical models (Clarida et al., 1999; Svensson, 2010) and international experience (Wheeler, 2015) suggest that the success of an inflation targeting policy depends on the ability of the central bank to anchor the inflation expectations of economic agents to its inflation target. Until recently, the inflation expectations of macroeconomic analysts (professional forecasters) and financial markets were considered to be of primary value for monetary policy decisions. Interest in household inflation expectations has recently begun to grow again (D'Acunto et al., 2024). Although such expectations are not rational, they contain a lot of useful information about people's ways of thinking, which influence their actions and, consequently, macro indicators.¹ Many researchers find links between household inflation expectations and consumption (Coibion et al., 2020; Duca-Radu et al., 2021; D'Acunto et al., 2022), saving and wage bargaining, and investment decisions (Armantier et al., 2016). This suggests that, no matter to what extent the mechanisms of the formation of household inflation expectations differ from those of other types of expectations, they should be taken into account when analysing macroeconomic processes.

The inflation expectations of households are far from rational. People make systematic mistakes when analysing economic information, and their perception of the situation is subject to cognitive distortions (Grishchenko et al., 2023). Nevertheless, researchers argue that the reason for their bounded rationality is a lack of information. For example, if households are informed about the inflation target, their inflation expectations are adjusted in the 'right' direction (Coibion et al., 2022).

One important trend in the literature on inflation expectations in recent years is the use of a tool from evidence-based medicine: randomized controlled trials (RCTs). This methodology is believed to allow the most reliable identification and analysis of causal relationships (Duflo et al., 2017).

In our paper, we conduct an RCT using data from the 6th wave of the Survey of Consumer Finance (OFD), which was held in the spring and summer of 2024. Our goal is to determine which information significantly affects the inflation expectations of Russian households. The respondents are randomly divided into 6 groups – control and 5 treatment groups. And each treatment group receives one or another piece of information (past actual inflation, the central bank's target and success in achieving it, respondents' expectations from another (inFOM) household survey, or the growth rate of the money supply). We conclude that respondents significantly adjust their inflation expectations when they receive information about the previous year's broad money dynamics.² The conclusions from the study may be used to develop monetary policy strategy and to improve the Bank of Russia's communication and financial literacy programmes.

¹ As Reis (2023) notes, '...People may be wrong, misguided, or foolish in their expectations, but these are the same people who then choose how much to spend, work, and charge... Should a central bank respond to noisy upside risk in measured expected inflation? Yes, unless it is very confident that the increase in the measure of expected inflation is purely noise that not even the respondents will act on.'

² Due to organisational constraints (the small sample size relative to the number of treatments), we do not explicitly test the role of the reaction of expectations to a high numerical value of growth in the money supply. This is what is called the 'anchoring effect', when expectations unconsciously approach a large or small number. Such testing is done by means of the inclusion of a 'placebo treatment', information about the high numerical value of an indicator not related to inflation. Nevertheless, in the statistical tests conducted, we do not find an 'attraction effect' for small numerical values in the information reported. If there is an attraction effect, it should be equally reflected on information about any numerical values, not only on large ones.

The paper is structured as follows. Section 2 provides a review of the literature on the application of RCTs to various macroeconomic variables, including inflation expectations. Section 3 describes the experimental design and the data. Section 4 discusses the methods used and makes estimates based on them. Section 5 tests the robustness of the results. Section 6 concludes.

2. LITERATURE REVIEW

In this paper, we test the effect of information on inflation expectations using an RCT.

Household inflation expectations differ substantially from other types of expectations. They:

- deviate significantly and persistently (across time and countries) from the central bank's inflation target and the inflation expectations of analysts and the financial markets (Weber et al., 2022);
- depend on current inflation and have a long memory of inflationary spikes observed in the past (Malmendier et al., 2016);
- are highly sensitive to short-term news but are almost unaffected by traditional central bank communication (D'Acunto et al., 2024);
- are related to the consumer experience of households and their socio-demographic characteristics;
- react weakly to changes in interest rates.

In other words, it is difficult to treat them as rational. People do not use advanced forecasting techniques, and they do not have their own models of the economy in the form of systems of equations. Nevertheless, the patterns of behaviour of consumer and financial decisions, which depend on the level of inflation expectations, which are revealed in practice, are quite reasonable. One way to resolve this contradiction is to assume that their rationality is bounded due to a lack of information. For example, if households receive information about the inflation target, their inflation expectations adjust in the 'right' direction (Coibion et al., 2022). In this paper, we test the effect of information on inflation expectations using an RCT.

RCTs are a fairly new method that came to economics from biomedical research. The logic and design of the experiment are quite simple and can be described as follows. First, a sample from the general population is randomly generated. This sample is then randomly divided into two parts: an experimental group which is affected and a control group which is not affected. If the sample is large enough, the law of large numbers guarantees the identity of the experimental and control groups by the mean values of their characteristics. That is, up to the moment of treatment, the two groups are identical and are considered 'twin objects' due to the fact that the randomisation procedure eliminates systematic differences between the groups. The only difference between the experimental and control groups is thus that only the former is exposed to the intervention. In this case, the difference between the mean values of the two groups will show the quantitative effect of the treatment (Duflo et al., 2007; Deaton, 2010).

This method has recently been actively used in macroeconomic research. It is convenient because it allows more precise statements about causality by simple means compared to standard³ experiments. In the economic literature, RCTs have been used to study how new information affects expectations in various areas, such as the business cycle (Roth et al., 2020), asset prices (Beutel et al., 2023), consumption (Coibion et al., 2023), or house prices (Armona et al., 2019; Roth et al., 2023). The literature has explored the expectations of both households and of firms (Coibion et al., 2018b; Bottone et al., 2022; Baumann et al., 2024).

A large number of results have been accumulated in the analysis of the impact of different types of information on inflation expectations. The authors of such studies, on average, reach the general conclusion that respondents, when given certain inflation-relevant information, update their inflation expectations in the direction and in proportion to the strength of the signal they receive (Armantier et al., 2016). However, the magnitude by which individuals update their beliefs about future inflation rates depends largely on their prior knowledge, socio-demographic characteristics, the inflationary environment in which individuals find themselves, and their level of attentiveness and willingness to learn (Weber et al., 2023).

It can also be useful for policy to see how exogenous information effects on expectations are then translated into individuals' behavior, such as their consumption decisions, as demonstrated in (Coibion et al., 2023).

The design of experiments to test the role of certain information content on inflation expectations varies slightly across studies, but generally follows the next logic: first, respondents are asked about their perception of future price increases, then they are randomly provided with inflation-related information. They are then asked again about their inflation expectations, and the question is asked in a slightly different form than in the first case, in order to avoid directly linking respondents to their first answers and so as not to mislead them by duplicating the question (for example, in the form of point estimates and in the form of a distribution).

An experimental design similar to the one described above is presented in (Coibion et al., 2022), which is unique in terms of the scale of the study and contains the responses of 20,000 respondents. The large sample size allows the division of the survey participants into 9 groups, a control group and 8 experimental groups, each of which is offered as information one of the following eight types of central bank communication: 1) the actual inflation rate (CPI) over the past twelve months (2.3%); 2) the Federal Reserve's inflation target; 3) the FOMC's 2018 inflation forecast; 4) the most recent FOMC statement; 5) USA Today's coverage of the most recent FOMC decision; 6) unemployment data (as an attempt to test whether respondents are aware of the Phillips curve); 7) national average gasoline price inflation over the previous three months (since people often extrapolate significant changes in individual commodity prices to overall inflation); 8) and a fact about U.S. population growth over the past 2 years as a placebo effect. At the same time, before and after the information is provided, all respondents are asked for a quantitative assessment of their inflation expectations.

Providing households with simple inflation statistics, such as the last recorded inflation rate, inflation target or inflation forecast, is found to have a statistically significant impact on inflation expectations, with people adjusting their own estimates of future inflation towards the numerical

³ In a standard experiment, in contrast to an RCT, the same object is explored before and after the treatment to detect the effect of the impact. The difficulty with this approach is that the object must be isolated from any influences other than the given treatment.

values in the information received. Moreover, the impact of the information proves to be moderately persistent: in subsequent waves, respondents' estimates of future inflation are lower than their initial estimates, but gradually increase, indicating the need for regular communication by central banks.

In (Binder et al., 2018), respondents are asked for their quantitative estimates of inflation expectations three times. The first time in the survey, respondents are asked for their estimate of inflation expectations. Then, each of the two subgroups of the total sample is provided with information about the Fed's inflation target or asked to review inflation data for the past several years. Next, inflation expectations are asked a second time. The respondents are then provided with a second piece of information they have not received before, and their inflation expectations are then asked a third time. This experimental design is chosen to observe how the announcement of a specific numerical inflation target affects the expectations of respondents who are already aware of past inflation and vice versa. It turns out that respondents perceive information about the inflation target as a more accurate signal and adjust their assessment to the target level with any sequence of messages during the experiment.

The experiment (Dräger et al., 2023) is structured somewhat differently. It consists of two steps. In the first step, the sample of respondents is randomly divided into two parts, and one of them is given an 'inflation literacy' course: they are given a short text containing information about inflation, but the information is only textual and does not contain any numerical values. The respondents are then asked to estimate the current and future inflation rates, and it is tested whether the information has had a significant effect on their estimates. In the second step of the experiment, the sample is again divided randomly. Regardless of whether a respondent received the textual message or not, he or she falls into the control group or into one of 4 experimental groups. The latter receive the following messages during the experimental part of the survey: 1) the ECB's inflation target; 2) the ECB's inflation target and the message that the ECB is keen to take into account the impact of climate change on the stability of the financial system; 3) the German inflation rate for the last available period; and 4) the Bundesbank's inflation forecast for the next 3 years. Traditionally, respondents are then asked to give their assessment of inflation over the past and future 12 months. The authors conclude that the textual information that respondents receive in the first step has no impact on their quantitative assessment of inflation, although respondents remember the meaning of the text, which is verified 3 months later in a follow-up survey. As for the second step of the experiment, the results are as follows: respondents in the experimental groups adjust their estimates of past and future inflation according to the quantitative information they receive, regardless of whether or not they have taken an 'inflation literacy' course in the first step. However, only those who are exposed to the inflation text in the first step of the experiment are more confident in their forecasts, which is reflected in their probability estimates of whether past or future inflation falls into a particular numerical range. It is also interesting that the impact of the text on inflation in the first stage is two-fold in relation to the level of respondents' confidence in monetary policy institutions: on the one hand, those who receive the text on inflation have a higher level of confidence than the control group. However, if in the second stage these respondents are again in the treatment group and receive information that the current inflation rate is high, they reduce their level of trust to a significant extent compared to those from the control group in the first stage of the experiment.

(Huber et al., 2023) conduct an RCT to investigate whether there is a causal relationship between individuals' perceptions of past inflation and their inflation expectations. For this purpose, the authors randomly divide the sample of respondents into 4 groups: a control group and 3 experimental groups. No information is given to the control group. The effect of information on the remaining 3 groups is as follows: the first and the second groups are informed about the CPI and

harmonised CPI, respectively, and the third group receives as information the value of the CPI excluding energy and food prices. However, all respondents are asked for quantitative estimates of current and future inflation before the information is provided, and afterwards, they are asked to provide estimates of the same indicators in a slightly different way (through minimum and maximum values) in order to avoid linking respondents to their answers from earlier in the survey. As a result, the authors conclude that the individuals in treatment groups 1 and 2 do indeed adjust their inflation expectations in the direction of the indicators they are told during the experiment. In addition, the authors obtain empirical evidence of the large impact of inflation perceptions on both short- and medium-term inflation expectations.

(Hajdini et al., 2023) use an RCT to study the causal relationship between the inflation expectations of consumers and their expectations for income growth. For this purpose, survey respondents are randomly divided into 6 groups: a control group and 5 experimental groups. Three of them are given different inflation-related information, one treatment group is given wage-related information, and the fifth group receives a placebo treatment (information about the U.S. population) to determine whether consumers respond to receiving any information at all. Also, as in most surveys, respondents' expectations are quantitatively measured twice in the study's survey, before and after additional information is communicated to them for the purposes of the experiment. The authors conclude that 4 types of information treatment (all but the placebo treatment) have a significant impact on inflation expectations. Moreover, the negative estimates of the regression coefficients indicate that the respondents who receive one of the types of treatment adjust their expectations towards the number received in the treatment.

Our contribution to this extensive literature is that we conduct the first such study for Russia. Using Russian data, we build on the general approach and design of the experiment in the articles of (Coibion et al. 2021, 2022). This study is interesting not only because it adds data from another country to the bulk of such studies but also because it analyses data that are likely to be qualitatively different from those for developed countries. Our data describe households under a short period of inflation targeting and also in a rather turbulent macroeconomic environment, with a large number of macroeconomic shocks in the years preceding the survey. This makes the question of the role of this or that information in inflation expectations particularly interesting.

Also, to the best of our knowledge, ours is one of the few studies to include information on the dynamics of the monetary aggregate as part of the information effects. For Russia, with its relatively recent experience of hyperinflation in the early 1990s, this relationship may be an important factor in expectations. In this case, the dynamics of monetary indicators may influence inflation both through money transactions and also indirectly through inflation expectations.

We also separately analyse the role of information about the inflation target and about the success of the central bank in achieving the inflation target in the recent past (2017–2020). Merely citing the inflation target may not be enough to attract the attention (trust) of respondents in countries with relatively little experience with inflation targeting.

Additionally, we test the extent to which inflation expectations do not simply respond to treatment in one or the other direction but approach the numerical values in the treatments. (Armantier et al., 2016) observe that people are quite conscious of the additional information they see. Therefore, there is no naive anchoring of the response to the number seen in the treatment, which is usually explained as a subconscious process (Tversky et al., 1974), but there is an adjustment of expectations in the right direction. The authors therefore conclude that the strict hypothesis – that inflation expectations are anchored at the level of the inflation target – is not worth testing (Dräger et al., 2024).

In the main part of this paper, we assess whether information effects reduce the absolute distance of expectations from the target.⁴ We find that there is no such convergence with treatment about the central bank's target or about past (low) inflation.

3. DATA AND EXPERIMENTAL DESIGN

The study uses data from the 6th wave of the All-Russian Household Survey of Consumer Finances (OFD). This project was launched in 2013, and since then, it has been conducted by Demoskop LLC with a frequency of every two years. It is longitudinal, i.e., the majority of households participate in several waves of the survey. The survey includes a wide range of questions which are standard for household surveys: respondents are asked extensive socio-demographic information, questions about personal finances, financial knowledge, expectations and behavior.

In the 6th wave of the OFD, almost 12,000 respondents from more than 6,000 households living in 32 constituent entities of the Russian Federation were personally interviewed. The survey is representative of the population of Russia. At the same time, the sample may underrepresent high-income groups of the population, which is typical for household surveys of this type (Bessonova et al., 2023).

To determine the minimum sample size for testing the statistical significance of the difference in mean inflation expectations (and, accordingly, for determining the maximum number of permissible treatments), we use the standard approach to determine the sample size. The minimum group size required to determine the difference in the mean value of inflation expectations at the 5% level of statistical significance was calculated by the following formula (assuming that the size of the control group and the treatment group is the same) (Ryan, 2013):

$$n_1 = n_2 = \frac{2(z_{\frac{\alpha}{2}} * \sigma)^2}{(\mu_1 - \mu_2)^2}$$

Where: $n_1 = n_2$ are the sizes of the control and treatment groups, $z_{\frac{\alpha}{2}} = 1.96$ is the value of the standard normal distribution for a two-sided test with level of type one error $\alpha = 5\%$, $\mu_1 - \mu_2$ is the minimum difference of the mean for which a test with a given level of significance and a given sample size is applicable, which is assumed to be equal to 1.1 percentage points for the measure of quantitative inflation expectations with a mean of 25%, and σ is the standard deviation of inflation expectations (= 17 pp).

Substitution gives a sample size of approximately 2,000 people:

$$n_1 = n_2 = \frac{2(1,96 * 17)^2}{(1,1)^2} \approx 2000$$

Thus, the more than 12,000 thousand respondents can be divided into 6 identical groups, one of which must be the control group.

The survey begins by identifying the respondent's socio-demographic characteristics and also asks for their expectations about the situation in the economy and questions about income. This is followed by the experimental part. Unlike many similar studies (Coibion et al., 2022; Coibion et al., 2023; Schnorpfel et al., 2023; Hajdini et al., 2023; Huber et al., 2023), our survey does not include

⁴ However, in Table A2 in the Appendix, we also provide the results of a test of the strict hypothesis.

the identification of individuals' initial perceptions of current and future inflation. The respondents are first asked for their assessment of these indicators only after the treatment has been realised. This is because the purpose of the experiment in this paper is not to detect the difference by which respondents revise their expectations after receiving new information. We are interested in whether people respond to communication, and if they do, to which type of communication and how they change their inflation expectations compared to those who do not receive additional information. We believe this method has three main advantages over the method in the literature involving the identification of inflation expectations both before and after treatment. First, the nudging effect is eliminated: when the respondent is asked again, he or she may start to think that apparently the initial answer has not satisfied the interviewer (for some reason). The respondent is likely to give a different answer as a result of this forcing. The respondent may also think that, if additional information is given after his or her answer, it has significance and should be taken into account when answering: the naturalness of information perception will therefore be disturbed. Second, to avoid asking two identical questions regarding inflation expectations, the questions are usually asked in different formats (point value of the indicator, probability distribution, selection from given intervals, or indication of possible highest and lowest value of the indicator). This approach is prone to measurement error, as there is a question of the comparability of the responses ;'before' and 'after' the treatment. Third, an additional question increases the total cost of the survey.

Thus, in our questionnaire, the inflation expectations indicator is estimated only after the information is communicated to the survey participants. To conduct the experiment, respondents are randomly assigned to one of six groups. Group zero is the control group and receives no information. Groups 1–5 are experimental and receive the information presented in the table.⁵

Table 1. Description of treatments

Group number, number of respondents (N)	Description of treatment	Designation in results tables
0, N = 1,986	Control group	T0
1, N = 1,953	According to official figures (Rosstat), the annual growth of the general price level for goods and services at the end of 2023 was approximately 7.4%.	T1: CPI

⁵ The randomisation of the distribution is provided by the organisation conducting the survey (Demoskop) and is carried out at the stage of the publication and distribution of the questionnaires. The interviewers of the organisation have professional skills in conducting experiments in surveys. In their work, they ask questions only as they are formulated in the questionnaire, do not give any personal comments, and emphasise that they are interested in the respondent's opinion based on how they themselves understand the question they hear. If clarification is needed, the question from the questionnaire is repeated to the respondent again.

2, N = 1,989	Monetary policy in Russia is conducted by the central bank. Its goal is to maintain a steady increase in the general price level of goods and services close to 4% per year.	T2: target π
3, N = 1,955	Monetary policy in Russia is conducted by the central bank. Its goal is to maintain a steady increase in the general price level of goods and services close to 4% per year. From 2017 to 2021, it managed to do so.	T3: target π + goal achievement
4, N = 1,997	According to a survey conducted by the Public Opinion Foundation (inFOM Survey), Russians expect the price level for goods and services to rise by about 14.2 per cent as of the end of 2024.	T4: FOM's IE
5, N = 1,955	According to the Bank of Russia, the volume of money in the Russian economy grew by about 20 per cent in 2023.	T5: broad money (M2) growth

The first three treatments, reporting the level of current inflation, the monetary regulator's target and the achievement of the target, are very typical of such studies (Coibion et al., 2022; Coibion et al., 2021; Hajini et al., 2023; Huber et al., 2023; Dräger et al., 2023). A number of studies also report the level of price increases expected by professional market participants as a treatment. In our paper, treatment No.4 communicates household expectations to assess how much respondents trust the opinion of other people in ordinary households. A similar treatment is communicated to respondents in (Aktug et al., 2024). Treatment No.5 in the current formulation is added to assess whether respondents understand the relationship between changes in the volume of money in the economy and changes in prices, although we recognise that the significance of this treatment does not necessarily mean that individuals understand the mechanism of the linkage of these macroeconomic indicators. Unfortunately, due to sample size requirements, we are not able to take into account a larger number of possible types of treatments.

According to the RCT method, to identify the effect of the information intervention on inflation expectations, we need only compare the mean values of the control group with the mean values in each of the intervention groups. This difference in averages shows how much inflation expectations change solely due to the information intervention, completely excluding other possible factors that may influence the difference in estimates of inflation expectations between the control

and experimental groups. This effect is possible due to the internal validity of RCTs thanks to the random assignment of the respondents into the control and experimental groups. In reality, however, it is difficult to check whether the experimental conditions are precisely observed and whether the randomisation of people into groups is perfect. To ensure that the experiment does have internal validity, it is possible to check how similar the groups are in terms of baseline characteristics (Deaton et al., 2018; Deaton, 2010; Dufflo et al., 2007). Krauss (2021) also notes that the overall validity of an RCT and that its causal effects are maximised when randomisation is maximised, i.e., when the differences in the baseline characteristics of all groups (both experimental and control) are minimised and the overall sample is representative.

A test of the success of the randomization of the respondents into the treatment groups is presented in Table A1 in the Appendix. It is similar to the analysis presented by (Baumann et al., 2024; Coibion et al., 2021; Dräger et al., 2024) in that it is not possible to predict in advance which treatment group an individual falls into based on the socio-demographic or other additional characteristics of the individual. We estimate the regression with a binary dependent variable using the least squares method, that is, we use a linear probability model (Deke, 2014) for each of the treatment groups and for the control group with the following regressors: gender, age, education, type of locality in which the respondent lives, employment status, size of the household, and the logarithm of income. All variables are found to be insignificant (except for the marginal significance of the logarithm of income variable for the fifth treatment group).

The result suggests that the randomisation of the respondents into groups is successful and that the experiment has internal validity.

Now let us take a closer look at the main variables for the purpose of this study: the variables characterising the expected price level. The variable of the perception of price increase in the last 12 months is analysed in section 5 on the robustness test of the results.

Information on inflation expectations is requested from respondents to the questionnaire in three forms: short-term (1 month ahead) and medium-term inflation expectations (12 months ahead) in categorical form and in the form of medium-term inflation expectations with the possibility to choose the numerical interval where the future inflation rate will fall (12 months ahead). We consider the latter indicator as a quasi-interval, as it has ordered categories which are represented by unequal intervals. However, in the further analysis, we consider it as a quantitative indicator using the average values of the intervals.

The exact wordings of the questions on inflation expectations are presented below.

1) Short-term:

Question K73.1 'How do you think the prices of food, non-food products and services will change in general over the next month?'

- 1) *Will grow faster than they do now*
- 2) *Will grow as they are now*
- 3) *Will grow slower than they do now*
- 4) *No change*
- 5) *Will decline*

2) Qualitative medium-term:

Question K73.2 'How do you think the prices of food, non-food products and services will change overall over the next 12 months?'

- 1) Will grow faster than they do now
- 2) Will grow as they are now
- 3) Will grow slower than they do now
- 4) No change
- 5) Will decline

3) Medium-term with interval answers (quasi-interval):

Question K74 'By how many percentage points do you think prices will rise over the next 12 months?'

2% OR LESS.....	01
3–5%	02
6–8%	03
9–12%	04
13–16%	05
17–20%	06
21–25%	07
26–30%	08
31–40%	09
41–50%	10
51% OR MORE.....	11

The literature discusses the advantages and disadvantages of identifying inflation expectations in surveys in qualitative or quantitative terms (Rumler et al., 2023; Andrade et al., 2023; Armantier et al., 2017).

Our survey uses a qualitative assessment of both inflation expectations and perceptions of inflation. This is done for two main reasons. First, it is generally difficult for respondents to quantify inflation expectations because many do not understand the economic meaning of this indicator. Because of this, people often refuse to answer the question, which significantly reduces the sample. The data of the 5th wave of this survey confirm this. The percentage of meaningful⁶ answers to the qualitative question about the expected inflation rate is 90%, but only 55% to the quantitative question. The question about quantitative inflation reduced the sample by almost half. At the same time, for the remaining 55% of numerical answers, it is difficult to assess exactly what the respondents put into this assessment or how thoughtful they were in answering the question posed, as the results range from 1% to 1000% with an average value of 38%. Given the fact that respondents indicated the value of expected future inflation as multiples of 5 or 10, they probably rounded their expectations

⁶ 'Meaningful' responses here and hereafter include all the respondent's answers to the question, excluding blank answers and 'No answer', 'Refusal to answer' and 'Difficult to answer' responses.

upwards (Manski et al., 2010). Given these facts, it can be said that qualitative assessments are more reliable in surveys (Das et al., 2019).

However, the qualitative assessment of inflation alone does not provide any quantitative insight into the respondents' expected inflation rate. Therefore, in this paper, we also use the average values of the intervals to obtain a rough quantitative estimate of inflation expectations. Such an estimate is preferable to point estimates of inflation, as it is easier for respondents to decide on an interval than a specific numerical value (Ellerby et al., 2021). That said, the choice of different intervals – 11 different intervals are represented in this study – allows respondents to communicate their view of the expected price level quite accurately. The use of interval averages for the analysis of interval and quasi-interval variables is found in the literature (Manski et al., 2002; Vellekoop et al., 2019). This approach is criticised on the grounds that ordinary least squares estimates based on such variables may be biased (Cook et al., 2012; Bettin et al., 2010).

The distributions of the shares of answers to questions K73.2 and K74 about the expected price level are presented in Figures 1 and 2. It should be noted that each of the three indicators of inflation expectations is presented in a form cleared of incomplete answers and in the same form the variables are used for further analysis.

Figure 1. Distribution of categorical inflation expectations for 12 months ahead (K73.2) by treatment groups

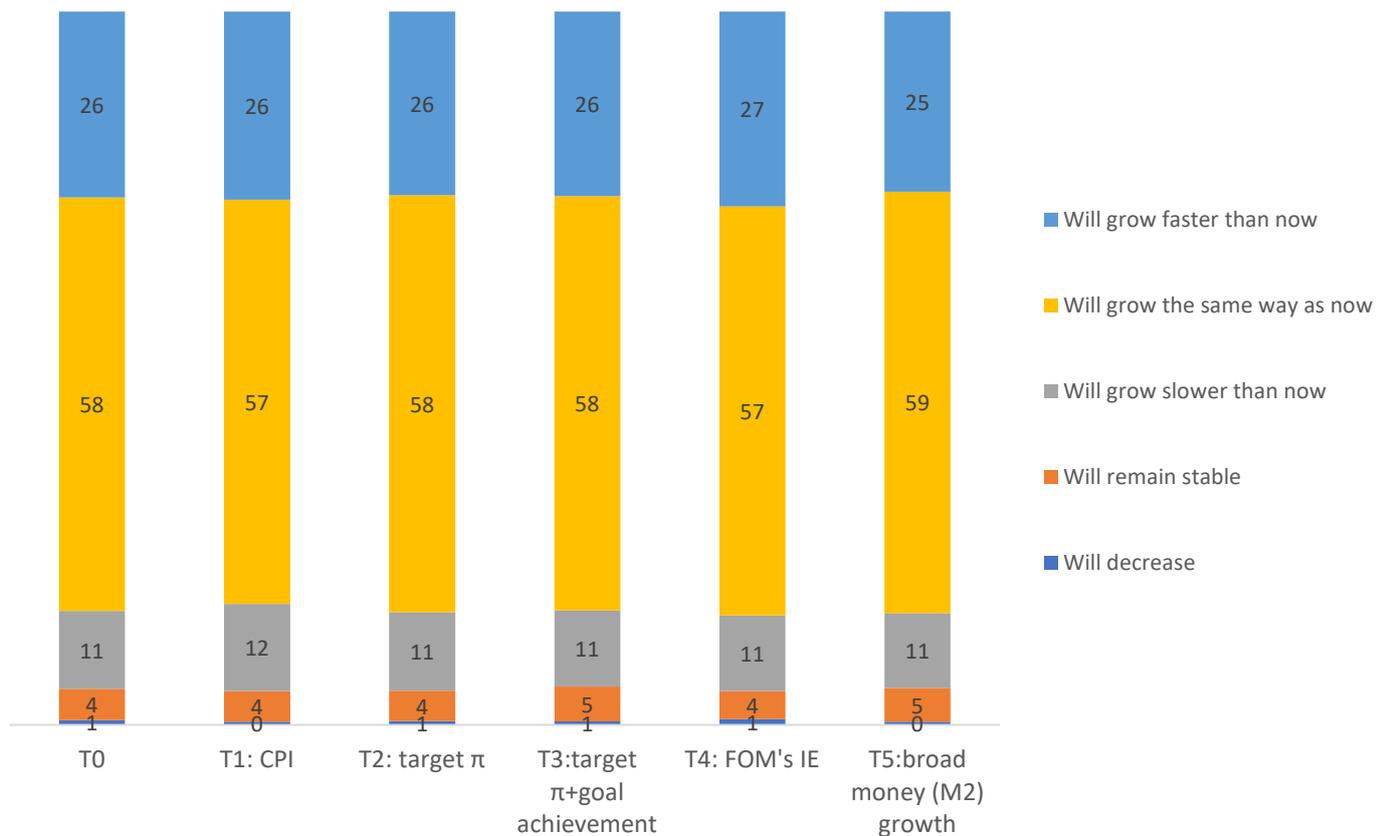
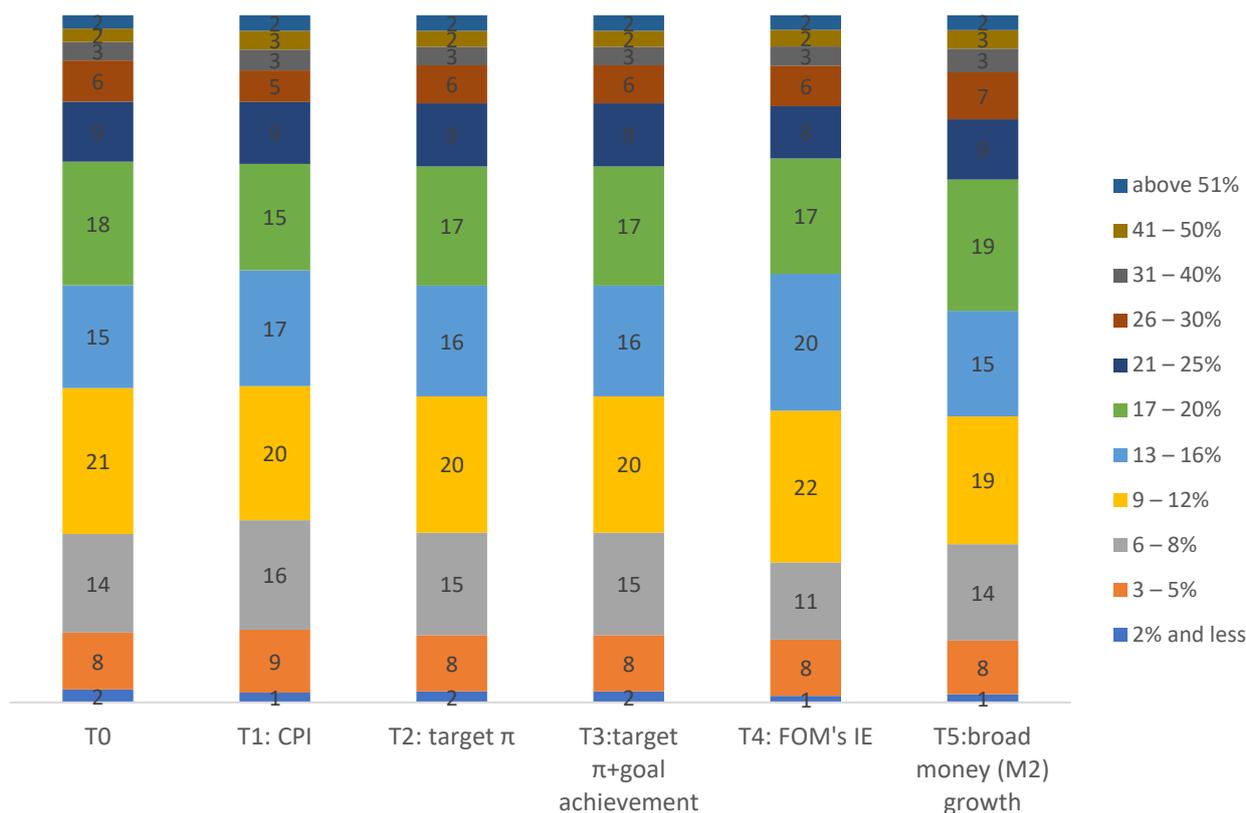


Figure 2. Distribution of quasi-interval inflation expectations for 12 months ahead (K74) by treatment groups



The figures above show that none of the types of information treatment obviously changes the distribution of the answers, i.e., it remains approximately the same for all treatment groups. This conclusion is confirmed by formal tests. The chi-squared test of independence is used to compare the frequency of responses in the control group with each of the treatment groups. For inflation expectations 1 and 12 months ahead, the test shows that the distribution of responses does not differ significantly between the groups. For the quasi-interval variable, it turns out that the distributions of the responses in the control and 4 treatment groups differ significantly (Table 2). The largest difference in response frequencies between the control and 4 treatment groups is observed for the 13–16% interval. Since we have established that our experiment has internal validity, the difference between the control group and the treatment group is due directly to the treatment. That is, people who receive information that the inflation expectations of the population are 14.2% according to FOM begin to choose the 13–16% interval more than respondents who do not receive this information. It is possible that in this case we observe an example of respondents linking their answers to the number received in the treatment.

Table 2. Frequency of selection of each interval in question K74 in control group and 4th treatment group.

Interval	Midpoint	Frequency of responses in control group	Frequency of responses in treatment group No. 4
2% or less	1	27	14

3–5%	4	120	122
6–8%	7	207	168
9–12%	10.5	307	329
13–16%	14.5	216	297
17–20%	18.5	260	250
21–25%	23	126	114
26–30%	28	87	88
31–40%	35.5	39	41
41–50%	45.5	28	36
51% or more	55.5	28	32
X-squared = 23.148, df = 10, p-value = 0.01021			

A *t*-test comparing the mean at the midpoints of the intervals is used to compare the quasi-interval inflation expectations in the control group with each of the treatment groups in pairs. The results of this test and the medians for each group are presented in Table 3.

Table 3: Descriptive characteristics of quasi-interval inflation expectations by treatment group

	T0	T1: CPI	T2: target π	T3: target π + goal achievement	T4: FOM's IE	T5: broad money (M2) growth
Number of observations	N = 1,986	N = 1,953	N = 1,986	N = 1,955	N = 1,997	N = 1,955
Medians	14.5	14.5	14.5	14.5	14.5	14.5
Medians (using interval series formula)	13.64	13.43	13.86	13.84	14.02	14.72
Averages	15.7	15.85	15.95	16.05	16.11	16.63

	<p>Two sample t-test: the mean values of expected inflation are significantly different in the control group and the 5 treatment group, $t = -2.3274$, $df = 2,877.9$, $p\text{-value} = 0.02001$</p>
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Since we have shown that the randomisation in the experiment is successful, we can already conclude on the basis of the test for significant differences in the mean values that the information about 20% growth in the volume of money in the Russian economy in 2023 increases the average inflation expectations of respondents by $16.63\% - 15.7\% = 0.93$ pp. However, in order to obtain more accurate estimates of the effect of the treatment based on all indicators of inflation expectations contained in the questionnaire, let us proceed to an empirical analysis based on the econometric approach, which is presented in the following section of the paper.

4. TREATMENTS AND INFLATION EXPECTATIONS

4.1 ESTIMATION OF BASELINE REGRESSION

In this part of the paper, we empirically assess how the different information treatments affect the inflation expectations of the respondents. The main source of data for the inflation expectations indicator in this section is the corresponding question from the questionnaire (K74), which reflects the respondents' expectations of price increases 12 months ahead. Econometric analyses for the measure of qualitative inflation expectations 1 month ahead (question K73.1), 12 months ahead (question K73.2), and for the measure of perceptions of inflation over the past 12 months (question K72) are used in the robustness check section (Section 5).

As mentioned above, the inflation expectations indicator based on question K74 is a *quasi-interval* indicator. In the empirical analysis, we treat this indicator as categorical (ordered) or, with certain caveats, as quantitative. Regarding the open bounds of the intervals, we defined the lower bound as 0% and the upper bound as 60%. People almost never expect deflation and do not indicate negative values of inflation expectations (Gorodnichenko et al., 2021), so in this paper, we also consider inflation expectations as non-negative and take inflation expectations lying between 0 and 2% as the lower interval. As for the upper bound, a value of 60% is chosen according to the standard approach adopted in statistics. The length of the open upper interval is equated to the length of the preceding interval, thus in our case, inflation expectations in the upper interval vary from 51% to 60%. In addition, by setting the boundary at 60%, we do not lose meaningful conclusions by excluding higher values of the upper boundary, as the clear figure of the right boundary of the interval does not give us additional information. What is important for us is the beginning of the interval – 51% – this figure conveys to us the respondent's exaggerated expectations about price growth, but also indicates that the respondent most likely does not understand the concept of inflation and chooses this estimate based on general feelings about his or her current or future financial situation or based on observations of price growth in his or her specific consumer basket.

Thus, each of the intervals listed as an answer to question K74 can be considered as a category. Since the intervals are strictly ordered, we obtain ordered categorical variable CAT , containing 11 categories, in which category 1 corresponds to the answer '2% or less', category 2 corresponds to '3–5%', and so on to category 11, which is '51% or more' (see the Appendix for more details on the category values for each specification with a particular treatment). A regression with a variable of this type is estimated using an ordered logit model or an ordered probit model, as in (Rumler et al., 2023). In this paper, we estimate the ordered logit regression equation:

$$\text{Logit}(P(CAT_i \leq k)) = b_{0k} + \sum_{j=1}^5 b_j T_i^{(j)}, \quad (1)$$

where $k = 1 \dots K - 1$, where K is the number of categories of the dependent variable. In our case, $K = 11$. For the i -th respondent, T_i^j is equal to 1 if the respondent receives the j -th treatment and equal to 0 otherwise; b_{0k} is a unique constant for each category k .

This ordered logit regression model fits the best for our dependent variable. However, the estimates obtained are interpreted in terms of odds ratios, where the odds refer to the ratio of the accumulated probabilities of falling into or not falling into a particular category. We further transform the quasi-interval variable into a quantitative variable to obtain more interpretable results. In doing so, we make the assumption that, in choosing the interval in which their inflation expectations fall, respondents do not have specific figures for the indicator in their heads. Consequently, they agree equally with any figure in the intervals they choose, including the average value of the interval. For the quantitative variable $Midpoint$ thus obtained, we estimate the regression in two ways, building on (Coibion et al., 2021; Dräger et al., 2024; Hajini et al., 2023). The first method is the ordinary least squares (OLS) method, and the second method is the Huber regression estimation, which is used to smooth out the possible impact of significant outliers in the dependent variable:

$$Midpoint_i = b_0 + \sum_{j=1}^5 b_j T_i^{(j)} + e_i, \quad (2)$$

where $T_i^{(j)}$ is a binary variable equal to 1 if the i -th respondent receives the j -th treatment and e_i is the random errors of the model.

In addition to baseline regressions (1) and (2), we estimate a regression with a vector of the control variables. Since we are dealing with a randomized controlled trial, the addition of the controls should not significantly affect the results of the baseline specifications and is done to further check the success of the randomisation. A lack of change in the coefficient estimates in this case should be due to the fact that the vector of the controls in a successful randomisation is orthogonal to the vector of the variable responsible for the effect of the treatment (Deaton, 2010). The following respondent characteristics are used as control variables in the regressions: gender, age, education level, household size, employment status, type of locality, and logarithm of income. This set of control variables is standardly used in similar studies (Coibion et al., 2022; Coibion et al., 2021; Huber et al., 2023; Dräger et al., 2024). Table 4 summarises the results of the estimation of the baseline regressions and the regressions with the addition of the control variables:

Table 4. Results of estimation of regression for quasi-interval inflation expectations indicator

	Dependent variable					
	CAT		Midpoint			
	(1)	(2)	(3)	(4)	(5)	(6)
Regression	Ordered logit		OLS		Huber	
Controls	No	Yes	No	Yes	No	Yes
T1: CPI	-0.066 (0.075)	0.029* (0.017)	0.024 (0.440)	0.048 (0.450)	-0.314 (0.340)	-0.285 (0.345)
T2: target π	0.021 (0.074)	0.010 (0.076)	0.162 (0.428)	0.089 (0.439)	0.065 (0.351)	0.029 (0.341)
T3: target π +goal achievement	-0.014 (0.076)	-0.035 (0.078)	-0.164 (0.423)	-0.290 (0.432)	-0.076 (0.362)	-0.158 (0.346)
T4: FOM's IE	0.123* (0.074)	0.100 (0.076)	0.596 (0.426)	0.432 (0.435)	0.480 (0.346)	0.356 (0.341)
T5: broad money (M2) growth	0.184** (0.075)	0.177** (0.077)	0.990** (0.436)	0.896** (0.444)	0.824** (0.359)	0.777** (0.356)
Constant			15.142*** (0.302)	10.117*** (2.544)	13.749*** (0.255)	6.666*** (2.022)
Observations	6,625	6,317	6,625	6,317	6,625	6,317

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. For models (3) to (6), robust standard errors are given in parentheses.

As a result, for each type of regression, we obtain consistent significance for the fifth treatment group, in response to which the respondents increase their inflation expectations. For the ordered logistic regression, a positive, significant estimate of the coefficient means an increase in the odds of moving to a higher category (choosing an interval with higher expected price increases) when given information compared to the control group. For the estimated baseline specifications (3) and (5), the

estimates under the variable 'T5: growth in the volume of money in the economy' imply an increase in respondents' inflation expectations by 0.99 pp and 0.82 pp, respectively.

Additionally, we estimate a Tobit model, which is also used in the case of an interval dependent variable (Rumler et al., 2019). This model is based on the maximum likelihood method. The results of the estimation of this model compared to the estimations of the linear models are presented in Table A3 in the Appendix. The Tobit model is more appropriate for estimating the interval indicator (Rumler et al., 2019), but since the regression results estimated using this model are not significantly different from the regressions estimated using the least squares method and robust regression, we use the linear model instead of the Tobit model in the further analysis without compromising the accuracy of the results obtained (Tisdell et al., 2002).

4.2 ESTIMATION ON SUBSAMPLES

To understand whether the impact of additional information varies by demographic or other respondent characteristics, we estimate regressions (1) and (2) on the following subsamples: gender (male/female), age group (under 40, 40–60, 60 and over), education level (secondary general and below/secondary specialised/complete or incomplete higher education), income level (low/middle/high based on categorical variable K65 of the survey – more details on the compilation of the variable are presented in Table A4 in the Appendix), income level (low/middle/high based on quantitative variable K58 of the survey⁷), based on the answer to question K66,⁸ and based on the level of financial literacy.⁹ The control variables are not included in the regressions on the subsamples.

Assessing the impact of additional information on inflationary expectations in specific subsamples is typical of the literature on randomized controlled experiments (Coibion et al., 2022; Coibion et al., 2021; Dräger et al., 2024; Baumann et al., 2021). Such analyses help researchers to identify narrower target groups to which they can subsequently target types of communication if necessary.

Table 5. Estimation of regression on subsamples by gender of respondents

	Male	Female	Male	Female	Male	Female
	(1)	(2)	(3)	(4)	(5)	(6)
Regression	Ordered logit		OLS		Huber	
T1: CPI	0.011	-0.076	0.798	-0.373	-0.006	-0.354

⁷ The respondents are divided into groups with low, medium and high monthly incomes by tercile: up to 26,000 rubles per month – low income, from 26,000 to 45,000 rubles per month – medium income, and from 45,000 rubles per month – high income. Thus, three groups are obtained, similar to the division by the categorical income indicator.

⁸ The wording of question K66 is: 'In your opinion, what is the best way to dispose of spare money at present: to save the money or to spend it?'

⁹ The financial literacy index is taken with a lag, i.e., the financial literacy index compiled from the data of the 5th wave of the OFD is used. This index is also used in the works of Andreev et al. (2024) and Sinyakov et al. (2023).

	(0.102)	(0.085)	(0.618)	(0.508)	(0.535)	(0.392)
T2: target π	0.196*	-0.091	1.311**	-0.438	0.892*	-0.442
	(0.102)	(0.084)	(0.602)	(0.502)	(0.495)	(0.412)
T3: target π +goal achievement	0.066	0.024	0.412	0.354	0.264	0.109
	(0.101)	(0.086)	(0.572)	(0.532)	(0.490)	(0.411)
T4: FOM's IE	0.043	0.101	0.391	0.481	0.097	0.404
	(0.100)	(0.084)	(0.576)	(0.509)	(0.482)	(0.385)
T5: broad money (M2) growth	0.276***	0.070	1.894***	0.284	1.268**	0.289
	(0.105)	(0.084)	(0.633)	(0.501)	(0.519)	(0.393)
Constant			15.276***	15.956***	13.982***	14.320***
			(0.410)	(0.359)	(0.368)	(0.280)
Observations	3,598	5,156	3,598	5,156	3,598	5,156

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. For models (3) to (6), robust standard errors are given in parentheses.

Table 6. Estimation of regression on subsamples by age of respondents

	<40	40–60	>60	<40	40–60	>60	<40	40–60	>60
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Regression	Ordered logit			OLS			Huber		
T1: CPI	-0.209*	-0.038	0.128	-0.702	-0.051	1.065	-1.116*	-0.212	0.630
	(0.112)	(0.114)	(0.113)	(0.657)	(0.726)	(0.661)	(0.575)	(0.535)	(0.501)
T2: target π	-0.121	0.104	0.078	-0.580	0.376	0.886	-0.645	0.542	0.337
	(0.113)	(0.112)	(0.112)	(0.646)	(0.703)	(0.653)	(0.542)	(0.526)	(0.489)
T3: target π + goal achievement	-0.047	0.164	-0.027	-0.126	0.773	0.283	-0.277	0.760	-0.130

	(0.113)	(0.113)	(0.115)	(0.655)	(0.712)	(0.660)	(0.554)	(0.535)	(0.477)
T4: FOM's IE	-0.073	0.072	0.224**	-0.273	0.070	1.471**	-0.455	0.265	0.992**
	(0.110)	(0.110)	(0.113)	(0.643)	(0.686)	(0.662)	(0.528)	(0.507)	(0.496)
T5: broad money (M2) growth	0.127	0.091	0.225**	0.832	0.029	1.864***	0.549	0.477	0.978*
	(0.112)	(0.114)	(0.114)	(0.661)	(0.692)	(0.694)	(0.555)	(0.537)	(0.509)
Constant				15.83***	16.38***	14.87***	14.50***	14.46***	13.64***
				(0.460)	(0.510)	(0.436)	(0.391)	(0.385)	(0.321)
Observations	2,957	2,990	2,807	2,957	2,990	2,807	2,957	2,990	2,807

Note: *p<0.1; **p<0.05; ***p<0.01. For models (3) to (6), robust standard errors are given in parentheses.

Table 7. Estimation of regression on subsamples by education level of respondents

	Special	Medium	Higher	Special	Medium	Higher	Special	Medium	Higher
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Regression	Ordered logit			OLS			Huber		
T1: CPI	-0.209*	0.145	-0.146	-0.702	0.982	-0.186	-1.116*	0.608	-0.805
	(0.112)	(0.122)	(0.117)	(0.657)	(0.732)	(0.714)	(0.575)	(0.618)	(0.548)
T2: target π	-0.121	0.109	-0.015	-0.580	0.471	-0.188	-0.645	0.516	-0.024
	(0.113)	(0.121)	(0.116)	(0.646)	(0.698)	(0.672)	(0.542)	(0.625)	(0.518)
T3: target π +goal achievement	-0.047	0.173	-0.019	-0.126	0.642	0.331	-0.277	0.807	-0.128
	(0.113)	(0.124)	(0.119)	(0.655)	(0.700)	(0.714)	(0.554)	(0.593)	(0.551)
T4: FOM's IE	-0.073	0.212*	-0.055	-0.273	1.296*	-0.162	-0.455	0.879	-0.358
	(0.110)	(0.121)	(0.116)	(0.643)	(0.729)	(0.693)	(0.528)	(0.581)	(0.536)

T5: broad money (M2) growth	0.127	0.167	0.041	0.832	0.909	0.174	0.549	0.763	0.195
	(0.112)	(0.123)	(0.116)	(0.661)	(0.726)	(0.677)	(0.555)	(0.638)	(0.529)
Constant				15.831***	15.174***	16.156***	14.500***	13.710***	14.611***
				(0.460)	(0.499)	(0.489)	(0.391)	(0.446)	(0.374)
Observations	2,957	2,475	2,757	2,957	2,475	2,757	2,957	2,475	2,757

Note: *p<0.1; **p<0.05; ***p<0.01. For models (3) to (6), robust standard errors are given in parentheses.

Table 8. Estimation of regression on subsamples by respondents' income levels based on qualitative income indicator

	Low	Medium	High	Low	Medium	High	Low	Medium	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Regression	Ordered logit			OLS			Huber		
T1: CPI	-0.063	0.002	-0.100	0.009	0.317	0.248	-0.300	-0.033	-0.407
	(0.148)	(0.078)	(0.229)	(1.075)	(0.423)	(1.489)	(0.814)	(0.383)	(1.161)
T2: target π	-0.145	0.114	-0.074	-0.174	0.616	-0.348	-0.803	0.527	-0.403
	(0.145)	(0.078)	(0.223)	(1.074)	(0.412)	(1.395)	(0.773)	(0.365)	(1.101)
T3: target π +goal achievement	0.107	0.044	-0.029	1.109	0.381	-0.820	0.649	0.175	-0.069
	(0.147)	(0.079)	(0.220)	(1.092)	(0.421)	(1.236)	(0.866)	(0.371)	(1.102)
T4: FOM's IE	-0.012	0.122	0.176	-0.001	0.631	1.130	-0.029	0.450	1.020
	(0.143)	(0.077)	(0.219)	(1.017)	(0.413)	(1.385)	(0.758)	(0.354)	(1.139)

T5: broad money (M2) growth	0.131	0.154**	0.336	1.141	1.013**	1.434	0.653	0.656*	1.854
	(0.145)	(0.079)	(0.229)	(1.078)	(0.428)	(1.373)	(0.792)	(0.375)	(1.219)
Constant				18.5***	14.8***	15.5***	16.7***	13.7***	14.1***
				(0.722)	(0.290)	(0.991)	(0.535)	(0.272)	(0.818)
Observations	1,697	6,137	742	1,697	6,137	742	1,697	6,137	742

Note: *p<0.1; **p<0.05; ***p<0.01. For models (3) to (6), robust standard errors are given in parentheses.

Table 9. Estimation of regression on subsamples by income levels of respondents based on quantitative income indicator

Regression	25,000 RUB–50,000 RUB			25,000 RUB–50,000 RUB			25,000 RUB–50,000 RUB		
	<25,000 RUB	>50,000 RUB	<25,000 RUB	<25,000 RUB	>50,000 RUB	>50,000 RUB	<25,000 RUB	>50,000 RUB	>50,000 RUB
T1: CPI	Ordered logit			OLS			Huber		
	-0.264**	0.091	0.002	-0.759	0.795	0.257	-1.201**	0.307	0.112
	(0.126)	(0.128)	(0.121)	(0.718)	(0.772)	(0.698)	(0.575)	(0.560)	(0.533)
T2: target π	-0.086	0.075	0.090	-0.586	0.069	1.250*	-0.328	0.289	0.435
	(0.124)	(0.126)	(0.122)	(0.670)	(0.710)	(0.752)	(0.553)	(0.542)	(0.548)
T3: target π +goal achievement	-0.144	0.173	-0.060	-0.774	0.464	0.201	-0.633	0.793	-0.225
	(0.126)	(0.129)	(0.125)	(0.677)	(0.716)	(0.733)	(0.571)	(0.607)	(0.547)
T4: FOM's IE	-0.147	0.305**	0.146	-1.113*	1.189*	1.541**	-0.657	1.307**	0.554
	(0.124)	(0.125)	(0.121)	(0.650)	(0.711)	(0.756)	(0.540)	(0.562)	(0.540)

T5: broad money (M2) growth	0.076	0.254**	0.207*	0.407	0.954	1.852**	0.400	1.107*	0.919
	(0.128)	(0.127)	(0.121)	(0.710)	(0.723)	(0.751)	(0.604)	(0.575)	(0.576)
Constant				16.192***	14.679**	14.800***	14.942***	13.255***	13.506***
				(0.494)	(0.519)	(0.485)	(0.401)	(0.395)	(0.371)
Observations	2,373	2,317	2,454	2,373	2,317	2,454	2,373	2,317	2,454

Note: *p<0.1; **p<0.05; ***p<0.01. For models (3) to (6), robust standard errors are given in parentheses.

Table 10: Estimation on sub-samples based on answer to question: 'Is it better to save or spend spare money?'

	Save (1)	Spend (2)	Save (3)	Spend (4)	Save (5)	Spend (6)
Regression	Ordered logit		OLS		Huber	
T1: CPI	-0.064 (0.090)	0.008 (0.108)	-0.161 (0.551)	0.661 (0.629)	-0.292 (0.395)	-0.002 (0.495)
T2: target π	0.010 (0.088)	0.063 (0.108)	-0.088 (0.530)	0.817 (0.631)	0.026 (0.388)	0.224 (0.495)
T3: target π + goal achievement	-0.035 (0.091)	0.110 (0.107)	-0.200 (0.550)	0.615 (0.587)	-0.202 (0.398)	0.517 (0.496)
T4: FOM's IE	0.062 (0.088)	0.115 (0.105)	0.222 (0.542)	0.723 (0.587)	0.130 (0.382)	0.515 (0.479)
T5: broad money (M2) growth	0.099 (0.089)	0.306*** (0.108)	0.315 (0.536)	1.961*** (0.630)	0.436 (0.400)	1.344*** (0.504)
Constant			15.194***	15.951***	13.556***	14.838***

			(0.386)	(0.415)	(0.281)	(0.349)
Observations	4,661	3,236	4,661	3,236	4,661	3,236

Note: * p<0.1; ** p<0.05; *** p<0.01. For models (3) to (6), the robust standard errors are given in parentheses

Table 11: Estimations on subsamples based on respondent's financial literacy level¹⁰

	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)
Regression	Ordered logit		OLS		Huber	
T1: CPI	-0.045	0.046	0.200	0.576	-0.283	0.135
	(0.101)	(0.103)	(0.647)	(0.581)	(0.479)	(0.431)
T2: target π	0.063	0.068	0.670	0.157	0.303	0.244
	(0.100)	(0.101)	(0.641)	(0.541)	(0.486)	(0.438)
T3: target π +goal achievement	0.042	0.075	0.753	0.267	0.133	0.299
	(0.102)	(0.103)	(0.663)	(0.549)	(0.497)	(0.453)
T4: FOM's IE	0.089	0.119	0.521	0.468	0.357	0.390
	(0.099)	(0.101)	(0.624)	(0.546)	(0.470)	(0.429)
T5: broad money (M2) growth	0.193*	0.086	1.507**	0.111	0.909*	0.346
	(0.099)	(0.103)	(0.647)	(0.537)	(0.496)	(0.445)
Constant			16.422***	14.704***	14.679***	13.511***
			(0.439)	(0.392)	(0.338)	(0.304)
Observations	3,667	3,591	3,667	3,591	3,667	3,591

¹⁰ Respondents with financial literacy index values less than the median value are categorised as having low financial literacy, while the remaining respondents are categorised as having high financial literacy. A similar division into groups by financial literacy index is used in (Dräger et al., 2024)

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. For models (3) to (6), the robust standard errors are given in parentheses

The results presented in Tables 5–11 allow us to conclude that the effect of additional information on the inflation expectations of respondents is quite heterogeneous. Moreover, with the exception of information about the previous year's inflation (T1), all treatments have an upward effect on inflation expectations. Respondents with low incomes (less than 25,000 rubles) or with specialised secondary educations adjust their inflation expectations downwards in response to information about the previous year's inflation. Male respondents react significantly to information about the inflation target of the Bank of Russia (T2), as well as to information about growth in the volume of money in the Russian economy (T5) by increasing their inflation expectations, while no significant results are found in the subsample of women. This result contradicts the findings of the academic literature, in which women tend to be more receptive to new information than men (Coibion et al., 2022; Binder et al., 2018). Regarding the division by age, respondents who are more than 60 years old are sensitive to the inflation expectations of other respondents at 14.2 per cent (T4) as well as to the growth of money in the Russian economy (T5), while the age variable is often insignificant in similar studies (Armantier et al., 2016; Dräger et al., 2024; Coibion et al., 2022). The results in Table 7 show that respondents with different levels of education respond to additional information in the same way on average, which may indirectly indicate the formality of education. People with average incomes are the most receptive to new information regardless of how income is measured, in particular to information on the inflation expectations of the population according to inFOM (T4) and money supply growth (T5), which is consistent with the findings in the literature (Coibion et al., 2022). According to the results in Table 10, only respondents who tend to spend their spare money rather than save it react significantly to information about the growth of the money in the Russian economy by 20 per cent (T5) by increasing their inflation expectations, a result that is robust regardless of the estimation methods. It is likely that people who prefer to spend rather than save are more active and attentive consumers whose inflation expectations are closer to the real value of the inflation indicator, so the numerical value of 20% obtained in the treatment puts upward pressure on their inflation expectations. Finally, the results in Table 11 again indicate the significance of the information about the growth in the money in the Russian economy by 20 per cent (T5), and only on the subsample of people with low levels of financial literacy. In this case, this result may indicate that the respondents mistake money growth for price growth and adjust their inflation expectations closer to this number. We also cannot exclude the hypothesis that people with low levels of financial literacy understand the narrative about the growth of the money supply most clearly, so it is the narrative that has a significant impact on their inflation expectations.

5. ROBUSTNESS CHECK

In this section, we check whether the results of the previous section are robust for alternative measures of inflation expectations, specifically for categorical indicators K73.1 and K73.2. In these questions, respondents are asked how prices will rise in 1 month and 12 months, respectively. Respondents can choose one of several options: 'prices will decrease', 'prices will remain at the same level', 'prices will grow slower', 'prices will grow the same' or 'prices will grow faster than before'. In addition, the regression is estimated for the indicator of current, rather than future, price growth, which corresponds to question K96 in the questionnaire:

K96. In your opinion, how did the prices for food, non-food products and services change in general over the past 12 months?

- Grew faster than before 1
- Grew the same as before 2
- Grew slower than before 3
- Remained at the same level, i.e., no change..... 4
- Decreased 5
- Difficult to say*..... 7
- Cannot answer* 8

The estimation of equation (1) using the ordered logit model yields the results presented in Table 12.

Table 12: Results of estimation of regression for categorical indicators of inflation expectations and for indicator of perception of current inflation

<i>Dependent variable:</i>			
	Inflation expectations for 1 month in advance K73.1 (1)	Inflation expectations for 1 month in advance K73.2 (2)	Perceptions of inflation over past 12 months K72 (3)
T1: CPI	-0.003 (0.064)	-0.012 (0.065)	-0.088 (0.068)
T2: target π	-0.021 (0.064)	-0.002 (0.065)	-0.055 (0.068)

T3: target π + goal achievement	0.045 (0.064)	-0.009 (0.065)	-0.112* (0.068)
T4: FOM's IE	0.016 (0.064)	0.059 (0.065)	-0.143** (0.067)
T5: broad money (M2) growth	0.008 (0.064)	-0.017 (0.065)	-0.139** (0.068)
Observations	11,111	10,760	11,444

Note: *p<0.1; **p<0.05; ***p<0.01

As a result, we do not obtain significant results for the categorical variables of inflation expectations. This may be due to the fact that the response categories for variables K73.1 and K73.2 are much more abstract compared to the clearer quantitative intervals of variable K74, which does not allow us to identify a clear significant effect of the treatment on inflation expectations.

For the indicator of perception of inflation over the last 12 months, the result is opposite to the result for the quasi-interval variable. Information treatments 4 and 5 have downward effects on this indicator.

This result may indicate that the measure of perception of inflation as presented in the questionnaire is not a good proxy variable for inflation expectations, despite the fact that the literature

indicates that respondents do not see much difference between the two and often report similar numerical values for these measures (Huber et al., 2023; Axelrod et al., 2018).

Overall, our analysis of the robustness of the results does not show that the results presented in the previous sections are robust to the use of current inflation as the dependent variable instead of the inflation expectations variable, nor to the use of categorical measures of inflation expectations instead of a quasi-interval measure. However, it is important to note that, in the case of both perception of inflation and inflation expectations, the main treatments that have a meaningful impact on the inflation indicator remain treatments T4 and T5, further indicating that respondents do not believe low inflation-related figures and perceive what is more in line with their personal consumer experience.

6. CONCLUSIONS AND DISCUSSION

In this paper, we use an RCT to estimate the causal relationships between different types of information and the inflation expectations of Russian households, which is the first such work on Russian data.

The results of all regressions with qualitative equivalents of the inflation expectations indicator turn out to be insignificant. On the one hand, such an indicator of inflation expectations should be easier to understand for respondents, for whom inflation expectations are most likely not a figure, but a certain feeling or emotional perception of the situation in the country as a whole. Nevertheless, it is not able to capture any significant effect of treatment. At the same time, the quantitative (quasi-interval) indicator of future price growth, on the contrary, turns out to be sensitive to treatments.

A simple comparison of the mean values of the inflation expectations in the control group with each of the treatment groups shows that only information about growth in the volume of money in the economy has a statistically significant impact on the inflation expectations of the respondents, and, due to the specificity of the RCT method, we can be confident in the correctness of the conclusions drawn from this comparison.

The estimation of the baseline specification using an ordered-logit model and the estimation of a linear regression yield similar conclusions. In addition, the estimation of the models on subsamples of the respondents allows us to refine our conclusions. Information about the growth of the volume of money in the past year turns out to be the most significant, and the most sensitive to it are men, those over 60 years old, those with average incomes, those with low levels of financial literacy, and those who prefer to spend spare money rather than save. A part of the respondents also turn out to be sensitive to information about the inflation expectations of the population according to inFOM, and a small part (namely men) are sensitive to information about the inflation target of the Bank of Russia. The inflation expectations of the respondents in the three treatment groups mentioned are significantly higher than those in the control group. At the same time, the effect of the anchoring of inflation expectations at a lower figure compared to the control group is found only in two cases: in respondents with specialised secondary educations and in low-income respondents who are informed about the previous year's inflation.

The significance of treatments on the inflation expectations of inFOM respondents for 2024 and especially of the growth of money supply in 2023 is probably due to the fact that, in the eyes of

the respondents, the figures contained in the treatment better correspond to what can be trusted (consistent with higher inflation). In order to understand whether people really realise the mechanism of the influence of the money supply on expected inflation, we can further include a placebo effect in the experiment which also contains a two-digit figure. If this placebo treatment has a significant upward effect, it will probably indicate that the respondents unconsciously link their answer to whatever figure they think is more reflective of reality (price increase according to their personal observations), but such a link would not make any sense from the point of view of economic theory.

The low receptivity of the respondents to communication about past inflation and the Bank of Russia's target may indicate, firstly, that people do not trust the information received, as they do not observe low inflation in reality. Also, insensitivity to the narratives mentioned may indicate that the respondents do not understand what is behind these figures. In this case, it is then possible to further expand the wording of the treatments by supplementing them with explanatory theses or even brief understandable statistics, as is done in (Dräger et al., 2024). This will make it possible to understand whether people are not receptive to relatively low figures when it comes to price increases, as they observe a discrepancy between the figures presented in the treatments and their personal consumer experience in recent months or if they are not receptive because they lack understanding of the information that the treatment contains.

In our experiment, almost 85% of respondents receive a treatment, but it has a significant impact on only a part of the respondents, and the impact is upward. In normal life, outside the experiment, a smaller percentage of citizens receives such information. Accordingly, the percentage of those people whose inflation expectations change depending on the information received is even smaller. In applied terms, this means that to anchor inflation expectations at a low level, other means besides communication are necessary, such as keeping inflation at a low level for a long time. In particular, this may entail a tighter monetary policy in the current situation compared to a situation in which communication has a broader and more meaningful impact.

REFERENCES

- Aktug, E. and Atesagaoglu, O.E. 2024. 'Inflation Expectations and Household Spending in High Inflation: Evidence From a Randomized Control Trial'. SSRN, Working papers no. 5041462.
- Allinger, K.M. and Rumler, F. 2023. 'Inflation Expectations in CESEE: The Role of Sentiment and Experiences'. SSRN, Working papers no. 247.
- Andrade, P., Gautier, E. and Mengus, E. 2023. 'What matters in households' inflation expectations?' *Journal of Monetary Economics*, **138**, pp. 50–68.
- Andreev A.V., Grishchenko, V.O., Lyman, M.S., Orlov, D.A. and Shubin, I.A. 2024. 'Factors in the Formation of Inflation Expectations as Recorded in the Russian National Survey of Consumer Finance'. *Economic Policy (Ekonomicheskaya Politika)*. **19**(5), pp. 54–83. (in Russian)
- Armantier, O., Nelson, S., Topa, G., Van der Klaauw, W. and Zafar, B. 2016. 'The price is right: Updating inflation expectations in a randomized price information experiment'. *Review of Economics and Statistics*, **98**(3), pp. 503–523.
- Armantier, O., Topa, G., Van der Klaauw, W. and Zafar, B. 2017. 'An overview of the survey of consumer expectations'. *Economic Policy Review*, **23**(2), pp. 51–72.

- Armona, L., Fuster, A. and Zafar, B. 2019. 'Home price expectations and behaviour: Evidence from a randomized information experiment'. *The Review of Economic Studies*, **86**(4), pp. 1371–1410.
- Axelrod, S., Lebow, D. E. and Peneva, E. 2018. 'Perceptions and expectations of inflation by us households'.
- Baumann, U., Ferrando, A., Georgarakos, D., Gorodnichenko, Y. and Reinelt, T. 2024. 'SAFE to Update Inflation Expectations? New Survey Evidence on Euro Area Firms'. (No. w32504). National Bureau of Economic Research.
- Bessonova, E.V. and Tsvetkova, A.N. 2023. 'Russian households' finances during the pandemic'. *Voprosy Ekonomiki*, **8**, pp. 123–146. (in Russian)
- Beutel, J. and Weber, M. 2023. 'Beliefs and portfolios: Causal evidence'. Chicago Booth Research Paper, (22-08).
- Binder, C. and Rodrigue, A. 2018. 'Household informedness and long-run inflation expectations: Experimental evidence'. *Southern Economic Journal*, **85**(2), pp. 580–598.
- Blinder, A.S. 2009. 'Talking about monetary policy: the virtues (and vice?) of central bank communication'.
- Bottone, M., Tagliabracchi, A., and Zevi, G. 2022. 'Inflation expectations and the ECB's perceived inflation objective: Novel evidence from firm-level data'. *Journal of Monetary Economics*, **129**, S15–S34.
- Burke, M.A. and Manz, M. 2014. 'Economic literacy and inflation expectations: Evidence from a laboratory experiment'. *Journal of Money, Credit and Banking*, **46**(7), pp. 1421–1456.
- Cameron, T.A. and Huppert, D.D. 1989. 'OLS versus ML estimation of non-market resource values with payment card interval data'. *Journal of environmental economics and management*, **17**(3), pp. 230–246.
- Carvalho, C. and Nechio, F.F. 2014. 'Household expectations and monetary policy'. Federal Reserve Bank of San Francisco.
- Clarida, R., Gali, J. and Gertler, M. 1999. 'The science of monetary policy: a new Keynesian perspective'. *Journal of economic literature*, **37**(4), pp. 1661–1707.
- Coibion, O., Gorodnichenko, Y. and Kamdar, R. 2018a. 'The formation of expectations, inflation, and the Phillips curve'. *Journal of Economic Literature*, **56**(4), pp. 1447–1491.
- Coibion, O., Gorodnichenko, Y. and Kumar, S. 2018b. 'How do firms form their expectations? New survey evidence'. *American Economic Review*, **108**(9), pp. 2671–2713.
- Coibion, O., Gorodnichenko, Y., Kumar, S. and Pedemonte, M. 2020. 'Inflation expectations as a policy tool?'. *Journal of International Economics*, **124**, pp. 103–297.
- Coibion, O., Gorodnichenko, Y. and Weber, M. 2021. 'Fiscal policy and households' inflation expectations: Evidence from a randomized control trial'. (No. w28485). National Bureau of Economic Research.
- Coibion, O., Gorodnichenko, Y. and Weber, M. 2022. 'Monetary policy communications and their effects on household inflation expectations'. *Journal of Political Economy*, **130**(6), pp. 1537–1584.

- Coibion, O., Georgarakos, D., Gorodnichenko, Y. and Van Rooij, M. 2023. 'How does consumption respond to news about inflation? Field evidence from a randomized control trial'. *American Economic Journal: Macroeconomics*, **15**(3), pp. 109–152.
- D'Acunto, F., Hoang, D. and Weber, M. 2022. 'Managing households' expectations with unconventional policies'. *The Review of Financial Studies*, **35**(4), pp. 1597–1642.
- D'Acunto, F., Malmendier, U. and Weber, M. 2023. 'What do the data tell us about inflation expectations?'. In Bachmann, R., Topa, G. and van der Klaauw, W. eds., *Handbook of economic expectations*: Academic Press, pp. 133–161.
- D'Acunto, F., Charalambakis, E., Georgarakos, D., Kenny, G., Meyer, J. and Weber, M. 2024. 'Household inflation expectations: an overview of recent insights for monetary policy'. ECB Discussion Paper Series, No. 24.
- Das, A., Lahiri, K. and Zhao, Y. 2019. 'Inflation expectations in India: Learning from household tendency surveys'. *International Journal of Forecasting*, **35**(3), pp. 980–993.
- Deaton, A. 2010. 'Instruments, randomization, and learning about development'. *Journal of economic literature*, **48**(2), pp. 424–455.
- Deaton, A. and Cartwright, N. 2018. 'Understanding and misunderstanding randomized controlled trials'. *Social science & medicine*, **210**, 2–21.
- Deke, J. 2014. 'Using the linear probability model to estimate impacts on binary outcomes in randomized controlled trials'. Mathematica Policy Research.
- Dräger, L. 2015. 'Inflation perceptions and expectations in Sweden—Are media reports the missing link?'. *Oxford Bulletin of Economics and Statistics*, **77**(5), pp. 681–700.
- Dräger, L. and Nghiem, G.H. 2023. 'Inflation literacy, inflation expectations, and trust in the central bank: A survey experiment'. (No. 709). Hannover Economic Papers (HEP).
- Duca-Radu, I., Kenny, G. and Reuter, A. 2021. 'Inflation expectations, consumption and the lower bound: Micro evidence from a large multi-country survey'. *Journal of Monetary Economics*, **118**, pp. 120–134.
- Duflo, E., Glennerster, R. and Kremer, M. 2007. 'Using randomization in development economics research: A toolkit'. *Handbook of development economics*, **4**, pp. 3895–3962.
- Duflo, E. and Banerjee, A., eds. 2017. *Handbook of field experiments* (Vol.1). Elsevier.
- Ellerby, Z. and Wagner, C. 2021. 'Do People Prefer to Give Interval-Valued or Point Estimates and Why?'. In 2021 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE) (pp. 1–6). IEEE.
- Grishchenko V.O., Gasanova, D.I., Fomin, E.V. and Korenyak, G.V. 2023. 'Visible Prices and Their Influence on Inflation Expectations of Russian Households'. Bank of Russia, Working Papers no. 117.
- Hajdini, I., Knotek II, E.S., Leer, J., Pedemonte, M., Rich, R.W. and Schoenle, R.S. 2023. 'Low passthrough from inflation expectations to income growth expectations: why people dislike inflation' (No. 22-21R).
- Haldane, A., Macaulay, A. and McMahon, M. 2020. 'The 3 E's of central bank communication with the public'.

- Huber, S.J., Minina, D. and Schmidt, T. 2023. 'The pass-through from inflation perceptions to inflation expectations' (No. 17/2023). Deutsche Bundesbank Discussion Paper.
- Krauss, A. 2021. 'Assessing the overall validity of randomized controlled trials'. *International studies in the philosophy of science*, **34**(3), pp. 159–182.
- Lane, P.R. 2021. 'Expectations surveys: a tool for research and monetary policy', Introductory remarks by Philip R. Lane, Member of the Executive Board of the ECB, at the Second joint European Central Bank – Federal Reserve Bank of New York conference, November.
- Malmendier, U. and Nagel, S. 2016. 'Learning from inflation experiences'. *The Quarterly Journal of Economics*, **131**(1), pp. 53–87.
- Manski, C.F. and Molinari, F. 2010. 'Rounding probabilistic expectations in surveys'. *Journal of Business & Economic Statistics*, **28**(2), pp. 219–231.
- Reis, R. 2023. 'Expected inflation in the euro area: measurement and policy responses'. London school of Economics and Political Science.
- Roth, C. and Wohlfart, J. 2020. 'How do expectations about the macroeconomy affect personal expectations and behavior?'. *Review of Economics and Statistics*, **102**(4), pp. 731–748.
- Roth, C., Wiederholt, M. and Wohlfart, J. 2023. 'The effects of monetary policy: Theory with measured expectations'.
- Ryan, T.P. 2013. *Sample size determination and power*. John Wiley & Sons
- Schnorpfeil, P., Weber, M. and Hackethal, A. 2023. 'Households' response to the wealth effects of inflation' (No. w31672). National Bureau of Economic Research Working Paper.
- Shleifer, A. 2019. 'The return of survey expectations'. *NBER Reporter*, **1**, pp. 14–17.
- Strobach, C. and van der Cruysen, C. 2015. 'The formation of European inflation expectations: One learning rule does not fit all'.
- Svensson, L.E. 2010. 'Inflation targeting'. In Friedman, B.M. and Woodford, M. eds., 2010. *Handbook of monetary economics*. Elsevier. (Vol. 3, pp. 1237–1302).
- Vellekoop, N. and Wiederholt, M. 2019. 'Inflation expectations and choices of households'.
- Weber, M., D'Acunto, F., Gorodnichenko, Y. and Coibion, O. 2022. 'The subjective inflation expectations of households and firms: Measurement, determinants, and implications'. *Journal of Economic Perspectives*, **36**(3), pp. 157–184
- Wheeler, G. 2015. 'Reflecting on 25 years of inflation targeting opening remarks'. *International Journal of Central Banking (IJCB)*, **11** (S1).
- Wilson, C. and Tisdell, C. 2002. 'OLS and Tobit Estimates: When is Substitution Defensible Operationally?'. University of Queensland, School of Economics, Economic Theory, Applications and Issues Working Papers.
- Zvereva, V., Sinyakov, A., and Shelovanova, T. 2024. 'Financial literacy and responsible financial behaviour of Russian households'. Bank of Russia Working Paper. September. No. 132.

APPENDIX

Table A1. Verification of randomness of respondents' distribution into groups

<i>Distribution of respondents by groups</i>						
	T0	T1: CPI	T2: target π	T3: target π +goal achievement	T4: FOM's IE	T5: broad money (M2) growth
	(1)	(2)	(3)	(4)	(5)	(6)
Gender (base category: female)						
Male	-0.002	0.008	-0.003	0.010	-0.004	-0.010
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Age	-0.001	-0.001	-0.001	0.0001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Education (base category: higher education)						
General secondary education and below	0.007	-0.013	0.004	0.0001	0.007	-0.005

Constant	0.179**	0.137	0.084	0.117	0.131	0.353***
	(0.089)	(0.090)	(0.089)	(0.089)	(0.092)	(0.093)

Note: *p<0.1; **p<0.05; ***p<0.01

Note: The table presents the results of the following regression for each of the treatment groups separately: $Treatment_i^k = X_i * b^{(k)} + e_i$, where $k = 6$, i is the index of the respondent, X is a vector of the control variables (individual characteristics of the respondents/households), and e_i is the random error. Thus, $Treatment_i^k$ is equal to 1 for a given k if the respondent receives a given treatment and zero otherwise. All coefficients are estimated with OLS. The robust standard errors are given in parentheses.

Table A2. Results of estimation of probit model for binary dependent variable based on quasi-interval inflation expectations indicator.

	<i>Dependent variable:</i>					
	IE0	IE1	IE2	IE3	IE4	IE5
	(1)	(2)	(3)	(4)	(5)	(6)
T1: CPI	-5.929	5.947	-0.000	-0.000	-0.000	0.000
	(107.119)	(107.526)	(151.778)	(151.778)	(151.778)	(151.778)

T2: target π	-5.929	0.000	5.399	-0.000	-0.000	-0.000
	(105.572)	(150.690)	(107.526)	(150.690)	(150.690)	(150.690)
T3: target π +goal achievement	-5.929	0.000	-0.000	5.395	0.000	0.000
	(108.431)	(152.706)	(152.706)	(107.526)	(152.706)	(152.706)
T4: FOM's IE	-5.929	0.000	-0.000	-0.000	6.305	0.000
	(105.855)	(150.888)	(150.888)	(150.888)	(107.526)	(150.888)
T5: broad money (M2) growth	-5.929	0.000	-0.000	-0.000	0.000	5.914
	(107.638)	(152.144)	(152.144)	(152.144)	(152.144)	(107.526)
Constant	-0.154***	-6.083	-6.083	-6.083	-6.083	-6.083
	(0.033)	(107.526)	(107.526)	(107.526)	(107.526)	(107.526)
<hr/>						
Observations	8,754	8,754	8,754	8,754	8,754	8,754

Note: * p<0.1; ** p<0.05; *** p<0.01.

Criterion for transforming variable K74 (CAT), which contains 11 categories (11 response intervals), into a binary variable: if the respondent chooses the interval in which falls the number contained in his treatment, or either of the two neighbouring intervals on the left and right, then the dependent variable equals 1, otherwise it equals 0. For example, if the respondent is in treatment group 4, where a number of 14.2% is reported, and chooses the inflation expectations interval of 13–16%, or the interval on the left (9–12%), or the interval on the right (17–20%), then the dependent variable IE4 = 1. Otherwise, it equals 0. The insignificance of the results is probably explained by the large number of zeros (about 8,300 observations) compared to the number of ones (about 400 observations).

Table A3. Results of estimation of Tobit model and linear models.

	Dependent variable: K74		
	(1)	(2)	(3)
Regression	OLS	Huber	Tobit
T1: CPI	0.103 (0.393)	-0.239 (0.333)	0.082 (0.384)
T2: target π	0.262 (0.386)	0.115 (0.330)	0.251 (0.381)
T3: target π +goal achievement	0.354 (0.391)	0.176 (0.339)	0.340 (0.386)
T4: FOM's IE	0.422 (0.382)	0.281 (0.306)	0.414 (0.382)
T5: broad money (M2) growth	0.914** (0.393)	0.673** (0.319)	0.893** (0.385)

Constant	15.687*** (0.271)	14.152*** (0.234)	15.577*** (0.272)
Observations	8754	8754	8754

Note: * p<0.1; ** p<0.05; *** p<0.01.

Table A4. Conversion of categorical income indicator variable K85

Formulation of category in <i>original</i> variable K85	Formulation of category in <i>transformed</i> variable K85
NOT EVEN ENOUGH MONEY FOR FOOD	Low income
THERE IS ENOUGH MONEY FOR FOOD, BUT NOT ENOUGH TO BUY CLOTHES AND SHOES	
THERE IS ENOUGH MONEY TO BUY CLOTHES AND SHOES, BUT NOT ENOUGH TO BUY LARGE HOUSEHOLD APPLIANCES	Average income level
WE HAVE ENOUGH MONEY TO BUY LARGE HOUSEHOLD APPLIANCES, BUT WE CAN'T BUY A CAR.	
I HAVE ENOUGH MONEY FOR EVERYTHING EXCEPT A FLAT (A HOUSE).	High level of income
WE HAVE NO FINANCIAL DIFFICULTIES. IF NECESSARY, WE COULD BUY A FLAT OR A HOUSE.	