Incentivizing Inflation Expectations*

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Abstract

Inflation expectations are crucial for economic modeling and policymaking. Despite the well-established role of incentives in experimental economics, all major surveys of inflation expectations pay a flat participation fee. This lack of marginal incentives extends to many information provision experiments—often designed as randomized controlled trials (RCTs). We introduce marginal incentives into a standard survey of inflation expectations. Marginal incentives significantly alter expectation distributions, reducing upward bias, cross-sectional disagreement, closing the gender expectations gap, and increasing effort. Further, in an embedded RCT, marginal incentives lead to greater responsiveness to information provision, contrasting with null effects under flat fees. These findings underscore the importance of marginal incentives for measurement in surveys and survey-based experiments to enhance data validity, strengthen empirical research, and better inform policymaking.

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1 Introduction

Survey and experimental economics methods each offer distinct advantages and limitations. In this study, we leverage key strengths of both—such as scalability, external validity, internal validity, and control over incentives—to examine whether integrating the two approaches can improve the measurement of inflation expectations. This is especially relevant in light of two recent developments in macroeconomics: the widespread integration of survey-based beliefs into empirical research and policymaking, and the adoption of information provision experiments embedded within economic surveys. The incorporation of survey-based belief data has markedly advanced our understanding of household expectations, provided deep insights into how households form these expectations and tested long-held fundamental assumptions—rational expectations in particular—within macroeconomic theory.[1] Additionally, central banks have increasingly relied on survey-based measures of inflation expectations to inform both conventional and unconventional policy decisions, underscoring the practical importance of accurately eliciting, measuring, and interpreting these beliefs. Concurrently, adopting information provision experiments, particularly randomized controlled trials (RCTs), embedded into large-scale surveys has enabled researchers to establish causal relationships between information dissemination and expectations, economic decision-making, expectations and economic outcomes, as well as central bank communication and expectations. These experiments typically involve providing participants with specific information or interventions and measuring the subsequent impact on their expectations and behaviors. By leveraging RCTs, economists can isolate the effects of information on expectations, thereby enhancing the robustness of their empirical findings.

Survey-based beliefs and information provision experiments almost always employ unincentivized or flat-fee incentive structures. In contrast, experimental economics has long recognized the value of marginal incentives in ensuring that participants reveal their true preferences and beliefs. The induced value theorem (Smith 1976) posits that marginal incentives align participants' self-interest with truthful reporting, thereby enhancing data quality.[2] Neglecting marginal incentives may inadvertently and unnecessarily introduce measurement errors and biases into macroeconomic belief surveys, potentially undermining the reliability

[1] For a review of this literature, see D'Acunto and Weber (2024) and Weber et al. (2022). For canonical examples, see Coibion and Gorodnichenko (2015a), Coibion et al. (2018). For a nice review of information provision experiments, see Haaland et al. (2023).

[2] There is ample evidence demonstrating the advantage of marginal incentives. For example, Nelson and Bessler (1989) and Palfrey and Wang (2009) found incentive-compatible scoring rules outperform alternatives. Gächter and Renner (2010), Wang (2011), and Trautmann and van de Kuilen (2014) showed that incentivized elicitation methods dominate unincentivized ones. Charness et al. (2021) suggest that simple incentivized methods outperform both unincentivized and more complex incentive-compatible approaches in eliciting beliefs. For further discussion see also Schlag et al. (2015) and Schotter and Trevino (2014).

of empirical conclusions drawn from such data.

In this paper, we design an experiment to test how marginal incentives—rooted in the induced value theorem posited by Smith (1976)—affect macroeconomic beliefs elicited via survey and learning rates within a simple information provision experiment. We replicate portions of the NY Fed's Survey of Consumer Expectations (SCE) methodology for eliciting inflation expectations and then add an information intervention following common RCT practices. Our focus on the SCE is due to its widespread use in both academic research and policymaking (e.g., see Armantier et al. (2024), D'Acunto and Weber (2024) and Weber et al. (2022)).

Participants in our experiment were sorted into one of four treatment conditions: *Flat*, *Prior*, *Post*, and *Both*. *Flat* serves as our baseline group, where participants received a fixed payment for participation regardless of their responses. This exactly mimics the incentive structure active in all major surveys of expectations and the majority of information provision experiments. In the *Prior* group, participants were offered marginal incentives based on the accuracy of their point forecasts for one-year-ahead inflation before any information was provided. In the *Post* group, marginal incentives were applied after participants received the Federal Open Market Committee's (FOMC) inflation outlook, rewarding accurate probabilistic forecasts. *Both* combined these approaches, offering incentives for both prior and posterior forecasts. We calibrate incentives so that the time-value of expected total earnings is constant across all treatments and aligns with participation remuneration in the NY Fed's SCE. This design allows us to evaluate how different incentive structures influence elicited inflation expectations and the extent to which participants update their beliefs in response to new information.

The macroeconomic literature is divided on whether incentivized elicitations improve belief accuracy. The problem of 'cheap talk' for elicited inflation expectations has been touched on by a few studies, raising doubt about data accuracy or reliability because respondents often lack proper economic incentives (Pesaran and Weale 2006, Manski 2004). For instance, Inoue et al. (2009) question the accuracy of reported inflation expectations, as they find that implicitly measuring inflation expectations through consumption data does a better job at predicting actual inflation than the reported beliefs, especially for the lower educated. Keane and Runkle (1990) question whether reported expectations are simply cheap talk or reflect actual beliefs. They find evidence for the latter—at least for the case of professional forecasters who have strong incentives to report rational and accurate expectations for reasons concerning their professional credibility and reputation. These circumstances do not directly apply to households. Armantier et al. (2015) find a strong correlation between non-incentivized inflation expectations and investment choices in an incentivized investment experiment, except for respondents of lower education and financial literacy, suggesting overall that marginal incentives might not always be necessary. Roth and Wohlfart (2020) report no significant effect of incentives on beliefs about the likelihood of a recession. Similarly, Andre et al. (2022) find no effects for incentives on reported unemployment expectations. Pooling unemployment and inflation expectations, the authors find no significant difference between incentivized and unincentivized beliefs overall in a joint test. However, they do find that incentivizing inflation expectations shifts these moderately closer to expert forecasts. In addition, incentives increase the time taken to respond, a measure for exerted effort. Notably, Andre et al. (2022) use a clever approach to explore whether incentives affect subjective beliefs by linking rewards to second-order beliefs—participants were incentivized to match the average expert's forecast rather than their own subjective inflation expectations. While this method provides valuable insights into how incentives might shape beliefs about expert opinion, it differs from approaches that focus on first-order beliefs, where forecasts are benchmarked against actual future outcomes.

Our approach builds on these insights but represents a significant departure from previous work by employing an incentive structure within a context closely aligned with the SCE. This ensures that the results from our treatments can be readily interpreted against a backdrop of previous studies, thus facilitating the interpretation and integration of our findings into the existing literature. Additionally, our incentive structure is both more direct and less complex. Our experiment *directly* incentivizes both point and probabilistic inflation forecasts, ensuring participants are motivated to provide accurate predictions and limiting the potential for confusion driven through complex incentives. Indeed, Danz et al. (2022), Abeler et al. (2023) and Drobot et al. (2025) demonstrate that complex incentive schemes can lead to misunderstandings, potentially resulting in less accurate or truthful reporting (see also Charness et al. (2021)). We also directly incentivize updating in our study. This requires participants to update their beliefs after receiving new information, a crucial component that allows us to observe how marginal incentives affect not just initial beliefs but also learning and belief adjustments over time. This design is crucial for understanding how participants process and incorporate new information, something previous studies have not fully explored.

Our findings reveal that imposing marginal incentives significantly alters the distribution of reported inflation expectations. Specifically, respondents subjected to marginal incentives provide significantly less extreme forecasts on average and exhibit a reduced upward bias (means of point expectations fall from 6.1% without marginal incentives to 2.7% with such incentives). Further, they exhibit significantly less cross-sectional forecast disagreement (the standard deviation of point expectations drops by a third from 23.78 to 16.98). These patterns emerge regardless of whether we consider elicited priors or posteriors. Incentives further cause elicited expectations to be more consistent with professional forecasts, and resolve gender differences in expectations. Moreover, we find that incentivized respondents pay higher attention to the survey, exert more effort, and rely less on backward-looking forecasting heuristics. In the context of RCTs, marginal incentives significantly enhance estimated learning rates, indicating that participants adjusted their beliefs more substantially and consistently in response to provided information. This effect was so strong that the estimated learning rates under marginal incentives led to a qualitatively different conclusion (that central bank forecasts can coordinate and manage inflation expectations) than those estimated using a traditional flat-fee scheme.

These results have important implications for empirical macroeconomic research and policymaking. First, they suggest that the current reliance on unincentivized survey methods may lead to biased or inaccurate measures of economic expectations, potentially distorting research findings and policy decisions by compromising measurement accuracy. In contrast, incentives can help elicit more accurate inflation expectations—especially among households for whom inflation is particularly salient and economically relevant. Secondly, incorporating marginal incentives into belief elicitation can enhance the validity of survey data, providing more reliable insights into household expectations. Lastly, our findings highlight the need for macroeconomic surveys and experiments to adopt incentive mechanisms to improve the integrity and accuracy of the data they collect or at least to account for the lack of incentives in their design and interpretation. On that note, incentives might enhance the replicability of RCTs embedded into surveys, as unincentivized survey results may fail to generalize across different economic conditions (e.g., high vs. low inflation) or household contexts (e.g., large planned purchases). This is because imposing marginal incentives may allow researchers more experimental control. Our approach could be incorporated into existing surveys to estimate the extent of measurement error due to the absence of incentives and correct for associated biases.

Our research also speaks directly to the rational inattention literature originated with Sims (2003). While this literature emphasizes that processing all available information is costly and that individuals face cognitive limitations, our findings highlight the crucial role of incentives in shaping attention and expectation formation more broadly. In the field, the incentives to pay attention can arise from changing economic conditions (Braitsch and Mitchell 2022, Bracha and Tang 2024, Weber et al. 2025) or from endogenous factors such as individual stakes and relevance (Gaglianone et al. 2022).

By bridging the gap between experimental economics and macroeconomic survey methodologies, our study underscores the critical importance of incentive structures in the collection of survey-based macroeconomic beliefs and in information provision experiments. Adopting marginal incentives not only enhances data quality but also strengthens the empirical foundations upon which economic theories and policies are built. As survey-based beliefs continue to play a pivotal role in shaping economic models and policy frameworks, improving their accuracy through appropriate incentive mechanisms becomes indispensable for advancing both academic research and policymaking.

2 Experimental Design

We pursue two primary objectives that shape our experimental design. First, we investigate whether and how the implementation of marginal incentives alters survey-based belief measures. Second, we examine whether marginal incentives can influence beliefs collected through a survey-based RCT, a widely adopted methodology in experimental macroeconomics. To achieve these aims, our experiment must generate reliable survey-based beliefs free from the influence of extraneous information provision while simultaneously conducting an information provision experiment.[3]

To address these objectives, we designed an individual-choice survey that elicits both prior and posterior one-year-ahead expectations of annual inflation from each participant. Figure 1 visualizes the key steps of the experiment. Specifically, we elicited priors as point expectations (see Figure A-9) and posteriors as probabilistic forecasts (see Figure A-17). In addition to eliciting priors, we also asked for their point beliefs about inflation over the past 12 months to control for perceived inflation (these were not incentivized in any of the treatments). Between these measures, participants received a summary of the Federal Open Market Committee's most recent inflation expectations, including median forecasts for 2024 and 2025 and corresponding range forecasts (see Figure A-12). This is the information provision intervention. Additionally, we collected participants' expectations for food and gas prices both before and after the information provision, ensuring that questions focused on inflation were adequately separated from the information provision and from each other to minimize bias (Haaland et al. 2023, Stantcheva 2023). Importantly, we based the wording, response options, and overall survey structure on the carefully designed New York Fed's Survey of Consumer Expectations (Armantier et al. 2024, 2017, Bruine de Bruin et al. 2010).[4] Worth noting is that we adopted the welcoming language of the SCE intended to activate

[3] The complete survey is shown in appendix A3. We use oTree to code the interface (Chen et al. 2016).

[4] The SCE measures U.S. consumers' expectations on key economic variables like inflation, aiding policymakers and researchers in understanding consumer sentiment and behavior. For example, it helps the Federal Reserve assess inflation expectations, guide interest rate decisions, and forecast spending and savings trends. Its questions are also widely used in academic research to study the formation of inflation expectations.

participants' intrinsic motivation (see Figure A-3).

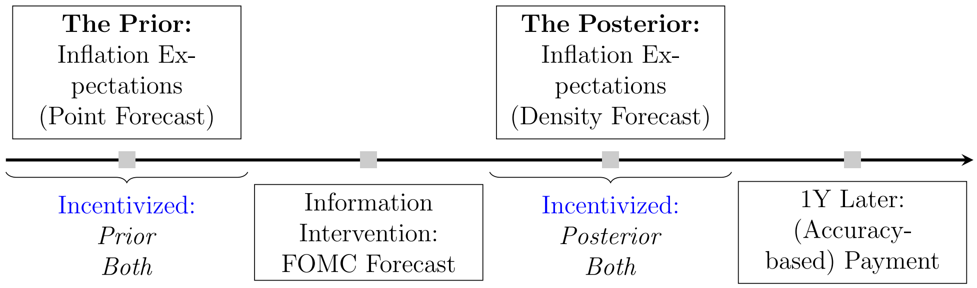


Figure 1: Experimental Design

Notes: The figure provides a simplified overview of the key steps in our survey (from left to right) as completed by all participants. Below the curly brackets are the two treatments in which inflation expectations were incentivized. In the other treatments, participants still provided their inflation expectations, but without an accuracy-based future payment for these responses.

We implemented a between-subjects design by randomizing participants into one of four treatments, summarized in Table 1. Our baseline treatment, *Flat*, provides participants with a fixed fee without any marginal incentives. To match the time-value of money earned by participants in the SCE, we scaled the *Flat* payment accordingly. This payment is divided into two parts: a fixed fee of \$2 paid immediately upon survey completion and an additional \$4 paid in September 2025, aligning with the forecast period. This delayed payment controls the timing of bonus payments necessary for other treatments and avoids potential selection effects.

Table 1: Overview of Treatments

Treatment	Prior	Posterior
Flat	Unincentivized	Unincentivized
Prior	Incentivized	Unincentivized
Post	Unincentivized	Incentivized
Both	Incentivized	Incentivized

Notes: The table shows the four treatments that differ in incentivizing elicited prior and/or posterior inflation expectations (before and after information provision). Priors are elicited using point forecast questions, while posteriors are elicited using probabilistic bin forecast questions.

The three additional treatments introduce marginal incentives based on the accuracy of participants' one-year-ahead inflation forecasts. In *Prior*, participants receive a bonus payment contingent on the forecast error relative to the realized annual Personal Consumption Expenditures (PCE) inflation reported by the Bureau of Economic Analysis (BEA) in September 2025. A perfect forecast earns a bonus of \$10. Each additional percentage-point (pp) forecast error reduces the bonus by half.[5] This scoring rule is common in learning-to-forecast experi-

[5]While Armantier and Treich (2013) highlight the potential for Proper Scoring Rules (PSRs) to distort beliefs when respondents have financial stakes or hedging opportunities, our inflation forecasting experiment

ments in experimental macroeconomics and is easy to explain.[6] In *Post*, we pay participants $\$10 * weight_i$ where $0 \leq weight_i \leq 1$ is the probability weight assigned by the participant to bin i that contains realized inflation. For example, if inflation turns out to be 5% and a participant assigned probability weight .2 to the bin for 4% to 8%, then the participant would earn $10*.2=$2.[7] For *Both*, a subject faced either the point or probabilistic marginal incentive scheme with equal likelihood. Table A-1 gives an overview of the payment structure by treatment.

The four treatments together form a design that cleanly isolates the role of marginal incentives in belief formation and updating within a survey-based information provision experiment. The *Flat* treatment serves as a benchmark without marginal incentives, which aligns with the incentives in widely-used economic surveys.[8] The *Prior* and *Post* treatments allow us to examine how incentives applied at different stages—before or after information provision—affect both the level of expectations and the degree of updating. For example, directing effort via incentives in the *Prior* treatment may reduce responsiveness to new information relative to *Flat*, while incentivizing the *Post* forecast may amplify updating by encouraging greater attention to the provided information. These treatments are particularly informative for understanding how incentivized attention or cognitive effort influences learning. The *Both* treatment holds incentives constant across the information intervention, allowing us to test whether consistency in incentive structure affects updating dynamics.

This design enables three key comparisons:

1. Comparing *Flat* to *Prior* and *Post* reveals whether marginal incentives shift beliefs at distinct stages of the elicitation process. Further, from a methodological perspective,

differs in several key ways. Unlike prediction markets or controlled probabilistic events, our respondents forecast a well-known macroeconomic variable, allowing them to anchor beliefs onto experience, news, or forecasts from credible institutions. This can minimize the distortions typically associated with PSRs in more abstract or game-theoretic settings. Further, inflation forecast is fundamentally a setting of ambiguity rather than risk, and our participants lack opportunities to hedge. Additionally, incentives in our setting weaken the link between inflation perceptions and expectations, and appeared to enhance attention and effort (see Section 3.2), while aligning forecasts more closely with professional expectations, consistent with thoughtful engagement rather than distortion.

[6] See McMahon and Rholes (2023) and Rholes and Petersen (2021) for examples. It elicits the median and is incentive-compatible under risk neutrality.

[7] While our incentives are not incentive-compatible, they are simple and have been used in experimental economics in several settings, including learning to forecast ones. We opted for simplicity because previous experimental studies suggest that simpler incentives can be more effective than more complex, incentive-compatible designs (e.g., Charness et al. (2021) or Danz et al. (2022)). In Drobot et al. (2025), we focus on the role of incentive-compatibility and complexity in designing incentives in the context of inflation expectations.

[8] Examples include the New York Fed's Survey of Consumer Expectations (SCE), the University of Michigan's Survey of Consumers, the Understanding America Study (UAS), the Panel Study of Income Dynamics (PSID), the Health and Retirement Study (HRS), the American Life Panel (ALP), the European Central Bank's Consumer Expectations Survey (CES), and the Bundesbank's Panel on Household Finances and Expectations (PHF-E).

these comparisons reveal whether paying for one forecast with certainty (*Prior* or *Post*) versus the probabilistic payment of one of the two (*Both*), affects the effectiveness of incentives.

2. Comparing *Post* to *Both* isolates whether holding incentives constant across information provision affects the magnitude or direction of belief updating

3. Comparing *Flat* to *Both* provides a clean test of whether marginal incentives systematically distort or enhance survey-based belief updating

To calibrate incentives, we analyzed average forecast errors using NY Fed's one-year-ahead forecasts and actual inflation data from FRED. The average forecast error was 1.68 pp across the entire historical sample and 1.16 pp in the most recent six observations. Based on an estimated annual discount rate ($\beta = 0.8$) from Warner and Pleeter (2001), we set the maximum payoff for a perfect forecast so that a participant's expected earnings in present-value terms align with the time-value for participants in the NY Fed's SCE. For our 5-minute survey, this results in a total payout of about \$6, with 33% (\$2) allocated as a show-up fee.

In *Prior*, we apply this marginal incentive scheme to the point forecast of inflation collected before the information provision. In *Post*, the scheme is applied to probabilistic forecasts collected after the information provision. In *Both*, we inform participants we will impose marginal incentives on either the point or probabilistic forecast with equal probability, but not both.

2.1 Hypotheses

Before moving on to the results, we offer two hypotheses regarding the impact of marginal incentives in our experiment. These hypotheses are grounded in the induced value theorem, namely the notion that performance-based financial incentives enhance cognitive effort and reduce biases in self-reported data, leading to more reliable and valid measures of economic beliefs. This logic is the basis of the foundational principle of employing marginal incentives to discipline choice data and reduce measurement error in experimental economics (Smith 1976, Smith and Walker 1993, Camerer and Hogarth 1999). While the induced value theorem was originally developed for valuation tasks (like auctions or market experiments), its logic can be extended to belief elicitation (see Schotter and Trevino (2014), Schlag et al. (2015) and Charness et al. (2021) for reviews). Specifically, in our context, we expect incentives to reduce upward bias, forecast errors, and the occurrence of outliers.[9] Further, they will

[9]In the inflation expectations literature, upward bias refers to the tendency of individuals or survey respondents to systematically overestimate future inflation compared to actual inflation outcomes. This bias has been widely documented in household surveys and was also present at the time of our survey.

increase individuals' attention to the provided information.

Hypothesis 1 (Survey-Based Beliefs): *The cross-sectional distribution of inflation expectations exhibits reduced upward bias (lower mean) and disagreement (lower variance) with marginal incentives. Further, with marginal incentives, forecasts are closer to those of professional forecasters.*

Hypothesis 2 (Learning Rates): *In the context of the RCT, marginal incentives increase the learning rates. Participants who receive marginal incentives adjust their beliefs more substantially and consistently in response to the information provided, compared to those without such incentives.*

2.2 Data

We collect 1,000 observations—250 per treatment—from US residents via Prolific on September 14, 2024. Prolific provides information on participants' demographic characteristics such as age, gender, income or race (see Table A-2 in appendix A1 for a comparison of demographic characteristics across treatment groups and with the SCE sample).[10] The chosen sample size is based on power calculations (see appendix A2). With few exceptions, we winsorize data at the 1% and 99% levels to mitigate the impact of extreme outliers on our main results.

3 Results

This section details the results of our survey. We first show how incentives affect elicited expectations, highlighting that incentivized expectations become more consistent with professional forecasts from the Survey of Professional Forecasters (SPF), exhibit lower disagreement, and diminish the puzzle of gendered expectations. Second, we show how incentives within an information provision experiment affect updated expectations and learning rates. Finally, we show how incentives raise participants' effort.

[10] Coincidentally, there is a relatively higher proportion of females in treatments Prior and Both. Previous studies have shown that females tend to have higher inflation expectations. Since we observe higher inflation expectations in the Flat treatment, we do not believe this affected our results. Further, we control for gender in our regressions.

3.1 The Effect of Incentives on Elicited Expectations

We first consider whether marginal incentives influence respondents' one-year-ahead inflation expectations, measured as point forecasts, which we illustrate in Section 3.1. This figure shows the cumulative distribution functions (CDFs) of inflation expectations across the different treatment groups, expressed in percentage points. The treatments imposing marginal incentives—*Both* (blue curve) and *Prior* (yellow curve)—are contrasted with *Flat* (red curve) and *Post* (green curve), which do not include marginal incentives. The *Flat* and *Post* treatments mimic the typical approach used in all major macroeconomic surveys and thus reflect the incentive mechanism underlying the majority of belief data used in belief-based research in empirical macroeconomics.

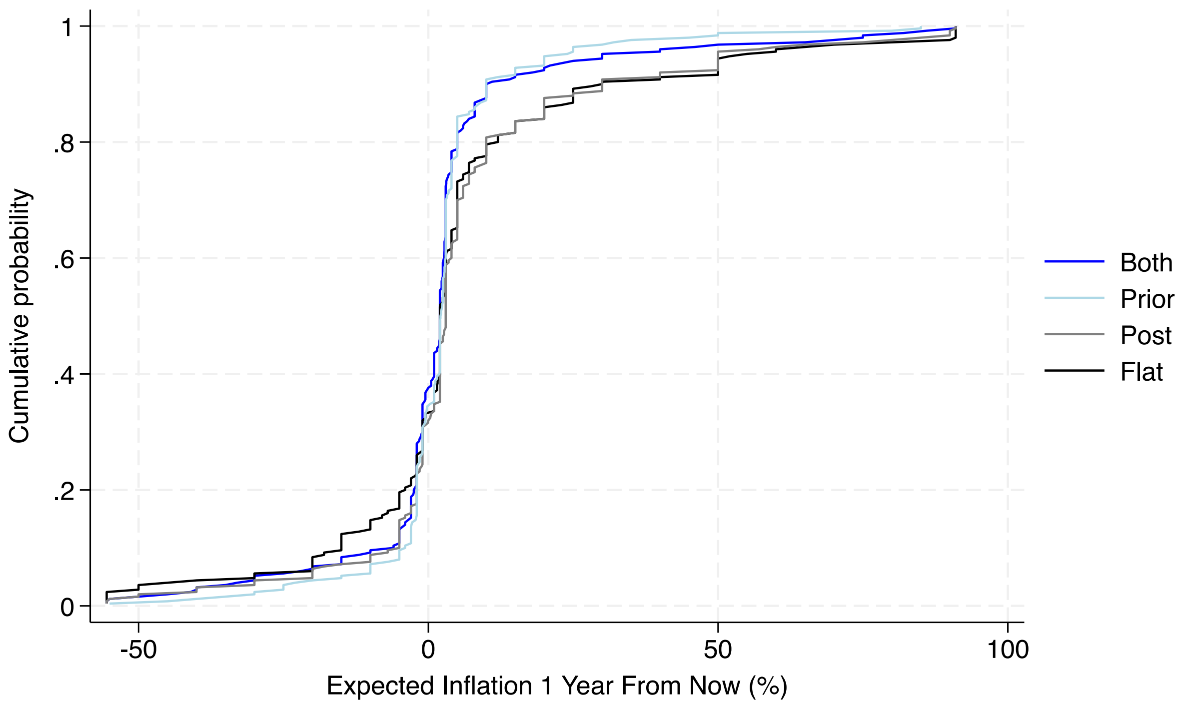


Figure 2: CDFs of Expected Inflation By Treatment

Notes: The figure shows cumulative distribution functions (CDFs) of inflation expectations across the different treatment groups, expressed in percentage points. Data are winsorized at the 1% and 99% levels. Treatments *Both* and *Prior* are incentivized and shown in shades of blue, while treatments *Post* and *Flat* are unincentivized, shown in gray and black.

Our results show that imposing marginal incentives when eliciting inflation expectations (i.e., in *Prior* and *Both*) generate significantly different belief distributions than do flat-fee incentives (i.e., the *Flat* and *Post* treatments). More specifically, imposing marginal incentives during belief elicitation leads participants, on average, to expect significantly less extreme inflation values. These incentivized expectations appear more reasonable when evaluated against historical inflation data, current inflation trends, professional forecasts and the Fed's contemporaneous policy stance and outlook. Put simply, the beliefs elicited under marginal incentives resemble more informed expectations.

The primary impact of these incentives manifests in the expectations of respondents who foresee inflation, rather than deflation. Under marginal incentives, respondents expecting inflation predict significantly lower price growth relative to unincentivized treatments. For those anticipating deflation, we similarly observe a muted expectation of price change under marginal incentives, suggesting that the incentives temper both inflationary and deflationary beliefs.

This distinction arises despite holding constant across treatments all other aspects of the incentives, including the timing and expected amounts of payments. We show that merely altering the structure of belief elicitation in a feasible way that imposes no additional cost relative to prevailing approaches can substantially change the nature of respondents' reported expectations. Importantly, this change occurs without modifying participants' perceptions of the data-generating process, introducing asymmetric information, or altering other fundamental aspects of the decision environment.

Table 2 summarizes the mean and standard deviation of point forecasts for participants who faced marginal incentives or not. The unincentivized group has a significantly higher mean (6.13) compared to the incentivized group (2.73), and the standard deviation is also larger in the non-incentivized group (23.78 vs. 16.98), indicating higher cross-sectional disagreement among unincentivized forecasters.

Table 2: Summary Statistics and Variance Comparison of Inflation Expectations

	Mean	**Standard Deviation**	**N**
Unincentivized	6.13	23.78	500
Incentivized	2.73	16.98	500
All Data	4.43	20.72	1,000

Test for Equality of Means and Variances

Test Type	**Test Statistic**	**p-value**
Welch's t-test (Difference in Means)	-2.61	$p < .001$
Levene's Test (Mean)	31.54	$p < .001$
Levene's Test (Median)	21.31	$p < .001$
Levene's Test (Winsorized Mean)	23.32	$p < .001$
F-Test (Variance Ratio)	1.9594	$p < .001$

Notes: This table shows mean and variances of the elicited prior belief of inflation $\mathbb{E}(\pi_{Prior})$ by incentive treatments. *Unincentivized* is comprised of treatments *Flat* and *Posterior*, while *Incentivized* is comprised of *Both* and *Prior*.

We test for the equality of variance across incentive schemes using both Levene's tests and the F-test for variance ratios. All tests strongly reject the null hypothesis that the variances are equal ($p-values < 0.001$). Thus, imposing marginal incentives reduces the mean of point inflation expectations (upward bias) and leads to lower cross-sectional forecast disagreement.

To quantify the effect of incentives on forecasts, we estimate the following regression:

$$|\mathbb{E}(\pi_{prior})| = \alpha + \gamma_i Treatment_i + \beta \mathbb{X} + \epsilon \tag{1}$$

where $i \in \{Flat, Post, Both, Prior\}$ denotes the incentive treatment groups, and $\mathbb{X}$ represents a vector of control variables. The results of this regression are displayed in Table 3. Column (1) provides baseline results without controls, and each subsequent column progressively introduces additional covariates.

Table 3: Effects of Incentives on Inflation Expectations

	(1)	(2)	(3)	(4)	(5)
Post	-1.770	-1.785	-1.473	-1.314	-0.994
	(1.916)	(1.915)	(1.865)	(1.891)	(1.832)
Both	-5.268***	-5.213***	-5.828***	-5.757***	-6.052***
	(1.802)	(1.804)	(1.778)	(1.791)	(1.732)
Prior	-7.794***	-7.779***	-8.492***	-8.540***	-8.705***
	(1.620)	(1.620)	(1.610)	(1.612)	(1.564)
Deflation		-1.248	-1.609	-1.609	-0.0966
		(1.183)	(1.197)	(1.196)	(1.156)
Male			-7.175***	-7.052***	-6.907***
			(1.147)	(1.153)	(1.112)
Higher_Ed.				-2.162*	-2.017*
				(1.184)	(1.141)
Constant	15.20***	16.86***	20.56***	21.56***	16.65***
	(1.411)	(2.179)	(2.422)	(2.443)	(2.326)
Sentiment	No	No	No	No	Yes
N	1,000	1,000	1,000	1,000	1,000

Robust standard errors in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

Notes: The table shows the effect of treatments on reported inflation expectations (the priors), relative to the *Flat* treatment. Regressions are estimated by OLS with robust standard errors. Data are winsorized at the 1% and 99% levels.

Our first hypothesis, detailed in Section 2, posits that marginal incentives significantly alter the distribution of inflation expectations. The results strongly support this hypothesis. As shown in Table 3, the coefficients for *Both* and *Prior* indicate that marginal incentives significantly reduce expectations of inflation and deflation rates, compared to the unincentivized *Flat* treatment. Specifically, respondents in the *Prior* group report significantly lower expectations for price changes compared to those in the *Flat* treatment, with absolute forecast values approximately half as large on average ($p < 0.001$). The effect in *Both* is somewhat less pronounced but still substantial, with respondents providing significantly lower absolute forecasts—about a third lower on average compared to *Flat* ($p < 0.01$). These effects are robust to controlling for the expected direction of price change (column (2)), for a participant's gender (column(3)), controlling whether a subject has at least an undergraduate degree (column (4)), and controlling for a participant's one-year-ahead economic sentiment (column (5)). As an additional exercise, we focus on the impact of incentives on extreme values and define the highest 10% of absolute prior inflation expectations as extreme forecasts. The logistic regression results in Table A-4 and Table A-5 indicate that respondents in the non-incentivized groups are more likely to report extreme values compared to the *Prior* and Both groups. Specifically, the *Flat* group is 222% more likely, the *Post* group is 181% more likely than in *Prior*. Interestingly, also the *Both* group is 91% more likely than in *Prior* to provide such forecasts.

The influence of incentives on expectations highlights the need for careful consideration when interpreting survey-based belief measures and the conclusions drawn from them. If belief elicitation is highly sensitive to the presence of incentives, it becomes crucial to either incorporate incentives to enhance reliability and accuracy or correct for potential biases that may arise in their absence.

We also find evidence that marginal incentives reduce upward bias and align respondents' expectations more closely to those of professional forecasters, who have historically exhibited greater accuracy (Carroll (2003)). Specifically, we compare data from each of our treatments with the most recent mean PCE forecast from the Survey of Professional Forecasters (SPF) in Table 4. While expectations under *Flat* (5.50%) and *Post* (6.75%) are relatively high and significantly higher than those of professional forecasters, implementing marginal incentives in *Prior* and *Both* leads to expectations (2.80% and 2.64% respectively) that align more closely with professional forecasts from the SPF (2.11%).[11]

We also consider how our various incentive schemes impact participants' hypothetical payoffs. To do this, we assume the Fed's forecast of median inflation for 2025 (π_{2025}) is closer to the realized value in expectation. Using this as a basis for comparison, we calculate a participant i's forecast error as $error_i = |\pi_{2025} - \mathbb{E}_i(\pi_{2025})|$ and her hypothetical bonus payment as

[11] Unfortunately, we do not have access yet to the microdata from the New York Fed SCE, which prevents us from conducting formal comparison tests between their data and ours. However, the New York Fed provided us with summary statistics, specifically the mean and standard deviation of winsorized forecasts for September 2024, which are 6.03 and 17.3, respectively. These figures suggest that the mean forecasts in our unincentivized samples are similar to those in the SCE, while the standard deviation tends to be higher in our data. This is perhaps due to the fact that some of the SCE respondents are experienced, e.g., see Kim and Binder (2023).

Table 4: Comparing Experimental Data to Professional Forecasts from SPF

	Treatment	SPF Mean (Std. Dev.)	Treatment Mean (Std. Dev.)	Difference	Welch's t-stat	p-value
Unincentivized	*Flat*	2.11 (0.286)	5.50 (24.798)	-3.389	2.160	0.032
	Post	2.11 (0.286)	6.75 (22.576)	-4.635	3.244	0.001
Incentivized	*Prior*	2.11 (0.286)	2.80 (14.313)	-0.690	0.761	0.447
	Both	2.11 (0.286)	2.64 (19.271)	-0.529	0.434	0.665

Notes: This table compares data the Survey of Professional Forecasters (SPF) to data from participants in *Flat*, *Post*, *Prior* and *Both* using Welch's t-tests. For comparison, the most recent inflation report preceding our experiment was 2.5% (July inflation released August 14th). Data from the SPF are for the mean PCE inflation forecast for Q4 2024 to Q4 2025 (PCEB) from the Q3 2024 survey, which most closely aligns with our experimental time frame of September 2024 to September 2025. Note that the sample size for SPF (N=33) is considerably smaller that those of our survey, so we use Welch's t-test to account for this. Treatments' data are winsorized at the 1% and 99% levels.

$10 * (2^{-error_i})$. We depict the distribution of payoffs calculated this way across treatments in Figure A-1 and explore the significance of these results in Table A-3.

The punchline is that marginal incentives significantly increase hypothetical earnings. In *Both*, we predict in Table A-3 that payoffs will increase between approximately 24% ($p < .1$) in our baseline regression specification and 34% ($p < .05$) in a specification controlling for gender, education, and economic sentiment. In *Prior*, hypothetical earnings increase between 33% ($p < .01$) in our baseline specification and 49% in our full specification.

3.1.1 Incentives and Gender Gap Puzzle in Inflation Expectations

There is a long-standing strand of the survey-based belief literature, summarized recently in Reiche (2023), that documents and attempts to rationalize gender differences in inflation expectations.[12] Concisely, female survey participants typically report significantly higher inflation expectations than men (e.g., Bruine de Bruin et al. (2010) or D'Acunto et al. (2021)). Our question is whether this puzzle survives the implementation of marginal incentives.

To do this, we estimate a series of OLS regressions for each treatment condition: *Flat*, *Post*, *Both*, and *Prior* where we project inflation expectations gathered before the information provision experiment (i.e. priors) onto an indicator variable denoting whether a participant was female. This method enables us to independently assess the impact of gender within each specific treatment context.

The regression equation for each treatment T is specified as:

$$\mathbb{E}(\pi_{Prior,T}) = \beta_{0,T} + \beta_{1,T}\text{Female} + \epsilon_T.$$

[12]Note that we use the terms gender and sex interchangeably in this paper, as is common in related literature, though we recognize that they may not always align. For accuracy, the variable we use specifically measures sex.

Additionally, we consider a final model where we pool our data across all four treatments and project inflation expectations onto a dummy variable capturing whether a participant was female, the incentive structure imposed on a participant, and the interaction of both terms. This specification allows us to test whether females exhibit a significantly different response to marginal incentives than males.

The interaction regression model is specified as:

$$\mathbb{E}(\pi_{Prior}) = \beta_0 + \beta_{1,i}\text{Treatment}_i + \beta_{2,i}\text{Female} + \beta_{3,i}(\text{Treatment}_i \times \text{Female}_i) + \epsilon_i$$

where our coefficient of interest is β_3.

The regression results, summarized in Table 5, reveal how incentives interact with gender to shape inflation expectations. In the absence of marginal incentives (*Flat*), female respondents have significantly higher inflation expectations (9.346, $p < .01$) than do their male counterparts. This finding is consistent with existing empirical literature that suggests that women often report higher inflation expectations. This result also appears in *Post*, albeit muted and only marginally significant.

However, marginal incentives eliminate the significant difference in inflation expectations across genders. This is true for *Both* (2.68, $p > .1$) and *Prior* (1.08, $p > .1$). Further, we observe in column (5) that marginal incentives are eliminating the gender difference in expectations observed in *Flat* because they act significantly more strongly on belief formation for females than they do for males (i.e., $Prior \times$Female $=-8.264$, $p < .05$, and $Both \times$Female $=-6.67$, $p < .1$).

These findings suggest that the puzzle of gendered expectations—where women report higher inflation expectations than men—diminishes under marginal incentives. Specifically, women appear to respond more strongly to incentives during belief elicitation, leading to more moderated and comparable expectations with men (see Figure 3). This responsiveness effectively resolves the observed gender discrepancies in survey-based belief measures, as incentivized belief elicitation promotes more consistent and aligned inflation expectations across genders.

3.2 The Effect of Incentives on Backward-Looking Heuristics, Attention and Effort

Why do incentivized expectations become more consistent with the SPF? A key factor appears to be cognitive effort. Rational inattention theory suggests that respondents do not fully process or recall all relevant economic information (e.g., CPI trends, interest rates)

Table 5: Effects of Incentives on the Gender Expectations Gap

	(1) Flat	(2) Post	(3) Both	(4) Prior	(5) All
Female	9.346***	4.779*	2.681	1.082	9.346***
	(2.941)	(2.836)	(2.204)	(1.634)	(2.941)
Post					3.970*
					(2.227)
Both					0.576
					(1.999)
Prior					1.743
					(1.802)
Post×Female					-4.568
					(4.085)
Both×Female					-6.665*
					(3.675)
Prior×Female					-8.264**
					(3.364)
Constant	0.356	4.326***	0.932	2.099**	0.356
	(1.489)	(1.656)	(1.334)	(1.015)	(1.489)
N	250	250	250	250	1,000

Robust sandard errors in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

Notes: The table shows the effect of treatments on reported inflation expectations (the priors) by gender. Regressions are estimated by OLS with robust standard errors. Data are winsorized at the 1% and 99% levels. Results are robust to the inclusion of the same control variables used in the previous section.

because of cognitive costs (see Maćkowiak et al. (2023) for a review). Indeed, a number of studies suggest that households tend to simplify by relying on rules of thumb, recent price experiences (like gas or groceries), or media headlines (e.g., Coibion and Gorodnichenko (2015b), Binder (2018), D'Acunto et al. (2021), Kilian and Zhou (2022), Aidala et al. (2024), D'Acunto and Weber (2024), Jo and Koplack (2025), Drobot (2025)).

Under flat incentives, there is little motivation to exert effort, retrieve information, recall knowledge, or offer more accurate responses. In contrast, when incentives are introduced, they increase the benefits of effort, leading to forecasts that are less biased and closer to expert forecasts.

3.2.1 Decoupling Inflation Expectations and Perceptions

A common heuristic for forming inflation expectations is to rely on inflation perceptions, resulting in individuals reporting future expected inflation that resembles their currently perceived inflation levels (e.g., Weber et al. (2022), Huber et al. (2023), Anesti et al. (2024)).

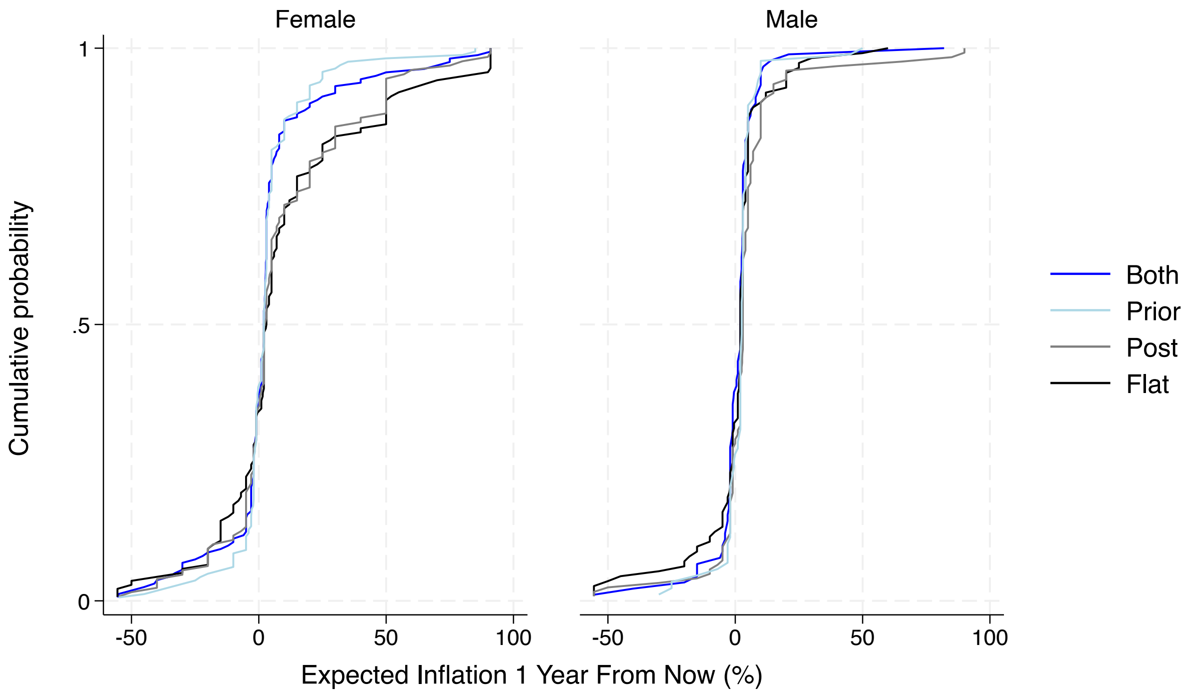


Figure 3: Effects of Incentives on Expectations by Gender

Notes: The figure shows cumulative distribution functions (CDFs) of inflation expectations by gender across the different treatment groups, expressed in percentage points. Data are winsorized at the 1% and 99% levels. Treatments *Both* and *Prior* are incentivized and shown in shades of blue, while treatments *Post* and *Flat* are unincentivized, shown in gray and black.

We find that incentives weaken the link between perceptions and expectations, suggesting that respondents move away from simple extrapolation of (perceived) past inflation.

Figure 4 shows this relationship, estimated by regressions where expected inflation is the dependent variable and perceived inflation is the independent variable. The findings indicate that in the incentivized group (*Prior*), this relationship is no longer statistically significant (see columns (1)-(4) in Table 6). Thus, incentives shift the range of values respondents consider likely, leading them to form expectations within a more informed range.

This result is particularly striking given that perceptions and expectations are elicited on the same survey page. One possible interpretation is that marginal incentives reduce reliance on simple backward-looking forecasting heuristics, which is a sensible response given the specific time period during which the survey was conducted. Instead, incentivized respondents seem to engage in more deliberate recall of information to generate more intentional inflation forecasts.

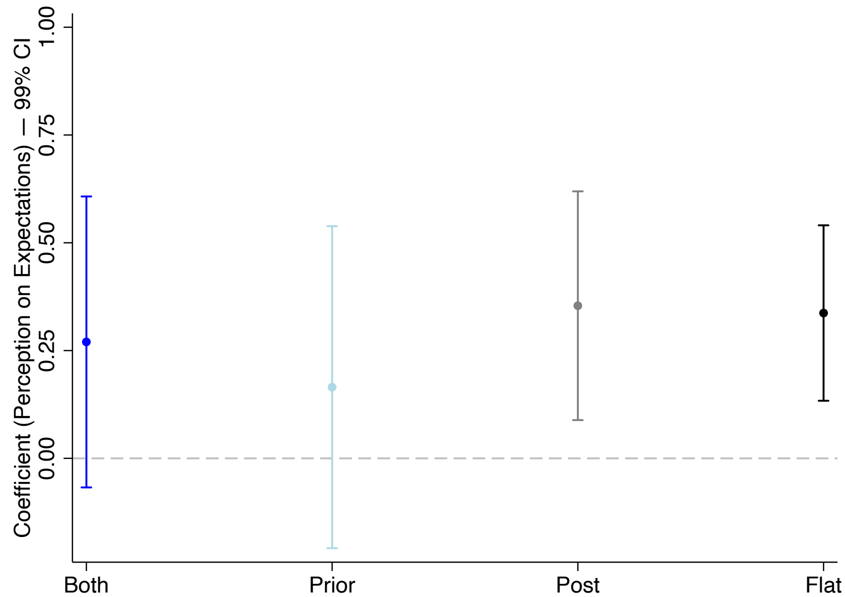


Figure 4: Inflation Expectations and Perceptions

Notes: The figure shows the relationship between perceived inflation and inflation expectations (prior point forecasts). The plotted coefficients are estimated by OLS regressions of inflation expectations on perceptions, including control variables (see Table 6 for details). Data are winsorized at the 1% and 99% levels. Treatments *Both* and *Prior* are incentivized and shown in shades of blue, while treatments *Post* and *Flat* are unincentivized, shown in gray and black. We include 99% confidence intervals.

3.2.2 Attention to the Survey

Another way to determine cognitive effort is through the attention paid to the survey. In a similar spirit to Bracha and Tang (2024), who examine perception errors in economic decision-making, we construct a measure of survey inattention as an Absolute Perception Error (APE)—the absolute difference between a respondent's perceived inflation and the most recent actual inflation rate available at the time of the survey.[13] Intuitively, the further a respondent's perception deviates from actual inflation, the less attention they are likely to pay to the survey (particularly the survey questions on inflation perceptions).

We find that marginal incentives play a crucial role in significantly reducing the APE gap. Incentivized groups exhibit significantly lower inattention (or, equivalently, greater attention) to the survey (see column (5) of Table 6). This is presumably because of spillover effects associated with incentives for the questions on inflation expectations. Specifically, respondents may use inflation perceptions as an input in their inflation expectations.

We observe a gender gap, as women have noticeably higher APE (see Table A-6). This result complements Braitsch and Mitchell (2022), who construct a measure of inattention based on

[13] The most recent PCE inflation preceding our experiment was 2.5% which was July inflation released August 14th.

the consistency of responses to the SCE point and density forecast questions and show that women are less attentive than men when forming inflation expectations.

Table 6: Effects of Incentives on Perceptions and Inattention

	(1) Flat $\mathbb{E}(\pi_{Prior})$	(2) Post $\mathbb{E}(\pi_{Prior})$	(3) Both $\mathbb{E}(\pi_{Prior})$	(4) Prior $\mathbb{E}(\pi_{Prior})$	(5) APE
Perception	0.337***	0.354***	0.270**	0.165	
	(0.079)	(0.103)	(0.131)	(0.145)	
Post					-2.034
					(2.175)
Both					-8.875***
					(2.050)
Prior					-11.479***
					(1.914)
Deflation	-29.908***	-23.802***	-19.134***	-14.827***	2.770**
	(2.815)	(2.668)	(2.223)	(1.754)	(1.456)
Male	-4.491**	-2.081	-0.723	-2.170*	-9.239***
	(2.258)	(2.581)	(1.836)	(1.271)	(1.321)
Higher_Ed.	3.158	-3.996*	1.596	-0.244	-3.589***
	(2.288)	(2.173)	(1.715)	(1.529)	(1.362)
Constant	9.496***	11.683***	6.225***	7.266***	23.498***
	(2.272)	(3.089)	(1.578)	(1.379)	(2.060)
N	250	250	250	250	1,000

Robust standard errors in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

Notes: Columns (1) through (4) show the correlation between perceived and expected inflation and demonstrate that marginal incentives break the link between the two measures. Column (5) shows the effect of treatment on Absolute Perception Error (APE). Regressions are estimated by OLS with robust standard errors. Data are winsorized at the 1% and 99% levels.

3.2.3 Effort

An essential consideration in survey-based research is the amount of effort participants invest when responding to questions, particularly when eliciting complex beliefs such as inflation expectations. Or similarly, how compliant participants are to consider provisioned information in RCTs (Knotek et al. 2024).

We quantify effort using survey completion time, a common metric in survey research used to approximate the cognitive resources participants allocate to answering questions (Malhotra 2008). We designed the survey take approximately five minutes, but anticipated variation based on individual differences in reading speed, comprehension, and the effort invested in considering responses. By comparing completion times across different incentive treatments, we can assess whether marginal incentives motivate participants to devote more time—and presumably more cognitive effort—to the survey tasks.

We estimate a series of ordinary least squares (OLS) regressions with data winsorized at the 5th and 95th percentiles to analyze the impact of marginal incentives on completion time. The regression equation is specified as

$$\text{CompletionTime}_i = \alpha + \gamma_1 \text{Post}_i + \gamma_2 \text{Both}_i + \gamma_3 \text{Prior}_i + \beta \mathbf{X}_i + \epsilon_i, \tag{2}$$

where $CompletionTime_i$ is the total time (in seconds) participant i took to complete the survey. $Post_i$, $Both_i$, and $Prior_i$ are dummy variables indicating the incentivized treatment group to which participant i was assigned, with the Flat treatment serving as the reference group. $\mathbf{X}_i$ is a vector of control variables, including participant gender (Male), education level (Higher_Ed), and forward-looking economic sentiment (included in(4)). We report regression results in Table 7.[14]

Table 7: Effect of Incentives on Effort

	(1) Completion Time	(2) Completion Time	(3) Completion Time	(4) Completion Time
Post	19.94	23.05	27.18	29.24
	(25.86)	(25.71)	(25.64)	(25.68)
Both	110.8***	104.6***	106.4***	104.0***
	(26.80)	(26.72)	(26.53)	(26.50)
Prior	58.43**	51.37**	50.11**	53.37**
	(25.29)	(25.13)	(25.16)	(25.20)
Male		-70.62***	-67.44***	-72.43***
		(18.63)	(18.60)	(18.56)
Higher_Ed.			-56.19***	-59.62***
			(18.26)	(18.26)
Constant	567.4***	599.0***	625.0***	585.9***
	(18.39)	(19.88)	(21.97)	(25.59)
Sentiment	No	No	No	Yes
N	1,000	1,000	1,000	1,000

Standard errors in parentheses
* $p < .1$, ** $p < .05$, *** $p < .01$

Notes: The table shows the effect of treatments on effort, as proxied by completion times. Regressions are estimated by OLS with robust standard errors. Data are winsorized at the 5% and 95% levels due to the relatively high variation in completion time.

Coefficients for *Both* and *Prior* are positive and statistically significant across all specifications, indicating that participants in these groups took significantly longer to complete

[14] We show the same results without winsorizing in Table A-8, located in appendix A1.

the survey compared to those in the *Flat* treatment. Specifically, participants in the *Both* treatment spent approximately 104 to 111 seconds more on the survey than those in the *Flat* group—a substantial increase given the survey's average completion time. Those in the *Prior* treatment took about 50 to 58 seconds longer than participants in the *Flat* treatment. Although the coefficients for the *Post* treatment are positive, they are not statistically significant, suggesting that marginal incentives applied only after the information provision do not significantly affect overall completion time.

These results support the hypothesis that marginal incentives enhance participant effort during belief elicitation, particularly when the incentives are applied at the initial stages of the survey, as in the *Prior* and *Both* treatments. The increased completion times indicate that participants are investing more effort into responses, leading to more thoughtful belief formation.

The regression results also reveal significant effects of participant gender and education level on completion time. The coefficient for male participants is negative and highly significant across specifications, indicating that males spent approximately 67 to 72 seconds less on the survey than females. This suggests that female participants generally invest more time and effort into completing the survey tasks. Additionally, participants with at least an undergraduate degree spent about 56 to 60 seconds less on the survey compared to those without higher education. This may reflect greater familiarity with the survey content or more efficient processing of the information among more educated participants. The inclusion of economic sentiment in column (4) does not substantially alter the coefficients of interest, and the main findings regarding the impact of marginal incentives on completion time remain robust.

3.2.4 Rounding Behavior

Another behavioral proxy for effort is the degree of numerical precision in reported forecasts. According to satisficing theory (Simon 1956, Krosnick 1991), individuals reduce cognitive effort when the marginal value of precision is low, often defaulting to coarser, rounded responses (e.g., to the nearest whole number or focal point). In our setting, if marginal incentives increase the perceived value of accuracy, they should lead participants to provide more precise, less rounded forecasts.

We define a forecast as rounded if the reported value is a multiple of 1, 5, or 10 percentage points (pp).[15] This captures meaningful reductions in numerical precision and serves as

[15] For instance, forecasts of 10 or 20 are classified as rounded to 10 pp; forecasts such as 5 or 15 are classified as rounded to 5 pp; and values like 7.0 or 3.0 are classified as rounded to 1 pp. Forecasts such as 7.3 or 3.7

our main behavioral measure of satisficing. We interpret a lower likelihood of rounding as evidence that participants are exerting greater cognitive effort in forming and reporting their expectations. Based on this definition, we construct two measures: (1) a binary indicator for whether a participant rounded their point forecast, and (2) a categorical variable capturing the degree of rounding. Using these, we show that marginal incentives significantly reduce rounding behavior—consistent with the interpretation that participants exert greater effort when precision is rewarded.

Supporting this interpretation, Figure 5 shows that 91.4% of unincentivized participants rounded their forecasts, compared to only 77.2% of those in incentivized treatments, which yields a 14.2 percentage point difference ($p < 0.01$). Probit regressions confirm that incentives tied to prior beliefs significantly reduce the likelihood of rounding (see Table 8). Further, Figure 5 illustrates that incentivized participants not only round less often but also round less coarsely. This pattern reinforces our interpretation that marginal incentives increase participant effort—not just in time spent, but also in the cognitive precision applied when forming and reporting expectations.

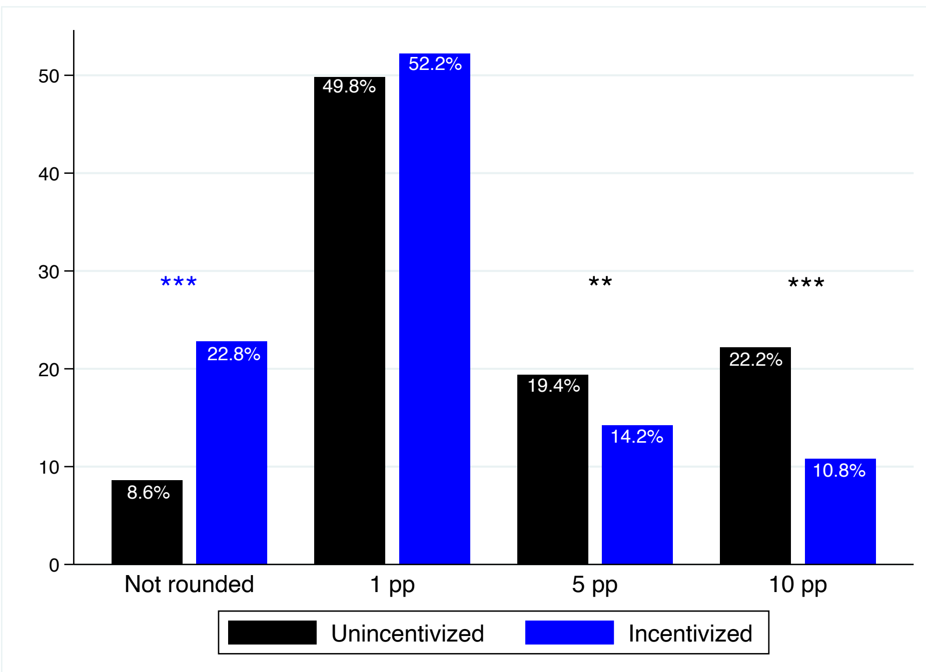


Figure 5: Percentage of Forecasts By Rounding Behavior

Notes: Stars indicate significance levels from the test of the equality of proportions as follows: $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

These findings contribute to a growing literature on the determinants of rounding behavior in inflation expectations. For example, Binder (2017) shows that rounding in survey-based

are classified as not rounded.

Table 8: The Probability of Rounding in Inflation Expectations

	(1)	(2)
Incentivized	-0.142^{***}	-0.146^{***}
	(0.023)	(0.023)
Controls	No	Yes
N	1,000	1,000

Robust standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: Table reports marginal effects from Probit regressions with robust standard errors. Rounding is defined as any rounding behavior to the nearest 1, 5, or 10 pp. Data are winsorized at the 1st and 99th percentiles. Column (1) includes no controls, while column (2) controls for age, sex, education, employment status, primary shopper status, and whether a respondent earns above or below median income.

belief measures can proxy for forecast uncertainty, while McMahon et al. (2025) use incentivized forecasting experiments to show that both individual-level uncertainty and the complexity of the forecasting environment causally affect rounding behavior.

3.3 Effect of Incentives in Information Provision Experiments

We now focus on the role that marginal incentives play in a simple information provision experiment. We find that marginal incentives can effectively bridge perception gaps, suggesting that RCTs without marginal incentives may systematically underestimate the impact of information on beliefs.

Recall that after eliciting a point expectation of one-year-ahead inflation, we provide each participant with a summary of the Fed's outlook on how inflation might evolve in 2025. We then collect data from a binned inflation forecast to estimate a subject's updated inflation expectation ("posteriors"), which we treat as our measure of interest throughout this section.[16] Recall that we adopt the same point and bin elicitation strategies followed by the NY Fed in its Survey of Consumer Expectations.[17]

As noted by Haaland et al. (2023), information provision experiments measuring beliefs and belief updating via quantitative measures typically quantify the extent to which respondents adjust their beliefs toward new information conveyed via some signal. They call this the *learning rate*, which one can estimate using

[16] We depict these expectations in Figure A-2 and explore whether marginal incentives impact the distributions of these expectations collected across treatment in Table A-7. For the sake of brevity, we report both in appendix A1. Similar to what D'Acunto et al. (2023) demonstrates for the SCE data, we find that the binned inflation forecasts exhibit less disagreement and a lower mean expected inflation than point forecasts.

[17] There is evidence from Becker et al. (2023) that the number, center, and width of bins can significantly alter expectations provided by survey respondents. Although beyond the scope of this paper, an interesting question for future research is whether and how this might interact with marginal incentives.

$$\text{Updating}_i = \beta_0 + \beta_1(\text{Treatment}_i \times \text{PercGap}_i) + \beta_2\text{Treatment}_i + \beta_3\text{PercGap}_i + \epsilon_i \qquad (3)$$

where $Updating_i$ is the distance between respondent i's posterior and prior one-year-ahead inflation expectation, $Treatment_i$ is an indicator variable denoting which incentive structure a respondent faced, and $PercGap_i$ (Perception Gap) is the distance between the Fed's forecast of median PCE inflation in 2025 and respondent i's prior for the same. Given these definitions, comparing across β_1 captures the extent to which incentive structure drives belief updating relative to our baseline treatment *Flat*, β_2 captures the average treatment effect on respondents' beliefs that does not depend on individual priors, and β_3 measures the extent to which changes in beliefs depend on the perception gap.[18]

We show results from estimating various versions of Equation (3) in Table 9, where $\beta_{1,i}$ are our primary coefficients of interest. Column (1) shows our baseline specification with no additional controls, and columns (2) through (4) include additional controls for sex, educational attainment, and economic sentiment. Regardless of the specification, $\beta_{1,Post}$ is significant at the 1% level, indicating that imposing marginal incentives in our simple information provision experiment led to significantly more belief updating. The same effect is true for *Both*, where subjects know that we will either pay for the accuracy of their prior or posterior belief about inflation. Interestingly, this effect (captured by $\beta_{1,Both}$ is roughly 30% smaller across all specifications and significant at only the 10% (baseline specification, column (1)) or 5% (columns (2) - (4)) levels.

Our analysis demonstrates that implementing marginal incentives significantly enhances belief updating among subjects. Specifically, the positive and statistically significant coefficient for the interaction term ($\beta_{1,Post},\ \beta_{1,Both}$) indicates that incentives designed to promote forecast accuracy significantly amplify the magnitude of belief updating in response to discrepancies between their prior beliefs and the Federal Reserve's forecasts. This result is particularly noteworthy given that our survey was conducted after a period of elevated inflation, presumably a time when inflation was more salient to respondents (Weber et al. 2025 and Bracha and Tang 2024). For this particular experiment, implementing marginal incentives leads to a qualitatively different conclusion about the ability of central bank forecasts to coordinate and guide inflation expectations.

It is important to note, however, that our marginal incentives treatments raise the benefit of getting future inflation right, while keeping the cost of information constant (i.e., information

[18] Haaland et al. (2023) argue that if priors are balanced across treatment, the researcher could use the posterior as the dependent variable. We cannot do that here, since treatment variation can induce systematic differences in the prior.

Table 9: Effect of Incentives on Learning Rates

	(1)	(2)	(3)	(4)
$\beta_{1,Post}$	0.0344***	0.0345***	0.0348***	0.0326***
	(0.0113)	(0.0113)	(0.0112)	(0.0111)
$\beta_{1,Both}$	0.0262*	0.0265**	0.0269**	0.0261**
	(0.0135)	(0.0134)	(0.0134)	(0.0126)
$\beta_{1,Prior}$	0.0189	0.0190	0.0194	0.0195
	(0.0230)	(0.0231)	(0.0232)	(0.0226)
$\beta_{2,Post}$	-0.448*	-0.444*	-0.452*	-0.492**
	(0.244)	(0.244)	(0.243)	(0.237)
$\beta_{2,Both}$	-0.212	-0.232	-0.239	-0.191
	(0.240)	(0.242)	(0.242)	(0.237)
$\beta_{2,Prior}$	-0.0648	-0.0881	-0.0904	-0.0511
	(0.239)	(0.241)	(0.241)	(0.236)
β_3	0.910***	0.909***	0.909***	0.913***
	(0.00772)	(0.00777)	(0.00779)	(0.00775)
Male		-0.155	-0.157	-0.0649
		(0.166)	(0.166)	(0.167)
Higher_Ed.			0.0598	0.0335
			(0.166)	(0.163)
Constant	0.0185	0.102	0.0756	0.485**
	(0.177)	(0.200)	(0.218)	(0.246)
Sentiment	No	No	No	Yes
N	1,000	1,000	1,000	1,000

Robust sandard errors in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

Notes: The table shows the effect of treatments on learning rates. These are relative to our baseline treatment *Flat*. Regressions are estimated by OLS with robust standard errors. Data are winsorized at the 1% and 99% levels.

is readily and freely provided, but processing costs remain), which impacts rational inattention to information provision (e.g., see Maćkowiak and Wiederholt (2024) or Maćkowiak et al. (2023)). Unincentivized RCTs might underestimate learning rates if participants disregard provided information due to incorrectly assessing their processing costs and their benefits from the provided information. By contrast, incentivizing RCTs might pick up learning effects from participants who misperceive the benefit of accurate inflation expectations without marginal incentives. Therefore, compared to unincentivized RCTs, the learning rates we find can be viewed as the upper bound to the potential impact of information on beliefs.

Additionally, we can consider how marginal incentives changed the distribution of probabilities participants assigned to each possible inflation bin. Recall, values assigned to each bin when forming a bin forecast denote the participant's belief about the likelihood of realized inflation falling into that particular bin. Figure 6 depicts the average weight assigned to each of the ten possible inflation bins presented to subjects who faced marginal incentives (blue dashed line) or did not (red solid line). Interestingly, imposing marginal incentives shifts significantly more weight to the bin containing the Fed's median forecast for 2025 inflation communicated in the information intervention and significantly reduces weights assigned to more extreme bins. This further reinforces our result that marginal incentives significantly alter the efficacy of information provision in such experiments.

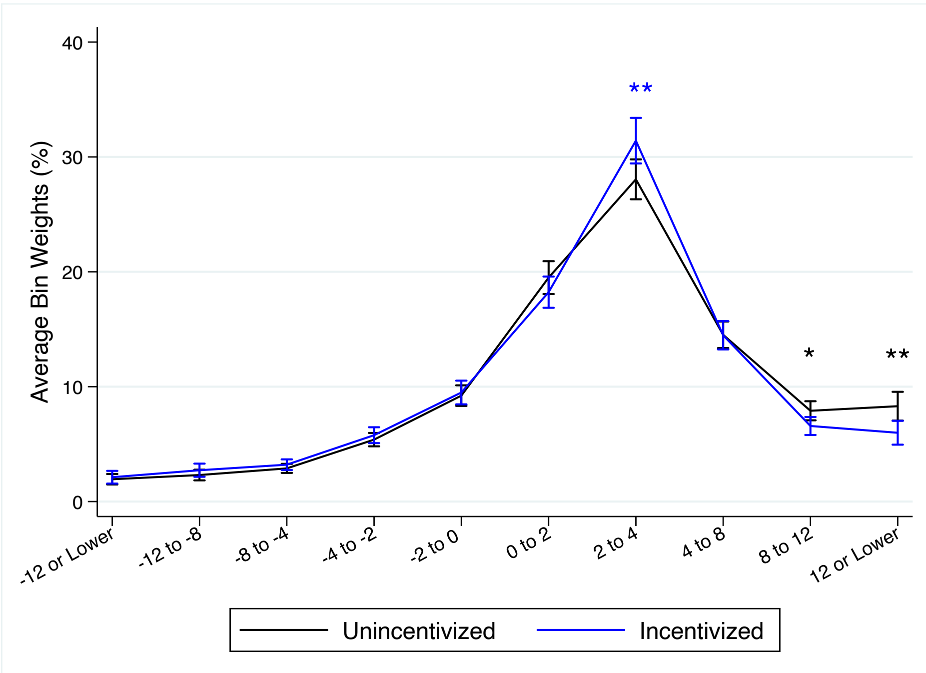


Figure 6: Average Bin Weights Across Incentives

Notes: The figure shows the average weight participants placed into the respective bins, distinguishing between unincentivized (*Flat* and *Prior*) and incentivized (*Post* and *Both*) treatments. Data are winsorized at the 1% and 99% levels. Stars denote significant differences in weights assigned to a bin, on average, between incentivized and unincentivized treatments. Blue stars indicate incentivized subjects placed more weight into that bin, on average, and black stars the opposite. Significance levels are indicated as follows: * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

4 Model-based Implications

Our findings have implications for how incentives shape the conclusions that can be drawn from integrating survey data with economic models.

To illustrate this point, we focus on how different degrees of backward-lookingness—calibrated to match the correlation between perceived and expected inflation in our experimental data—shape the propagation of shocks in a standard three-equation New Keynesian model. In our setup, agents form expectations as a weighted combination of backward-looking and model-consistent components. We simulate the model under three regimes of expectations formation: (i) a fully rational expectations equilibrium (REE), (ii) a heuristic rule calibrated to expectations under marginal incentives, and (iii) a heuristic rule calibrated to expectations without incentives.

We consider a standard three-equation New Keynesian model consisting of a New Keynesian Phillips Curve, a dynamic IS curve, and a Taylor-type monetary policy rule. The model includes two structural shocks: a demand shock u_t and a cost-push shock v_t.

$$\pi_t = \beta\,\mathbb{E}_t[\pi_{t+1}] + \kappa y_t + v_t \qquad \text{(New Keynesian Phillips Curve)} \tag{4}$$

$$y_t = \mathbb{E}_t[y_{t+1}] - \frac{1}{\sigma}(i_t - \mathbb{E}_t[\pi_{t+1}]) + u_t \qquad \text{(IS Curve)} \tag{5}$$

$$i_t = \phi_\pi \pi_t + \phi_y y_t. \qquad \text{(Taylor Rule)} \tag{6}$$

The shocks follow AR(1) processes:

$$u_t = \rho_u u_{t-1} + \varepsilon_t^u, \quad \varepsilon_t^u \sim \mathcal{N}(0, \sigma_u^2) \tag{7}$$

$$v_t = \rho_v v_{t-1} + \varepsilon_t^v, \quad \varepsilon_t^v \sim \mathcal{N}(0, \sigma_v^2). \tag{8}$$

Households form expectations via a convex combination of a model-consistent forecast and a backward-looking heuristic:

$$\mathbb{E}_t[\pi_{t+1}] = \eta \cdot \pi_{t+1}^{RE} + (1-\eta) \cdot \pi_{t-1}. \tag{9}$$

Here, π_{t+1}^{RE} denotes the model-consistent (rational) forecast of future inflation, while π_{t-1} represents a naive backward-looking expectation. The parameter $\eta \in [0,1]$ governs the degree of forward-lookingness: $\eta = 1$ yields fully rational expectations, whereas $\eta = 0$ corresponds to a purely backward-looking heuristic.

To calibrate η, we use data from our experiment. For each treatment group, we compute the correlation between participants' point forecast of inflation ($e_{\pi,t}$) and their inflation perception ($p_{\pi,t-1}$). We then map these correlations into values of η using a simple linear approximation:

$$\eta \approx 1 - \mathrm{Corr}(e_\pi, p_{\pi,t-1}). \tag{10}$$

The resulting treatment-level calibrations are provided in Table Table 10.

For our simulations, we adopt three benchmark values of η: rational expectations with

Table 10: Empirically Implied Calibration of η

Treatment	**Corr**$(e_\pi, p_{\pi,t-1})$	**Implied** $\eta \approx 1 - \text{Corr}(e_\pi, p_{\pi,t-1})$
Flat	0.373	0.627
Post	0.421	0.579
Both	0.283	0.717
Prior	0.188	0.812

Notes: The table shows the empirical correlation between participant forecasts and inflation perceptions by treatments, and implied calibration of η. Treatments *Flat* and *Post* are unincentivized, while *Both* and *Prior* are incentivized.

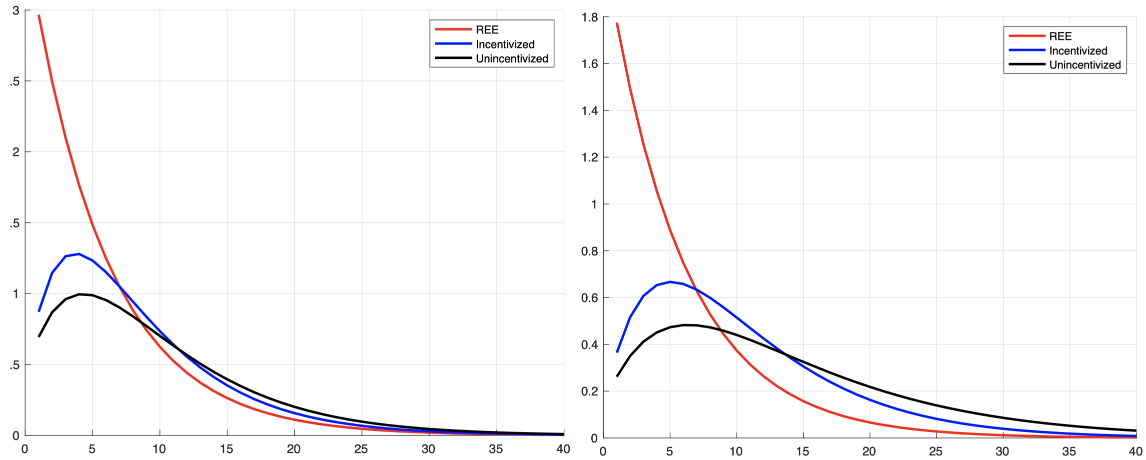
$\eta = 1$, a heuristic under incentives with $\eta = 0.75$ (from the incentivized *Prior* and *Both* treatments), and a heuristic without incentives with $\eta = 0.60$ (from the *Post* and *Flat* treatments). These calibrations allow us to compare how differences in expectations formation—grounded in observed behavior—alter the transmission and persistence of shocks in a stylized macroeconomic environment. All model parameters are shown in Table 11.

Table 11: Model Parameter Values

Parameter	**Description**	**Value**
β	Discount factor	0.99
σ	Intertemporal elasticity of substitution	1
ϕ_π	Taylor rule response to inflation	1.5
ϕ_y	Taylor rule response to output	0 or 0.5
κ	Slope of the Phillips Curve	0.104
ρ_u	Persistence of demand (IS) shock	0.841
ρ_v	Persistence of cost-push shock	0.841
σ_u	Std. dev. of demand shock	1
σ_v	Std. dev. of cost-push shock	1
η	Weight on rational expectation	$\{1.0, 0.75, 0.6\}$

Notes: The table shows the model parameters used for the demand and cost-push shocks. The three values of η correspond to the REE, incentivized, and unincentivized expectations regimes, respectively. We let $\phi_y = .5$ for the demand shock simulation and $\phi_y = 0$ for the cost-push shock. We choose these values to align with standard calibrations of the New Keynesian model (Galí 2015).

Figure 7 displays the impulse response of inflation to a one-standard-deviation cost-push shock in panel (a), and demand shock in panel (b), under three different expectations regimes. The red solid line represents the rational expectations equilibrium (REE), while the blue and black lines correspond to heuristic expectations calibrated to match the degree of backward-lookingness observed in the incentivized and unincentivized treatments, respectively. The figure shows that even modest increases in backward-lookingness substantially alter the dynamics of inflation. In both heuristic cases, inflation is more persistent and returns to steady state more slowly than under REE. Notably, the unincentivized treatment—which exhibits the greatest reliance on lagged inflation—produces the most persistent inflation path, with elevated inflation lasting longer than in the incentivized or REE cases.



(a) Response to cost-push shock **(b)** Response to demand shock

Figure 7: Inflation Dynamics under different expectation regimes

Notes: The figure shows impulse response functions for inflation following a one-standard-deviation cost-push shock (left) and demand shock (right) under different expectation regimes.

These findings highlight two critical methodological and policy-relevant implications that arise from how we measure expectations. First, empirical analyses seeking to understand the sources of inflation persistence must account carefully for the method used to elicit expectations. Our results suggest that researchers using unincentivized survey data may erroneously attribute excessive persistence in inflation to sluggish, backward-looking expectations rather than structural factors such as price rigidity. Consequently, reliance on unincentivized expectations data risks attenuating the perceived role of underlying structural mechanisms in macroeconomic models, potentially skewing our understanding of inflation dynamics.

Second, there are substantial policy implications arising from this mismeasurement of expectations. Policymakers may calibrate macroeconomic models using survey-based inflation expectations to guide monetary policy decisions. If unincentivized survey data overstate the backward-lookingness of expectations, policymakers might mistakenly infer greater inertia in expectation formation than truly exists. This misconception could lead them to pursue overly aggressive or unnecessarily prolonged policy interventions, based on the belief that inflation will only respond slowly to shocks and therefore requires sustained pressure. However, as our analysis demonstrates, agents may be more forward-looking in reality, which they reveal when facing tangible incentives. Thus, accurate measurement of expectations is not merely academically relevant but is crucial for calibrating monetary policy.

5 Discussion

Our experiment demonstrates that marginal incentives significantly impact the elicitation of macroeconomic beliefs and learning rates in information provision experiments in the context of inflation expectations' elicitation. Specifically, imposing incentives leads to household inflation expectations that are more consistent with expectations of professional forecasters, with respondents predicting lower and less extreme values, and exhibiting less cross-sectional forecast disagreement. Furthermore, incentives increase the rate at which participants update their beliefs in response to new information, suggesting that central bank communication could be more effectively coordinating expectations, even in environments where households are paying more attention to inflation. Importantly, the changes in the underlying distributions of beliefs arising from different incentive structures lead to qualitatively different conclusions about the efficacy of central bank communication. Our findings suggest that central banks can boost the effectiveness of their communication policies by exploring innovative ways to incentivize households to pay attention. Options include decreasing cognitive costs of paying attention, for example, by simplifying their communication.

These findings suggest that incorporating incentives into survey-based macroeconomic research may improve the accuracy of elicited beliefs, offering a valuable complement to the commonly used unincentivized or flat-fee structures. The substantial reduction in potential forecast errors and heightened learning rates observed with marginal incentives indicate that incentivized elicitation might provide a more reliable measure of household expectations, which are critical for understanding expectations' formation, economic modeling, and policymaking.

Notably, the same incentive structures that lead to higher learning rates also reduce upward bias and close the gender gap in inflation beliefs in point forecasts of one-year-ahead inflation, offering a simple resolution to a long-standing puzzle in the belief-based macroeconomic literature. This suggests that marginal incentives can mitigate some systematic biases observed in survey-based beliefs elicited via flat-fee incentives and serve as a diagnostic tool to discern which biases are more likely to be robust.

Incorporating marginal incentives into survey design leads to more consistent measurements of inflation expectations across respondents and brings household inflation forecasts closer to professional forecasters' consensus views. This reduction in cross-sectional disagreement and convergence towards expert predictions suggests that incentivized surveys may provide policymakers with more reliable measurements to understand household expectations, a crucial input for those focused on managing inflation dynamics and developing economic forecasting models. Notably, this change in incentive structure need not increase the cost of collecting expectations. Indeed, policymakers and researchers can leverage our approach to quantify the extent of measurement error due to the absence of incentives by incorporating incentives into subsamples of respondents.

Our findings also relate to the literature on the impact of external conditions on RCTs. Studies suggest that extraneous information conditions can mute the effects observed in RCTs. For instance, during periods when attention to inflation and monetary policy is high—as has recently been the case—the efficacy of information provision may appear diminished in unincentivized settings. Our results from the flat-fee setting align with this, showing that information provision without incentives does not significantly affect beliefs. However, introducing marginal incentives leads to a qualitatively different conclusion: information provision becomes effective in shifting expectations. This highlights the importance of incentive mechanisms in accurately assessing the impact of policy communications.

While our study underscores the benefits of incorporating marginal incentives, it is important to consider potential drawbacks. Two critical questions arise: What are we truly measuring when incentives are used, and do they allow us to accurately capture the genuine beliefs we seek to understand? While further research is needed to fully address these questions, an interpretation of our findings is that the expectations of respondents in the incentivized treatments more accurately reflect those of those households in the field for whom inflation expectations matter, play a significant role in their decision-making and thus are more likely to respond to policy announcements.

Another concern is that incentive schemes may induce behavior that does not reflect genuine beliefs but rather strategic reporting, such as looking up information online. Participants might engage in actions aimed at maximizing their payoffs rather than truthfully revealing their expectations. For example, Grewenig et al. (2022) find that providing incentives does not impact beliefs about personal earnings—–which are readily available to participants—–but improves beliefs about average public school spending, a less accessible piece of information for the average respondent. The authors highlight a trade-off between increased respondent effort and the risk of inducing online search activity when incentivizing beliefs in online surveys. However, in Drobot et al. (2025) we find little evidence in support of this channel. Specifically, only about 10%-15% of respondents report having looked up information about inflation rates online.

Additionally, Danz et al. (2022) provide evidence that more complex incentive schemes, while theoretically incentive-compatible, can lead to misunderstandings, potentially resulting in less truthful reporting. They find that truthful reporting increases when information about incentives is absent compared to a baseline condition that provides full details about how incentives are determined using a binarized scoring rule (BSR). This suggests that overly complicated incentive mechanisms may confuse participants, undermining the very accuracy they are intended to enhance. In Drobot et al. (2025), we compare the simple incentives we employed in this paper with more complex, incentive-compatible schemes, and find evidence that simpler incentives are more effective in eliciting more consistent and potentially accurate inflation expectations.

Overall, while marginal incentives can improve data quality by motivating participants to invest more effort and report more consistent beliefs, careful consideration must be given to the design of these incentives. Simplicity and transparency are crucial to avoid inducing strategic behavior or confusion that could compromise the integrity of the data.

In conclusion, our study suggests that incorporating marginal incentives into surveys positively enhances elicited beliefs, which could improve the robustness of empirical findings in macroeconomic research. By motivating participants to engage more deeply when forming beliefs, incentivized mechanisms can lead to more reliable data. Future studies should consider integrating such mechanisms to improve data quality also in the context of other macroeconomic expectations. Balancing the benefits of increased effort and accuracy against the risks of strategic behavior and misunderstanding is essential for advancing survey-based measures of economic expectations and informing theoretical models as well as more effective policy decisions.

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Appendix

A1 Other Tables and Figures

Table A-1: Incentive Structure by Treatment

	Prior	*Post*	*Both*	*Flat*
Immediately	\$2	\$2	\$2	\$2
In 1Y	Up to \$10	Up to \$10	Up to \$10	\$4
Structure	Accuracy-based: $\$10 \times 2^{-\lvert\pi-\mathbb{E}(\pi)\rvert}$	Accuracy-based: $\$10 \times P$	Accuracy-based: Prior or Post	Fixed fee, time-value matched

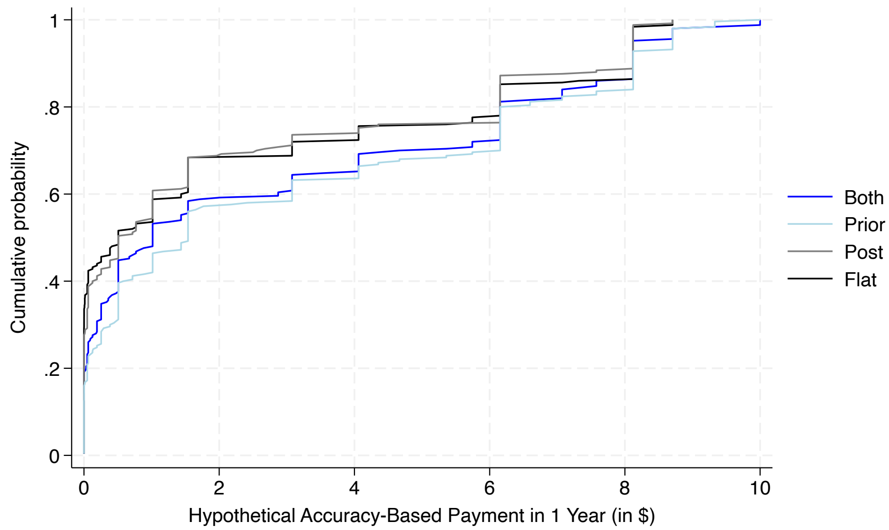
Notes: This table provides an overview of the payment composition (amount, timing and incentive structure) by treatment. The top row indicates the treatment group. P represents the probability weight a participant assigned to the bin that contains realized inflation. In the *Both* treatment group, either the prior or the posterior forecast is chosen at random for payment with equal probability.

Table A-2: Sample Comparisons: Across Groups and SCE

	Flat	Prior	Posterior	Both	Full Sample	SCE Sample
Age						
Under 30	18.8	17.2	17.6	14.4	17.0	11.7
30-39	26.8	26.0	28.4	26.8	27.0	19.0
40-49	25.2	24.0	26.8	24.0	25.0	18.8
50-59	15.2	18.8	14.4	18.0	16.6	20.6
60 or over	14.0	14.0	12.8	16.8	14.4	29.9
Gender						
Female	54.8	65.2	50.8	63.6	58.6	48.1
Male	44.8	34.8	49.2	36.0	41.2	51.9
Prefer not to say	0.4			0.4	0.2	
Income						
Less than \$50,000	48.8	43.6	39.2	38.4	42.5	42.8
\$50,000-\$99,999	30.0	34.0	36.4	39.6	35.0	34.5
\$100,000 or more	21.2	22.4	24.4	22.0	22.5	22.7
Race/Ethnicity						
Asian	6.0	7.2	7.6	8.0	7.2	3.5
Black	14.4	13.6	6.4	14.0	12.1	10.4
White	73.2	69.6	73.6	70.8	71.8	81.8
Other	6.4	9.6	12.4	7.2	8.9	4.4

Notes: Each value in the table represents the percentage of the sample belonging to the corresponding category. Survey of Consumer Expectations (SCE) sample values are taken from Armantier et al. (2017).

Figure A-1: Hypothetical Earnings from Inflation Expectations (The Priors)



Notes: The figure shows how treatments impact the hypothetical payoffs of participants calculated comparing point forecasts formed before information provision the Fed's 2025 inflation forecast. This shows—assuming the Fed's forecast is correct in expectation—that expected payoffs are significantly higher for subjects facing marginal incentives. Data are winsorized at the 1% and 99% levels. Treatments *Both* and *Prior* are incentivized and shown in shades of blue, while treatments *Post* and *Flat* are unincentivized, shown in gray and black.

Table A-3: Hypothetical Earnings From Point Forecasts of Inflation (The Priors)

	(1) Payoff	(2) Payoff	(3) Payoff	(4) Payoff
Post	-0.0606	-0.110	-0.150	-0.197
	(0.270)	(0.264)	(0.264)	(0.262)
Both	0.545*	0.644**	0.626**	0.613**
	(0.281)	(0.277)	(0.277)	(0.275)
Prior	0.755***	0.867***	0.880***	0.874***
	(0.282)	(0.275)	(0.275)	(0.274)
Male		1.127***	1.096***	1.112***
		(0.202)	(0.202)	(0.202)
Higher_Ed.			0.546***	0.537***
			(0.195)	(0.195)
Constant	2.296***	1.791***	1.538***	1.795***
	(0.193)	(0.203)	(0.219)	(0.268)
Sentiment	No	No	No	Yes
N	1,000	1,000	1,000	1,000

Robust standard errors in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

Notes: The table shows the effect of treatments on hypothetical earnings, as proxied by distance between reported priors and the Fed's median 2025 forecast. Regressions are estimated by OLS with robust standard errors. Data are winsorized at the 1% and 99% levels.

Table A-4: Treatment Effects on Extreme Forecasts: Logistic Regression Results

	(1) EV	(2) EV	(3) EV	(4) EV
Both	0.649*	0.651*	0.671*	0.688*
	(0.371)	(0.371)	(0.373)	(0.374)
Flat	1.172***	1.172***	1.300***	1.310***
	(0.348)	(0.348)	(0.351)	(0.352)
Post	1.032***	1.031***	1.205***	1.237***
	(0.353)	(0.353)	(0.357)	(0.358)
Deflation		-0.048	-0.094	-0.092
		(0.226)	(0.229)	(0.229)
Male			-1.248***	-1.232***
			(0.262)	(0.263)
Higher_Ed.				-0.333
				(0.218)
Constant	-2.987***	-2.971***	-2.658***	-2.523***
	(0.296)	(0.305)	(0.311)	(0.321)
N	1,000	1,000	1,000	1,000

Standard errors in parentheses

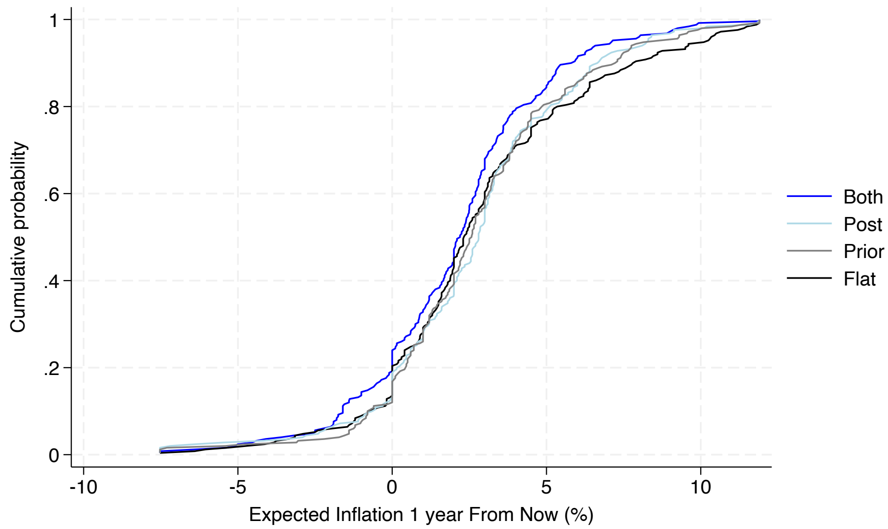
* $p < .1$, ** $p < .05$, *** $p < .01$

Notes: The table presents the results of a logistic regression analyzing the relationship between treatment assignment and the likelihood of reporting an extreme forecast value. Extreme values are defined as the highest 10% of absolute prior inflation expectations. *Prior* treatment group serves as the reference category.

Table A-5: Treatment Effects on Extreme Forecasts: Logistic Regression Results

Variable	**Coefficient**	**p-value**	**Odds Ratio**	**Interpretation**
Constant	-2.987***	0.000	0.050	Baseline probability of extreme forecast reporting is very low.
Both	0.649*	0.080	1.914	Respondents in *Both* group are 91% more likely to report an extreme forecast relative to *Prior* group, but the effect is only marginally significant.
Flat	1.172***	0.001	3.228	Respondents in *Flat* group are 222% more likely to report an extreme forecast (highly significant).
Post	1.032***	0.003	2.807	Respondents in *Post* group are 181% more likely to report an extreme forecast (highly significant).

Figure A-2: CDFs of Inflation Expecations After Information Provision



Notes: The figure shows cumulative distribution functions (CDFs of inflation expectations elicited after the information intervention. Expectations are shown by the different treatment groups and expressed in percentage points. Data are winsorized at the 1% and 99% levels.

Table A-6: Summary Statistics and Variance Comparison of APE

	Mean	**Std**	**Median**	**IQR**	**N**
Unincentivized - Male	10.43	19.18	2.8	6.7	235
Unincentivized - Female	23.48	28.03	9.8	30.0	265
Incentivized - Male	5.71	12.87	1.8	4.0	177
Incentivized - Female	11.52	19.87	2.8	11.7	323
All Data	13.41	22.16	3.2	12.0	1,000

Notes: This table shows mean, median, standard deviation and IQR of the absolute perception error (APE) by gender and incentive treatments. *Unincentivized* is comprised of treatments *Flat* and *Posterior*, while Incentivized is comprised of *Both* and *Prior*.

Table A-7: Effects of Incentives on Updated Inflation Expectations (The Posteriors)

	(1)	(2)	(3)	(4)	(5)
Post	-0.162	-0.163	-0.149	-0.115	-0.0885
	(0.232)	(0.232)	(0.231)	(0.233)	(0.222)
Both	-0.642***	-0.624***	-0.652***	-0.637***	-0.688***
	(0.227)	(0.227)	(0.227)	(0.228)	(0.219)
Prior	-0.339	-0.344	-0.377	-0.387*	-0.426*
	(0.234)	(0.234)	(0.234)	(0.234)	(0.222)
Deflation		-0.316	-0.321	-0.315	-0.0673
		(0.246)	(0.245)	(0.245)	(0.243)
Male			-0.325**	-0.299*	-0.241
			(0.163)	(0.162)	(0.157)
Higher_Ed.				-0.459***	-0.430***
				(0.159)	(0.152)
Constant	4.571***	4.613***	4.759***	4.971***	4.681***
	(0.171)	(0.175)	(0.192)	(0.207)	(0.216)
Sentiment	No	No	No	No	Yes
N	1,000	1,000	1,000	1,000	1,000

Robust standardd errors in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

Notes: This table reports the results of a series of OLS regressions (with robust standard errors) wherein we project inflation expectations estimated using participants' probabilistic inflation forecasts onto a series of dummies denoting treatment and other conditioning information. Data are winsorized at the 1% and 99% levels.

Table A-8: Effects of Incentives on Effort

	(1) Completion Time	(2) Completion Time	(3) Completion Time	(4) Completion Time
Post	27.06	30.49	35.13	37.26
	(29.01)	(28.86)	(28.75)	(28.86)
Both	127.5***	120.6***	122.7***	119.6***
	(30.55)	(30.47)	(30.26)	(30.23)
Prior	58.49**	50.69*	49.28*	53.15*
	(27.39)	(27.19)	(27.19)	(27.28)
Male		-77.99***	-74.41***	-80.11***
		(20.97)	(20.90)	(20.85)
Higher_Ed.			-63.14***	-67.40***
			(20.55)	(20.54)
Constant	572.3***	607.2***	636.4***	590.7***
	(19.99)	(21.76)	(24.28)	(27.78)
Sentiment	No	No	No	Yes
N	1,000	1,000	1,000	1,000

Robust standard errors in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

Notes: The table shows the effect of treatments on effort, as proxied by completion times. Regressions are estimated by OLS with robust standard errors. Data are winsorized at the 5% and 95% levels.

A2 Power Analysis

Table A-9: Sample Size Calculation

α	$1-\beta$	**N**	N_C	N_T	Δ	μ_C	μ_T	σ
0.01	0.80	1,172	586	586	0.2	0	0.2	1
0.01	0.80	524	262	262	0.3	0	0.3	1
0.01	0.80	296	148	148	0.4	0	0.4	1
0.01	0.80	192	96	96	0.5	0	0.5	1
0.01	0.80	134	67	67	0.6	0	0.6	1
0.01	0.80	100	50	50	0.7	0	0.7	1
0.01	0.80	78	39	39	0.8	0	0.8	1
0.01	0.80	62	31	31	0.9	0	0.9	1
0.01	0.80	52	26	26	1.0	0	1.0	1
0.05	0.80	788	394	394	0.2	0	0.2	1
0.05	0.80	352	176	176	0.3	0	0.3	1
0.05	0.80	200	100	100	0.4	0	0.4	1
0.05	0.80	128	64	64	0.5	0	0.5	1
0.05	0.80	90	45	45	0.6	0	0.6	1
0.05	0.80	68	34	34	0.7	0	0.7	1
0.05	0.80	52	26	26	0.8	0	0.8	1
0.05	0.80	42	21	21	0.9	0	0.9	1
0.05	0.80	34	17	17	1.0	0	1.0	1
0.10	0.80	620	310	310	0.2	0	0.2	1
0.10	0.80	278	139	139	0.3	0	0.3	1
0.10	0.80	156	78	78	0.4	0	0.4	1
0.10	0.80	102	51	51	0.5	0	0.5	1
0.10	0.80	72	36	36	0.6	0	0.6	1
0.10	0.80	52	26	26	0.7	0	0.7	1
0.10	0.80	42	21	21	0.8	0	0.8	1
0.10	0.80	32	16	16	0.9	0	0.9	1
0.10	0.80	28	14	14	1.0	0	1.0	1

Notes: Results are sorted by α and Cohen's D (i.e. μ_T).

Here we determine the necessary sample size for detecting effects of various magnitudes with a significance level of 0.05 and a power of 0.80. Effect magnitudes are specified in terms of Cohen's d, ranging from 0.2 to 1.0 in increments of 0.1. The effect magnitude(Cohen's d) is calculated as the standardized mean difference between the treatment and control groups. Specifically, Cohen's d is defined as:

$$d = \frac{M_1 - M_2}{SD_{pooled}}$$

where M_1 and M_2 are the means of the treatment and control groups, respectively, and SD_{pooled} is the pooled standard deviation of the two groups. We assume $M_1 = 0$, treating it as the control group.

Conventional thresholds for interpreting the magnitude of effect sizes:

- **Small effect size:** $d = 0.2$
- **Medium effect size:** $d = 0.5$
- **Large effect size:** $d = 0.8$

We base our sample size on this ex-ante power calculation. Our desire to precisely estimate null effects led us to choose a sample size of 250 subjects per treatment. This would allow us to detect small differences via pair-wise comparisons at a one-percent level of significance and $\beta = .8$.

A3 Inflation Expectations Survey

This section presents the full survey used in this study, which elicits inflation expectations and implements an information provision intervention.

Figure A-3: Welcome

Welcome!

We want to learn about your current economic well-being and your outlook for the future. This survey should take about five minutes. You will receive participation fee of $2 for completing the survey. Additionally, you have the chance to earn a bonus payment of up to $10 when completing this survey. There are two questions in our survey where we offer a bonus payment based on the accuracy of your decision. We will explain exactly how this works when you arrive at each of these two questions. **We will randomly select one of these two questions with equal chance and pay you for your response to that question.**

We will clearly indicate during the survey the **two questions** that can earn you a bonus payment of up to $10.00. We will explain the structure of the bonus payment on the screen that displays that question. We will pay you your participation fee within the next 1-3 days. We will pay you any additional bonus payment in September of 2025. This delay in payment is necessary because of the structure of your potential bonus payment.

Most of the questions in this survey have no right or wrong answers - we are interested in your views and opinions. Your responses are confidential, and it helps us a great deal if you respond as carefully as possible. After inputting your answer to a question, just click on 'NEXT' until the next question appears.

Thank you for your participation!

Next

Notes: This figure shows the welcome page for the *Both* treatment group. Slight variations in wording occur between treatments to reflect the different incentive structures. Screenshots of other treatment groups are available upon request.

Figure A-4: General Questions

Please answer the following questions about your financial well-being:

Do you think you (and any family living with you) are financially better or worse off these days than you were twelve months ago? --------

And looking ahead, do you think you (and any family living with you) will be financially better or worse off twelve months from now than you are these days? --------

Looking ahead, do you think the economy in the United States will be stronger or weaker twelve months from now than these days? --------

Next

Figure A-5: Explanations

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.

In some of the following questions, we will ask you to think about the percent chance of something happening in the future. Your answers can range from 0 to 100, where 0 means there is absolutely no chance, and 100 means that it is absolutely certain.

For example, numbers like:

2 and 5 percent may indicate "almost no chance"
18 percent or so may mean "not much chance"
47 or 52 percent chance may be a "pretty even chance"
83 percent or so may mean a "very good chance"
95 or 98 percent chance may be "almost certain"

Next

Figure A-6: Inflation Point Forecast (Flat)

Inflation

This question asks you to forecast inflation. We will use your forecast to compare to the Personal Consumption Expenditures (PCE) inflation for the U.S., which is the Federal Reserve's preferred measure of inflation. This is typically the measure of inflation the Fed discusses and, consequently, you hear discussed publicly.

Over the past twelve months...

Do you think that there was **inflation or deflation**? --------

And how much **inflation/deflation** do you think there was?

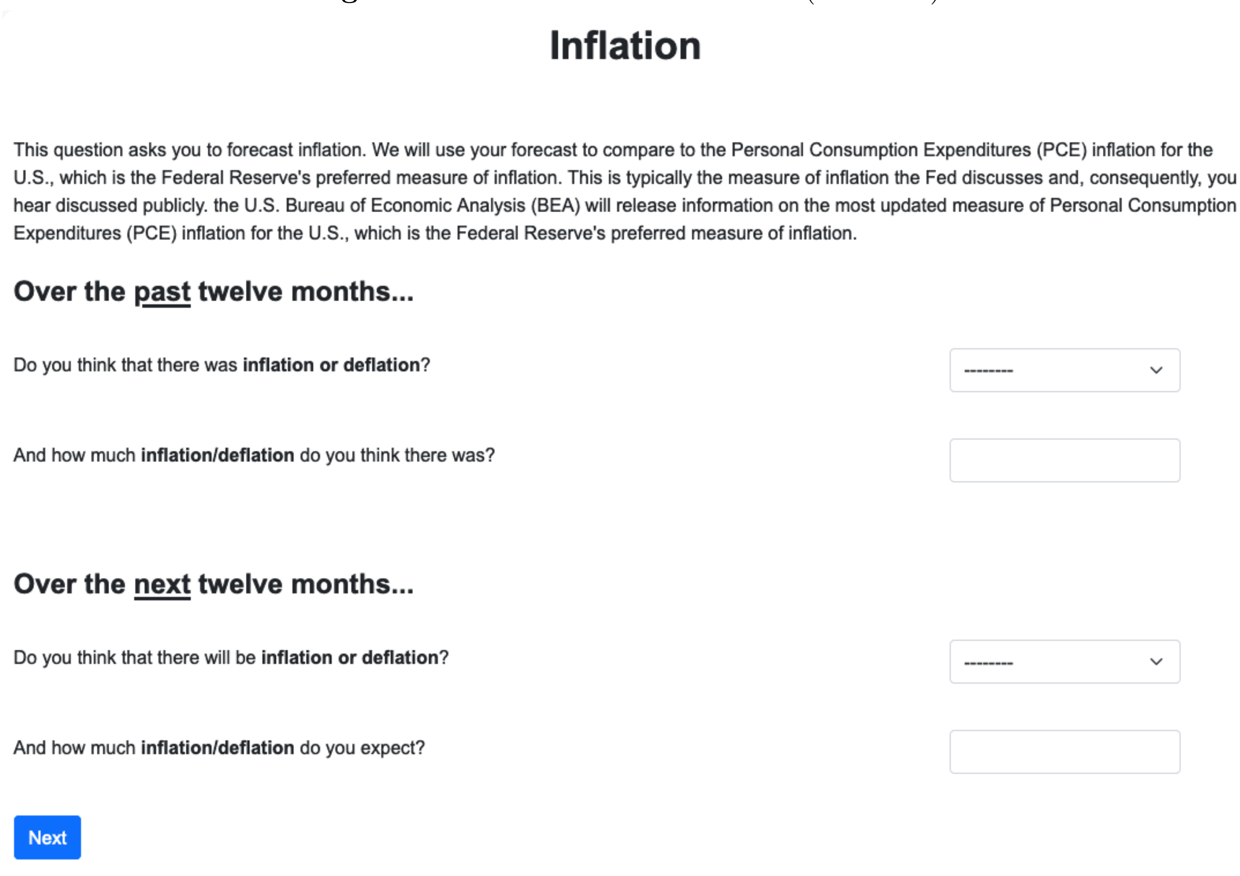
Over the next twelve months...

Do you think that there will be **inflation or deflation**? --------

And how much **inflation/deflation** do you expect?

Next

Figure A-7: Inflation Point Forecast (Posterior)



Inflation

This question asks you to forecast inflation. We will use your forecast to compare to the Personal Consumption Expenditures (PCE) inflation for the U.S., which is the Federal Reserve's preferred measure of inflation. This is typically the measure of inflation the Fed discusses and, consequently, you hear discussed publicly. the U.S. Bureau of Economic Analysis (BEA) will release information on the most updated measure of Personal Consumption Expenditures (PCE) inflation for the U.S., which is the Federal Reserve's preferred measure of inflation.

Over the past twelve months...

Do you think that there was **inflation or deflation**? --------

And how much **inflation/deflation** do you think there was?

Over the next twelve months...

Do you think that there will be **inflation or deflation**? --------

And how much **inflation/deflation** do you expect?

Next

Figure A-8: Inflation Point Forecast (Prior)

Inflation

Bonus Payment: YOU CAN RECEIVE A BONUS PAYMENT FOR THIS QUESTION. THIS IS THE ONLY QUESTION IN OUR SURVEY FOR WHICH YOU CAN RECEIVE A BONUS PAYMENT.

You can earn up to $10 for this task. This is in addition to your participation fee. In September of 2025, the U.S. Bureau of Economic Analysis (BEA) will release information on the most updated measure of Personal Consumption Expenditures (PCE) inflation for the U.S., which is the Federal Reserve's preferred measure of inflation.

Once the BEA publishes the actual PCE inflation reported in 12 months, we will compare your forecast to it and pay you based on the accuracy of your forecast. Your bonus payment halves each time your forecast increases by 1 percentage point.

For example:
If your forecast matches the inflation rate exactly, you will earn $10.
If your forecast is 1 percentage point above or below the inflation rate, you will earn $5.
If your forecast is 2 percentage points above or below the inflation rate, you will earn $2.5.

Over the past twelve months...

Do you think that there was **inflation or deflation**? --------

And how much **inflation/deflation** do you think there was?

Over the next twelve months...

Do you think that there will be **inflation or deflation**? --------

And how much **inflation/deflation** do you expect?

Next

Figure A-9: Inflation Point Forecast (Both)

Inflation

Bonus Payment: YOU MAY RECEIVE A BONUS PAYMENT FOR THIS QUESTION. THIS IS ONE OF THE TWO QUESTIONS IN OUR SURVEY FOR WHICH YOU CAN RECEIVE A BONUS PAYMENT.

If randomly selected for payment, you can earn up to $10 for this task. This is in addition to your participation fee. In September of 2025, the U.S. Bureau of Economic Analysis (BEA) will release information on the most updated measure of Personal Consumption Expenditures (PCE) inflation for the U.S., which is the Federal Reserve's preferred measure of inflation.

Once the BEA publishes the actual PCE inflation reported in 12 months, we will compare your forecast to it and pay you based on the accuracy of your forecast. Your bonus payment halves each time your forecast increases by 1 percentage point.

For example:
If your forecast matches the inflation rate exactly, you will earn $10.
If your forecast is 1 percentage point above or below the inflation rate, you will earn $5.
If your forecast is 2 percentage points above or below the inflation rate, you will earn $2.5.

Over the past twelve months...

Do you think that there was **inflation or deflation**? --------

And how much **inflation/deflation** do you think there was?

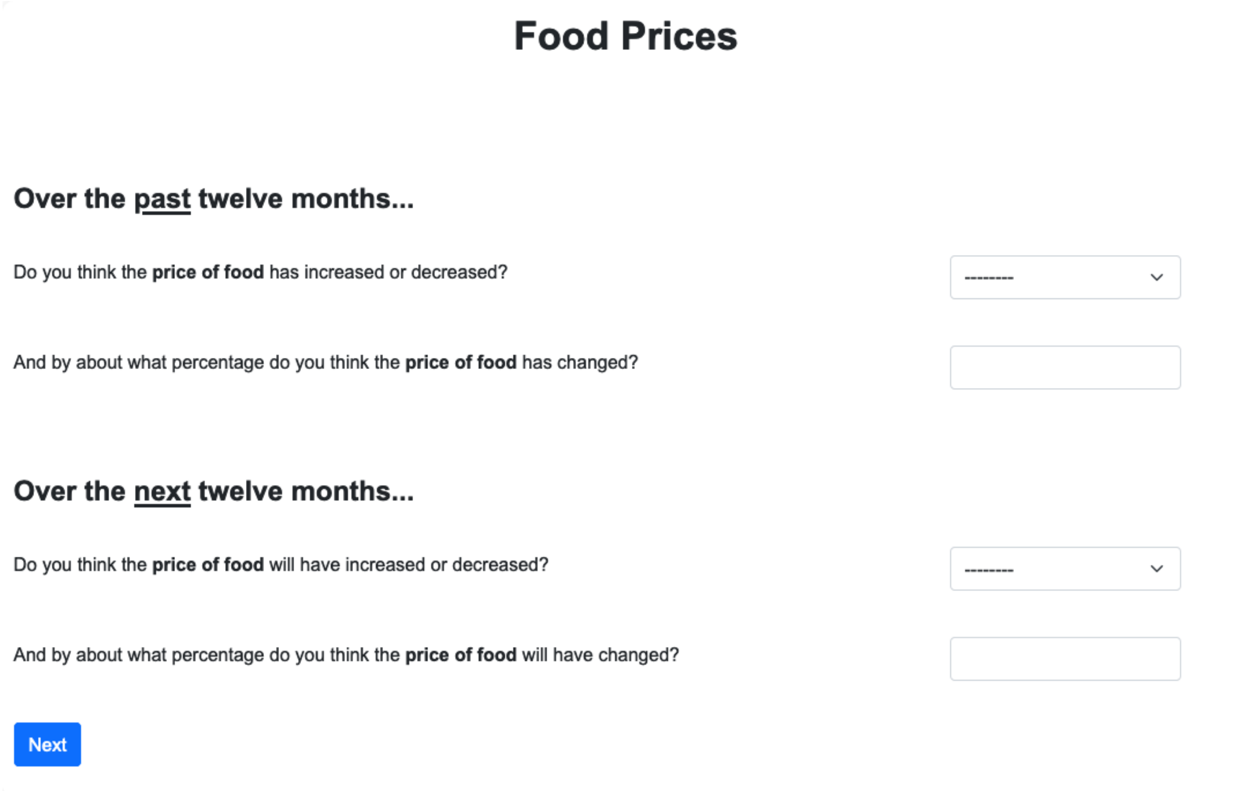
Over the next twelve months...

Do you think that there will be **inflation or deflation**? --------

And how much **inflation/deflation** do you expect?

Next

Figure A-10: Food Point Forecast



Food Prices

Over the past twelve months...

Do you think the **price of food** has increased or decreased?

And by about what percentage do you think the **price of food** has changed?

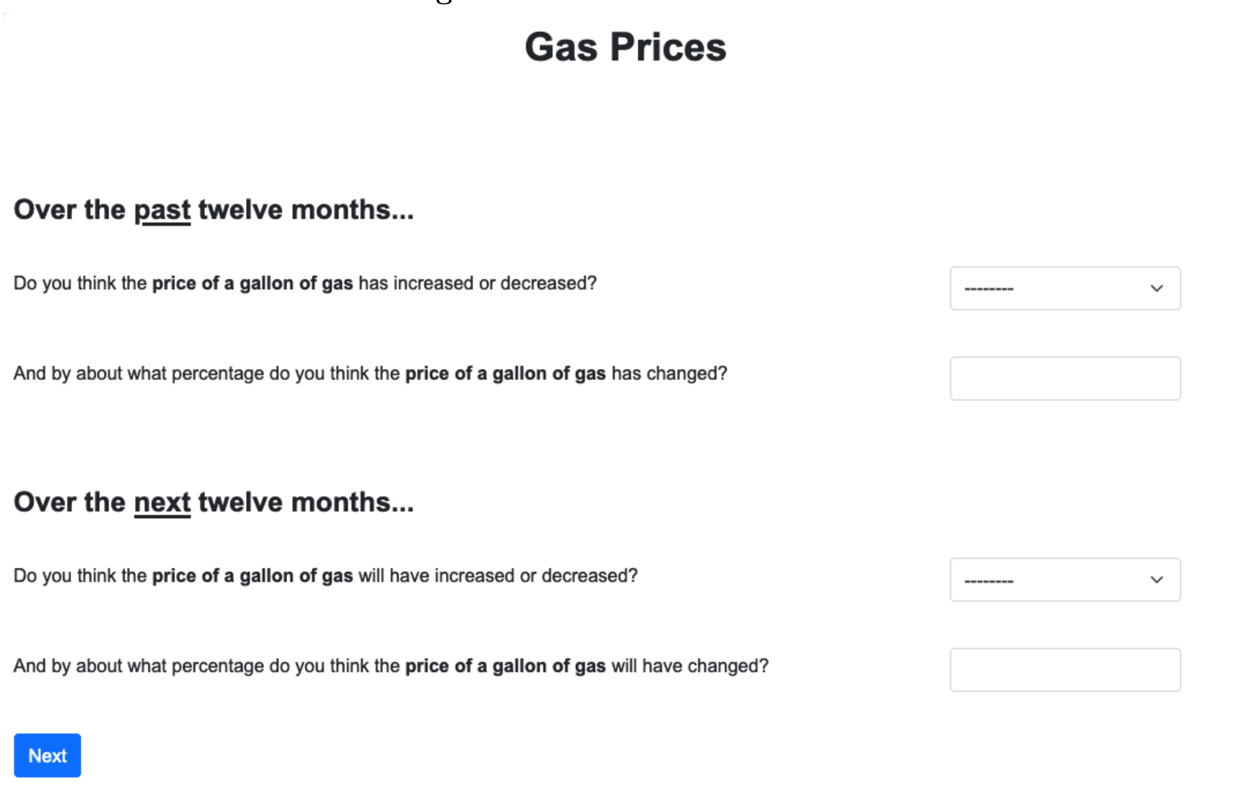
Over the next twelve months...

Do you think the **price of food** will have increased or decreased?

And by about what percentage do you think the **price of food** will have changed?

Next

Figure A-11: Gas Point Forecast



Gas Prices

Over the past twelve months...

Do you think the **price of a gallon of gas** has increased or decreased?

And by about what percentage do you think the **price of a gallon of gas** has changed?

Over the next twelve months...

Do you think the **price of a gallon of gas** will have increased or decreased?

And by about what percentage do you think the **price of a gallon of gas** will have changed?

Next

Figure A-12: Information Intervention

We provide below the most recent official economic forecast data from the Federal Reserve, which is the central bank for the United States. Economic forecasts are very important for the Fed because policymakers there use forecasts to help them make good policy decisions when guiding our economy.

In conjunction with the Federal Open Market Committee (FOMC) meeting held on June 11–12, 2024, meeting participants submitted their projections of the most likely outcomes for inflation for each year from 2024 to 2026 and over the longer run. We have summarized these projections in the following table:

Variable	Median 2024	Range 2024	Median 2025	Range 2025
PCE inflation	2.6	2.5–3.0	2.3	2.2–2.5

Next

Figure A-13: Food Bin Forecast

Food Prices

Now we would like you to think about the different things that may happen to **food prices** over the **next twelve months**. We realize that this question may take a little more effort.

Below, we will ask you to assign a percent (%) chance that food prices twelve months from now will fall into a certain range. The sum of the numbers you enter should equal 100%. For example, if you think there is a 20% chance that food prices will be 12% or higher, and a 30% chance that it will be between 8% and 12%, you should indicate this by entering the values 20 and 30 into each corresponding field. In this scenario, you would need to allocate the remaining 50%.

In your view, what would you say is the percent chance that, **over the next twelve months**...

the price of food will increase by 12% or higher: %

the price of food will increase by between 8% and 12%: %

the price of food will increase by between 4% and 8%: %

the price of food will increase by between 2% and 4%: %

the price of food will increase by between 0% and 2%: %

the price of food will decrease by between -2% and 0%: %

the price of food will decrease by between -4% and -2%: %

the price of food will decrease by between -8% and -4%: %

the price of food will decrease by between -12% and -8%: %

the price of food will decrease by -12% or lower: %

Next

Figure A-14: Gas Bin Forecast

Gas Prices

Now we would like you to think about the different things that may happen to **gas prices** over the **next twelve months**. We realize that this question may take a little more effort.

Below, we will ask you to assign a percent (%) chance that gas prices twelve months from now will fall into a certain range. The sum of the numbers you enter should equal 100%. For example, if you think there is a 20% chance that gas prices will be 12% or higher, and a 30% chance that it will be between 8% and 12%, you should indicate this by entering the values 20 and 30 into each corresponding field. In this scenario, you would need to allocate the remaining 50%.

In your view, what would you say is the percent chance that, **over the next twelve months**...

the price of a gallon of gas will increase by 12% or higher:	%
the price of a gallon of gas will increase by between 8% and 12%:	%
the price of a gallon of gas will increase by between 4% and 8%:	%
the price of a gallon of gas will increase by between 2% and 4%:	%
the price of a gallon of gas will increase by between 0% and 2%:	%
the price of a gallon of gas will decrease by between -2% and 0%:	%
the price of a gallon of gas will decrease by between -4% and -2%:	%
the price of a gallon of gas will decrease by between -8% and -4%:	%
the price of a gallon of gas will decrease by between -12% and -8%:	%
the price of a gallon of gas will decrease by -12% or lower:	%

Next

Figure A-15: Inflation Bin Forecast (Flat and Prior)

Inflation

Now we would like you to think about the different things that may happen to **inflation** over the **next twelve months**. We realize that this question may take a little more effort.

Below, we will ask you to assign a percent (%) chance that inflation months from now will fall into a certain range. The sum of the numbers you enter should equal 100%. For example, if you think there is a 20% chance that inflation will be 12% or higher, and a 30% chance that it will be between 8% and 12%, you should indicate this by entering the values 20 and 30 into each corresponding field. In this scenario, you would need to allocate the remaining 50%.

In your view, what would you say is the percent chance that, **over the next twelve months**...

the rate of inflation will be 12% or higher:	%
the rate of inflation will be between 8% and 12%:	%
the rate of inflation will be between 4% and 8%:	%
the rate of inflation will be between 2% and 4%:	%
the rate of inflation will be between 0% and 2%:	%
the rate of deflation (opposite of inflation) will be between 0% and 2%:	%
the rate of deflation (opposite of inflation) will be between 2% and 4%:	%
the rate of deflation (opposite of inflation) will be between 4% and 8%:	%
the rate of deflation (opposite of inflation) will be between 8% and 12%:	%
the rate of deflation (opposite of inflation) will be 12% or lower:	%

Next

Figure A-16: Inflation Bin Forecast (Posterior)

Inflation

Now we would like you to think about the different things that may happen to **inflation** over the **next twelve months**. We realize that this question may take a little more effort.

Below, we will ask you to assign a percent (%) chance that inflation months from now will fall into a certain range. The sum of the numbers you enter should equal 100%. For example, if you think there is a 20% chance that inflation will be 12% or higher, and a 30% chance that it will be between 8% and 12%, you should indicate this by entering the values 20 and 30 into each corresponding field. In this scenario, you would need to allocate the remaining 50%.

Bonus Payment: YOU CAN RECEIVE A BONUS PAYMENT FOR THIS QUESTION. THIS IS THE ONLY QUESTION IN OUR SURVEY FOR WHICH YOU CAN RECEIVE A BONUS PAYMENT.

You can earn up to $10 for this task. This is in addition to your participation fee. In September of 2025, the U.S. Bureau of Economic Analysis (BEA) will release information on the most updated measure of Personal Consumption Expenditures (PCE) inflation for the U.S., which is the Federal Reserve's preferred measure of inflation. This value of inflation will fall into one of the bins you see here. Your bonus payment will be $10 multiplied by the weight (i.e. % chance) you assigned to that bin. For example:

- If you assign a 10% chance to a bin and the actual inflation falls into that bin, you will earn $10 * 0.10 = $1.00.
- If you assign a 25% chance to a bin and the actual inflation falls into that bin, you will earn $10 * 0.25 = $2.50.
- If you assign a 90% chance to a bin and the actual inflation falls into that bin, you will earn $10 * 0.9 = $9.00.

In your view, what would you say is the percent chance that, **over the next twelve months**...

the rate of inflation will be 12% or higher: %

the rate of inflation will be between 8% and 12%: %

the rate of inflation will be between 4% and 8%: %

the rate of inflation will be between 2% and 4%: %

the rate of inflation will be between 0% and 2%: %

the rate of deflation (opposite of inflation) will be between 0% and 2%: %

the rate of deflation (opposite of inflation) will be between 2% and 4%: %

the rate of deflation (opposite of inflation) will be between 4% and 8%: %

the rate of deflation (opposite of inflation) will be between 8% and 12%: %

the rate of deflation (opposite of inflation) will be 12% or lower: %

Next

Figure A-17: Inflation Bin Forecast (Both)

Inflation

Now we would like you to think about the different things that may happen to **inflation** over the **next twelve months**. We realize that this question may take a little more effort.

Below, we will ask you to assign a percent (%) chance that inflation months from now will fall into a certain range. The sum of the numbers you enter should equal 100%. For example, if you think there is a 20% chance that inflation will be 12% or higher, and a 30% chance that it will be between 8% and 12%, you should indicate this by entering the values 20 and 30 into each corresponding field. In this scenario, you would need to allocate the remaining 50%.

Bonus Payment: YOU MAY RECEIVE A BONUS PAYMENT FOR THIS QUESTION. THIS IS ONE OF THE TWO QUESTIONS IN OUR SURVEY FOR WHICH YOU CAN RECEIVE A BONUS PAYMENT.

If randomly selected for payment, you can earn up to $10 for this task. This is in addition to your participation fee. In September of 2025, the U.S. Bureau of Economic Analysis (BEA) will release information on the most updated measure of Personal Consumption Expenditures (PCE) inflation for the U.S., which is the Federal Reserve's preferred measure of inflation. This value of inflation will fall into one of the bins you see here. Your bonus payment will be $10 multiplied by the weight (i.e. % chance) you assigned to that bin. For example:

- If you assign a 10% chance to a bin and the actual inflation falls into that bin, you will earn $10 * 0.10 = $1.00.
- If you assign a 25% chance to a bin and the actual inflation falls into that bin, you will earn $10 * 0.25 = $2.50.
- If you assign a 90% chance to a bin and the actual inflation falls into that bin, you will earn $10 * 0.9 = $9.00.

In your view, what would you say is the percent chance that, **over the next twelve months**...

the rate of inflation will be 12% or higher:	%
the rate of inflation will be between 8% and 12%:	%
the rate of inflation will be between 4% and 8%:	%
the rate of inflation will be between 2% and 4%:	%
the rate of inflation will be between 0% and 2%:	%
the rate of deflation (opposite of inflation) will be between 0% and 2%:	%
the rate of deflation (opposite of inflation) will be between 2% and 4%:	%
the rate of deflation (opposite of inflation) will be between 4% and 8%:	%
the rate of deflation (opposite of inflation) will be between 8% and 12%:	%
the rate of deflation (opposite of inflation) will be 12% or lower:	%

Next

Figure A-18: End of Survey

Thank You for Completing Our Survey!

Thank you for taking the time to participate in our survey. Your responses are valuable and will contribute significantly to our research.

We would like to remind you that you will receive your payment approximately twelve months from today in September of 2025.

Remember, we will randomly select to provide a bonus payment for either your point forecast or your bin forecast of one-year-ahead inflation. We will pay you for one or the other, but not for both. Thus, you may earn a bonus payment of up to **$10**. We will send your bonus payment in September of 2025 after the BEA releases its monthly measure of PCE inflation for the United States.

We appreciate your participation and will notify you via email once the payment is processed. If you have any questions or concerns, please do not hesitate to contact us.

Thank you again for your valuable contribution! We will redirect you to Prolific on the next page.

Next

Notes: This figure shows the final page for the *Both* treatment group. Slight variations in wording occur between treatments to reflect the different incentive structures. Screenshots of other treatment groups are available upon request.