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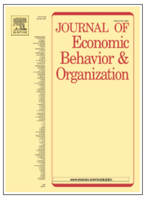

Inflation expectations and cognitive uncertainty ⋆

Joscha Beckmann [a], Jennifer Brunne [b], Timo Heinrich [c,*]

[a] Chair of Macroeconomics, FernUniversität in Hagen, Kiel Institute for the World Economy and SGH Warsaw School Of Economics, Hagen, 58084, Germany
[b] Chair of Macroeconomics, FernUniversität in Hagen, Hagen, 58084, Germany
[c] Institute for Digital Economics, Hamburg University of Technology, Am Schwarzenberg-Campus 4, Hamburg, 21073, Germany

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ABSTRACT

This paper provides a new perspective on the formation of inflation expectations based on a sample of 1036 US residents. In our information provision experiment, the participants were provided with professional forecasts of different historical accuracy and complexity. Our novel experimental design allows us to assess the influence of cognitive uncertainty while controlling for the uncertainty associated with forecasts and priors. Consistent with cognitive uncertainty we find that more complex forecasts lead to smaller updates of inflation expectation.

1. Introduction

Inflation expectations are of key relevance for monetary policy transmission, for example via the Phillips curve (Coibion and Gorodnichenko, 2015). Central banks therefore devote substantial effort to managing inflation expectations via the communication of monetary policy. However, influencing household inflation expectations through communication is difficult: Coibion et al. (2020) highlight the limits of policymakers' ability to actively manage inflation expectations and Blinder et al. (2024) argue that communication with the general public has to date had limited success. While there is a broad consensus that messages should be easy to understand, it remains unclear what constitutes effective communication and how different information structures shape the formation of expectations.

We conducted an information provision experiment to shed more light on the way in which readily available information is – or is not – incorporated into inflation expectations. Our experimental design is novel in two respects. First, providing forecasts that differ in historical accuracy allows us to measure how participants take into account the uncertainty associated with the inflation information provided to them. Second, varying the complexity of the forecast presentation allows us to assess the role of cognitive uncertainty in the formation of inflation expectations.

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* Corresponding author.
E-mail addresses: joscha.beckmann@fernuni-hagen.de (J. Beckmann), jennifer.brunne@fernuni-hagen.de (J. Brunne), timo.heinrich@tuhh.de (T. Heinrich).

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Enke and Graeber (2023) introduced the concept of cognitive uncertainty and proposed a model in which decision makers are uncertain about what the optimal response is. Uncertainty stems from the prior over the optimal response and from cognitive noise generated by deliberation. In belief-updating tasks, for example, decision makers may have difficulty implementing Bayes' rule and put more weight on their mental default. In recent decades, research in psychology and economics has found that people make several systematic errors when forming probabilistic beliefs (see, e.g., the survey by Benjamin, 2019). Enke and Graeber (2023) find that common biases in probabilistic reasoning can be explained by cognitive uncertainty, i.e., the more subjective uncertainty people attribute to their own predictions, the more they rely on defaults. The authors build on recent theoretical and experimental literature on Bayesian models of cognitive noise (see, e.g., Woodford, 2019; Gabaix, 2019; Frydman and Jin, 2022; Khaw et al., 2021) as well as on earlier work focusing on topics such as over- and under-confidence (Erev et al., 1994) or probability weighting (Viscusi, 1989).[1]

For our experiment, we recruited a sample of 1036 US residents using Prolific's representative sample feature, which employs stratified sampling based on age, gender and ethnicity quotas. The experiment was conducted in late June 2020, a period of low and stable inflation with less pronounced uncertainty compared to the subsequent surge in inflation. We exogenously varied the information provided to participants by using professional inflation forecasts from the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters. Each participant was randomly assigned one such forecast together with a summary measure of that forecaster's historical accuracy.[2] We experimentally varied the complexity of inflation forecasts in two ways: (i) by presenting information in reduced or compound form and (ii) by presenting information only graphically or directly in numerical form. After receiving the information, the respondents could revise their beliefs. We then evaluated (i) updates in inflation expectations and (ii) changes in self-reported uncertainty about these expectations. Exogenously varying the sets of forecast information and their format provided enabled us to disentangle the effects of forecasts, forecast uncertainty and cognitive noise on updates. To reduce additional noise from misconceptions about the concept of inflation, participants had to pass a small quiz before reporting their inflation expectations.

We find that, consistent with standard Bayesian updating, providing subjects with forecasts leads to updates in the direction of the forecast. In line with cognitive uncertainty, however, more complex forecasts also lead to smaller updates. Thus, our findings imply that simpler communication of monetary policy may increase the impact of these messages. In addition, forecasts of lower historical accuracy lead to greater uncertainty in expectations and relatively smaller updates. Yet, we do not observe a statistically significant effect of forecast complexity on the reported uncertainty in updated beliefs.

Our study contributes to a recent body of literature that focuses on how households or consumers adapt their inflation expectations based on the information available. While several studies point to the role of communication in shaping inflation expectations, our study is the first to vary the complexity of information in order to analyze whether cognitive noise affects inflation expectations. It is well established that financial experts are attentive to monetary policy announcements, whereas households do not react systematically to these announcements, as observed by Lamla and Vinogradov (2019). Blinder et al. (2024) discuss this evidence and highlight the potential of simpler and more targeted communication for managing expectations. Consistent with this view, information provision experiments have shown that participants who are directly provided with relatable information on monetary policy do adjust their inflation expectations (see, e.g. Binder and Rodrigue, 2018, Coibion et al., 2018, Coibion et al., 2022, and Coibion et al., 2023). Furthermore, altering inflation expectations has the potential to affect real-world economic decisions, such as the purchase of durable goods (Roth and Wohlfart, 2020; Coibion et al., 2020, 2023). At the same time, heterogeneity in information processing is evident, as households' information channels and lifetime experience concerning inflation are systematically associated with heterogeneity in inflation perceptions, expectations and uncertainty (Conrad et al., 2022). Moreover, high inflation itself appears to increase the complexity and difficulty of household economic decision-making (Binetti et al., 2024), highlighting the importance of understanding how households process inflation-related information.

We also contribute to the literature on the link between uncertainty and inflation expectations. Empirical work has demonstrated that uncertainty concerning inflation can reduce economic activity, increase inflation expectations and affect household decisions (Georgarakos et al., 2024; Binder et al., 2025). Uncertainty can also reduce public trust in central banks (Istrefi and Piloiu, 2020). In our experiment, we examine whether cognitive uncertainty is reflected in self-reported inflation uncertainty, distinct from uncertainty stemming from the historical accuracy of the information provided.

2. Hypotheses

In their work, Enke and Graeber (2023) observe a human tendency to be insensitive to variation in probabilities; they attribute this to cognitive noise from deliberation. They collect certainty equivalents in choices under risk, posterior beliefs in a Bayesian updating task and threshold probability estimates in survey expectations.[3] In addition, they collect self-reported uncertainty about these responses as a measure of cognitive uncertainty. They find that cognitive uncertainty increases in more complex settings, explaining the insensitivity to variation in probabilities and probability estimates closer to a mental default.

Enke and Graeber (2023) also point out that cognitive noise can be relevant for the formation of inflation expectations. Thus, we adopt their concept based on the signal-extraction problem presented by Gabaix (2019): an individual has a normally distributed prior with mean x_d and variance σ_x^2. They then receive the expert forecast $f = x_f + \epsilon_f$ as a signal with a normally distributed error

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[1] As pointed out by Woodford (2019), the idea of modeling cognitive imprecision goes back at least to Fechner (1860) and Thurstone (1927).

[2] The complete instructions can be found in Online Appendix B.

[3] With respect to survey expectations, they do not elicit point forecasts on economic variables. Instead, they elicit the percent chance a $100 S&P 500 investment is below a specific randomly chosen one-year value, or that one-year-ahead inflation will be below a specific percentage.

term with mean zero and variance σ_f^2.[4] A rational individual updating their beliefs based on the forecast f will obtain the following posterior:

$$p^* = x_d + \frac{\sigma_x^2}{\sigma_x^2 + \sigma_f^2}(f - x_d). \tag{1}$$

However, if an individual experiences cognitive noise in the sense of Enke and Graeber (2023), they will have difficulty calculating p^*. Being aware of the cognitive noise involved in processing the information, the individual will put more weight on the prior and less weight on the result of their calculation. We assume that an individual observes the forecast f, but that cognitive noise increases the effective uncertainty of the forecast information. This means that we represent the cognitive noise from deliberation as an additional variance term σ_s^2 on the forecast, so that the individual updates their expectation based on an error variance of $\sigma_f^2 + \sigma_s^2$. Accordingly, we assume that the individual generates the posterior

$$p = x_d + \frac{\sigma_x^2}{\sigma_x^2 + \sigma_f^2 + \sigma_s^2}(f - x_d). \tag{2}$$

Thus, the posterior is a linear combination of the prior and the forecast, as in Eq. (1) and the absence of all uncertainty ($\sigma_f^2 = \sigma_s^2 = 0$) would result in a full update of expectations. In contrast, with increasing uncertainty ($\sigma_f^2 \neq 0$ or $\sigma_s^2 \neq 0$), updates are attenuated and the posterior regresses toward the prior.[5]

In our experiment, we vary the nature of the expert forecast an individual receives. First, this allows us to change the forecast f as well as the variance of its error σ_f^2 exogenously, while keeping the prior variance σ_x^2 constant. Thereby we can study the influence of specific forecasts and their uncertainty on an individual's posterior. Second, following Enke and Graeber (2023), we vary the complexity of the forecast, which we interpret as altering the cognitive noise captured by the additional variance σ_s^2.

Following the working paper version Enke and Graeber (2019) of Enke and Graeber (2023), we adopt the standard deviation of the posterior in the signal-extraction problem as our indicator of posterior uncertainty

$$\sigma_{PU} = \frac{\sigma_x \sigma}{\sqrt{\sigma_x^2 + \sigma^2}} \tag{3}$$

where $\sigma^2 = \sigma_f^2 + \sigma_s^2$ is the overall variance from forecast uncertainty and cognitive noise.[6] We refer to σ_{PU} as the posterior uncertainty, reflecting the individual's total uncertainty about future inflation. Holding forecast uncertainty σ_f^2 fixed, the cognitive-noise term σ_s^2 varies with forecast complexity across treatments and, thus, changes in σ_{PU} can be interpreted as changes in cognitive uncertainty. Empirically, we proxy σ_{PU} by participants' self-reported uncertainty about their posterior.

Based on previous work, we formulate two null hypotheses. We assume that a rational individual will not be influenced by an exogenous increase in cognitive noise. Such an increase will not change the weight this individual puts on their prior (see Eq. (1)), as this is only driven by the uncertainties in the forecast and the prior. For the same reasons, cognitive noise will also not influence the uncertainty in their posterior (see Eq. (3)). Accordingly, we formulate the following null hypotheses:

Hypothesis 1. The revision of expectations is not influenced by the complexity of the forecast.

Hypothesis 2. The uncertainty of the posterior is not influenced by the complexity of the forecast.

If a more complex display of information increases cognitive noise, however, we will be able to reject these hypotheses and the revisions will decrease, while uncertainty of the posterior will increase. The test of Hypothesis 1 is an indirect test of the role complexity plays in incorporating forecast information, while the test of Hypothesis 2 directly tests whether posterior uncertainty is influenced by the complexity of forecasts.[7]

In general, cognitive noise will result in an under-reaction to information. As $\sigma_s^2 > 0$ with cognitive noise, an individual will put more weight on the prior in Eq. (2) than in Eq. (1) as the noise increases. We rewrite Eq. (2) as

$$p = (1 - \beta)x_d + \beta f = x_d + \beta(f - x_d) \tag{4}$$

with $\beta = \sigma_x^2/(\sigma_x^2 + \sigma_f^2 + \sigma_s^2)$ representing the weight an individual puts on the forecast f (see Cavallo et al., 2017). To test Hypothesis 1, we estimate the size of the revisions using the equation

$$p - x_d = \alpha + \beta(f - x_d) + \gamma t + \delta t(f - x_d) + \eta. \tag{5}$$

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[4] Professional forecasts are widely considered to be relevant predictors of future inflation and an important source of information for forming inflation expectations (see, e.g., Ang et al., 2007, and Carroll, 2003).

[5] With binary probability elicitation, as in Enke and Graeber (2023), this yields estimated probabilities closer to a 50:50 default, see Footnote 3.

[6] This measure coincides with the expression of cognitive uncertainty in Enke and Graeber (2019) in the special case in which one's optimal action is identical to truthfully reporting the belief about the state of the world (i.e., their scaling parameter B equals 1) and when there is no noise in the forecast ($\sigma_f = 0$).

[7] For the interpretation of our results, it will be important to note that a direct test does not necessarily imply a larger effect size.

where α captures spurious trends that are not influenced by the provided information, t denotes a treatment dummy for increased forecast complexity and η is a normally distributed error term (see Lybbert et al., 2007 and Fuster et al., 2022 for similar approaches). Thus, a test of $\delta = 0$ provides us with a test of Hypothesis 1, while a negative estimate $\delta < 0$ implies that the complexity of the forecast reduces the response to the signal.

To test Hypothesis 2 it is important to note that posterior uncertainty as defined in Eq. (3) is increasing in σ_x, σ_f and σ_s. We approximate this relationship by the following linear equation:

$$\sigma_{PU} = \alpha + \beta\sigma_f + \gamma t + \delta\sigma_x + \eta \tag{6}$$

where $\delta\sigma_x$ denotes the weight assigned to the uncertainty of the prior. In addition, the remaining expression $\alpha + \beta\sigma_f + \gamma t$ captures the contribution from σ, i.e., from the combined uncertainty arising from the forecast error and from cognitive noise. More specifically, $\beta\sigma_f$ captures changes in posterior uncertainty induced by changes in forecast uncertainty and γt indicates the cognitive uncertainty induced by treatment-specific levels of cognitive noise (see Coibion et al., 2018, p. 2700, for a similar approach). Finally, the constant α captures the baseline level of posterior uncertainty that is not explained by the other terms, including the contribution of cognitive noise to posterior uncertainty in the baseline treatment ($t = 0$). We are interested in how cognitive noise influences posterior uncertainty. Thus, a test of $\gamma = 0$ provides us with a test of Hypothesis 2, while a positive estimate $\gamma > 0$ implies that the complexity of the forecast increases posterior uncertainty.

In the signal-extraction model, σ_x, σ_f and σ_{PU} denote standard deviations. In our experiment, we cannot observe these directly. Instead, we operationalize uncertainty on a common scale: respondents report how many out of ten times their prediction concerning inflation would deviate from realized inflation by more than one percentage point. For each professional forecaster, we compute the analogous historical frequency using the ten most recent annual forecasts. Throughout the empirical analysis, we interpret these frequencies of deviation as proxies for σ_x, σ_f and σ_{PU}.

3. Experimental design

We develop a new elicitation method that jointly elicits respondents' point expectations and their self-reported uncertainty about future inflation. The experimental design has two dimensions. First, we exogenously vary the content and precision of the information provided, i.e., the expert forecast and its historical accuracy. Second, we exogenously vary the complexity of the information provided, which we interpret as changing the potential amount of cognitive noise. Before explaining these treatment variations and our procedures, we first describe our elicitation method. We conclude this section with information on the characteristics of our dataset.

3.1. Elicitation method

In our experiment, participants receive one of four distinct combinations of expert inflation forecasts along with the respective historical forecast errors. These forecasts are sourced from the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters, ensuring that the information reflects real professional predictions and the actual associated errors. We elicit the inflation expectations of participants before and after providing the information by asking for a point prediction together with a self-reported measure of uncertainty.[8]

Our first question (Fig. 1) asks about participants' expected inflation in the upcoming 12 months. This question builds on the NY Fed Survey of Consumer Expectations and is taken from Coibion et al. (2023). Different from their format, we do not elicit a full probability distribution. Instead, we design a simple measure of uncertainty by asking participants how certain they are about their predictions. More precisely, we ask in the second question *"Imagine you made the same type of prediction about inflation 10 times. How often do you think your prediction will be off by more than 1%?"*. The participants then use a slider to select a number between 0 and 10. We also provide an example in order to improve understanding.[9] This elicitation method allows us to present forecast uncertainty and respondents' self-reported uncertainty in a comparable format.[10] Moreover, it applies Enke and Graeber's (2023) approach to the study of inflation expectations by jointly eliciting a point prediction and respondents' self-reported uncertainty.

3.2. Treatments and procedures

Our information provision experiment was conducted online using Qualtrics for data collection. Our study proceeded as follows: All participants needed to give informed consent after deciding to participate. In the first part of the experiment, which was the same for all participants, they were provided with brief descriptions of inflation, unemployment and the Federal Reserve. These

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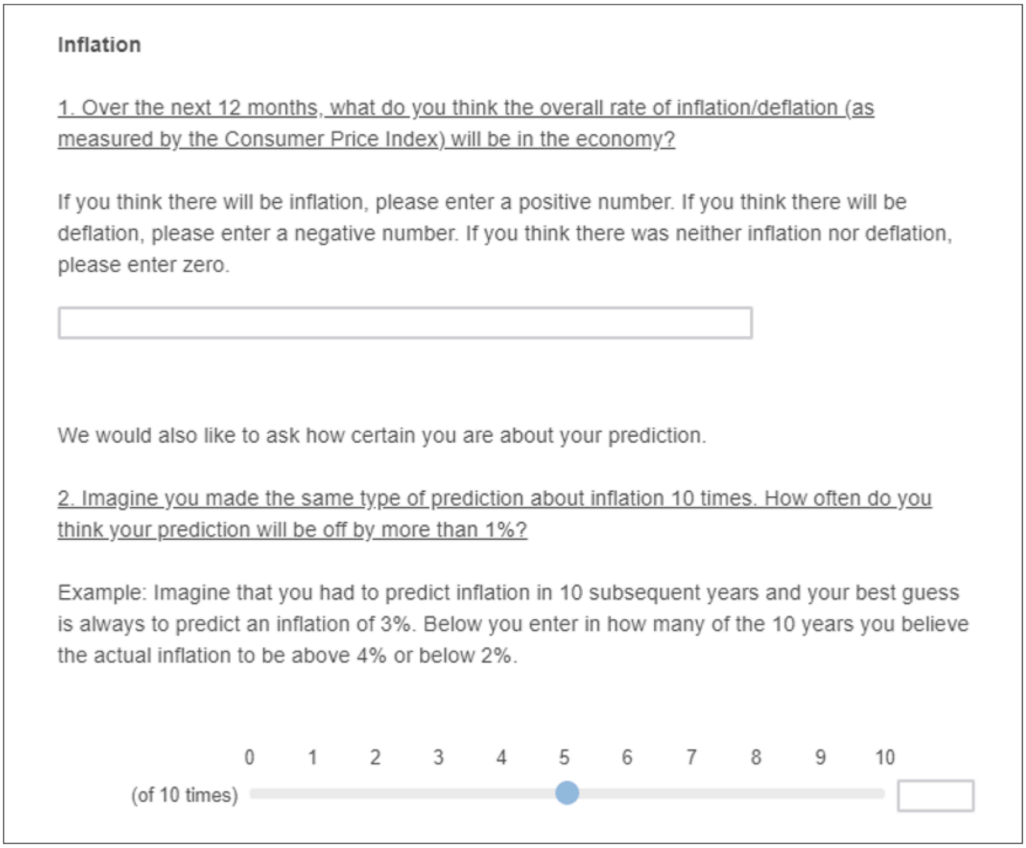
[8] While some studies suggest that financial incentives may affect reporting of inflation expectations (Andre et al., 2022; Drobot et al., 2025), we follow standard survey practice by not incentivizing predictions. This approach maintains comparability with major consumer surveys, including the Survey of Consumer Expectations conducted by the NY Fed (Armantier et al., 2017).

[9] Our example of a specific inflation rate (which is also used in the control questions) was randomly varied between -3% and 5% in steps of two percentage points. While these values could serve as anchors, Kruskal-Wallis tests reveal no significant differences in their distribution across treatments (p = .332) or tuples (p = .230). We leave a systematic analysis of anchoring effects for future research.

[10] For a recent alternative see Goldfayn-Frank et al. (2026).



Inflation

1. Over the next 12 months, what do you think the overall rate of inflation/deflation (as measured by the Consumer Price Index) will be in the economy?

If you think there will be inflation, please enter a positive number. If you think there will be deflation, please enter a negative number. If you think there was neither inflation nor deflation, please enter zero.

We would also like to ask how certain you are about your prediction.

2. Imagine you made the same type of prediction about inflation 10 times. How often do you think your prediction will be off by more than 1%?

Example: Imagine that you had to predict inflation in 10 subsequent years and your best guess is always to predict an inflation of 3%. Below you enter in how many of the 10 years you believe the actual inflation to be above 4% or below 2%.

Fig. 1. Expectation elicitation.

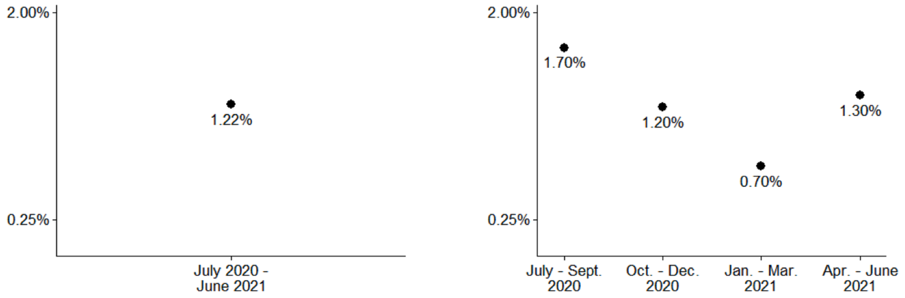
were followed by a quiz on inflation consisting of one question concerning the definition of inflation and another on the economic interpretation of inflation in terms of real interest rates. Only participants who were able to answer these questions correctly were included in our sample. Participants were then asked about their inflation expectations as described in the previous section.

In the second part, participants were randomly allocated to one of four treatments explained below. Within each treatment, participants were randomly provided with the current forecast of one of four professionals participating in the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters. The four forecasts were selected from all professionals who had continuously made quarterly forecasts over the previous ten years. We then chose the two forecasts with the highest (2.90) and the two with the lowest values (0.35 and 1.22).

Prior studies have provided participants with only a numerical value of a professional forecast (Coibion et al., 2018; Weber et al., 2025), sometimes supplemented by the range of forecasts (Armantier et al., 2016; Coibion et al., 2023). In contrast, we supplemented the numerical forecast with information on the historical accuracy of the respective forecaster. We proxied forecast uncertainty σ_f by the number of times the forecaster's prediction deviated from the actual inflation rate by more than one percentage point in the ten most recent annual forecasts. Among forecasters who had continuously been involved over the past ten years, this measure ranged from 2 to 6 such deviations. The four forecasts used in the experiment spanned this range of historical accuracy. The resulting forecast and error tuples (f, σ_f) presented to participants were (2.90; 6), (2.90; 2), (0.35; 2) and (1.22; 3). Each participant was exposed to only one of these treatment-specific forecast-error combinations. We emphasized to the participants that these figures were based on actual forecasts by professionals. This approach allowed us to vary both the signal provided to participants and the associated noise in a between-subjects design. After receiving the respective information, the participants were again asked to enter their expectations and uncertainty.

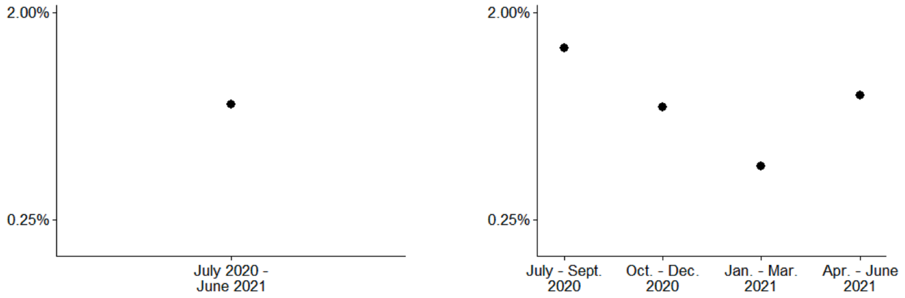
Our treatment variations follow the complexity manipulations used in the lottery tasks described by Enke and Graeber (2019). The authors observe that cognitive uncertainty increases (i) when probabilities have to be combined, as in compound lotteries, and (ii) when probabilities are left ambiguous. We vary the display of information along similar dimensions: Fig. 2 illustrates the four treatment cells for a forecaster with $(f, \sigma_f) = (1.22; 3)$, i.e., a forecast value of 1.22 and a historical error rate of 3.

Across all treatments, we ask participants to provide their expectations for the next 12 months. In the compound treatment, denoted **C** (Compound), we provide four annualized quarterly rates instead of a single 12-month forecast. In theory, recovering the corresponding 12-month forecast requires recognizing that these four annualized quarterly forecasts interact multiplicatively across



Baseline

C



G

C and G

Fig. 2. Information provision treatments.

quarters. Using the arithmetic mean instead of the geometric mean (as used in the Survey of Professional Forecasters) yields very similar annualized forecasts in our setting, however.[11]

In the graphical treatment, denoted by **G** (Graphical), forecast values need to be inferred from the labels on the y-axis rather than read as printed numbers. This intentionally turns a precise point estimate into a visually inferred range, adding steps of visual and cognitive integration (and thus potentially cognitive noise) while holding the informational content of the signal fixed. To further increase the complexity of the task, the labels on the y-axis are spaced 1.75 percentage points apart (instead of, for example, one or two percentage points).[12] Our **Baseline** treatment applies neither of the two manipulations, while our **C and G** (Compound and Graphical) treatment applies both.

For all forecast tuples, the geometric mean of the four quarterly rates shown in treatments **C** and **C and G** equals the 12-month forecast shown in **Baseline** and **G**. Furthermore, the associated historical error σ_f is identical across formats. Our analysis focuses on the responses to f and σ_f and accordingly treats the quarterly information on f in **C** and **C and G** as a redundant decomposition of the same signal. However, we note that some participants may hold beliefs about the intra-year path of inflation, a factor that could make the quarterly decomposition informative.

To sum up, treatment **C** mirrors the increase in complexity from compound lotteries, while treatment **G** mirrors the increase from ambiguous lotteries studied in Enke and Graeber (2019) and further discussed in Enke and Graeber (2023). The combination in treatment **C and G** implements both complexity levers simultaneously. Across all treatments, the underlying signal (f, σ_f) is held constant. Only the representation of the signal varies and thus, any attenuation in responsiveness can be attributed to an increase in cognitive noise rather than to changes in informational content.[13]

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[11] Under arithmetic averaging, two of the four (f, σ_f) forecast tuples are unchanged to two decimal places. The two other tuples shift by 0.01, namely from $(2.90; 2)$ to $(2.91; 2)$ and from $(1.22; 3)$ to $(1.23; 3)$.

[12] We chose the upper label by rounding up the highest quarterly forecast of the specific forecaster and then subtracted 1.75 percentage points for the lower label.

[13] The instructions in Online Appendix B show an inflation anchor of 3% and a forecast of $(f, \sigma_f) = (2.90; 6)$ in treatment **G**. At the end of the first part, participants were asked to provide various demographic information based on the Survey of Consumer Expectations conducted by the NY Fed. The selected questions allow for similar controls as in Coibion et al. (2022). At the end of the second part, we included a set of questions on monetary policy and on the Covid-19 pandemic based on Binder (2020). As Cavallo (2024) notes, the inflation experienced by consumers may differ more strongly from official statistics, as the consumption bundle has shifted during the pandemic. The last set of questions included an attention check that all participants had to pass in order to be included in our sample. We also elicited expectations on future unemployment, which we do not consider in the current paper.

3.3. Sample characteristics

Of the 1246 recruited participants, 208 failed the preceding comprehension questions and two failed an attention check during the course of the survey, resulting in a sample size of 1036.[14] Participants needed 10.5 minutes on average to complete the survey, with a median value of 8.5 minutes, a minimum value of 2.1 minutes and a maximum value of 63.6 minutes. The data were collected at the end of June 2020, before the beginning of the new quarter.[15]

All participants were current US residents and reported being fluent in English. We used Prolific's representative sample feature, which stratifies participants by sex, age and ethnicity to match US Census Bureau population estimates from 2015. Prolific samples individuals based on Census proportions for sex (male, female), ethnicity (White, Mixed, Asian, Black and Other) and age (18 to 24, 25 to 34, 35 to 44, 45 to 54 and above 54). We also collected demographic data independently. We did not ask for ethnicity, as this is "special category data" under the EU's "General Data Protection Regulation". However, comparing our sample to the more recent 2019 census estimates, our age distributions do not differ from the expected distributions for men and women ($p \geq .429$, χ^2-tests). Further disaggregation of the 55+ group reveals an over-representation of women aged 55 to 64 ($p < .001$), whereas the male age distribution remained consistent with the Census proportions ($p = .222$).[16]

4. Results

4.1. Overview

Table 1 summarizes key descriptive statistics for the entire sample after adjusting for outliers by applying Huber weights.[17] Initially, participants across treatments expect an average inflation rate of 2.61 percent, a value that exceeds the average presented expert forecast of 1.84 percent. Overall, participants across treatment groups adjust their posterior expectations towards these expert forecasts, with an average posterior inflation expectation of 2.10 percent. The participants mostly update their predictions in the direction of the forecast: within each treatment, posterior expectations are higher when participants receive the higher expert forecasts ($f = 2.90$) than when they receive the lower forecasts ($f = 0.35$ or $f = 1.22$). Also, there is an apparent pattern in how complexity attenuates updating for the lowest forecast $f = 0.35$: the average posterior is 1.18 in **Baseline**, 1.29 in **C**, 1.33 in **G** and 1.70 in **C and G**, indicating weaker adjustment in more complex display formats.

With respect to aggregate prior inflation uncertainty (measured by the expected number of deviations greater than one percentage point across ten predictions), participants initially expect 4.91 out of ten deviations, well above the average historical expert accuracy of 3.25 they are presented with. After treatment, there is little change in aggregate posterior uncertainty at an average deviation of 4.87. However, posterior uncertainty increases with forecast uncertainty, ranging from 3.88 to 5.25 when $\sigma_f = 2$, from 4.24 to 5.29 when $\sigma_f = 3$ and from 5.19 to 5.41 when $\sigma_f = 6$ (Table 1).[18]

4.2. Expectation revisions

The first exogenous variation we examine is the level of the professional forecasts. Our summary statistics suggest that participants revise their expectations upon receiving new information. We now quantify these revisions as a function of the deviation between the provided forecasts and participants' priors and we test whether updates are attenuated if the same information is presented in more complex formats.

Table 2 presents the regression results using expectation revision as the dependent variable. The models follow Eq. (5) and include dummy variables for a compound display of information (**C**), a graphical display (**G**) and the combination of the two as an interaction term (**C** × **G**). The main independent variable of interest is the deviation between the signal that participants receive and their prior ($Deviation$). The concept of cognitive uncertainty suggests that the effect of the signal is attenuated by a more complex display of the forecast. Thus, we focus on the interaction between the deviation and the variation in complexity. Table 2 includes models both

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[14] The share of excluded participants is lower than that reported by (Enke and Graeber, 2023). For samples recruited using MTurk and Prolific, they screened out 54 percent of potential participants in their treatments eliciting beliefs about threshold probabilities.

[15] In designing our study, we aimed for a power of 80 percent to identify a treatment difference at the 5 percent level using a two-sided t-test. The calculation was done with respect to Hypotheses 1 and 2 for our treatments. In the absence of previous studies on cognitive uncertainty in the prediction of inflation, we aimed to recruit a sample of at least 1,000. This would allow us to identify a small effect size of $d = 0.18$.

[16] See https://researcher-help.prolific.com/en/article/e6555f for details concerning the sampling procedure applied by Prolific. The age distributions are shown in Figure A.3 in Online Appendix A. In addition, strictly speaking, the resulting sample can only be representative of a sub-population in the US receptive to learning about the concept of inflation. We believe this sub-population to be most relevant for those designing monetary policy announcements. To gauge the population-wide effects of forecast provision, additional data of those ignorant of the concept of inflation would need to be collected. As updating behavior is likely to be noisier in those participants, including this group would reduce the overall effect of information provision while making the theory more difficult to test.

[17] Each treatment includes all four forecast tuples, ensuring that differences across treatments reflect variation in cognitive uncertainty rather than differences in signal accuracy. The distribution of tuples across treatments does not differ significantly from a uniform distribution ($p \geq .423$, χ^2-tests). In Table A.1 of the Online Appendix, we provide descriptive statistics without adjusting for outliers.

[18] Of 1036 participants, 328 do not update their inflation expectations. This aligns with the literature on rational inattention, where some participants do not respond to new information. At the same time, it confirms that professional forecast information is informative for most participants. Figures A.1 and A.2 in Online Appendix A show the distributions of priors and respective posteriors.

Table 1
Descriptive statistics with outlier correction (applying Huber weights).

	Prior Inflation Rate	Posterior Inflation Rate	Prior Uncertainty	Posterior Uncertainty	Number of Participants
Baseline	2.74	2.07	4.82	4.90	**269**
	(3.83)	(1.56)	(2.15)	(2.24)	
$(f, \sigma_f) = (2.90; 6)$	2.96	2.71	4.87	5.29	65
	(4.08)	(1.20)	(2.03)	(2.06)	
$(f, \sigma_f) = (2.90; 2)$	2.90	2.60	4.76	4.28	66
	(4.42)	(1.13)	(2.15)	(2.12)	
$(f, \sigma_f) = (0.35; 2)$	2.23	1.18	5.07	5.25	65
	(3.01)	(1.76)	(2.17)	(2.36)	
$(f, \sigma_f) = (1.22; 3)$	2.83	1.74	4.62	4.84	73
	(3.65)	(1.59)	(2.26)	(2.31)	
C	2.70	2.12	4.92	4.83	**259**
	(3.87)	(1.66)	(2.31)	(2.27)	
$(f, \sigma_f) = (2.90; 6)$	3.13	2.88	4.85	5.20	64
	(5.74)	(1.78)	(2.24)	(2.02)	
$(f, \sigma_f) = (2.90; 2)$	2.47	2.56	5.40	5.01	63
	(2.95)	(1.48)	(2.26)	(2.28)	
$(f, \sigma_f) = (0.35; 2)$	2.83	1.29	4.62	4.89	66
	(3.03)	(1.36)	(2.24)	(2.33)	
$(f, \sigma_f) = (1.22; 3)$	2.37	1.79	4.83	4.24	66
	(3.17)	(1.54)	(2.49)	(2.37)	
G	2.44	2.18	5.22	4.99	**242**
	(2.65)	(1.55)	(2.22)	(2.22)	
$(f, \sigma_f) = (2.90; 6)$	2.54	2.78	5.34	5.41	64
	(2.25)	(1.43)	(2.23)	(2.15)	
$(f, \sigma_f) = (2.90; 2)$	2.31	2.50	5.25	4.33	63
	(2.58)	(1.43)	(2.31)	(2.20)	
$(f, \sigma_f) = (0.35; 2)$	1.88	1.33	5.11	5.07	64
	(3.25)	(1.46)	(2.13)	(2.45)	
$(f, \sigma_f) = (1.22; 3)$	3.16	2.04	5.18	5.22	51
	(2.24)	(1.54)	(2.26)	(1.87)	
C and G	2.55	2.03	4.77	4.81	**266**
	(3.33)	(2.27)	(2.08)	(2.09)	
$(f, \sigma_f) = (2.90; 6)$	2.51	2.57	4.61	5.19	66
	(2.67)	(1.57)	(2.13)	(1.99)	
$(f, \sigma_f) = (2.90; 2)$	2.15	2.11	4.30	4.62	65
	(2.63)	(2.24)	(2.06)	(2.11)	
$(f, \sigma_f) = (0.35; 2)$	2.78	1.70	4.46	3.88	66
	(4.84)	(3.30)	(2.02)	(1.93)	
$(f, \sigma_f) = (1.22; 3)$	2.72	1.75	5.29	5.29	69
	(2.73)	(1.55)	(2.03)	(2.05)	
Total	2.61	2.10	4.91	4.87	**1036**
	(3.46)	(1.78)	(2.20)	(2.20)	

The table shows the arithmetic means after correction for outliers by applying Huber weights.
Standard deviations are given in parentheses.

with and without additional controls.[19] To analyze treatment effects, we follow Coibion et al. (2018), among others, and employ Huber-robust regressions to control for outliers and influential observations. However, our main results are robust to a variety of outlier corrections. In Section 4.4 we provide results for sub-samples with high and low education levels and high and low income groups as robustness checks.

The results (Table 2) indicate that professional forecasts significantly impact updating of expectations, as suggested by the summary statistics: in the **Baseline** treatment, a one-percent deviation between prior and signal results in an update between 0.766 and 0.857 percentage points, as indicated by the *Deviation* variable ($p < .001$).

The interactions between the *Deviation* and complexity variation dummy variables provide a test of Hypothesis 1. The results in columns (1) and (2) include the dummy variable for a compound display of information (**C**), revealing significant dampening of expectation revisions by 0.117 and 0.119 percentage points, respectively ($p < .001$). This supports the notion that providing four annualized forecast values rather than one value generates additional cognitive noise. In contrast, columns (3) and (4) include the

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[19] We consider gender, age and region as control variables. Including these control variables reduces the sample size to 1029 observations, since seven participants did not report their gender. Based on the work by Binder (2020), we also incorporate a Covid-19 index as a proxy for an individual's financial, health-related and food-related concerns due to the Covid-19 pandemic with three levels of concern ('Not at all concerned', 'Somewhat concerned' and 'Very Concerned'). However, none of these controls affect the main results. In Online Appendix A we present the summary statistics for the control variables by treatment (Table A.2) and by forecast tuple (Table A.3).

Table 2
Expectation revision.

	Dependent variable: $p - x_d$					
	(1)	(2)	(3)	(4)	(5)	(6)
Deviation	0.769^{***} (0.008)	0.766^{***} (0.008)	0.823^{***} (0.007)	0.820^{***} (0.007)	0.857^{***} (0.009)	0.857^{***} (0.009)
C (Compound)	-0.114 (0.071)	-0.111 (0.072)			0.011 (0.101)	0.008 (0.101)
Deviation × **C**	-0.119^{***} (0.011)	-0.117^{***} (0.011)			-0.089^{***} (0.014)	-0.094^{***} (0.014)
G (Graphical)			-0.135^{*} (0.069)	-0.137^{*} (0.071)	-0.007 (0.102)	-0.011 (0.102)
Deviation × **G**			-0.275^{***} (0.010)	-0.272^{***} (0.011)	-0.238^{***} (0.019)	-0.245^{***} (0.019)
C × **G**					-0.261^{*} (0.144)	-0.245^{*} (0.144)
Deviation × **C** × **G**					-0.056^{**} (0.024)	-0.034 (0.024)
Controls	No	Yes	No	Yes	No	Yes
Constant	0.094^{*} (0.050)	0.017 (0.321)	0.085^{*} (0.048)	0.081 (0.318)	0.082 (0.070)	0.076 (0.327)
Observations	1036	1029	1036	1029	1036	1029
Residual Std. Error	0.904	0.899	0.830	0.894	0.913	0.908
AIC	5558.2	5542.1	5477.9	5462.3	5429.2	5417.2
BIC	5582.9	5606.3	5502.6	5526.5	5473.7	5501.1

The dependent variable is the difference between the posterior (p) and the prior inflation expectation (x_d).

${}^{*}p < .1$; ${}^{**}p < .05$; ${}^{***}p < .01$

Huber robust standard errors are given in parentheses.

Controls include gender, age, age^2, region and a Covid-19 index.

dummy variable for a more complex graphical display of information (**G**). This factor significantly reduces the reaction to the signal by between 0.272 and 0.275 percentage points ($p < .001$), consistent with the notion that inferring information graphically generates additional cognitive noise.

Our findings suggest that revisions tend to be smaller given a graphical display than a compound display. When including an additional dummy variable for the combination of compound and graphical display formats (**C** × **G**) in columns (5) and (6), we find significant differences between display types ($p < .001$ in two-sided Wald tests).

Although the results listed in column (5) suggest a complementary effect of a graphical *and* compound display (*Deviation* × **C** × **G**), this effect is no longer significant when including the controls shown in column (6) ($p = .120$).

Overall, our results suggest that expectation updates are significantly larger under simpler representations of information, whereas more complex representations tend to dampen revisions, prompting participants to place greater weight on their prior beliefs. This pattern rejects Hypothesis 1 and supports the conclusion that cognitive uncertainty matters in the formation of expectations. We summarize our finding as follows.

Result 1. *Contrary to Hypothesis 1, expectation revisions are significantly reduced by more complex forecasts.*

4.3. Posterior uncertainty

The second exogenous variation we examine is the uncertainty associated with the professional forecasts. As implied by Eq. (3), a higher forecast uncertainty should translate into a higher posterior uncertainty, holding prior uncertainty fixed. Our summary statistics suggest that posterior uncertainty tends to be higher for less accurate forecasters. We now quantify this relationship and test whether displaying the same information in a more complex format adds to the posterior uncertainty, holding forecast uncertainty fixed.

Focusing on our primary treatment variations, Table 3 provides estimates for posterior uncertainty, applying the models following Eq. (6). Forecast and initial uncertainties strongly affect the posterior uncertainty across specifications. To test Hypothesis 2, we again

Table 3
Posterior uncertainty.

	Dependent variable: σ_{PU}					
	(1)	(2)	(3)	(4)	(5)	(6)
Forecast Uncertainty	0.165*** (0.039)	0.166*** (0.039)	0.165*** (0.039)	0.167*** (0.039)	0.166*** (0.039)	0.167*** (0.039)
Initial Uncertainty	0.515*** (0.029)	0.513*** (0.029)	0.513*** (0.029)	0.514*** (0.029)	0.514*** (0.029)	0.514*** (0.029)
G (Graphical)	-0.033 (0.127)	-0.014 (0.127)			-0.068 (0.182)	-0.060 (0.181)
C (Compound)			-0.024 (0.128)	-0.045 (0.127)	-0.058 (0.179)	-0.094 (0.178)
C × **G**					0.073 (0.256)	0.099 (0.255)
Controls	No	Yes	No	Yes	No	Yes
Constant	1.830*** (0.208)	1.613*** (0.607)	1.835*** (0.212)	1.633*** (0.610)	1.860*** (0.226)	1.667*** (0.617)
Observations	1036	1029	1036	1029	1036	1029
Residual Std. Error	1.880	1.955	1.900	1.935	1.894	1.944
AIC	4369	4344	4368.7	4343.8	4372.6	4347.4
BIC	4393.7	4408.1	4393.4	4408	4407.2	4421.5

The dependent variable is respondents' self-reported posterior uncertainty (σ_{PU}).
$^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$
Huber robust standard errors are given in parentheses.
Controls include gender, age, age^2, region and a Covid-19 index.

examine the variation in the complexity of forecasts, focusing on a graphical display (**G**), a compound display (**C**) and their interaction (**C** × **G**). The results (Table 3) indicate that neither dimension significantly affects posterior uncertainty ($p > .600$).

Hence, our results do not point to a significant effect of complexity on posterior uncertainty. Thus, we summarize the results as follows.

Result 2. *Consistent with Hypothesis 2, more complex forecasts do not increase posterior uncertainty.*

Considering our findings on expectation updates, the failure to reject Hypothesis 2 may seem surprising at first glance. Two features of our design are important to keep in mind. First, all treatments are relatively complex, so we may only observe differences in cognitive noise within a specific range. Second, our self-reported uncertainty measure was by design restricted to values between 0 and 10, limiting the range of observable variation.

Moreover, the rejection of Hypothesis 1 highlights that a direct measure of posterior uncertainty (self-reported posterior uncertainty) does not necessarily produce larger effect sizes than an indirect measure (forecast revision). A comparison of Eqs. (2) and (3) clarifies the reason why: a small variation in cognitive noise (σ_s) only leads to a small variation in posterior uncertainty (σ_{PU}), ceteris paribus. Yet, such a small variation may have a large effect on the posterior (p) when there is a large difference between the forecast and the prior ($f - x_d$).

4.4. Robustness checks

D'Acunto et al. (2021) observe that cognitive abilities can help to explain cross-sectional variation in inflation expectations across households, indicating that cognitive processes affect the formation of inflation expectations. To ensure that our results on expectation revisions are attributable to our manipulations of the signal's complexity rather than differences in the participants' cognitive ability, we re-estimate our main regressions for expectation revisions and posterior uncertainty for different sub-samples. Our dataset does not contain any direct measure of financial literacy or cognitive ability. However, we did collect information on education and income, factors that have been found to be positively related to cognitive ability (Heckman et al., 2006; Hanushek and Woessmann, 2008; Deming, 2022).

The first proxy we consider is the education level. We split the sample into those with at least a bachelor's degree (high education, $N = 596$) and those without (low education, $N = 439$).[20] The second proxy we consider is the income. We divide respondents into

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[20] For the education split, we exclude a single respondent who selected 'Other' for level of education.

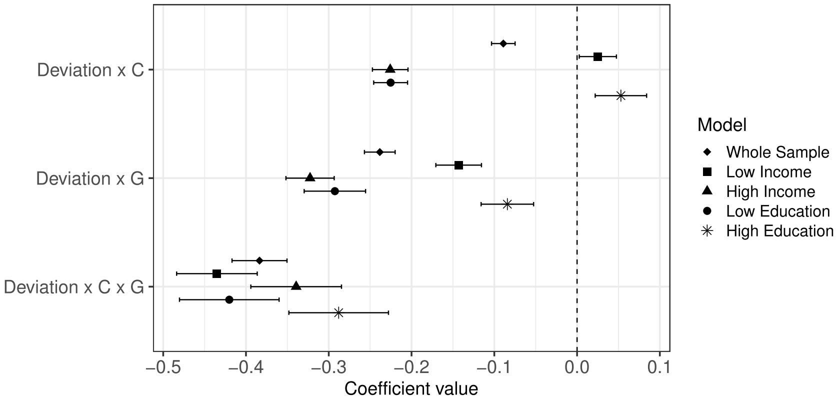

Fig. 3. Coefficients of the regressions for expectation revision across samples. *Note:* This figure includes the coefficients and 95% confidence intervals of our treatment variables for inflation expectation updates (Eq. (5)) for the three-way interaction model specification without control variables as in column (5) in Table 2 for the whole sample and as in Tables A.4 to A.7 in the Online Appendix for the respective sub-sample. Regressions in the low and high income (education) specification are estimated for the respective sub-samples. The values displayed for $\mathit{Deviation} \times \mathbf{C} \times \mathbf{G}$ are calculated as the sum of coefficients $\mathit{Deviation} \times \mathbf{C}$, $\mathit{Deviation} \times \mathbf{G}$ and $\mathit{Deviation} \times \mathbf{C} \times \mathbf{G}$.

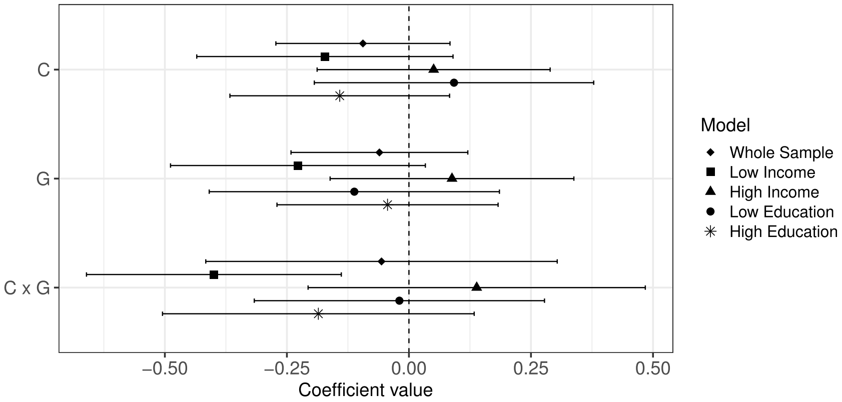

Fig. 4. The coefficients of the regressions for posterior uncertainty across samples. *Note:* This figure includes the coefficients and 95% confidence intervals of our treatment variables for posterior uncertainty (Eq. (6)) for the two-way interaction model specification without control variables as in column (5) in Table 3 for the whole sample and as in Tables A.8 to A.11 in the Online Appendix for the respective sub-samples. Regressions in the low and high income (education) specification are estimated for the respective sub-samples. The values displayed for $\mathbf{C} \times \mathbf{G}$ are calculated as the sum of coefficients $\mathbf{C}$, $\mathbf{G}$ and $\mathbf{C} \times \mathbf{G}$.

those earning less than $60,000 (low income, $N = 517$) and those earning $60,000 or more (high income, $N = 519$). The shares of high-education and high-income participants do not vary significantly across treatments or forecast tuples ($p \geq .593$, χ^2-tests, Tables A.2 and A.3 in Online Appendix A).

Figs. 3 and 4 contain plots of the main coefficients used to test Hypothesis 1 and 2 with 95% confidence intervals, alongside estimates for the four sub-samples. To avoid overfitting, we report the model with the three-way interaction and without additional controls. This is also the preferable specification based on the BIC criterion.[21] For interpretability, the combined effect of compound and graphical display formats, $\mathit{Deviation} \times \mathbf{C} \times \mathbf{G}$ in Fig. 3, is calculated as the sum of $\mathit{Deviation} \times \mathbf{C}$, $\mathit{Deviation} \times \mathbf{G}$ and $\mathit{Deviation} \times \mathbf{C} \times \mathbf{G}$ for the whole sample and each sub-sample.

For the revisions in inflation expectation, the coefficients (Fig. 3) exhibit some variation across sub-samples. However, we do not find conclusive evidence that cognitive ability – as proxied by education level or income – mediates the effect of cognitive uncertainty. The two proxies point in different directions: On the one hand, participants in the high-income sample tend to revise expectations more strongly relative to the whole sample if information is represented in compound form ($\mathit{Deviation} \times \mathbf{C}$) or only graphically ($\mathit{Deviation} \times \mathbf{G}$). On the other hand, participants in the high education sample tend to revise their expectations *less* strongly relative to whole sample. Consistent with the main analysis, posterior uncertainty is virtually unchanged across treatments in all sub-samples (Fig. 4).

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[21] Regression tables for all sub-samples can be found in Online Appendix A.

5. Conclusion

This paper provides a new perspective on the formation of inflation expectations based on a sample of 1036 US residents. Using a novel experimental design, we disentangle the effects of forecasts, forecast uncertainty and complexity-induced cognitive noise on the formation of expectations by analyzing updates and changes in self-reported uncertainty. The cognitive-uncertainty perspective emphasizes the distinction between uncertainty in the signal (forecast accuracy) and in how the forecast information is communicated and processed (cognitive noise). The findings show that these two components are distinct and partly substitutable. This framework would allow central banks to assess how much additional impact on expectations they can gain from clearer communication relative to improving forecast accuracy. Overall updating is broadly in line with standard Bayesian inference: providing participants with forecasts of lower historical accuracy leads to higher uncertainty about future inflation, while higher deviations between prior and signal lead to stronger updates, demonstrating that both the precision and the level of the signal affect expectations. In line with cognitive uncertainty interpretation, more complex displays of forecasts lead to smaller updates in expected inflation, indicating that greater cognitive noise dampens the updating of beliefs.

Our results are consistent with existing evidence that points to the need for simpler and more targeted communication of monetary policy to affect inflation expectations. Uncertainty surrounding the signal and a more complex representation of information tend to reduce the revisions of inflation expectations and make it more difficult to adjust or re-anchor prior beliefs, albeit through different channels. Two tentative policy recommendations emerge: First, central banks should prioritize pre-aggregated, single-horizon numbers and avoid formats that require compounding or rely on visual inference. This aligns with the results by Andre et al. (2022), who argue that providing simple statistics about inflation can substantially affect inflation expectations. Second, central banks should communicate forecast accuracy – potentially through explicit confidence intervals – so that audiences can weigh the signal appropriately.

Our results also highlight the relevance of studying the cognitive processes that underlie the formation of expectations. We find that signal complexity – not differences in cognitive ability (as proxied by education and income) – drives expectation updating. This suggests two directions for future research. First, one could examine how financial literacy moderates the responses to complex inflation information. Dräger and Nghiem (2025) find that high financial literacy can result in stronger anchoring of inflation expectations in response to qualitative statements, suggesting that cognitive noise has weaker effects on inflation updates in those with high financial literacy. Second, one could examine how personal inflation experience and the complexity of information jointly affect expectation revisions over time. This would clarify whether central banks can meaningfully influence revisions through simpler communication, or whether personal experience dominates forecast messages in shaping expectations.

Data availability

Data and code can be found on OSF under https://osf.io/3wgyq/overview?view_only=2aed37d21db64b3cba76387a4e135aba.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at 10.1016/j.jebo.2026.107437

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