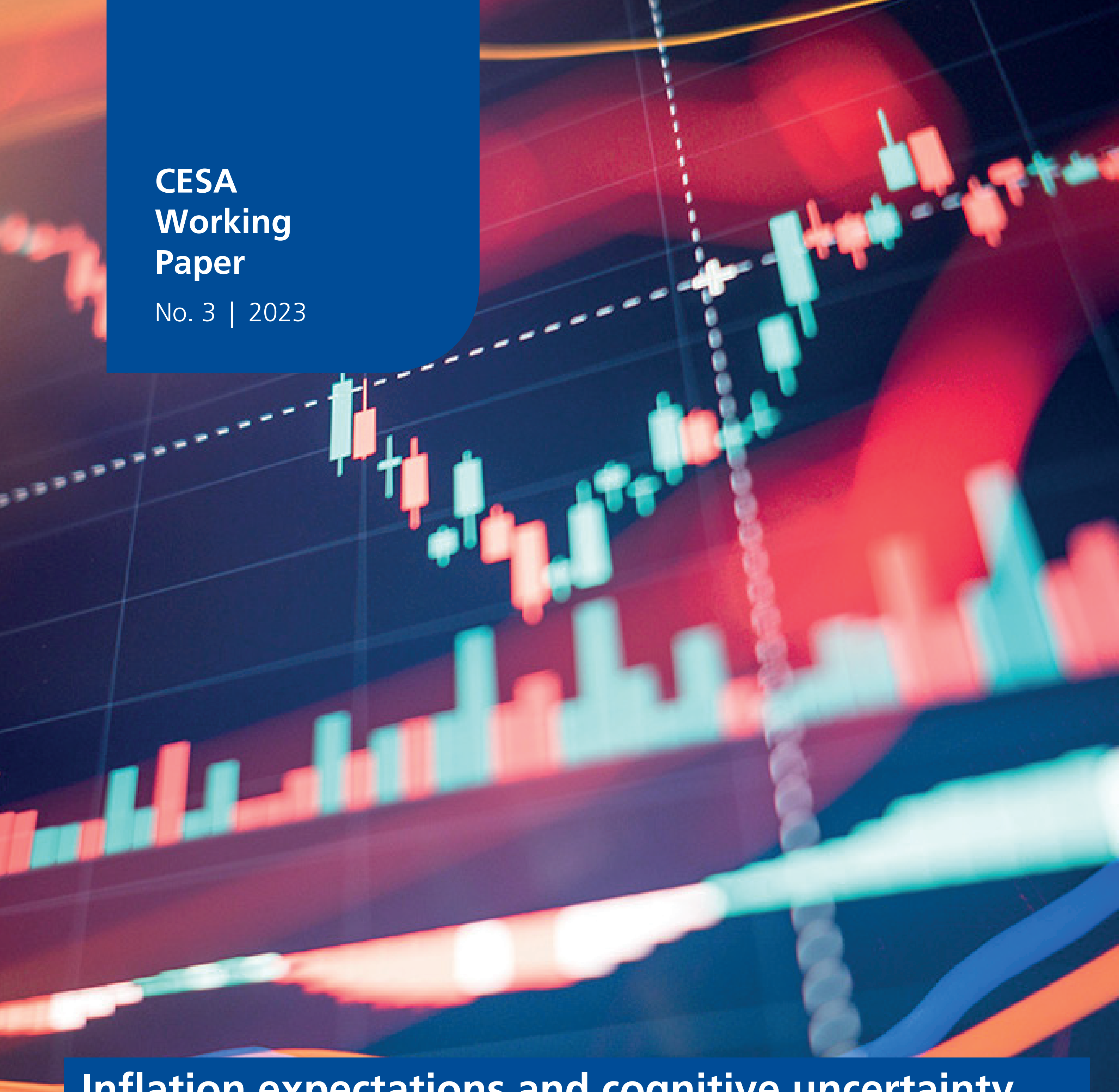

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Inflation expectations and cognitive uncertainty

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Abstract

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

Keywords: Cognitive uncertainty, expectation formation, inflation, information provision experiment

JEL: D83, D84, E31, E71

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1 Introduction

For several decades, the full-information rational expectations assumption has been the mainstay of models in macroeconomics and finance. A new stream of the literature has challenged the assumption that people access all available information and build their expectations accordingly. A recent survey by D'Acunto et al. (2021) summarizes the empirical evidence: Expectations are highly dispersed across households and often biased. Moreover, the literature has shown that the predictability of forecast errors of households and professionals reflects information rigidities (as observed in the seminal studies by Coibion and Gorodnichenko, 2012, 2015).

This growing literature has assessed inflation expectations formation from a theoretical and empirical perspective, improving our understanding of its determinants and their role for monetary policy transmission and communication. Survey experiments have proven to be particularly useful because they allow for the creation of exogenous variation of expectations by providing participants with varying pieces of information, as pointed out by Fuster and Zafar (2022).[1] They also highlight key research questions that follow from these findings. In particular, they call for more analyses of theories that explain the heterogeneity in updating behavior. In addition, they ask for systematic work on how to present information in survey experiments.

In this study we address both issues. We explore how cognitive uncertainty can explain the formation of inflation expectations. Enke and Graeber (2023) introduce the concept of cognitive uncertainty and propose a model whereby uncertainty stems from the uncertainty in prior beliefs as well as from cognitive noise generated through an imperfect updating process. Over the last 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., by the subjective uncertainty people attribute to

[1] See also Haaland et al. (2020) for a review of the methodology of information provision experiments.

their own predictions. They build on a 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).[2]

We run an information provision experiment using a representative sample of the US population in order to shed more light on the way in which readily available information is – or is not – incorporated into inflation expectations. We exogenously vary the information provided to participants by presenting them with a professional inflation forecast from the Federal Reserve Bank of Philadelphia survey. These forecasts vary with regard to the forecasted inflation and their historic adequacy, which participants were informed about.

The design of our experimental survey is novel in two respects. First, providing forecasts of different historic accuracy allows us to measure how participants take into account the uncertainty associated with information provided to them. Second, varying the complexity of forecast presentation allows us to assess the role of cognitive uncertainty in the formation of inflation expectations. We vary the complexity in two ways: (i) by presenting information in reduced or compound form and (ii) by presenting it only graphically or also directly in numerical form. After receiving the information, respondents can revise their beliefs. We then evaluate (i) updates in inflation expectations and (ii) changes in confidence in these expectations. Exogenously varying the sets of forecast information provided enables us to disentangle the effects of forecast, forecast uncertainty and cognitive uncertainty on updates.

We find that, in line with standard Bayesian updating, providing subjects with forecasts leads to updates in the direction of the forecast. In addition, forecasts of lower historic accuracy lead to higher uncertainty of expectations and smaller updates. In line with cognitive uncertainty, more complex forecasts lead to smaller updates in expected inflation. Inflation expectations have been found to go hand-in-hand with real-world economic decision making, such as the purchase of durable goods (Roth and Wohlfart, 2020; Coibion et al., 2020;

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

Coibion et al., 2023). Thus, our findings imply that simpler communication of monetary policy will increase the impact of messages. However, we do not find evidence of a direct link between forecast complexity and uncertainty of updated beliefs, which may be due to a relatively smaller effect size.

We contribute to a recent stream of the literature that focuses on how households or consumers adapt their inflation expectations based on the information available. While it is clear that financial experts are well aware of monetary policy announcements, household expectations do not react systematically to these announcements, as observed by Lamla and Vinogradov (2019). Blinder et al. (2022) discuss the existing evidence and conclude that central banks have not been very successful in influencing inflation expectations in the past. Yet, they point to the potential of simpler and more targeted communication for managing expectations. Furthermore, survey participants who are directly provided with central bank information do respond to respond to it systematically (see, e.g. Binder and Rodrigue, 2018, Coibion et al., 2018, Coibion et al., 2022, and Coibion et al., 2023). Our findings are also in line with recent findings by D'Acunto et al. (2021). They observe that cognitive abilities can help to explain cross-sectional variation in inflation expectations across households, indicating that cognitive processes play an important role for the formation of inflation expectations.[3]

2 Hypotheses

In their work, Enke and Graeber (2023) observe a human tendency to be insensitive to variation in probabilities that they coin cognitive uncertainty. They collect probability estimates with respect to choices under risk, belief updating and survey expectations. In addition,

[3]Related work has also found demographics, such as gender, income or education to drive differences in inflation expectations (see, e.g., Bruine de Bruin et al., 2010, Madeira and Zafar, 2015, and Weber et al., 2022). Furthermore, lifetime experiences of inflation have been found to be positively associated with expectations of future inflation (see, e.g., Ehrmann and Tzamourani, 2012, Malmendier and Nagel, 2016, and Diamond et al., 2020). A similar association has been observed for the experience of price changes (see, e.g., Cavallo et al., 2017, Coibion and Gorodnichenko, 2015, D'Acunto et al., 2021).

they collect self-reported uncertainty about these estimates. Their findings reveal that those who report higher cognitive uncertainty are more likely to estimate probabilities closer to a default of 50:50. Furthermore, they observe that cognitive uncertainty increases in more complex settings. For example, when lotteries are compounded or probabilities are given as mathematical expressions.

Enke and Graeber (2023) also point out that cognitive noise can be relevant for the formation of inflation expectations. Thus, we adapt 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. She then receives a forecast $f = x_f + \epsilon_f$ in the form of expert forecasts with a normally distributed error term with mean zero and variance σ_f^2.[4] A rational individual updating her beliefs based on the forecast f will obtain the posterior

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

Yet, if an individual suffers from cognitive noise as in Enke and Graeber (2023), she has trouble calculating p. Being aware of the cognitive noise, she will put more weight on the prior and less weight on the result of her calculations as the noise increases. We assume that an individual who experiences cognitive noise receives forecasts as a signal $s = x_f + \epsilon = x_f + \epsilon_f + \epsilon_s$. That means, we simplify the exposition by treating cognitive noise as an additional source of error from the forecast we provide. Accordingly, we assume individuals generate the posterior

$$p_{CU} = x_d + \sigma_x^2/(\sigma_x^2 + \sigma_f^2 + \sigma_s^2)(f - x_d). \tag{2}$$

Thus, the posterior is a linear combination of the prior and the forecast, as in (1) and the absence of $s = x_f + \epsilon = x_f + \epsilon_f + \epsilon_s$ would result in a full update of expectations.

In our experiment we will vary the nature of the expert forecasts an individual receives.

[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).

This allowed us to change the forecast f as well as the variance of its error σ_f exogenously while keeping the error terms related to the prior (σ_x) and to cognitive noise (σ_s) constant. Thereby we can consider the influence of specific forecasts and their uncertainty on an individual's posterior belief. As in Enke and Graeber (2023), we can additionally vary the complexity of the forecast, thereby varying the error term related to cognitive noise (σ_s).

We adapt a simple definition of cognitive uncertainty as

$$\sigma_{CU} = \sigma_x \sigma (\sigma_x^2 + \sigma^2)^{-0.5} \tag{3}$$

where $\sigma^2 = \sigma_f^2 + \sigma_s^2$. As in Enke and Graeber (2023), cognitive uncertainty (σ_{CU}) is measured by the self-reported confidence related to the posterior.[5]

Based on previous work, we are able to formulate two null hypotheses with respect to cognitive uncertainty. We assume that a rational individual will not be influenced by an exogenous increase of cognitive noise. Contrary to cognitive uncertainty, such an increase will not increase the weight an individual puts on his prior (see equation (2)) as this is only driven by the uncertainties of the signal and the prior. For the same reasons it will also not influence the uncertainty of the posterior (see equation (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 treatment increases cognitive noise, however, we will be able to reject these hypotheses and the revisions will decrease, while uncertainty of the posterior will increase. Furthermore, it is important to note that both null hypotheses follow from equation

[5] Note that this definition resembles the definition of cognitive uncertainty in the working paper version by Enke and Graeber (2019).

(2). The test of Hypothesis 1 is an indirect test of the role complexity plays in incorporating forecasts, while the test of Hypothesis 2 directly tests whether uncertainty is influenced by the complexity of forecasts. For the interpretation of our results, however, it will be important to note that a direct test does not necessarily imply a larger effect size.

In general, cognitive noise will cause an under-reaction to information. As $\sigma_s^2 > 0$ with cognitive noise, an individual will put more weight on the prior in equation (2) than in equation (1) as the noise increases. To statistically test Hypothesis 1 we rewrite equation (2) as

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

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 estimate the size of the revisions, we estimate the following equation

$$p_{CU} - x_d = \alpha + \beta(f - x_d) + \eta \tag{5}$$

where α captures spurious trends that are not influenced by the provided information and η is a normally distributed error term (see Lybbert et al., 2007, and Fuster et al., 2022, for similar approaches). To identify a treatment difference we introduce a treatment dummy t as follows

$$p_{CU} - x_d = \alpha + \beta(f - x_d) + \gamma t + \delta t(f - x_d) + \eta. \tag{6}$$

Thus, a test of $\delta = 0$ provides us with a test of Hypothesis 1 while a negative and significant estimate implies that the complexity of the forecast reduces the response to the signal.

To statistically test Hypothesis 2 it is important to note that cognitive uncertainty as defined in equation (3) is increasing in σ_x, σ_f and σ_s. We approximate this relationship with the following equation

$$\sigma_{CU} = \alpha + \beta\sigma_f + \gamma t + \delta\sigma_x + \eta \tag{7}$$

where $\delta\sigma_x$ models the weight put on the uncertainty of the prior. In addition, $\alpha + \beta\sigma_f + \gamma t$ captures the uncertainty from σ. More specifically, the constant α captures any systematic spurious adjustments and the baseline uncertainty σ_s, while γt captures any additional uncertainty that σ_s created in the respective treatment (see Coibion et al., 2018, p. 2700, for a similar approach). We are interested in how cognitive noise influences cognitive uncertainty through σ_s. Thus, a test of $\gamma = 0$ provides us with a test of Hypothesis 2.

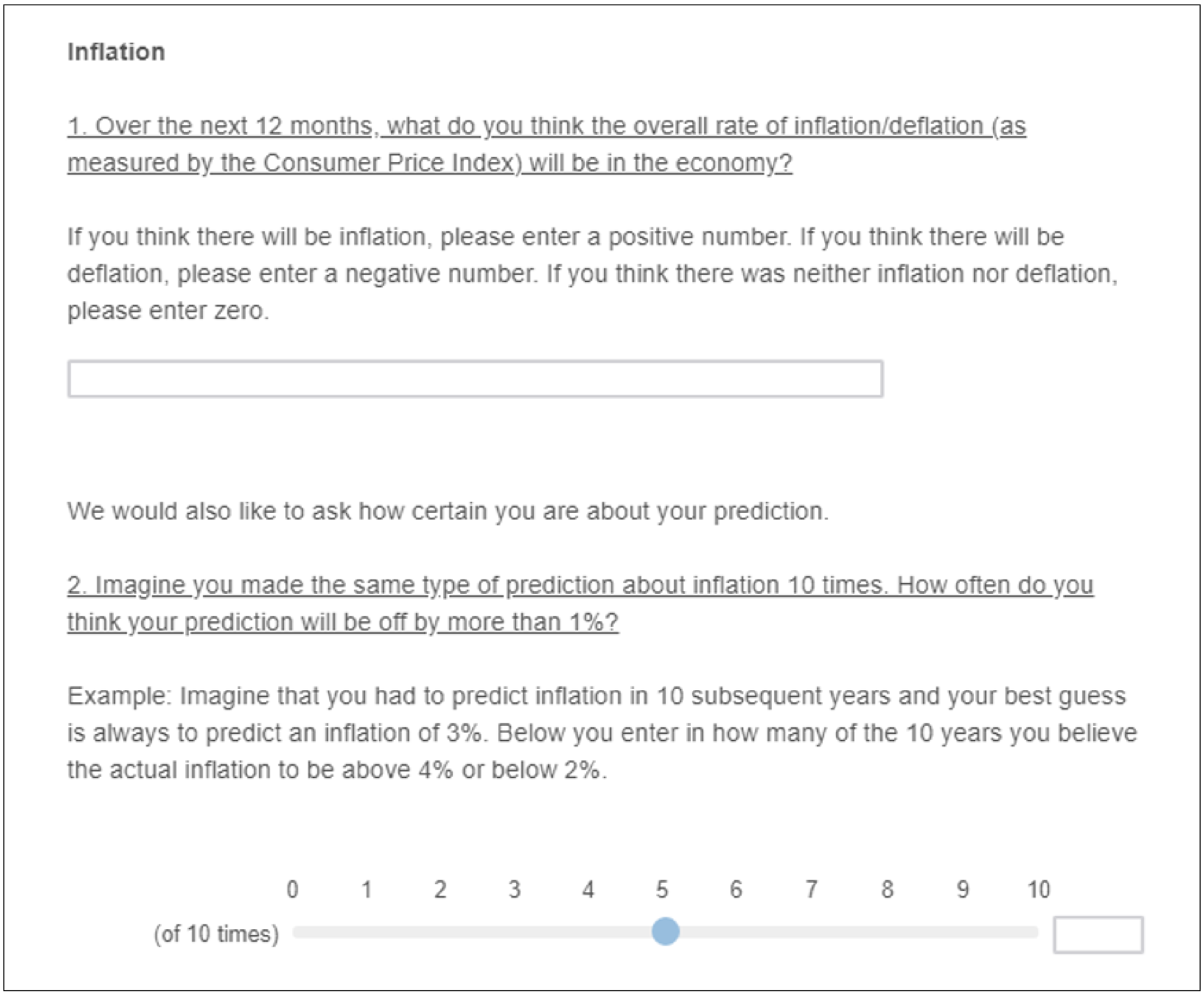
3 Experimental design

Our study measures inflation expectations and belief updating. We develop a new elicitation method to include the elicitation of cognitive uncertainty building on the work by Enke and Graeber (2023). First, we exogenously vary the content of the information provided, i.e., the noise of the signal. Second, we exogenously vary the complexity of the information provided, thereby systematically assessing the role of cognitive noise created from a more complex display of information. Before explaining these treatment variations and our procedures, we will describe our elicitation method. We will conclude this section with details of the characteristics of our data set.

3.1 Elicitation method

The information we provide in our experiment consists of different expert forecasts of inflation. We elicit inflation expectations of participants before and after providing the information by asking for a point prediction together with a measure of confidence. Our first question, shown in Figure 1, asks about participants' expected inflation in the upcoming 12 months. This question builds on the New York Fed Survey of Consumer Expectations and is taken from Coibion et al. (2023). Different from them, we do not elicit a full probability distribution. Instead, we designed a simple measure of uncertainty. More precisely, we ask *"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%?"*. Participants can then use a slider to select a number between 0 and 10. We also provide an example in order to improve understanding.

Figure 1: Expectation elicitation



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%.

0 1 2 3 4 5 6 7 8 9 10

(of 10 times)

The advantage of this approach is its simplicity and the direct link to the methodology by Enke and Graeber (2023). For example, when analyzing decisions under risk, they first elicit certainty equivalents for lotteries using the BDM technique. Then they measure cognitive uncertainty for the certainty equivalents of the respective lotteries. For this purpose, they also do not elicit the full probability distribution. To foster participant comprehension, they instead elicit a simple summary statistic that captures the uncertainty implied in the distribution instead. More specifically, when asking how much a lottery is worth to them, participants in their study are presented with a one-dollar range around their certainty equivalent x. They are then asked *"How certain are you that you actually value this lottery somewhere between getting \$(x-0.50) and \$(x+0.50)?"*. Participants answer this question by selecting a value between 0% and 100% using a radio button. Thus, as in our case, Enke and Graeber (2023) elicit a percentage measurement of certainty for a fixed interval. While they ask for the likelihood with which the participant thinks his choice falls inside a given interval, we ask for the likelihood it falls outside a given interval. Our elicitation method is not only a straightforward application of the study of inflation expectation of Enke and Graeber's (2023) approach. It also allows us to present information on the uncertainty surrounding forecasts in the same way, as described in the following section.

3.2 Treatments and procedures

Our information provision experiment was conducted online using Qualtrics to collect expectation measures. Participants were recruited via Prolific.[6] Our study proceeded in the following steps: After their decision to participate, subjects had to give informed consent. 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 were followed by a quiz on inflation consisting of one question on 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 are included in our sample. Participants were then asked about their inflation expectations as described in the previous

[6] As Palan and Schitter (2018) argue, because Prolific is designed specifically for research purposes it has advantages in comparison to the commonly used MTurk as it provides more transparency for participants and researchers. Peer et al. (2017) compare Prolific with MTurk and conclude that the data quality is comparable but that Prolific provides a more naïve and diverse population.

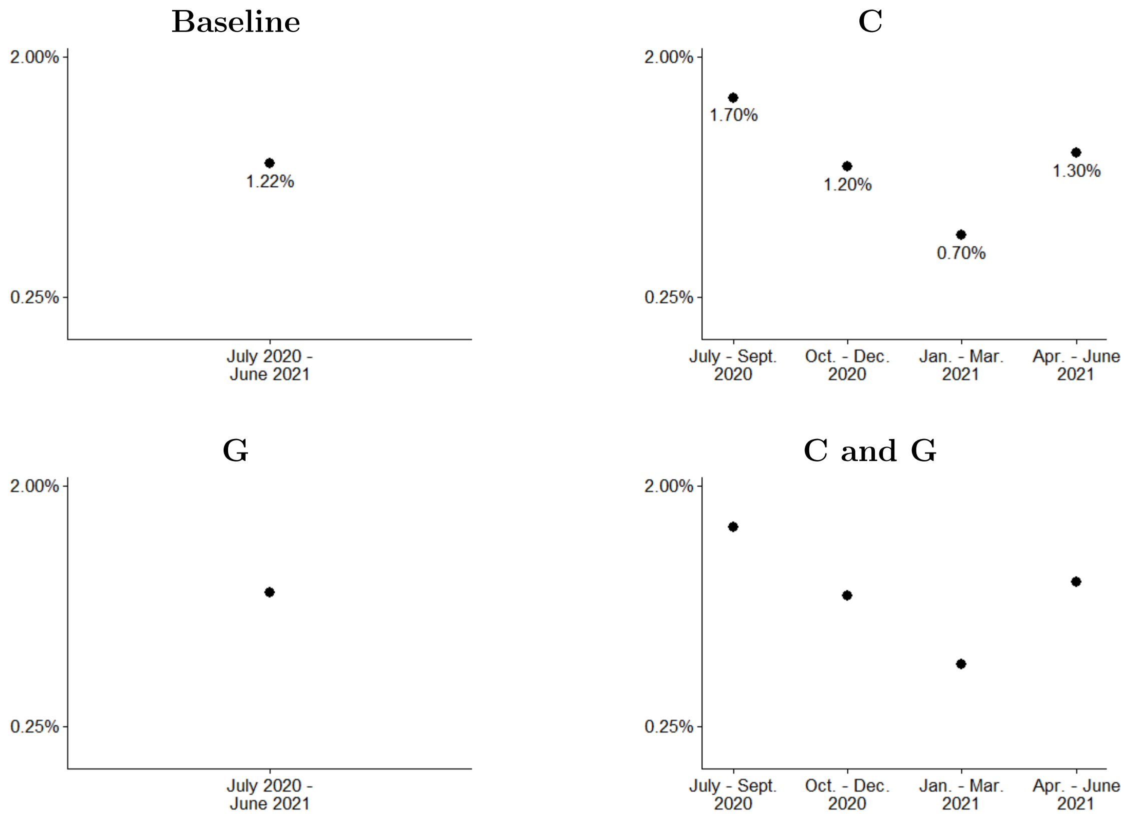
section.

In the second part, subjects 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 quarterly survey of professional forecasters. To determine the set of forecasts we provide, we selected all forecasters 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 forecasts with the lowest forecast values (0.35 and 1.22). As a proxy for σ_{fi}, we used the number of times the predictions of these forecasters had been off by more than 1% in the last ten available annual forecasts. As a result, these forecasts provide us with different values for σ_f covering the complete range from two to six deviations we observe over the previous ten years. The resulting forecast and error tuples (f, σ_f) are: (2.90; 6), (2.90; 2), (0.35; 2) and (1.22; 3). We present the treatment-specific forecast and the error to all subjects in the experiment. This way, we vary the signal we provide to participants and the noise associated with it. After receiving the respective information, participants were asked for their expectations and confidence again.[7]

Our treatment variations closely follow the complexity variations developed in Enke and Graeber (2023). First, they observe that cognitive uncertainty increases if given probability figures have to be combined, for example in the case of compound lotteries. Second, they observe that cognitive uncertainty increases when probabilities are given as mathematical expressions rather than directly. Thus, we first vary the display of the forecast based on the

[7]Within our treatments we also varied an inflation anchor. Our example of a specific inflation rate (which is also used in the control questions) is randomly varied between -3% and 5% in steps of two percentage points. The complete instructions are provided in Online Appendix B for an inflation anchor of 3% and a forecast of $(f, \sigma_f) = (2.90; 6)$. At the end of the first part, participants are 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 include a set of questions on monetary policy and on the Covid-19 pandemic based on Binder (2020). As Cavallo (2020) notes, the experienced inflation of consumers may differ more strongly from official statistics as the consumption bundle has shifted during the pandemic. The last set of questions also includes an attention check, which 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.

Figure 2: Information provision treatments



idea that compounding information generates cognitive noise which translates into increased cognitive uncertainty. In our case, this applies to the forecast we provide. In the compound case, denoted by **C**, we provide four annualized quarter forecasts rather than one 12-month forecast. Second, we vary whether inflation forecasts are provided directly as figures within a graph or whether they have to be derived from the labels on the y-axis. We denote the latter case by **G**. This variation is based on the idea that the additional task of inferring the information graphically generates cognitive noise as well. To increase complexity further, the labels on the y-axis are spaced 1.75% apart (instead of 1% or 2%, e.g.).[8] Our **Baseline** treatment applies neither of the two manipulations, while our **C and G** treatment combines the two. Figure 2 shows the four resulting variants for the forecaster with $(f, \sigma_f) = (1.22; 3)$.

[8]We chose the upper label by rounding up the highest quarterly forecast of the specific forecaster and then subtracted 1.75% for the lower label. Note that our experiments builds on an earlier working paper version of Enke and Graeber (2019). This version did not yet contain the complex number manipulation.

3.3 Sample characteristics

Out of 1,246 recruited participants, 1,036 answered the control questions and an attention check correctly and are thus included in our sample. Participants needed 10.5 minutes 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.[9]

All participants were current US residents and reported to be fluent in English. We rely on Prolific to provide a representative sample of the US population, which was stratified based on sex, age and ethnicity following the US Census Bureau population group estimates from 2015. However, we checked that the resulting sample meets these criteria by asking for demographics ourselves. The average age and share of junior college graduates lies a little above the US average. The share of female participants and the average income are representative for the US population.[10]

Table 1: Descriptive statistics

	Prior Inflation Rate	Posterior Inflation Rate	Prior Uncertainty	Posterior Uncertainty	Number of Participants
Baseline	2.69	2.28	4.83	4.95	269
	(7.87)	(3.74)	(2.19)	(2.25)	
C	2.78	2.30	4.97	4.9	259
	(6.29)	(3.17)	(2.27)	(2.28)	
G	2.18	2.25	5.22	5.06	242
	(4.48)	(1.97)	(2.2)	(2.24)	
C and G	3.04	2.55	4.68	4.81	266
	(7.24)	(5.66)	(2.09)	(2.16)	
Total	2.68	2.35	4.92	4.93	1,036
	(6.64)	(3.90)	(2.2)	(2.23)	

The table shows the arithmetic means. Standard deviations are given in parentheses.

[9] In the design of 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. This calculation was done with respect to Hypotheses 1 and 2 for our treatment variations. In the absence of previous studies that vary cognitive uncertainty in the prediction of inflation, we aimed to recruit a representative sample of the US population of at least 1,000. This would allow us to identify a small effect size of $d = 0.18$. The final dataset consists of 1,036 participants.

[10] See https://researcher-help.prolific.co/hc/en-gb/articles/360019238413 for the sampling procedure applied by Prolific. Note that we did not ask for race as this is "special category data" in the sense of the EU's "General Data Protection Regulation".

4 Results

4.1 Overview

Table 1 summarizes key descriptive statistics. Without further information, participants initially expect an average inflation rate of 2.68 percent. This is above the average forecast of 2.20 percent made by the professional forecasters. Accordingly, participants adjust posterior expectations downwards in each of the four treatments. They range from 2.30 to 2.55 percent. Aggregate prior inflation uncertainty, measured as the expected number of deviations of more than 1% in ten predictions, ranges from 4.68 in treatment **C and G** to 5.22 in treatment **G**. The posterior uncertainty is virtually the same on aggregate, with 4.92 deviations out of ten before and of 4.93 after the treatment.[11] To analyze our 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.

4.2 Expectation revisions

The first exogenous variation we consider are the different numerical inflation forecasts participants receive. In general, our summary statistics suggests that participants revise their expectations based on the information provided. Receiving a professional forecast predicting an inflation of 0.35 percent leads to a posterior of 2.31 percent, while a forecast of 1.22 percent leads to posterior of 2.02 percent. Based on the average prior of 2.68 this illustrates a substantial update in the direction of the signal.[12]

We now turn to our main treatments that vary the complexity of the information provided. Table 2 provides regression results with the expectation revision as the dependent variable. The models follow equation (6) and include dummies for a compound display of

[11] Note that 328 of 1,036 participants did not update their inflation expectations. This is in line with the existing literature on rational inattention in the sense that some participants do not respond to new information. At the same time, this finding confirms that information about professional forecasts is informative for the large majority of participants.

[12] Figure A.1 in Online Appendix A shows the distributions of the prior and the respective posteriors.

information ($\mathbf{C}$), a graphical display ($\mathbf{G}$) and the combination of the two ($\mathbf{C} \times \mathbf{G}$). Our main independent variable of interest, however, is the deviation between the signal participants receive and their prior (*Deviation*). 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 of the deviation with our dummies indicating the respective complexity variation. Furthermore, Table 2 includes models with and without additional controls.[13]

Across the models of Table 2, we find that the professional forecasts significantly influence the expectation update as suggested by our summary statistics: In the **Baseline** treatment, a one-percent difference between prior and signal leads to an update of between 0.767 and 0.857 percentage points, as indicated by the *Deviation* variable ($p < 0.001$).

The interactions of the *Deviation* variable with our dummies for complexity variation provide us with tests of Hypothesis 1. The results in columns (1) and (2) include our dummy for a compound display of information ($\mathbf{C}$). They reveal that such a display significantly dampens the revisions of expectations between 0.117 and 0.119 percentage points ($p < 0.001$). This is in line with the idea that providing *four* forecast values rather than *one* generates additional cognitive noise. In columns (3) and (4) we include the dummy for our more complex graphical display of information ($\mathbf{G}$) instead. The results reveal that the reaction to the signal is significantly reduced by between 0.272 and 0.275 percentage points ($p < 0.001$). This finding is in line with the idea that the task of inferring information graphically generates additional cognitive noise.[14]

Our results also seem to suggest that the revisions are smaller when using the graphical display rather than the compound version. However, when including an additional dummy for the combination of compound and graphical information provision ($\mathbf{C} \times \mathbf{G}$) in columns

[13]We consider gender, age and income as control variables. Furthermore, based on the work by Binder (2020), we include a Covid-19 index as a proxy for an individual's financial, health-related and food-related concerns due to the Covid-19 pandemic. However, none of these controls appear to affect the main results. Table A.1 in Online Appendix A provides the summary statistics for our control variables across treatments.

[14]Recall that each of the four treatments includes the provision of four different forecasts. Thus, these effects do not depend on the accuracy of the signal but reflect the effect of our variations of cognitive uncertainty.

(5) and (6), we find significant differences between the two types of display ($p < 0.001$ in a two-sided Wald test). Furthermore, even though the results of column (5) suggest a complementary effect of a graphical *and* compound display ($Deviation \times \mathbf{C} \times \mathbf{G}$), this effect is not significant anymore when including controls in column (6) ($p = 0.120$).

Yet, overall our results imply that expectation updates are much larger in the case of a simpler information representation, or, vice versa, that a more complex representation reduces revisions since participants put higher weight on their prior belief. This leads to a rejection of Hypothesis 1 and to the conclusion that cognitive uncertainty matters for expectation formation. We summarize our finding as follows.

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

4.3 Posterior uncertainty

The second exogenous variation we consider is the uncertainty associated with the professional forecasts. We proxy the uncertainty by counting the number of times the respective forecasters have been off by more than 1% in their ten most recent forecasts. Our summary statistics suggest that – in line with theory – the uncertainty of forecasts is positively related to the uncertainty of participants' posteriors, i.e. cognitive uncertainty. We observe an average of 4.92 deviations by more than 1% for participants' priors. The resulting uncertainties of the posteriors are 5.35 and 4.71 for historical forecast errors of 6 and 2. Similar to the relationship between professional forecasts and inflation updates, these effects suggest that participants consider the professional forecasts to be informative.[15] Posterior uncertainty increases if uncertainty surrounding the signal exceeds prior uncertainty and vice versa.[16]

[15] As a robustness check, we estimate two separate regressions for those who received a signal with high uncertainty (i.e. 6 deviations of more than 1% within the last ten predictions) and low uncertainty (i.e. 2 deviations). Inflation updates tend to be smaller when forecast uncertainty is high and larger when uncertainty is low. When adding a dummy variable indicating high forecast uncertainty to our regressions, we find a complementary effect of forecast uncertainty additional to the effect of display complexity.

[16] Figure A.2 in Online Appendix A shows the distributions of the prior and the respective posteriors.

Table 2: Expectation revision

	Dependent variable: $p_{CU} - x_d$					
	(1)	(2)	(3)	(4)	(5)	(6)
Deviation	0.769***	0.767***	0.823***	0.820***	0.857***	0.857***
	(0.008)	(0.008)	(0.007)	(0.007)	(0.009)	(0.009)
C (Compound)	−0.114	−0.112			0.011	0.008
	(0.071)	(0.072)			(0.101)	(0.101)
Deviation × **C**	−0.119***	−0.117***			−0.089***	−0.093***
	(0.011)	(0.011)			(0.014)	(0.014)
G (Graphical)			−0.135*	−0.141**	−0.007	−0.015
			(0.069)	(0.071)	(0.102)	(0.102)
Deviation × **G**			−0.275***	−0.272***	−0.238***	−0.243***
			(0.010)	(0.011)	(0.019)	(0.019)
C × **G**					−0.261*	−0.248*
					(0.144)	(0.144)
Deviation × **C** × **G**					−0.056**	−0.037
					(0.024)	(0.024)
Controls	No	Yes	No	Yes	No	Yes
Constant	0.094*	0.021	0.085*	0.090	0.082	0.085
	(0.050)	(0.327)	(0.048)	(0.324)	(0.070)	(0.335)
Observations	1,036	1,029	1,036	1,029	1,036	1,029
Residual Std. Error	0.904	0.901	0.830	0.889	0.913	0.923

*p<0.1; **p<0.05; ***p<0.01
Huber robust standard errors are given in parentheses.
Controls include gender, age, age^2, region and a Covid-19 index.

Next we consider, our main treatment variations. Table 3 provides our estimates for posterior uncertainty. This time, the models follow equation (7). The posterior uncertainty is strongly affected by the forecast uncertainty and the initial uncertainty across specifications. To test Hypothesis 2, we again consider the complexity variations with regard to our forecasts along the dimensions graphical display (**G**) and compound display (**C**). The findings in Table 3 show that neither of the two dimensions has a significant effect on posterior uncertainty as a measure of cognitive uncertainty ($p > 0.600$).

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

Result 2 *In line with Hypothesis 2, the uncertainty of the posterior is not increased by more complex forecasts.*

Based on our findings on expectation updates this failure to reject Hypothesis 2 may be surprising. One may argue that the variation of complexity of the signals we provide is rather subtle. Stronger variations in complexity might lead to a larger and, thus, significant effect on cognitive uncertainty. But why do we reject Hypothesis 1 at the same time? While our elicitation of confidence in the posterior provides a *direct* measure of cognitive uncertainty, our treatments variations are *indirect* in the sense that they are designed to influence cognitive uncertainty by manipulating cognitive noise. Yet, a comparison of equations (1) and (2) makes clear that a small variation in cognitive noise (σ_s) will lead to small variations in cognitive uncertainty (σ_{CU}) ceteris paribus. At the same time, however, these subtle variations may have a large effect on the posterior expectation (p_{CU}) if the deviation between forecast and prior ($f - x_d$) is relatively large. In other words, a direct measurement of cognitive uncertainty (through the confidence in the posterior) does not imply a larger effect size than an indirect measurement (through the forecast revision).

Table 3: Posterior uncertainty

	Dependent variable: σ_{CU}					
	(1)	(2)	(3)	(4)	(5)	(6)
Forecast Uncertainty	0.165^{***}	0.167^{***}	0.165^{***}	0.166^{***}	0.166^{***}	0.167^{***}
	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)
Initial Uncertainty	0.513^{***}	0.514^{***}	0.515^{***}	0.513^{***}	0.514^{***}	0.513^{***}
	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)
C (Compound)	-0.024	-0.044			-0.058	-0.093
	(0.128)	(0.127)			(0.179)	(0.178)
G (Graphical)			-0.033	-0.016	-0.068	-0.061
			(0.127)	(0.127)	(0.182)	(0.180)
$\mathbf{C} \times \mathbf{G}$					0.073	0.097
					(0.256)	(0.254)
Controls	No	Yes	No	Yes	No	Yes
Constant	1.835^{***}	1.611^{***}	1.830^{***}	1.590^{**}	1.860^{***}	1.647^{***}
	(0.212)	(0.621)	(0.208)	(0.620)	(0.226)	(0.626)
Observations	1,036	1,029	1,036	1,029	1,036	1,029
Residual Std. Error	1.900	1.933	1.880	1.946	1.894	1.957

*p<0.1; **p<0.05; ***p<0.01
Huber robust standard errors are given in parantheses.
Controls include gender, age, age^2, region and a Covid-19 index.

5 Conclusion

This paper provides a new perspective on inflation expectation formation based on a representative sample of US households. Based on a novel experimental design, we disentangle the effects of forecasts, forecast uncertainty and cognitive uncertainty on expectation formation by analyzing updates in inflation expectations and changes in confidence. We find that in line with standard Bayesian updating, providing subjects with forecasts of lower historic accuracy leads to higher uncertainty of expectations and smaller updates, illustrating the that first and second moment of expectation updates are affected by the signal. In line with cognitive uncertainty, more complex forecasts lead to smaller updates in expected inflation.

Our result align with existing evidence that points to the need for simpler and more targeted monetary policy communication to affect inflation expectations. Uncertainty surrounding signals and communication tends to reduce inflation revisions and makes it harder to adjust or re-anchor inflation expectations. Our results also highlight the relevance of studying the cognitive processes underlying expectation formation. However, an open research question from our study concerns the link between the complexity of the display and perceived uncertainty among participants. A more granular treatment of uncertainty surrounding the second moment of the signal might shed more light on the underlying dynamics.

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Online appendix

A Additional figures and tables

Figure A.1: Distributions of inflation expectations – Prior and posteriors by forecasts

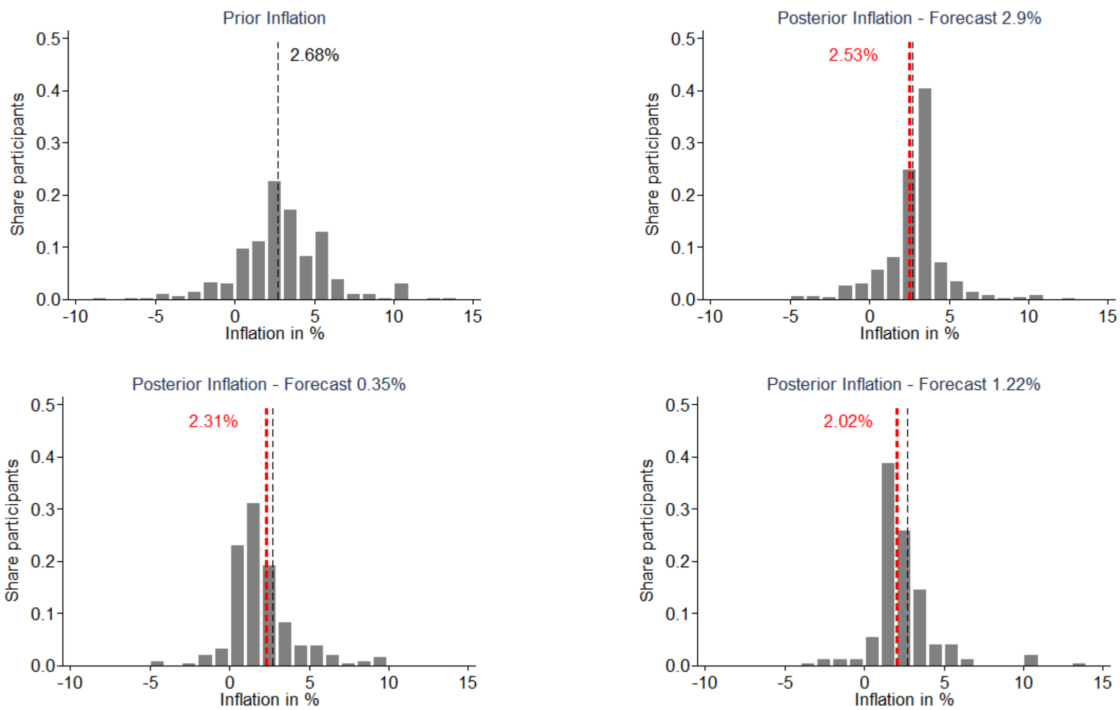


Figure A.2: Distributions of uncertainty – Prior and posteriors by forecasts

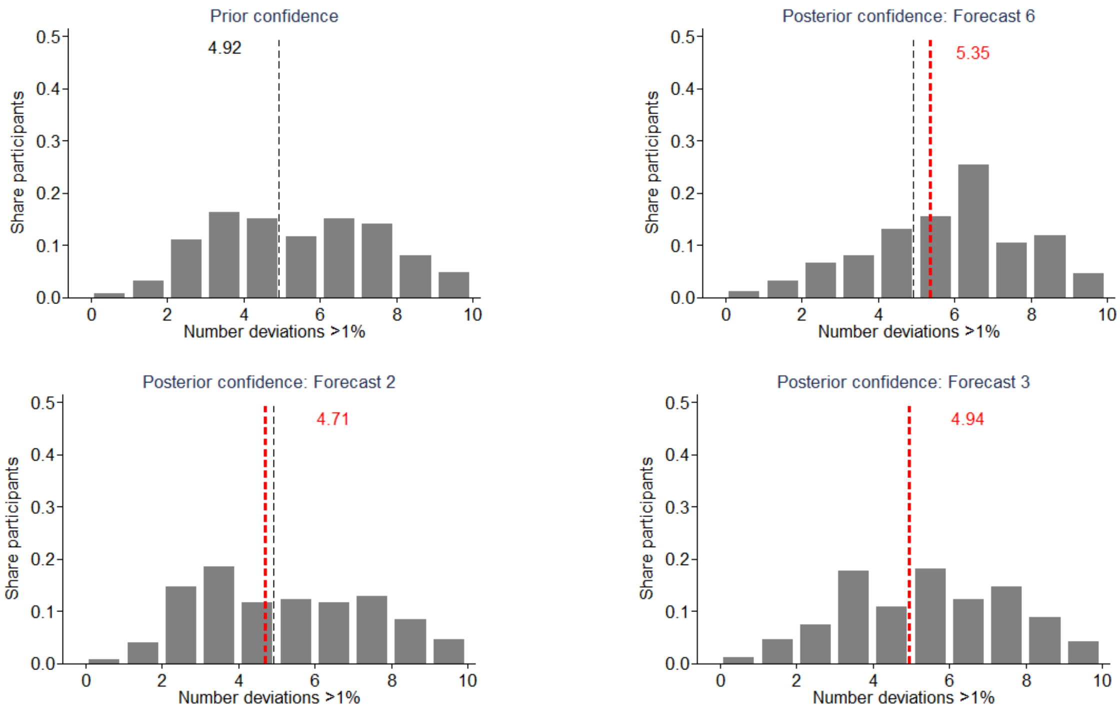


Table A.1: Summary statistics

	Baseline	**C**	**G**	**C and G**	Total	F-Test
Age	46.037	45.761	45.529	45.064	45.599	F= 0.175
	(15.446)	(16.544)	(16.068)	(16.239)	(16.055)	
Female	0.517	0.486	0.521	0.517	0.51	F= 0.261
	(0.501)	(0.501)	(0.501)	(0.501)	(0.5)	
Region 1 = Northeast	0.182	0.185	0.223	0.173	0.19	F= 0.79
	(0.387)	(0.389)	(0.417)	(0.379)	(0.393)	
Region 2 = Midwest	0.216	0.193	0.178	0.188	0.194	F= 0.425
	(0.412)	(0.395)	(0.383)	(0.391)	(0.396)	
Region 3 = South	0.394	0.402	0.347	0.361	0.376	F= 0.736
	(0.49)	(0.491)	(0.477)	(0.481)	(0.485)	
Region 4 = West	0.208	0.22	0.252	0.278	0.239	F= 1.462
	(0.407)	(0.415)	(0.435)	(0.449)	(0.427)	
Covid-19 index	0.989	0.973	0.917	1.026	0.978	F= 0.708
	(0.844)	(0.878)	(0.851)	(0.844)	(0.854)	
Observations	269	259	242	266	1,036	

*p<0.1; **p<0.05; ***p<0.01

The table shows the arithmetic means by treatment. Standard deviations are given in parentheses. F-Test for differences over treatment groups.

B Instructions

B.1 First part

Inflation 3%

Q3

Inflation and Unemployment (1/5)

Please carefully read the following text.

Rate of inflation

Inflation is a general, sustained upward movement of prices for goods and services in an economy. A general, sustained downward movement of prices for goods and services in an economy is known as deflation.

A 3 percent inflation rate means that (on average) a dollar buys 3 percent fewer goods and services than it did last year.

The most widely reported measure of inflation is the consumer price index (CPI) by the U.S. Bureau of Labor Statistics. The CPI measures the average change over time in the prices paid by urban consumers for a market basket of consumer goods and services.

Unemployment rate

The unemployment rate represents the number of unemployed people as a percentage of the labor force.

Labor force data are restricted to people 16 years of age and older, who currently reside in the United States, who do not reside in institutions (e.g., penal and mental facilities, homes for the aged), and who are not on active duty in the Armed Forces.

IMPORTANT: On the next page you will be asked two comprehension questions about the text above. Not answering both questions correctly will result in non-acceptance of your submission (and, thus, no payment to you).

Page Break

Q4

Skip to

End of Survey if Overall price level of good... Is Not Selected

Inflation and Unemployment (2/5)

In order to continue with the experiment please answer the following two questions about the text on the previous screen.

1. The rate of inflation in an economy is best described as the rate of increase in the

- Overall price level of goods and services
- Overall level of money wages
- The long-term interest rate
- Value of money

Q5

Skip to

End of Survey if Less than today Is Not Selected

Inflation and Unemployment (3/5)

2. Imagine the interest rate on your savings account was 1% per year and inflation was 3% per year. After one year, how much would you be able to buy with the money in this account?

- More than today
- Exactly the same
- Less than today

Q6

Inflation and Unemployment (4/5)

Next, we would like to ask you for your expectations about the economy. Of course, no one can know the future. These questions have no right or wrong answers - we are interested in your views and opinions.

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.

Q7

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%.

	0	1	2	3	4	5	6	7	8	9	10
(of 10 times)											

Unemployment

Q40

Inflation and Unemployment (5/5)

Unemployment

3. Over the next 12 months, what do you think the average rate of unemployment will be in the US economy?

Q41

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

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

	0	1	2	3	4	5	6	7	8	9	10
(of 10 times)											

Demographics

Q17

You and your household (1/2)

We would like to ask you some additional questions about you and your household. By household we mean everyone who usually lives in your primary residence (including yourself), excluding non-relatives (like roommates and renters).

1. What is your gender?

Please select only one.

- ○ Male
- ○ Female
- ○ Other
- ○ Prefer not to say

Q18

2. What is your current age?

Please enter a number in the box below. I'am

Q26

years old.

Q20

3. In which region is your primary residence?

Please select only one.

- ○ Northeast (CT, ME, MA, NH, NJ, NY, PA, RI, VT)
- ○ Midwest (IA, IL, IN, KS, MI, MN, MO, ND, NE, OH, SD, WI)
- ○ South (AL, AR, DC, DE, FL, GA, KY, LA, MD, MS, NC, OK, SC, TN, TX , VA, WV)
- ○ West: (AK, AZ, CA, CO, HI, ID, MT, NM, NV, OR, UT, WA, WY)
- ○ I live outside the US

Page Break

Q21

You and your household (2/2)

4. Which category represents the total combined pre-tax income of all members of your household (including you) during the past 12 months?

Please include money from all jobs, net income from business, farm or rent, pensions, interest on savings or bonds, dividends, social security income, unemployment benefits, Food Stamps, workers compensation or disability benefits, child support, alimony, scholarships, fellowships, grants, inheritances and gifts, and any other money income received by members of your household who are 15 years of age or older.

Please select only one.

- ○ Less than $10,000
- ○ $10,000 to $19,999
- ○ $20,000 - $29,999
- ○ $30,000 - $39,999
- ○ $40,000 - $49,999
- ○ $50,000 - $59,999
- ○ $60,000 to $74,999
- ○ $75,000 to $99,999
- ○ $100,000 to $149,999
- ○ $150,000 to $199,999
- ○ $200,000 or more
- ○ Prefer not to say

Q22

5. What is the highest level of school you have completed, or the highest degree you have received? *

Please select only one.

- ○ Less than high school
- ○ High school diploma (or equivalent)
- ○ Some college but no degree (including academic, vocational, or occupational programs)
- ○ Associate/Junior College degree (including academic, vocational, or occupational programs)
- ○ Bachelor's Degree (For example: BA, BS)
- ○ Master's Degree (For example: MA, MBA, MS, MSW)
- ○ Doctoral Degree (For example: PhD)
- ○ Professional Degree (For example: MD, JD, DDS)
- ○ Other

Q24

6. What is your current employment situation? *

Please select all that apply.

- ☐ Working full-time (for someone or self-employed)
- ☐ Working part-time (for someone or self-employed)
- ☐ Not working, but would like to work
- ☐ Temporarily laid off
- ☐ On sick or other leave
- ☐ Permanently disabled or unable to work
- ☐ Retiree or early retiree
- ☐ Student, at school or in training
- ☐ Homemaker
- ☐ Other

B.2 Second part

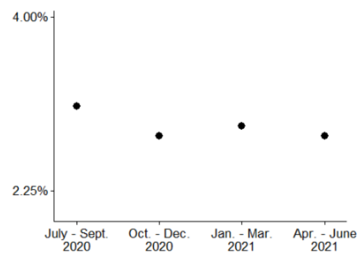
Q115

Professional prediction (1/2)

Before you give us your responses to the following questions, we would like you to know the following.

Survey of Professional Forecasters

The Survey of Professional Forecasters is a quarterly survey of professional economists. According to the latest data, one of these professional economists expects the inflation rate over the next 4 quarters displayed below.



Professional economists are not always correct in their predictions. Over the last 10 available years, **6 of the 10 annual predictions by this economist have been off by more than 1%** (i.e. the actual inflation rate has been more than 1% higher or lower).

Inflation

1. Considering the additional information, 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.

Q117

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%?

0 1 2 3 4 5 6 7 8 9 10

(of 10 times)

Page Break

Q118

Professional prediction (2/2)

Unemployment

3. Over the next 12 months, what do you think the average rate of unemployment will be in the economy?

Q119

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

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

0 1 2 3 4 5 6 7 8 9 10

(of 10 times)

Fed / Corona

Q52

Federal Reserve (1/2)

We would like to ask you some questions about monetary policy.

Federal Reserve

The Federal Reserve System is the central banking system of the United States.

The objectives as mandated by Congress are promoting maximum employment, which means all Americans that want to work are gainfully employed, and stable prices for the goods and services.

1. Since the beginning of this year, have you heard or read any news about the Federal Reserve?

- Yes
- No

Q53

Display this question

If Federal Reserve (1/2) We would like to ask you some questions about monetary policy. Federal... Yes Is Selected

1b. What news have you heard or read about the Federal Reserve?

Please select all that apply.

- The Fed raised interest rates
- The Fed cut interest rates
- The Fed purchased securities or assets
- The Fed increased lending
- Other

Page Break

Q23

Federal Reserve (2/2)

2. This is a simple attention check. What is 5 times 20?

Please select only one.

- 10
- 100
- 1000
- None of the above

Q55

3. Would you say the Federal Reserve is doing a good job with regard to it's objectives, only a fair, or a poor job?

Please select only one.

- Good Job
- Only Fair Job
- Poor Job
- No opinion

Page Break

Q49

Coronavirus outbreak (1/1)

We would like to ask you some more questions about you and your household in the current situation. As a reminder, by household we mean everyone who usually lives in your primary residence (including yourself), excluding non-relatives (like roommates and renters).

Coronavirus

The World Health Organization (WHO) upgraded the global risk from the coronavirus outbreak to "very high" in February. In the United States, cases have been confirmed in all states by now, according to researchers at Johns Hopkins University.

1. Have you purchased food or supplies due to coronavirus concerns?

Please select only one.

- Yes
- No

Q51

2. How concerned are you about the effects that the coronavirus might have on your health or the health of members of your household?

Please select only one.

- Not at all concerned
- Somewhat concerned
- Very concerned

Q58

3. How concerned are you about the effects that the coronavirus might have on the financial situation of your household?

Please select only one.

- Not at all concerned
- Somewhat concerned
- Very concerned

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