Complexity and Uncertainty Both Cause Heaping: Experimental Evidence *

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Abstract

Researchers consider at least two alternative explanations for the observation of rounded answers and heaping in survey data: task complexity and uncertainty. Subjects may reduce the complexity of answering open-ended numerical survey questions by providing a satisfactory but imperfect response. However, heaping may also be the consequence of participants' underlying uncertainty about their answers to the survey question. We provide novel experimental evidence that complexity *and* uncertainty causes heaping using data from two inflation forecasting experiments that collected more approximately 20,000 incentivized, individually-linked measures of inflation forecasts and forecast uncertainty. We document a highly significant relationship between rounded forecasts and forecast uncertainty at the individual level, which remains even after controlling for demographics and measures of economic literacy.

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1 Introduction

This study investigates a phenomenon often observed in responses to open-ended, quantitative survey questions: the heaping of responses at rounded or salient numbers, defined as 'satisficing' by Simon (1956). Existing literature predominantly attributes satisficing to task complexity, where heaping arises due to the adoption of heuristics where respondents opt for a 'good enough' answer when precision seems costly. Our research explores an alternative explanation for respondents' satisficing – subjective uncertainty about their own forecasts.

We elucidate the distinction between these two sources of satisficing using a simple framework, introduced by Krosnick (1991), that links the probability of satisficing to person i's expected task difficulty ($D_{\tau,i}$), motivation (M_i), and ability (A_i):

$$P(\text{Person i satisficing in task } \tau) = \frac{D_{\tau,i}}{M_i \times A_i} \tag{1}$$

Within this framework, there is no explicit role for uncertainty as an explanation for satisficing. Suppose instead that we treat $D_{\tau,i}$ as a composite term capturing both the uncertainty and the complexity associated with answering a question so that $D_{\tau,i} = U_{\tau,i} + C_{\tau,i}$.

We delineate how complexity and uncertainty lead to satisficing with two simple examples. First, consider a survey task that requires respondents to calculate the exact number of seconds in a year without any aids. The inherent complexity of this calculation, involving extensive arithmetic and memory recall, may prompt respondents to opt for a 'good enough' rounded answer, like 'about 30 million seconds', instead of the precise figure (31,536,000 seconds). This illustrates how complexity ($C_{\tau,i}$) can lead to satisficing: respondents understand the task but deem the effort for precision disproportionate to the benefit. What about uncertainty? Consider a survey asking respondents to estimate the average gas price per gallon in their city over the next month. While respondents might be aware that gas prices took on a range of values in the recent past — say, \$3.15 to \$3.85 — the exact average price for gas in the following month is uncertain due to market forces and daily price fluctuations. In such cases, respondents are likely to satisfice by rounding their estimates to a figure that seems reasonable, such as 'about \$3.50 per gallon,' rather than attempting an implausibly precise calculation like '\$3.43' or '\$3.57'. Rounded answers may reflect uncertainty inherent in a question rather than the simplification of a complex calculation.[1]

[1] There is also likely a relationship between A_i, and i's perception of $U_{\tau,i}, C_{\tau,i}$, but we leave that aside for

In this paper, we disentangle the roles played by task complexity and uncertainty in heaping using data from two different forecasting experiments–comprising thousands of participants and around 20,000 decisions–that produced incentivized, individually linked point and range forecasts of future inflation. We achieve exogenous variation in uncertainty and complexity via variation in central bank communication provided to subjects during the inflation forecasting task. First, we show that an isolated change in task complexity leads to a quantitatively significant increase in the likelihood of rounding. Second, we demonstrate that an isolated change in uncertainty causes an increase the likelihood of rounding, thereby providing novel evidence in support of the uncertainty interpretation (i.e. the importance of $U_{\tau,i}$ as a component of $D_{\tau,i}$) of rounded answers to open-ended, quantitative questions.[2] Crucially, we do this without relying on distributional assumptions or structural choices. This relationship holds even after controlling for demographics and economic literacy, further confirming the role of uncertainty as a statistically and quantitatively significant driver of satisficing that is orthogonal to task complexity.

The concept of satisficing, grounded in task complexity, has been extensively discussed in various scientific fields. It is argued that heaping at round numbers occurs as subjects employ satisficing as a heuristic to reduce cognitive complexity (Krosnick et al. 1996, Krosnick 1999, Gideon et al. 2017). This theory has been influential in psychology Oppenheimer et al. (2009), Mertens (2019), economics Caplin et al. (2011), Artinger et al. (2022), Da Silveira and Lima (2022), and higher education research Barge and Gehlbach (2012).

Another popular interpretation of this phenomenon is that rounding in survey responses indicates underlying uncertainty. The idea is that respondents are simply uncertain about their answer to a question, even one they have carefully considered. Binder (2017) summarizes this literature and introduces a now widely adopted method for quantifying the uncertainty underlying round responses in economic surveys. This idea plays a particularly important role in economics, where macroeconomists are increasingly relying on surveys of households, firms, and professional forecasters to study economic expectations.[3] Our study seeks to contribute to this discourse by empirically investigating the uncertainty dimension of satisficing.

now.

[2]For other examples of recent work on the role of complexity in decision making, see Oprea (2020), Banovetz and Oprea (2023), Gabaix and Graeber (2023) or Arrieta and Nielsen (2023) for recent work regarding task complexity and decision-making.

[3]See Fuster and Zafar (2022) for a recent review of this literature.

Our results align with the limited experimental evidence on the relationship between rounding and uncertainty. Ruud et al. (2014) exogenously induces aggregate uncertainty by varying the difficulty of solving a color detection task and shows that solutions include more heaping whenever the task is more difficult. In the framework discussed above, this is akin to assuming $D_{\tau,i} \equiv U_{\tau,i} \equiv C_{\tau,i}$. Huttenlocher et al. (1990) show that asking respondents to recall the date of an event leads to heaping around salient timelines (7 days, 14 days, 30 days, etc.) and that this behavior increases for events more distant in the past. Khaw et al. (2017) show in a laboratory experiment where subjects must predict the probability of a binary outcome that subjects prefer to report round number probabilities even at the cost of exerting additional effort.

Our experiments are different from these in a few meaningful ways. First, our experiments collect linked, incentivized measures of both a point forecast and the corresponding forecast uncertainty, enabling us to study the effects of individual-level uncertainty on rounding. Second, we study a setting where subjects are predicting the future state of a complex dynamical system (i.e. inflation) so that experimental variation in uncertainty does not derive from variation in task complexity as in Ruud et al. (2014) or depend upon memory as in Huttenlocher et al. (1990).

The rest of the paper is organized as follows: Section 2 provides an overview of our experimental designs, Section 3 details our results, and Section 4 provides a brief discussion.

2 Experimental Design

This section summarizes the three different forecasting experiments used to collect our data. First, we use data from a series of learning-to-forecast experiments (LtFEs) wherein participants provide both point and range forecasts,where the range forecast represents forecast uncertainty, of inflation in experimental economies that evolve endogenously according to those expectations. We refer to this data as RPU data. We also use data from an inflation forecasting task where subjects provide point and range forecasts of an exogenous inflation process. We call this data our MRC data. We next provide a brief overview of the experiments that generated our RPU and MRC data.

2.1 RPU

RPU data is from Rholes and Petersen (2021) and Petersen and Rholes (2022), which both study the role of higher-order information in central bank forecasts. The design used in both experiments produces rich panel data, which allows us to try and disentangle the effects of uncertainty and cognitive complexity on rounding. Overall, the combined data from these experiments consists of 17,328 decisions from 584 unique subjects collected from October 2019 through October 2020 in a series of 54 experimental sessions conducted both online and in a physical laboratory.

Participants in both RPU experiments acted as inflation forecasters tasked with providing incentivized inflation forecasts in period t for periods $t+1$ and $t+2$ in experimental economies that evolved endogenously. In addition to point forecasts of inflation, subjects also provided incentivized measures in each period t of their subjective forecast uncertainty for both forecast horizons. We incentivized subjects' point forecasts and measures of forecast uncertainty at both horizons using approaches qualitatively identical to those described in Section 2.2.

Economies in both experiments were based on a linearized, three-equation New Keynesian (NK) model where we eliminate the need for expectations about the output gap, which yields a dynamical system closed under subjects' one- and two-period-ahead inflation expectations. These economies evolved according to subjects' aggregated expectations and persistent aggregate demand shocks. Each experimental session consisted of seven subjects who formed individual inflation expectations privately using common information for two independent sequences of 30 sequential periods each.

At the start of period t, subjects had information about inflation, interest rates, demand shocks, and their inflation forecasts for all preceding periods. Subjects also knew the value of the current-period demand shock. In one treatment (NoComm) subjects received no central bank communication. In the remaining treatments, the central bank communicated to subjects either a point forecast (Point), a point and density forecast (PointDensity), or just a density forecast (DensityOnly) of inflation for the next five periods.

Compared to NoComm, Point reduces complexity by providing a precise inflation forecast to subjects without also conveying the central bank's forecast uncertainty. Compared to Point, Point&Density and DensityOnly increase uncertainty because, as shown in the original RPU studies, communicating central bank forecast uncertainty can causally increase individual-level forecast uncertainty. We exploit these exogenous shifts in task complexity and uncertainty to quantify the relative importance of task complexity and uncertainty on rounding behavior in our forecasting task.

Based on this information, subjects formed incentivized inflation forecasts (point and range) for the next two periods ($t+1$ and $t+2$) in basis points. Once all subjects provided forecasts, our software selected median inflation forecasts for $t+1$ and $t+2$ as the aggregate expectations, fed those values into the underlying NK model, provided participants with information about the realized value of aggregate inflation, and proceeded to the next decision period.[4]

The experimental interface was programmed in Redwood. The sessions took place from October 2019 to October 2021 in physical labs and in online experiments at Texas A&M University and Simon Fraser University. Subjects were recruited using ORSEE (Greiner 2015) and SONA.

2.2 MRC

MRC data is from McMahon and Rholes (2023), which explores the relationship between a central bank's historical forecast performance and the public's perception of the bank as a credible inflation forecaster. There are 10,812 decisions total from 1,808 unique subjects in the MRC data. We collected this data using a series of 20 treatments programmed in oTree (Chen et al. 2016) and deployed online via Prolific between February and August of 2022 using American subjects.

Participants in this individual-choice experiment acted as atomistic inflation forecasters tasked with providing two incentivized sets of inflation forecasts (Initial Forecasts and Updated Forecasts) in 3 sequential, independent decision periods. Each set of inflation forecasts comprised an incentivized point forecast and an incentivized measure of corresponding forecast uncertainty.

Subjects began the experiment by completing a pre-experiment survey that elicited a measure of economic literacy and self-reported measures of trust and understanding of the Federal Reserve along a five-point scale. We use this survey data as a way to control for cognitive ability and other idiosyncratic characteristics when isolating $U_{\tau,i}$ in Equation (1).

[4] This is a common design feature of learning-to-forecast experiments. See Petersen and Rholes (2022) for a discussion of how aggregating by averaging instead can lead to unrealistically unstable inflation dynamics.

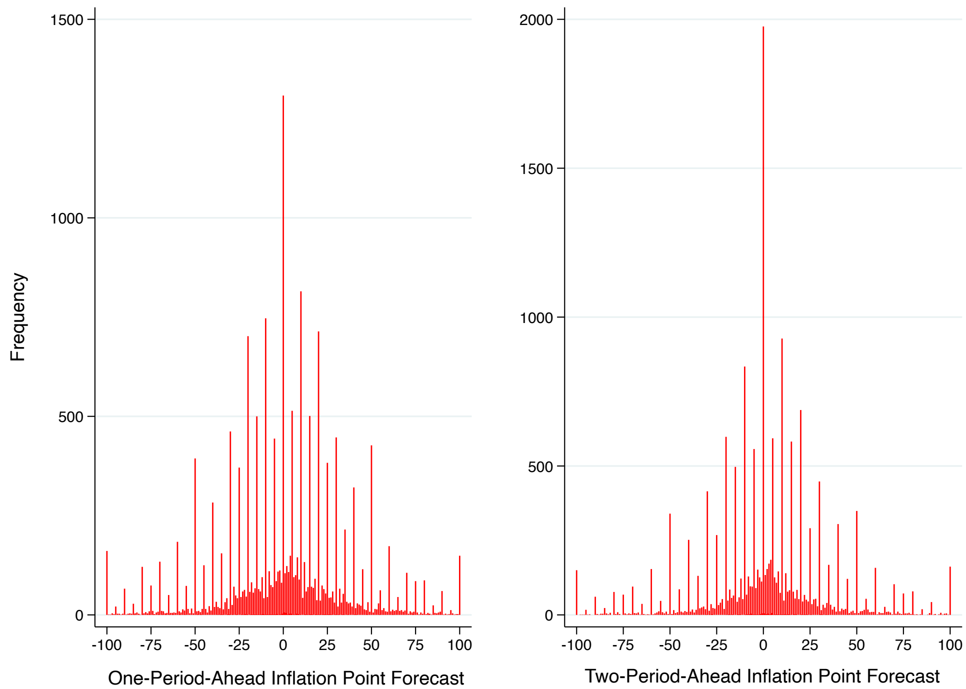
Following this, subjects progressed to decision periods. We began each decision period by revealing a 12-quarter economic history consisting of realized values of inflation alongside a central bank's corresponding inflation forecast. Based on this history, subjects submitted Initial Forecasts. Next, we revealed the central bank's forecast for the following period and allowed subjects to update their forecast (Updated Forecasts) based on the central bank's forecast. All central bank forecasts in MRC were point forecasts and did not convey the central bank's own forecast uncertainty.

For both the Initial and Updated Forecasts, subjects first submitted a point forecast that we incentivized using a symmetric scoring rule that penalized a subject's absolute forecast error. Subjects then provided a range forecast of inflation, which necessarily contained the subject's point forecast but was otherwise unrestricted. We incentivized range forecasts using a piece-wise incentive scheme introduced in Rholes and Petersen (2021). If actual inflation fell outside a subject's range forecast, they earned nothing for that range forecast. If actual inflation was within the bounds of a subject's range forecast then they earned a positive payoff that was decreasing in the magnitude of the forecast uncertainty. Economic histories constituted treatment variation in this experiment, which we exploited to study the causal relationship between a central bank's historical forecast performance and its credibility as a forecaster.

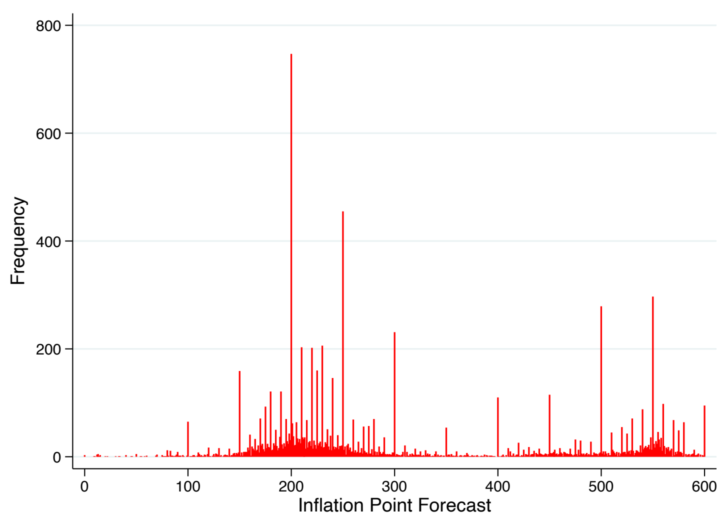
3 Results

We first consider point forecast data for both RPU and MRC, which we show in Figure 1. The top two panels of Figure 1 depict histograms of point forecasts of one-period-ahead (left) and two-period-ahead (right) inflation from our RPU data. Participants in RPU sessions submitted point forecasts at both horizons in terms of basis points (x-axis). The bottom panel of Figure 1 depicts a histogram of point forecasts of one-period-ahead inflation from our MRC data. Participants in RPU sessions submitted point forecasts at both horizons in percentage-point terms (x-axis).

Our primary interest is in whether and how individual-level uncertainty can explain the heaping we observe in Figure 1. To answer this question, we must first decide what constitutes rounding in our data. To this end, we created four groups of participants in each experiment. Denote participant i's inflation forecast in period t for horizon $t+h$ as $\mathbb{E}_{i,t}\pi_{t+h}$. Then a participant rounds if $(\mathbb{E}_{i,t}\pi_{t+h} \ mod \ x) = 0$ for appropriate values of x. In our MRC



(a)



(b)

Figure 1: This figure shows histograms of inflation point forecasts for RPU (panel a) and MRC (panel b) data.

data, subjects input forecasts as percentages and could use up to two decimal places. For this data, we consider - in basis points - $x_{MRC} \in \{25, 50, 100\}$ for $h = 1$. In our RPU data, subjects submitted inflation forecasts in basis points as integer values. For this data, we consider $x_{RPU} \in \{10, 20, 50\}$ for $h = 1$ and $h = 2$. Table 1 shows the outcome of this classification exercise for both MRC and RPU data.[5]

Table 1: Rounding Decisions and Uncertainty

				RPU Data (h=1/h=2)		
	(1) **Abv.**	(2) **Decisions**	(3) **%**	(4) **% Cum.**	(5) **Mean U.**	(6) **Std. Error U.**
No Rounding	$(r_{NR}^{RPU,h})$	8,973 / 8,654	51.78 % / 49.94 %	51.78 % / 49.94 %	19.69/20.98	.22/.24
$(\mathbb{E}_{i,t}(\pi_{t+h})\ mod\ 10) = 0$	$(r_{10}^{RPU,h})$	2,986 / 3,045	17.23 % / 17.57%	69.02% / 67.52 %	23.12/27.6	.39/.48
$(\mathbb{E}_{i,t}(\pi_{t+h})\ mod\ 20) = 0$	$(r_{20}^{RPU,h})$	2,756 / 2,478	15.90 % / 14.30 %	84.92% / 81.82%	27.188/30.32	.49/.6
$(\mathbb{E}_{i,t}(\pi_{t+h})\ mod\ 50) = 0$	$(r_{50}^{RPU,h})$	2,613 / 3,151	15.08 % / 18.18 %	100%	31.40/38.06	.53/.58

				MRC Data		
	(1) **Abv.**	(2) **Decisions**	(3) **%**	(4) **% Cum**	(5) **Mean U.**	(6) **Std. Error U.**
No Rounding	(r_{NR}^{MRC})	7,244	67 %	67 %	121	1
$(\mathbb{E}_{i,t}(\pi_{t+1})\ mod\ 25) = 0$	$(r_{.25}^{MRC})$	534	4.94 %	71.94 %	122	3
$(\mathbb{E}_{i,t}(\pi_{t+1})\ mod\ 5) = 0$	$(r_{.5}^{MRC})$	1,279	11.83 %	83.77 %	131	3
$(\mathbb{E}_{i,t}(\pi_{t+1})\ mod\ 100) = 0$	(r_{1}^{MRC})	1,755	16.23 %	100 %	152	3

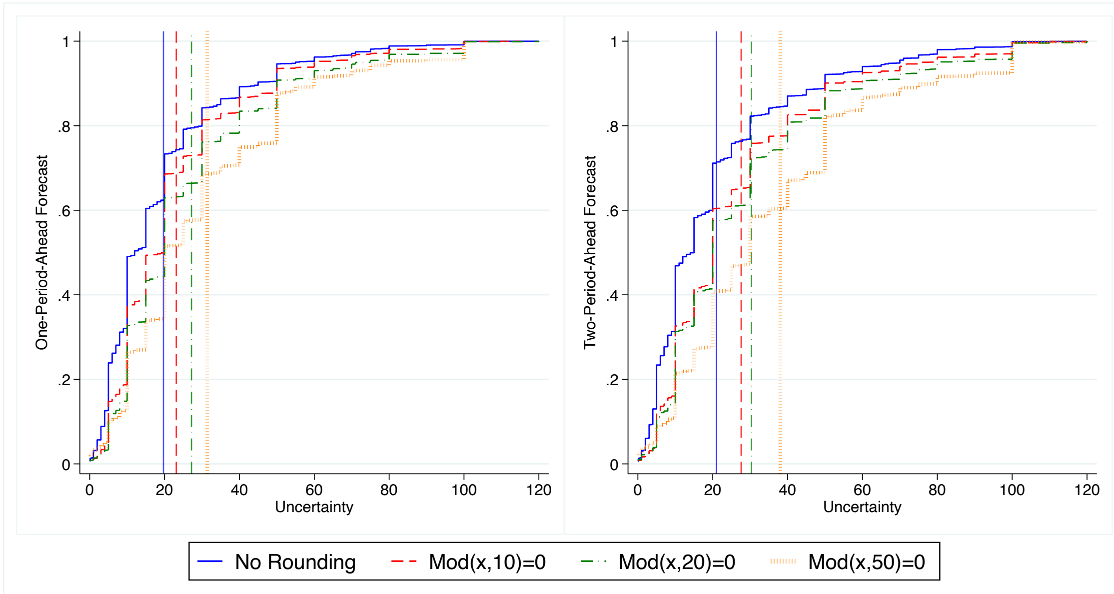
This table shows the result of classification at the decision level. There are 10,812 decisions total from 1,808 unique subjects in the MRC data. There are 17,328 decisions total from 584 unique subjects in the RPU data. Mean values of forecast uncertainty (**Mean U.**) and corresponding standard errors (**Std. Error U.**) are in basis points. Here, $(\mathbb{E}_{i,t}(\pi_{t+h})\ mod\ x) = 0$ means that $\frac{\mathbb{E}_{i,t}(\pi_{t+h})}{x} \in \mathbb{I}$.

Under uncertainty-driven satisficing, uncertainty should be systematically different across the rounding classifications (r^{MRC} and $r^{RPU,h}$). To determine if this is true in our data, we first consider the cumulative distribution function of forecast uncertainty by rounding groups for both the RPU and MRC dataFigure 4.[6] We see in both data sets a positive relationship between the coarseness of inflation forecasts and forecast uncertainty.

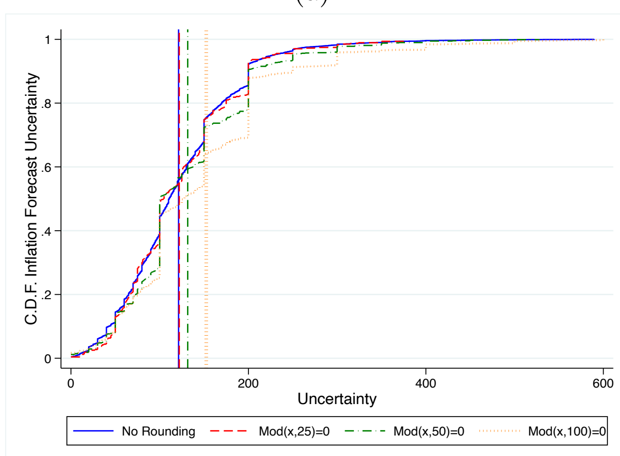
Using the groups produced by our rounding classification exercise as ordinal measures, we can determine whether and how individual-level uncertainty helps explain the heaping we

[5]Discuss difference in scales here.

[6]We also provide histograms of both individual-level forecast uncertainty and point forecasts in Section 5.1.



(a)



(b)

Figure 2: This figure shows cumulative distribution functions of individual-level forecast uncertainty for different rounding groups from both the RPU (panel a) and the MRC (panel b) data. for the RPU data, we show CDFs for one-period ahead (left) and two-period-ahead (right) inflation forecasts. For the MRC data, we show CDFs using pooled data for all histories, and for both initial and updated forecasts. Here, mod(x,y)=0 indicates that the forecast (x) is a multiple of y (i.e. that a forecast is rounded to y). Vertical lines are corresponding means.

observe in Figure 1. Table 2 reports results from a series of ordered-Probit regressions using $r^{RPU,1}$ (*RPU: One-Period-Ahead*), $r^{RPU,2}$ (*RPU: Two-Periods-Ahead,*) and r^{MRC} (*MRC*) as the dependent variables. We use Ordered-Probit models to estimate the relationship between ordinal dependent variables (rounding classifications in our case) and a set of independent variables. This relationship manifests as an underlying score estimated as a linear combination of independent variables and a set of cutpoints. This score predicts the probability that a participant is of a certain ordinal classification (i.e. a certain rounding type).

More concretely, we use an ordered-Probit model to estimate the probability that a participant p is of classification type j using

$$Pr(classification_p = j) = Pr(c_{j-1} < \beta_1 x_{1,p} + \beta_1 2 x_{2,p} + ... + \beta_k x_{k,p} + \mu_p \leq c_j) \tag{2}$$

where $classification_p = j$ means that participant p is a type-j rounder. Note that this corresponds to i in $r_i^{RPU,h}$ and in r_i^{MRC}.

In (*RPU: One-Period-Ahead*), (*RPU: Two-Periods-Ahead*), and *MRC* column (1) reports estimation results using an empty model. In (*RPU: One-Period-Ahead*), (*RPU: Two-Periods-Ahead*) column (2) includes indicator variables denoting whether a participant received some form of central bank communication, and column (3) includes controls for most recent realizations of inflation (π_{t-1}) inflation volatility ($|\pi_{t-1} - \pi_{t-2}|$), a participant's forecast error ($|\mathbb{E}_{i,t-h-1}(\pi_{t-1}) - \pi_{t-1}|$), and a demand shock. In *MRC*, column(2) includes controls for demographics (MALE and Age), a measure of economic literacy (QuizScore), and self-reported measures of trust and understanding of the Federal Reserve (TrustFed and UnderstandFed, respectively). Column (3) also includes treatment fixed effects.

Results from all specifications in all three panels of Table 2 indicate that individual-level uncertainty is a significant determinant of rounding. That is, the probability that a participant submits a rounded forecast is increasing in her corresponding forecast uncertainty. Further, the more uncertain a participant is about her forecast, the more likely she is to use a more coarse point forecast of inflation. Comparing results in (*RPU: One-Period-Ahead*), (*RPU: Two-Periods-Ahead*), we see that this relationship is slightly stronger further into the term structure of expectations.

Table 2: What Causes Rounding?

RPU: One-Period-Ahead

	(1)	(2)	(3)
	$r_{RPU,1}$	$r_{RPU,1}$	$r_{RPU,1}$
Uncertainty	0.206***	0.191***	0.183***
	(0.0257)	(0.0255)	(0.0264)
$\mathbb{1}$[Point]		-0.174***	-0.176***
		(0.0642)	(0.0642)
$\mathbb{1}$[PointDensity]		-0.153**	-0.164**
		(0.0639)	(0.0652)
$\mathbb{1}$[DensityOnly]		0.102	0.0433
		(0.0834)	(0.0815)
$\lvert \mathbb{E}_{i,t-2}(\pi_{t-1}) - \pi_{t-1} \rvert$			0.00112**
			(0.000550)
π_{t-1}			-0.000767**
			(0.000310)
$\lvert \pi_{t-1} - \pi_{t-2} \rvert$			0.00213***
			(0.000572)
DemandShock$_t$			-0.0000459
			(0.0000875)
Cut Points			
$r_{10}^{RPU,1}$	0.0435	-0.0361	0.0610
	(0.0273)	(0.0463)	(0.0484)
$r_{20}^{RPU,1}$	0.505***	0.428***	0.523***
	(0.0239)	(0.0446)	(0.0469)
$r_{50}^{RPU,1}$	1.055***	0.981***	1.076***
	(0.0265)	(0.0450)	(0.0478)
N	17328	17328	15999

RPU: Two-Periods-Ahead

	(1)	(2)	(3)
	$r_{RPU,2}$	$r_{RPU,2}$	$r_{RPU,2}$
Uncertainty	0.266***	0.240***	0.226***
	(0.0255)	(0.0248)	(0.0265)
$\mathbb{1}$[Point]		-0.251***	-0.251***
		(0.0681)	(0.0690)
$\mathbb{1}$[PointDensity]		-0.169**	-0.179**
		(0.0688)	(0.0700)
$\mathbb{1}$[DensityOnly]		0.191**	0.135
		(0.0845)	(0.0842)
$\lvert \mathbb{E}_{i,t-3}(\pi_{t-1}) - \pi_{t-1} \rvert$			0.00102**
			(0.000419)
π_{t-1}			-0.000295
			(0.000294)
$\lvert \pi_{t-1} - \pi_{t-2} \rvert$			0.00254***
			(0.000442)
DemandShock$_t$			-0.000226***
			(0.0000828)
Cut Points			
$r_{10}^{RPU,2}$	-0.00532	-0.0991**	0.0133
	(0.0284)	(0.0488)	(0.0533)
$r_{20}^{RPU,2}$	0.467***	0.378***	0.494***
	(0.0256)	(0.0473)	(0.0523)
$r_{50}^{RPU,2}$	0.939***	0.855***	0.970***
	17328	17328	15361
N	17328	17328	15361

MRC

	(1)	(2)	(3)
	r_{MRC}	r_{MRC}	r_{MRC}
Uncertainty	0.148***	0.147***	0.151***
	(0.022)	(0.022)	(0.022)
MALE		0.003	0.003
		(0.046)	(0.047)
Age		0.002	0.002
		(0.002)	(0.002)
QuizScore		-0.017	-0.024
		(0.022)	(0.022)
TrustFed		0.013	0.008
		(0.022)	(0.022)
UnderstandFed		0.033	0.040*
		(0.021)	(0.021)
Cut Points			
$r_{.25}^{MRC}$	0.441***	0.573***	0.463***
	(0.023)	(0.127)	(0.155)
$r_{.5}^{MRC}$	0.586***	0.718***	0.609***
	(0.023)	(0.127)	(0.156)
r_{1}^{MRC}	0.990***	1.122***	1.018***
	(0.023)	(0.127)	(0.156)
N	9283	9235	9235
Treatment FEs	No	No	Yes

Robust standard errors clustered at the individual level in parentheses.

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

Overall, results using RPU data suggest two things. First, reducing cognitive complexity reduces rounding. Second, individual-level uncertainty is a highly significant determinant of rounding even after we attempt to control for the role of satisficing. When considering the average forecast uncertainty in our RPU data (23 and 26 basis points for one- and two-period-ahead forecasts), we can loosely conclude that the effect of individual-level uncertainty on rounding is about as important as that of removing central bank communication. Results from *MRC* indicate that demographics, economic literacy, and understanding and trust of the Federal Reserve play no role in determining whether a subject rounds her point forecast. A robust finding in household inflation surveys is that females exhibit significant upward bias in their inflation expectations relative to men (see Brischetto et al. (1999), D'Acunto et al. (2020) for survey examples and Burke and Manz (2014) for an experimental example). Our results suggest that this effect is not caused by gender differences in rounding behavior.

3.1 Comparing Task Complexity and Uncertainty

In this section, we consider how exogenously reducing task complexity or increasing forecast uncertainty impacts rounding behavior in point forecasts. To do this, we first compare rounding behavior in our NoComm and 55 Point RPU treatments (task complexity), and then in Point and Point&Density and DensityOnly treatments (uncertainty).

3.1.1 Task Complexity and Rounding

In this subsection, we explore the impact of task complexity on the rounding behavior of subjects' point forecasts. To assess this, we compare two different sets of central bank communication treatments from our RPU data. First, we compare rounding behavior in our NoComm and Point treatments. The NoComm treatment lacks central bank communication. In contrast, the Point treatment features a five-period-ahead point forecast of inflation from the central bank, which significantly lowers the level of complexity involved in forming a precise point forecast and therefore ought to reduce rounding, according to Equation (1). For example, a subject who treats the forecast as fully credible will provide round-number forecasts only if they coincide with the central bank's outlook. Our hypothesis is that a reduction in task complexity, from NoComm to Point, will reduce the probability that a participant rounds her point forecast of inflation.

To test this hypothesis, we employ a regression framework that allows us to estimate the causal impact of task complexity on rounding. Specifically, we define two binary outcome variables, Rounded$1, i$ and Rounded$2, i$, representing whether a subject rounds her one-period-ahead and two-period-ahead inflation forecasts, respectively. The key independent variable in our analysis is a binary indicator of treatment, Complexity$_i$, which equals 0 for the NoComm treatment and 1 for the Point treatment.

We estimate the following regression equations separately for one-period-ahead and two-period-ahead forecasts:

$$Rounded_{t+j,i} = \alpha + \beta_1 \text{Complexity} + \boldsymbol{\epsilon}_{t+j,i} \tag{3}$$

$$Rounded_{t+j,i} = \alpha + \beta_1 \text{Complexity} + \boldsymbol{\gamma X} i + \boldsymbol{\epsilon}_{t+j,i} \tag{4}$$

In Equation (3), Equation (4) $Rounded_{t+j,i}$ is the dependent variable for period t, and Complexity is the independent variable of interest. The coefficients β_1 in both equations capture the average treatment effect of reducing task complexity on rounding behavior. The error terms $\boldsymbol{\epsilon}_{1,i}$ and $\boldsymbol{\epsilon}_{2,i}$ capture unobserved factors influencing rounding behavior that are not accounted for by treatment assignment. $\boldsymbol{X}_i$ represents controls for the magnitude of the most recent realizations of inflation (π_{t-1}) inflation volatility ($|\pi_{t-1} - \pi_{t-2}|$), a participant's forecast error ($|\mathbb{E}_{i,t-h-1}(\pi_{t-1}) - \pi_{t-1}|$), and the demand shock. Additionally, $\boldsymbol{X}_i$ contains our individual-level measure of forecast uncertainty for the corresponding forecast horizon, which further ensures $\tilde{Beta}_1$ does not also capture the impact of uncertainty on rounding. We estimate these regressions using a panel data model appropriate for binary outcome variables, and we report robust standard errors clustered at the individual level to account for within-subject correlation over time.

Results (top panel, Table 3) indicate a significant negative relationship between task complexity and the likelihood of rounding. In the simplest model (Column 1), a decrease in task complexity (moving from NoComm to Point treatment) reduces the probability of rounding a one-period-ahead forecast by ($P < .01$). The marginal effect (M.E.) of this reduction is -8.7% ($P < .01$). Even when controlling for additional variables that include a subject's own forecast uncertainty(Column 3), this negative relationship persists ($P < .05$) with a marginal effect of -6.4% ($P < .05$). This suggests that lower complexity, as experienced in the Point treatment, significantly reduces the propensity to round forecasts. The effect of

Table 3: Impact of Task Complexity on Rounding Behavior and Marginal Effects

	One-Period-Ahead Forecasts				Two-Period-Ahead Forecasts			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Empty	M.E.	Full	M.E.	Empty	M.E.	Full	M.E.
				Comparing NoComm to Point				
Complexity	-0.279***	-0.087***	-0.203**	-0.064**	-0.435***	-0.130***	-0.359***	-0.108***
	(0.089)	(0.027)	(0.087)	(0.027)	(0.102)	(0.030)	(0.093)	(0.027)
$Uncertainty_{j=1}$			0.218***					
			(0.046)					
$Uncertainty_{j=2}$							0.242***	
							(0.050)	
Constant	0.024		-0.077		0.151**		0.080	
	(0.063)		(0.063)		(0.072)		(0.075)	
lnsig2u	-0.533***		-0.619***		-0.330***		-0.434***	
	(0.087)		(0.097)		(0.102)		(0.106)	
N	9836	9836	9049	9049	9836	9836	8679	8679
				Comparing DensityOnly to Point&Density				
Complexity	-0.361***	-0.108***	-0.285**	-0.085**	-0.631***	-0.179***	-0.543***	-0.154***
	(0.123)	(0.036)	(0.126)	(0.037)	(0.135)	(0.037)	(0.160)	(0.044)
$Uncertainty_{j=1}$			0.150***					
			(0.036)					
$Uncertainty_{j=2}$							0.185***	
							(0.039)	
Constant	0.280**		0.115		0.585***		0.373***	
	(0.113)		(0.101)		(0.116)		(0.143)	
lnsig2u	-0.289**		-0.297**		-0.155		-0.221*	
	(0.118)		(0.131)		(0.098)		(0.119)	
N	7492	7492	6950	6950	7492	7492	6682	6682

Note: This table estimates the causal impact of task complexity on the likelihood of rounding a point forecast using a random-effects Probit model. Columns 1-4 present regression results for one-period-ahead forecasts while 5-8 present results from two-period-ahead forecasts. Even-numbered columns present marginal effects (M.E.) for the preceding odd-numbered column. Bootstrapped standard errors (100 replications) are shown in parentheses. * p¡.1, ** p¡.05, *** p¡.01

task complexity on rounding behavior is even more pronounced for two-period-ahead forecasts. The reduction in the likelihood of rounding is significant in our empty regressions (Column 5, $p < .01$), with a marginal effect of -13.0% ($P < .01$). This effect remains robust after including controls (Column 7, $p < .01$), with a marginal effect of -10.8% ($P < .01$).

Moreover, the reduction in the likelihood of rounding due to decreased task complexity is more pronounced for two-period-ahead forecasts compared to one-period-ahead forecasts.

The marginal effects for two-period-ahead forecasts (-13.0% in the simplest model and -10.8% in the controlled model) are larger than those for one-period-ahead forecasts (-8.7% and -6.4% respectively). This suggests that the influence of task complexity becomes more significant as the forecast horizon lengthens. This is true even after controlling for a participant's subjective forecast uncertainty, suggesting that other complexity-related factors are at play. One plausible explanation lies in the inherent nature of forecasting over different horizons. For two-period-ahead forecasts, forecasters face a compounded decision-making process. They must consider a broader range of variables and potential developments over a longer horizon, leading to an inherently more complex task. This complexity is multiplicative, in some sense, because the second period's forecast depends on the outcomes of the first. Therefore, any simplification provided, such as a precise point forecast from the central bank, becomes significantly more valuable in reducing cognitive load and aiding decision-making in these more complex, two-period-ahead forecasts.

Additionally, we compare rounding behavior in our Point&Density and DensityOnly treatments. These two treatments, similar to our NoComm versus Point comparisons, differ only in whether inflation forecasts provided by the central bank contain a precise point forecast. However, different from our first comparison, these two treatments both feature central bank inflation forecasts that convey an identical, non-zero level of inflation forecast uncertainty. We again rely on Equation (3), Equation (4) $Rounded_{t+j,i}$ where Complexity$_i$, equals 0 for our DensityOnly treatment and 1 for the Point&Density treatment. Our hypothesis is that a reduction in task complexity, from DensityOnly to Point&Density, will reduce the probability that a participant rounds her point forecast of inflation (i.e. $\hat{\beta}_1 < 0$).

Results from this exercise (bottom panel, Table 3) again indicate a significant negative relationship between task complexity and the likelihood of rounding. In the simplest model (Column 1), a decrease in task complexity (moving from NoComm to Point treatment) reduces the probability of rounding a one-period-ahead forecast by ($P < .01$). The marginal effect of this reduction is -10.8% ($P < .01$). This effect is robust (Column 3, $p < .05$), with a marginal effect of -8.5% ($P < .05$). Again, we find a significant reduction in the likelihood of rounding at the longer forecast horizon (Column 5, $p < .01$), with a marginal effect of -17.9% ($P < .01$). This effect remains robust after including controls (Column 7, $p < .01$), with a marginal effect of -15.4% ($P < .01$).

The comparison between DensityOnly and Point&Density is particularly revealing. Unlike the NoComm treatment, which represents a complete lack of central bank communication, the DensityOnly treatment still contains a non-zero level of uncertainty. The additional reduction in rounding observed in the Point&Density treatment suggests that the presence of a point forecast has a more pronounced effect on reducing rounding when there is already some level of uncertainty communicated. This could imply that in the presence of inherent uncertainty, a point forecast serves as a more concrete anchor for forecasts, thereby reducing the tendency to resort to rounding as a heuristic.

3.1.2 Uncertainty and Rounding

To do this, we first regress the potentially endogenous variable, uncertainty, on the instrument, CommType.

$$\text{Uncertainty}_{t,i} = \alpha + \beta_1 \text{CommType}_i + \boldsymbol{\gamma_3} \boldsymbol{X}_i + \varepsilon_i \tag{5}$$

where CommType = 0 for Point and CommType = 1 for Point&Density treatment. We restrict focus to these two treatments for simplicity, since we know that introducing precise central bank communication into the RPU forecast task causally reduces participants' individual-level forecast uncertainty relative to baseline treatments with no central bank communication (Rholes and Petersen 2021, Petersen and Rholes 2022). This satisfies the corresponding exclusion restriction because CommType is a randomly-assigned, exogenous manipulation.

Equation (5) projects our potentially endogenous variable of interest onto the space spanned by our instrument variable, CommType, and controls $\boldsymbol{X}_i$. Thus, ε_i captures the unobserved factors influencing Uncertainty that could also be affecting rounding behavior. These residuals are, by construction, orthogonal to our instrument and other control variables, capturing only the variation in Uncertainty that is not explained by these factors. Including these residuals Equation (6) allows us to control for this endogenous variation, ensuring that our estimates of our coefficient of interest, $gamma_1$ are unbiased and consistent.

Using these predicted residuals from the first stage, we can use dynamic Probit estimation where our outcome of interest is whether a subject rounded her one-period-ahead (t=1) or two-period-ahead (t=2) point forecast of inflation.

Table 4: Impact of Uncertainty on Rounding Behavior and Marginal Effects

	One-Period-Ahead Forecasts				Two-Period-Ahead Forecasts			
	No Controls	M.E.	Controls	M.E.	No Controls	M.E.	Controls	M.E.
Uncertainty	0.419**	0.131**	0.380*	0.118*	0.607***	0.185***	0.569**	0.172**
	(0.209)	(0.065)	(0.225)	(0.069)	(0.230)	(0.069)	(0.247)	(0.074)
Residuals	-0.236		-0.204		-0.411*		-0.386	
	(0.209)		(0.223)		(0.227)		(0.246)	
Constant	-0.131***		-0.265***		-0.105**		-0.239***	
	(0.049)		(0.071)		(0.051)		(0.082)	
lnsig2u	-0.567***		-0.517***		-0.435***		-0.391***	
	(0.098)		(0.098)		(0.099)		(0.107)	
N	9976	9976	8914	8914	9976	9976	8914	8914

Bootstrapped standard errors (500 repetitions) in parentheses
$*p < .1, **p < .05, ***p < .01$

$$\Pr(\text{Rounded}_{t,i} = 1) = \Phi(\gamma_0 + \gamma_1 \text{Uncertainty}_{t,i} + \gamma_2 \epsilon_{t,i} + \boldsymbol{\gamma_3} \boldsymbol{X}_{t,i}) \tag{6}$$

Where $\text{Rounded}_{t,i}$ is a binary variable capturing whether a subject rounded her forecast and $\boldsymbol{X}_i$ represents controls for the magnitude of the for the most recent realizations of inflation (π_{t-1}) inflation volatility ($|\pi_{t-1} - \pi_{t-2}|$), a participant's forecast error ($|\mathbb{E}_{i,t-h-1}(\pi_{t-1}) - \pi_{t-1}|$), and the demand shock. We report results from this estimation procedure in **??**.

In the analysis of one-period-ahead forecasts, the positive and significant coefficients for "Uncertainty" in both the uncontrolled (Column 1) and controlled models (Column 3) indicate that an increase in forecast uncertainty leads to a higher likelihood of rounding. The marginal effects quantitatively support this observation, revealing an increase in the likelihood of rounding by 13.1% ($P < .05$) and 11.8% ($P < .1$) in the respective models. The impact of uncertainty on rounding behavior is further pronounced in the context of two-period-ahead forecasts. Here again, the positive relationship between uncertainty and rounding is evident, with the likelihood of rounding increasing by 18.5% ($P < .01$) and 17.2% ($P < .05$) in the uncontrolled and controlled models (Columns 5 and 7), respectively. These larger marginal effects for two-period-ahead forecasts, compared to one-period-ahead forecasts, underscore the compounding effect of uncertainty over longer forecast horizons.

4 Discussion and Conclusion

The phenomenon of heaping in survey and task data, often manifested as rounding in responses, presents a critical challenge across various scientific disciplines. This study contributes to the longstanding discourse regarding heaping by further dissecting the underlying causes behind this phenomenon, particularly focusing on the roles of complexity and uncertainty. Through a series of experiments that capture individually-linked, incentivized measures of inflation expectations and corresponding forecast uncertainty, we delve into the relationship between individual-level forecast uncertainty and the propensity to round point forecasts.

Our findings reveal a robust and statistically significant relationship between forecast uncertainty and rounding behavior. This relationship holds even after accounting for factors such as the cognitive complexity of the forecasting task, demographics, economic literacy, and participants' trust and understanding of central banks. Notably, our analysis underscores the importance of uncertainty as a determinant of rounding, independent of task complexity. The implication is clear: in environments where individual-level uncertainty is prevalent, responses tend to skew towards rounded or salient figures, suggesting a heuristic approach to dealing with uncertain scenarios.

Additionally, we establish that the reduction in task complexity, achieved through varying degrees of central bank communication, causally impacts rounding behavior independent of uncertainty. This finding is crucial as it suggests that both the simplification of tasks and the presence of uncertainty are separate yet significant determinants of how individuals approach forecasting tasks.

Furthermore, the study reveals that the impact of both task complexity and uncertainty on rounding behavior is more pronounced for longer-term forecasts. This nuanced understanding underscores the layered nature of decision-making processes, particularly in economic forecasting, where the compounding effects of uncertainty and task complexity over time play a pivotal role. Moreover, our study sheds light on how this rounding behavior varies with the forecast horizon. The impact of uncertainty on rounding is more pronounced for longer-term forecasts, underscoring the compounding nature of uncertainty over time. This finding has significant implications for the design and interpretation of economic forecasts and surveys. It highlights the need for careful consideration of the underlying uncertainty and suggests that strategies to manage or communicate this uncertainty could be crucial in enhancing the accuracy and reliability of economic predictions.

Binder (2017) reports that more than 41% of point inflation forecasts are rounded to the nearest 5% level in data from the Michigan Survey of Consumers and 48% of numerical survey responses exhibit rounding in an average month over the same period. Reiche and Meyler (2022) document that the average level of rounded responses in the European Commission Consumer Survey (ECCS) from 2004 through 2020 has been around 70%. We see that approximately 30% of inflation responses are rounded in our MRC data and about 50% in our RPU data. Thus, we observe a comparable level of rounding in both experimental frameworks we consider here (RPU and MRC), even though our subjects face marginal incentives.

Additionally, we see in our data that rounders often form more extreme expectations than non-rounders, which aligns with Reiche and Meyler (2022), who show empirically that rounding in ECCS survey data can lead to average inflation expectations that consistently overestimate inflation. This matches with evidence from Monte Carlo simulations that suggest rounding leads to higher average inflation expectations.

To show this, we average over 1,000 simulations, each comprising a sample size of 2,000 individual forecasts where inflation forecasts follow a lognormal distribution. To simulate the heaping effects often seen in survey responses, we clone inflation data and then introduce rounding into the date using two rounding schemes based on a random uniform distribution that round approximately thirty percent of forecasts to the nearest multiple of five and another twenty percent to the nearest multiple of ten. We chose the extent of rounding in our simulation to approximate the level of heaping found in actual survey data and our experimental data. Importantly, these rounding mechanisms feature no upward rounding bias. This approach allows us to compare the genuine distribution of inflation forecasts with their rounded counterparts.

Our findings indicated that rounding results in a significantly higher average expected inflation whenever we choose mean and variance parameters so that the underlying, non-heaped mean inflation expectations are close to average U.S. inflation from roughly 2005 through 2020 (see Figure 6 for kernel density functions of heaped and non-heaped inflation expectations from all simulations and Figure 7 for the corresponding cumulative distribution functions of mean inflation expectations from the individual simulations). This is also true if we increase these parameters to produce higher expected inflation and higher variance in the non-heaped data (see Figure 8 and Figure 9). However, it is also possible that heaping could lead to underestimating inflation whenever mean inflation in the non-heaped data is sufficiently close to zero, suggesting that surveys could lead policymakers to believe mean expected inflation is too pessimistic during prolonged episodes of sufficiently low inflation (see Figure 10 and Figure 11).

This evidence also brings to light a critical issue in survey-based research: the reliability of statistical measures derived from heaped data. Heaping can potentially distort both the mean expectations and the sample variance. Such misrepresentations can lead to incorrect standard errors and, consequently, affect the accuracy of coefficient estimates. This distortion is particularly problematic in survey data, where decision-making often relies on precise statistical analyses. Thus, understanding and accounting for heaping effects is essential for accurate data interpretation and making informed inferences from survey results. This highlights the importance of considering data quality and handling practices in survey-based research to ensure validity and reliability.

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5 Appendix

5.1 Additional Figures

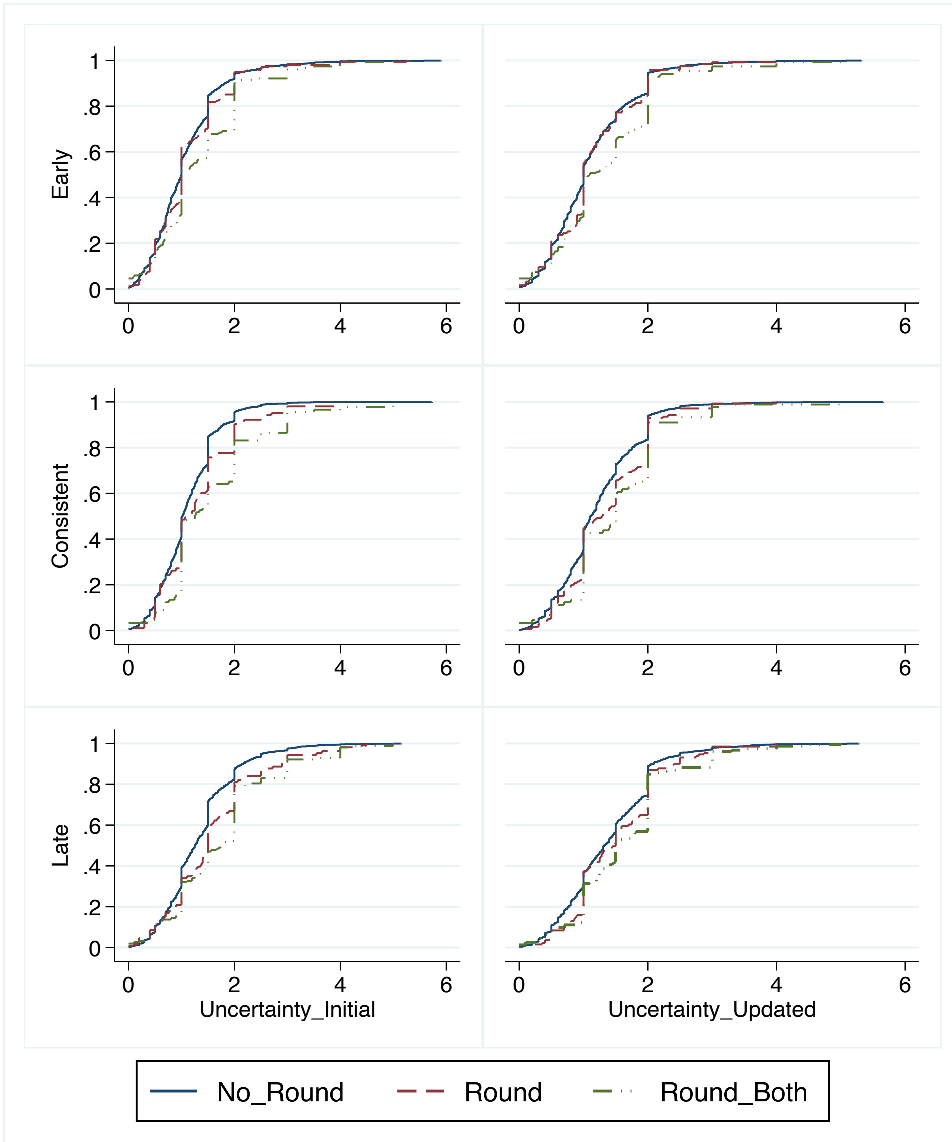
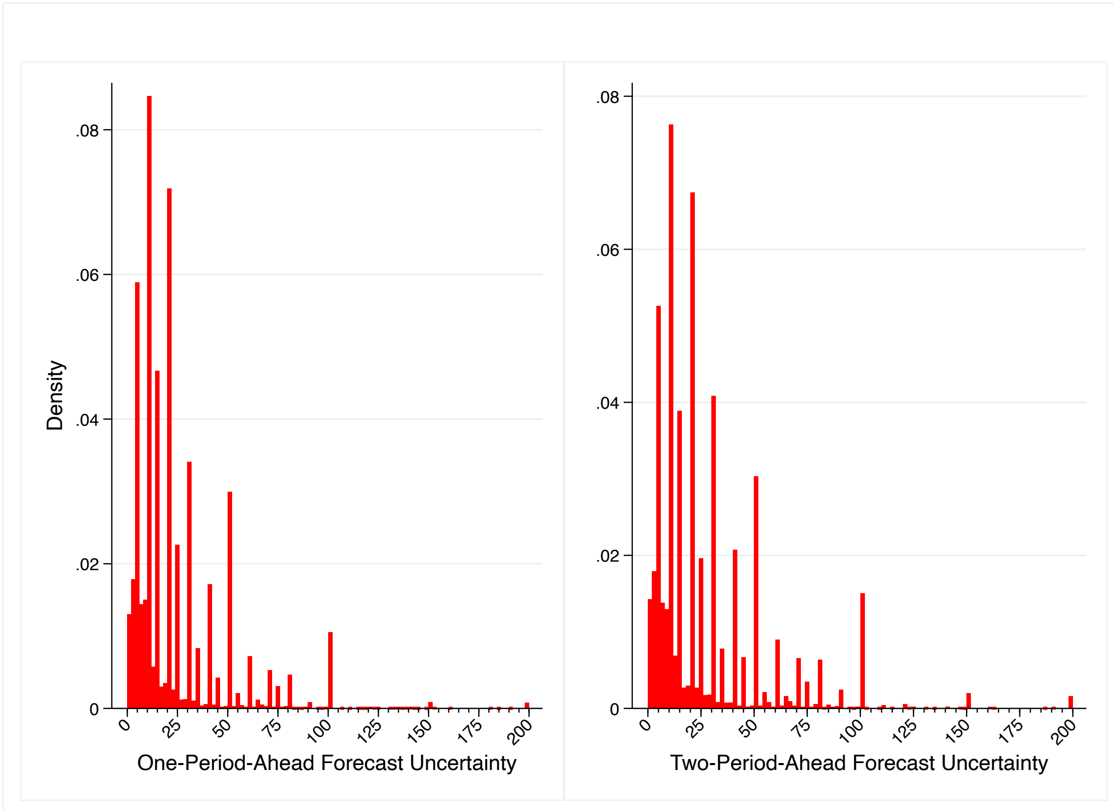
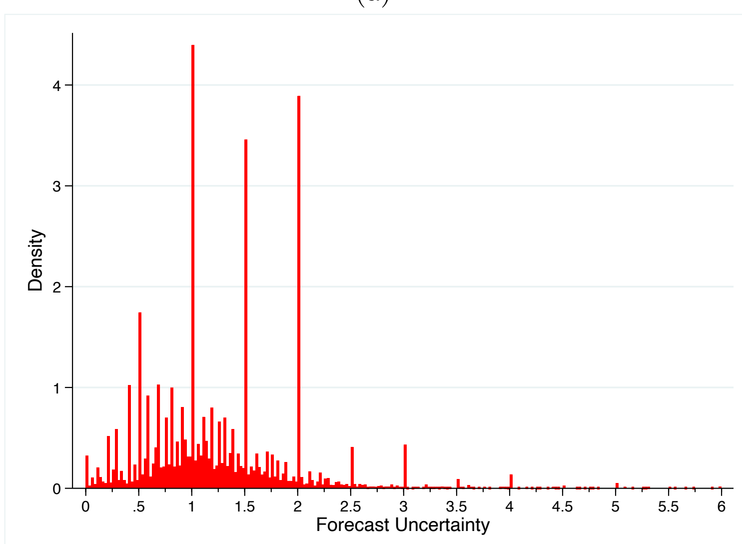


Figure 3: This figure shows cumulative density functions (CDFs) of individual-level forecast uncertainty before (left) and after (right) the central bank publishes its own point projection. 'Round' means a subject rounded for only the corresponding inflation forecast. 'Round_Both' means the subject rounded when providing both the initial and updated forecasts for that history. We define a rounder as any subject i where $(\mathbb{E}_{i,t}\pi_{t+1} \ mod \ 1)$=0.



(a)



(b)

Figure 4: This figure shows histograms of individual-level forecast uncertainty for RPU (panel a) and MRC (panel b) data.

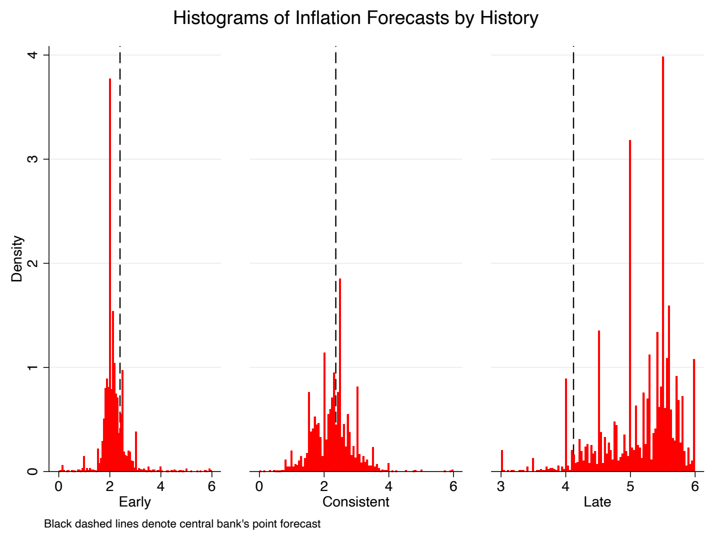


Figure 5: This figure shows histograms of point forecasts for *Early*, *Consistent*, and *Late*.

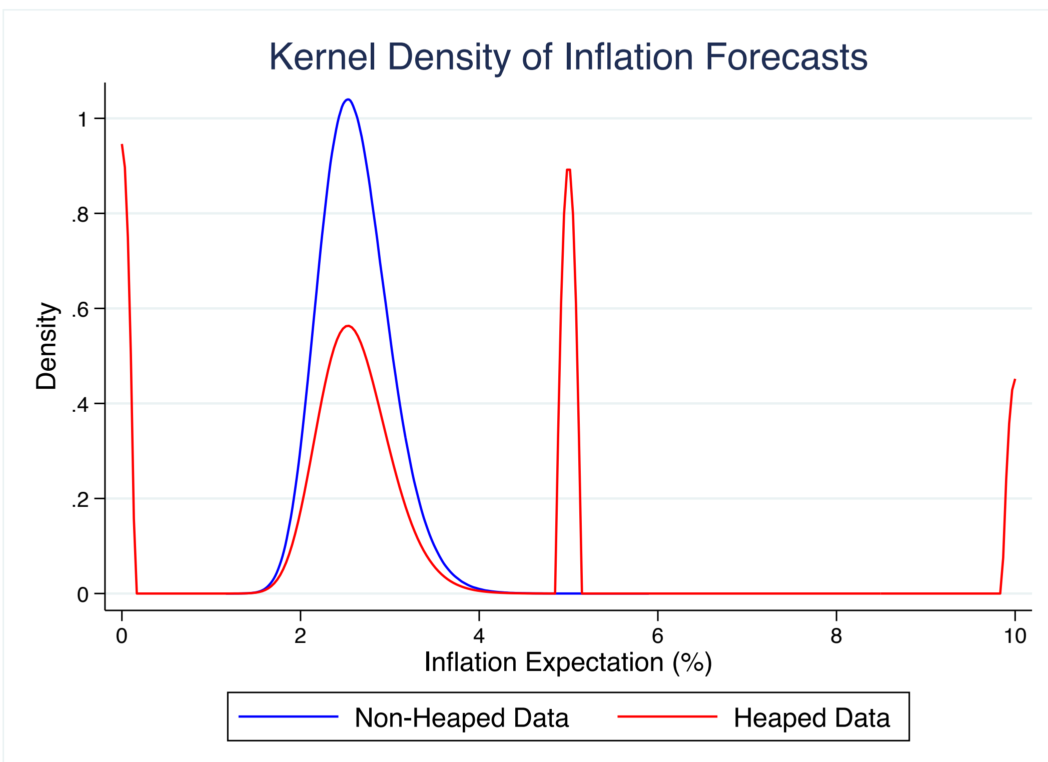


Figure 6: Kernel density functions of inflation expectations - Low mean and variance

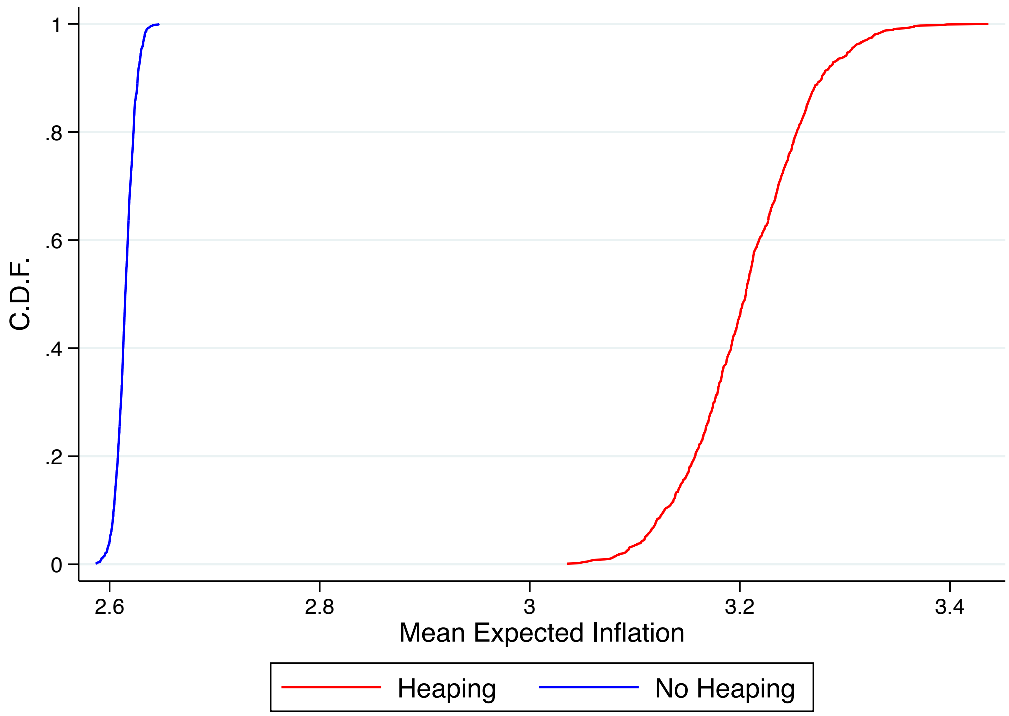


Figure 7: Cumulative density functions of average expected inflation across simulations - Low mean and variance

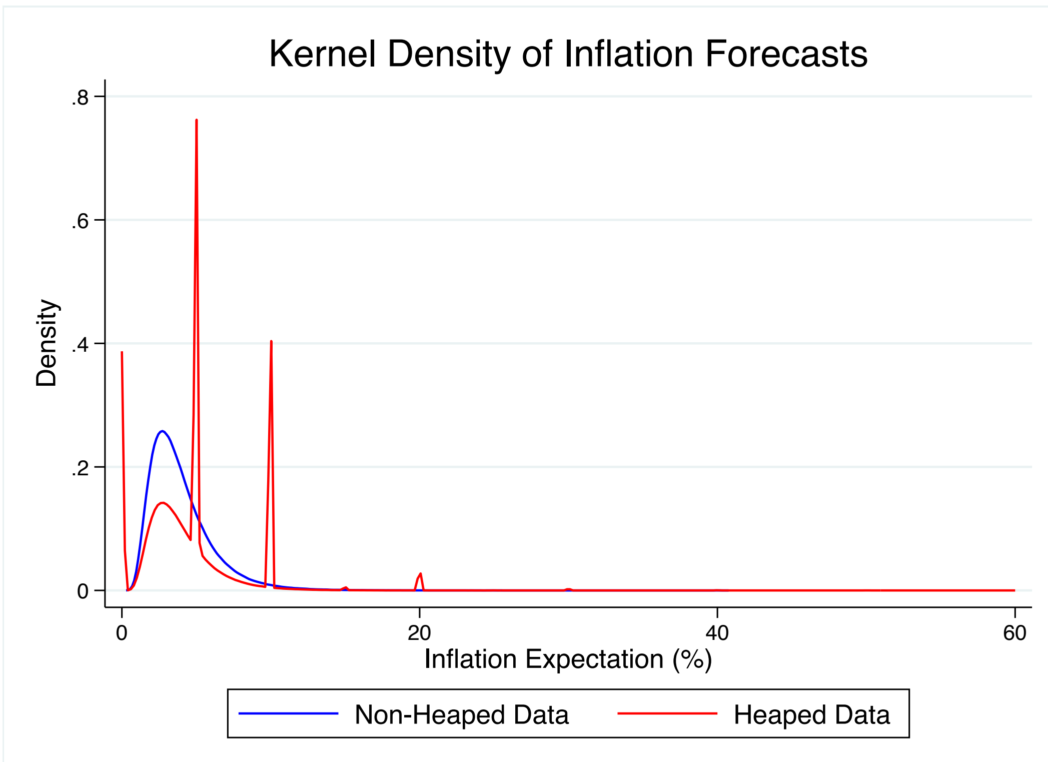


Figure 8: Kernel density functions of inflation expectations - Higher mean and variance

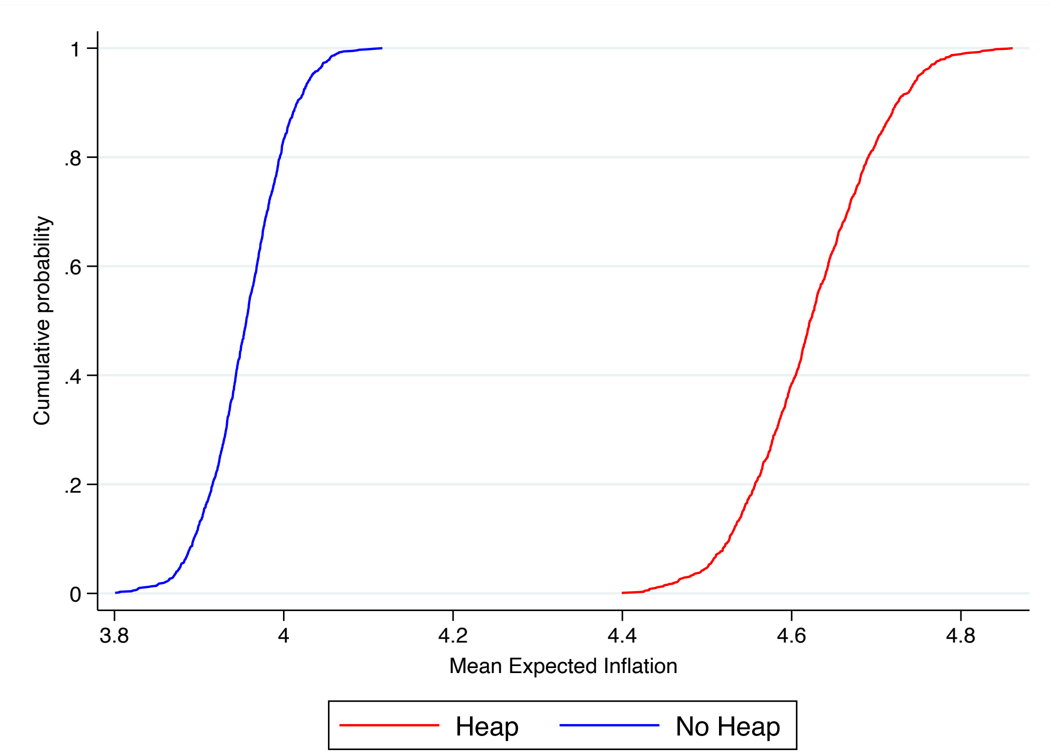


Figure 9: Cumulative density functions of average expected inflation across simulations - Higher mean and variance

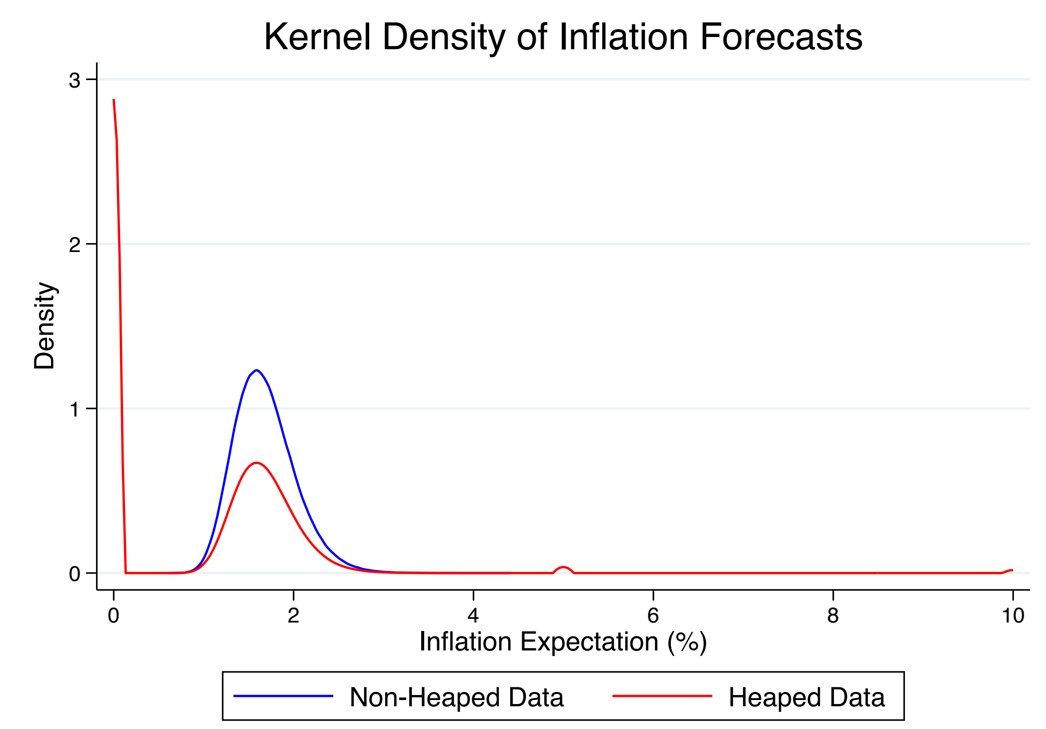


Figure 10: Kernel density functions of inflation expectations - nearly-zero mean with low variance

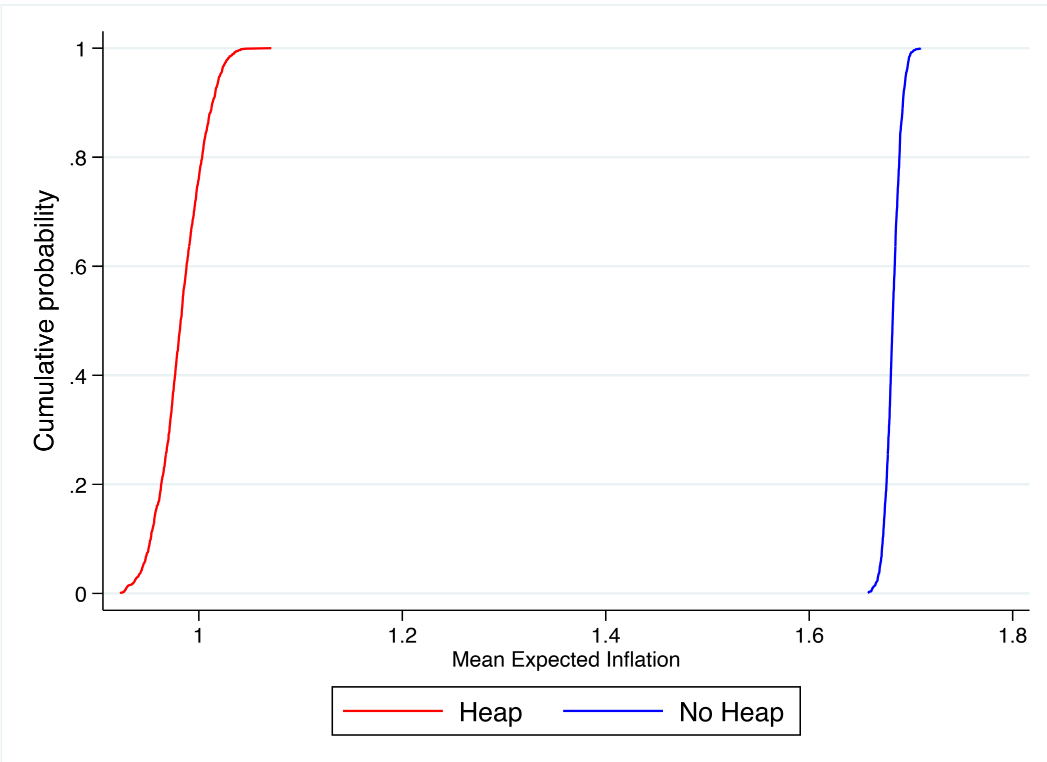


Figure 11: Cumulative density functions of average expected inflation across simulations - nearly-zero mean with low variance

5.2 Additional Tables

5.3 Reclassifying 0s in RPU data

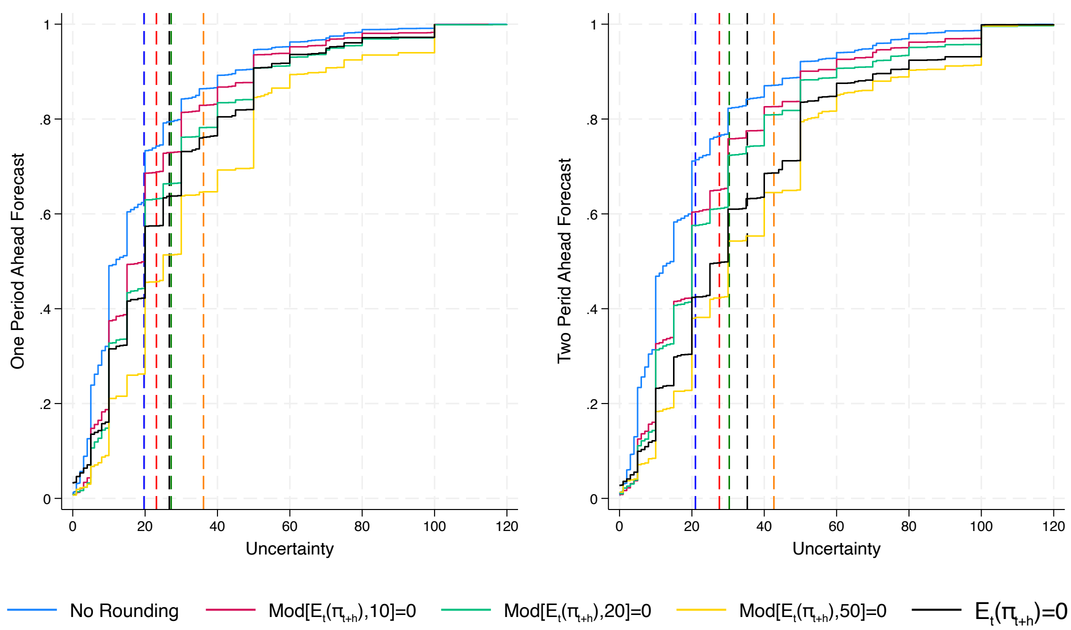
Because the stochastic steady state in the RPU experiments is zero, inflation outcomes in that data are often close to zero. Because of this, it is unclear exactly how we ought to classify subjects in that setting who forecast inflation to be exactly 0. For example, these may be rational forecasters. On the other hand, a forecast of zero aligns with any of our rounding classifications.

In our main analysis, these subjects are classified $r_{50}^{RPU,h}$. Section 5.3 shows the frequency of these sorts of forecasts in the RPU data. However, we might also consider giving these subjects their own unique classification. To do this, we add a fourth rounding category for our RPU data – $r_0^{RPU,h}$ for any forecast of inflation being exactly equal to zero at the $t+h$ horizon.

Table 5: Rounding Decisions and Uncertainty - Reclassifying Zeros

	RPU Data (h=1/h=2)					
	(1) **Abv.**	(2) **Decisions**	(3) **%**	(4) **% Cumulative.**	(5) **Mean**	(6) **Std. Error**
No Rounding	$(r_{NR}^{RPU,h})$	8,973 / 8,654	51.78 % / 49.94 %	51.78 % / 49.94 %	19.69/20.98	.22/.24
$(\mathbb{E}_{i,t}(\pi_{t+h}) = 0$	$(r_0^{RPU,h})$	2,986 / 3,045	17.23 % / 17.57%	69.02% / 67.52 %	23.12/27.6	.39/.48
$(\mathbb{E}_{i,t}(\pi_{t+h})\ mod\ 10) = 0$	$(r_{10}^{RPU,h})$	2,986 / 3,045	17.23 % / 17.57%	69.02% / 67.52 %	23.12/27.6	.39/.48
$(\mathbb{E}_{i,t}(\pi_{t+h})\ mod\ 20) = 0$	$(r_{20}^{RPU,h})$	2,756 / 2,478	15.90 % / 14.30 %	84.92% / 81.82%	27.188/30.32	.49/.6
$(\mathbb{E}_{i,t}(\pi_{t+h})\ mod\ 50) = 0$	$(r_{50}^{RPU,h})$	2,613 / 3,151	15.08 % / 18.18 %	100%	31.40/38.06	.53/.58

This table shows the result of classification at the decision level in the RPU data where an inflation forecast of zero receives its own classification. There are 17,328 decisions total from 584 unique subjects in the RPU data. Mean values and corresponding standard errors are in basis points. Here, $(\mathbb{E}_{i,t}(\pi_{t+h})\ mod\ x) = 0$ means that $\frac{\mathbb{E}_{i,t}(\pi_{t+h})}{x} \in \mathbb{I}$.



(a)

Figure 12: This figure shows cumulative distributions functions of individual-level forecast uncertainty for different rounding groups from the RPU data where we include a unique classification for inflation forecasts of zero.