Should central banks communicate uncertainty in their projections?*

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Abstract

This paper provides original empirical evidence on the emerging practice by central banks of communicating uncertainty in their inflation projections. We compare the effects of point and density projections in a learning-to-forecast laboratory experiment where participants' aggregated expectations about one- and two-period-ahead inflation influence macroeconomic dynamics. Precise point projections are more effective at managing inflation expectations. Point projections reduce disagreement and uncertainty while nudging participants to forecast rationally. Supplementing the point projection with a density forecast mutes many of these benefits. Relative to a point projection, density forecasts lead to larger forecast errors, greater uncertainty about own forecasts, and less credibility in the central bank's projections. We also explore expectation formation in individual-choice environments to understand the motives for responding to projections. Credibility in the projections is significantly lower when strategic considerations are absent, suggesting that projections are primarily effective as a coordination device. Overall, our results suggest that communicating uncertainty through density projections reduces the efficacy of inflation point projections.

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1 Introduction

Central banks have become increasingly transparent over the last few decades, with most banks now disclosing information surrounding operations, procedures, economic outlook and policy. This transparency revolution is driven largely by a deeper understanding of the importance of expectations, central bank credibility, and of the ability of communication to function as a policy tool.

A prominent feature of transparency is the publication of macroeconomic projections. As argued by Greenspan (2004), forming and communicating macroeconomic projections plays as an important role in the preemptive response of policy makers to inflationary pressures. Such forecasts not only play an important internal role in policy deliberations, but also provide market participants with insight into how the central bank thinks the economy and policy rate may evolve. Projections align private-sector expectations and improve forecast accuracy in theory (Geraats (2002), Woodford (2005), Rudebusch and Williams (2008), Gosselin et al. (2008), Blinder et al. (2008)), experiments (Kryvtsov and Petersen, 2015, 2020, Mokhtarzadeh and Petersen 2018, Ahrens et al. 2019), and in practice (Brubakk et. al. (2017), Hubert (2014, 2015), Blinder et al. (2008), and Kool and Thornton (2015)).

However, central banks are communicating in an uncertain world. Not only are the timing and magnitude of the effects of monetary policy uncertain, but so are the shocks the economy faces. Consequently, many central banks publish density forecasts, rather than just point projections, in an effort to convey a subjective measure of uncertainty about economic outlook and the future path of policy and to preserve credibility. Density forecasts typically convey the same information contained in point forecasts, but also present the central bank's uncertainty surrounding its projections (second moment) and the bank's outlook on risk (third moment). The Bank of England was the first to publish 'fan charts' of its macroeconomic projections in 1998, with the Federal Reserve, the European Central Bank, the Reserve Bank of Australia, the Bank of Canada, and the Swedish Riksbank following suit.

Despite the growing trend of central banks communicating uncertainty by publishing density forecasts, there exists almost no empirical or theoretical evidence that this improves the ability of central bank projections to influence markets, or coordinate and improve private forecasts. One exception is Rholes and Sekhposyan (2020) who show that short-term yields respond at least as strongly to revisions of the second- and third-moments of the BoE's density forecasts as they do to revisions of the first-moment of the same density forecasts.[1] In closely related experimental work, Mokhtarzadeh and Petersen (2018) show that density projections (that present both the point forecast and a confidence interval) are effective at managing expectations if they are relevant and easy to understand. Their findings, however, do not isolate the effect of density forecasts from the point projections.

This paper provides original empirical evidence on the effects of point and density forecasts on the management and formation of inflation expectations. We systematically vary inflation projection announcements communicated by the economy's automated central bank within a macroeconomic learning-to-forecast laboratory experiment where groups of participants simultaneously form inflation expectations. We incentivize participants to form accurate one- and two-period-ahead inflation expectations. Aggregated expectations endogenously influence macroeconomic dynamics. Given participants' potentially bounded rationality, there is a role for central bank communication to guide expectations. We also elicit participants' confidence about their forecasts, allowing us to clearly identify the transmission of central bank uncertainty to forecasters.

We consider three levels of central bank communication in a between-subject design: No supplementary communication, five-period ahead point projections, and five-period ahead point and density projections. Both projections are based on the assumption that agents form ex-ante rational expectations. Density projections are symmetric one-standard deviation confidence intervals around the point projection. This variation allows us to disentangle the effects of communicated uncertainty on expectation formation.

Relative to a baseline of no communication, we find that point projections reduce disagreement and uncertainty about future inflation, and medium term (two-period-ahead) forecast errors. Moreover, point projections increase the proportion of inexperienced participants who forecast one-period-ahead inflation as if they were ex-ante rational by 72 percentage points for a total of 86% of participants.

Density projections mute the beneficial effects of point projections. Compared to point projections, communicating density forecasts significantly increase forecast errors, uncertainty, and disagreement about two-period-ahead inflation. Credibility in the central bank's point projection is significantly lower when it includes a density forecast. Only 57% of inexperi-

[1] Uncertainty about monetary policy can have negative economic effects. See Neely (2005), Swanson (2006), Bauer (2012), Husted, Rogers, and Sun (2018, 2019) for discussion.

enced participants in density treatments form rational one-period-ahead expectations.

It is also important to understand why projections have proven effective at managing real-word expectations. Is it because economic agents use publicly communicated projections purely as a coordination device or do the projections provide valuable information that forecasters and market participants use to improve forecast accuracy? To answer this question, we conduct the same communication treatments in an individual-choice environment absent any strategic considerations. In both Individual and Group treatments, the projection provides information and, more importantly, reduces the complexity of the forecasting problem. In the Group treatments, there is an additional strategic consideration. Group participants should use the projection if and only if they believe the majority of participants will.

Thus, our individual-choice treatments have participants play the role of the representative forecaster, with their own expectations employed as the aggregate expectation driving macroeconomic dynamics. Our motivation for this treatment is to investigate whether people choose to use projections because of their information content or as a coordination device. Thus, our individual-forecaster treatment eliminates any coordination motives. Though this individual setting lacks some degree of external validity, it allows us to tease apart and understand the motives underlying central bank projections. We expose participants in our individual-choice treatments to the same three levels of central bank communication used in our group setting. This allows us to draw inference about the effect of strategic motives on how subjects use central bank forecasts when forming expectations. To the best of our knowledge, this is the first learning-to-forecast experiment to compare individual vs. group forecasting behaviour.

Absent strategic motives, participants are significantly more heterogeneous in their forecasts and form larger forecast errors. Individual forecasters also anticipate making larger forecast errors when they have no supplementary communication from the central bank, suggesting that the wisdom of the group improves confidence. Point projections reduce individuals' two-period-ahead forecast errors, though not as effectively as in group settings. Neither point projections nor density projections consistently reduce disagreement or uncertainty in Individual treatments. Our findings suggests that the information content associated with projections is not as valuable as their ability to serve as a coordination device.

Finally, our experimental results provide useful guidance for the modeling of inflation expectations. First, we find ample evidence to suggest that a large majority of participants will adopt an as-if rational heuristic when they observe a rationally-constructed inflation point projection. Second, most participants use the same heuristics to formulate both their short and medium term expectations.

2 Experimental Design

Our experiment seeks to understand how central bank point and density projections influence expectations and aggregate dynamics. To this end, we study a 'learning-to-forecast (LTF)' experimental macroeconomy that uses either the aggregate expectations of groups or the expectations of individuals, depending on the treatment, to influence aggregate variables. Such experimental economies are well-studied. Macroeconomists have used similar experiments to study expectation formation and equilibria selection (Adam, 2007), the effects of different monetary policy rules and targets on expectation formation (Pfajfar and Žakelj 2014, 2018; Assenza et al. 2013, Hommes et al. 2019a; Cornand and M'Baye, 2018a), expectation formation at the zero lower bound (Arifovic and Petersen 2017, Hommes et al. 2019b), and the endogenous dynamics of expectations and real decisions (Bao et al., 2013). Learning-to-forecast experiments have been shown to reasonably match inflation forecasting patterns observed in surveys of households, firms, and professional forecasters (Cornand and Hubert, 2019).

We are also interested in understanding how subjects' own uncertainty about future inflation responds to both precise and noisy central bank projections. Pfajfar and Žakelj (2016) also explore uncertainty in response to different inflation targeting regimes. Similarly, our paper is closely related to Cornand and M'baye (2018b), in which the authors use an LTF framework to explore the relative merits of point and band inflation targeting. The authors find that during periods of low uncertainty, band targeting better stabilizes inflation. Also, point targeting with tolerance bands leads to a lower and less volatile output gap and interest rate. The authors also find that both regimes are equally ineffective at stabilizing macroeconomic dynamics during periods of high uncertainty. Our paper differs from theirs in that, rather than varying the central bank's targeting regime, we use a single point inflation target and vary the central bank's communication strategy.

We begin by describing the design of our baseline environment, which involves groups of seven participants playing the roles of forecasters in an environment with no supplementary central bank communication. In Section 2.3, we describe how the environment changes as we allow for individually-driven economies and central bank projections.

We summarize the flow of information, decisions, and outcomes throughout the experiment in Figure 1. Each experiment consists of two different sequences of 30 sequentially linked periods. In each period $t \in [1, 30]$, participants submit forecasts about $t+1$ and $t+2$ inflation, as well as predictions about the magnitude of their forecast errors.

At the beginning of each period, subjects observe all historical information about inflation, the nominal interest rate, and demand shocks. Importantly, subjects can also observe the value of the current-period demand shock.[2] Subjects also observe their own history of one- and two-period-ahead inflation forecasts and total earnings.

Insert Figure 1

Subjects had 65 seconds to form forecasts in periods 1-9 of each sequence and 50 seconds thereafter. Inflation expectations and corresponding uncertainty forecasts were submitted in basis points. Inflation forecasts could be positive, negative, or zero. Uncertainty measures could be either zero or positive. All submissions were unbounded. Since we collect forecast in terms of basis points, subjects could submit forecasts with a precision of $\frac{1}{100}$th of 1%.

After all subjects submitted expectations or time elapsed, participants moved onto the next period. The economy's data-generating process, which will be described in the next subsection, relies on aggregate one- and two-period-ahead inflation expectations. We use the median forecasts, rather than the average, as the aggregate expectations to curtail the impact that any one subject can have on our experimental economies. This has the effect of making it as though forecasters are atomistic.

2.1 Data-generating process

Each treatment shares a common data-generating process, which is derived from a log-linearized, representative-agent New Keynesian (NK) framework We re-write this model to eliminate the need for expectations about the one-period-ahead output gap. This manipulation of the NK model allows us to use a system of equations driven by one- and two-period-ahead inflation expectations and aggregate disturbances. Thus, we need only elicit $\mathbb{E}_t\{\pi_{t+1}\}, \mathbb{E}_t\{\pi_{t+2}\}$ from our subjects. See the Online Appendix Section B for details about the differences in stability and forecast errors in the two formalizations.

[2]Subjects have sufficient information to calculate the expected value of future shocks and can incorporate this, if they desire, into current-period forecasts.

We begin with a standard 4-equation, reduced-form NK model

$$\pi_t = \beta \mathbb{E}_t\{\pi_{t+1}\} + \kappa x_t \tag{1}$$

$$i_t = \phi_\pi \pi_t + \phi_x x_t \tag{2}$$

$$x_t = \mathbb{E}_t\{x_{t+1}\} - \sigma^{-1}[i_t - \mathbb{E}_t\{\pi_{t+1}\} - r_t^n]. \tag{3}$$

We eliminate the need to elicit $\mathbb{E}_t\{x_{t+1}\}$ by rewriting (3), iterating forward, taking expectations, applying the law of iterated expectations, and substituting to obtain:

$$x_t = (\kappa^{-1} + \sigma^{-1})\mathbb{E}_t\{\pi_{t+1}\} - \beta\kappa^{-1}\mathbb{E}_t\{\pi_{t+2}\} - \sigma^{-1}i_t + \sigma^{-1}r_t^n. \tag{4}$$

Substitutions yield a representation of (3) that depends only on inflation expectations,

$$\pi_t = [\beta + \kappa\gamma_1\gamma_2]\,\mathbb{E}_t\{\pi_{t+1}\} - \gamma_1\beta\mathbb{E}_t\{\pi_{t+2}\} + \kappa\gamma_1\sigma^{-1}r_t^n, \tag{5}$$

where we use the following variable substitutions

$$\gamma_1 = \left(\frac{\sigma + \phi_\pi\kappa + \phi_x}{\sigma}\right)^{-1} \tag{6}$$

$$\gamma_2 = (\kappa^{-1} + \sigma^{-1} - \sigma^{-1}\phi_\pi\beta). \tag{7}$$

This yields a dynamical system that can be solved using $\mathbb{E}_t\{\pi_{t+1}\}, \mathbb{E}_t\{\pi_{t+2}\}$, r_t^n. Here, r_t^n represents a demand shock that evolves following an AR(1) process,

$$r_t^n = \rho_r r_{t-1} + \epsilon_{r,t} \tag{8}$$

where $\epsilon_{r,t}$ is i.i.d. $\sim \mathcal{N}(0, \sigma_r)$ and ρ_r is a persistence parameter. The data-generating process is calibrated to match moments of Canadian data following Kryvtsov and Petersen (2015); $\sigma = 1$, $\beta = 0.989$, $\kappa = 0.13$, $\phi_\pi = 1.5$, $\phi_x = 0.5$, $\rho_r = 0.57$, and $\sigma_r = 113$ bps, with a steady state of $\pi^* = x^* = 0$

Given these parameters, the system of equations reduces to

$$\pi_t = 1.54\mathbb{E}_t\{\pi_{t+1}\} - 0.58\mathbb{E}_t\{\pi_{t+2}\} + 0.08r_t^n \tag{9}$$

$$i_t = 4.44\mathbb{E}_t\{\pi_{t+1}\} - 3.12\mathbb{E}_t\{\pi_{t+2}\} + 0.41r_t^n. \tag{10}$$

We use aggregate expectations provided by participants to close the model. Aside from Adam (2007), this is the only experiment within a NK framework that elicits expectations for two future time periods. However, this particular formulation of the NK model is novel to the learning-to-forecast literature. This formulation accomplishes two things. First, it reduces the cognitive complexity subjects face by allowing them to focus on forecasting a single time series. Second, it allows us to understand how these information conditions affect expectations further into the future than would be possible otherwise.

Worth noting here is the counter-balancing effect of expectations on this system. Equation (9) and Equation (10) retain the familiar feature that one-period-ahead expectations are self-fulfilling, but we also observe, counter-intuitively, that two-period-ahead expectations are not self-fulfilling. However, this counter-balancing of expectations makes sense from the perspective of consumption smoothing. Expecting higher prices tomorrow encourages an agent to consume more today to avoid the higher prices tomorrow. This behavior puts upward pressure on prices today, leading to higher inflation today. If an agent also expects inflation two days from now, then they will want to have more money to spend tomorrow than otherwise, so that an agent can similarly avoid paying higher prices two days from now. As we show in the Online Appendix, this particular presentation of the DGP does not alter the qualitative benefits of rationally–constructed central bank projections.

2.2 Payoffs

We incentivized forecasts using the scoring rule described by Equation (11). Notice that F_{it} exhibits exponential decay as that forecaster $i's$ absolute forecasting error increases.

$$F_{it} = 2^{-.5|\mathbb{E}_{i,t-1}\{\pi_t\}-\pi_t|} + 2^{-.5|\mathbb{E}_{i,t-2}\{\pi_t\}-\pi_t|} \tag{11}$$

Subjects received payoffs for all forecasts about $t+1$ formed in $t \in [1, 29]$ and $t+2$ forecasts formed in $t \in [1, 28]$. Subjects in our experiment also provided measures of uncertainty about their one- and two-period-ahead inflation forecasts, which we denote here as $u_{i,t+1}, u_{i,t+2} \in \mathbb{N}_0$. This measure of uncertainty creates a subject-level density forecast in each period for both forecast horizons. We assume a subject's forecast uncertainty is symmetric around her point forecasts, which is similar to our assumption about the central bank's forecast uncertainty. We incentive this uncertainty measure using a piece-wise scoring rule.[3] A subject earns nothing if actual inflation fall outside her density forecast (i.e., her uncertainty bands). Otherwise, a subject earns $U_{i,t+k}$, where $k = \{1, 2\}$:

[3] A concern here is that this scoring rule may only be incentive-compatible with risk-neutral agents. A risk-loving agent may slightly under-report her uncertainty while a risk-averse agent may slightly over-report uncertainty. However, we can distinguish neither risk-loving behavior from overconfidence nor risk-averse behavior from under-confidence.

$$U_{i,t+k} = \frac{15}{10 + u_{i,t+k}} \tag{12}$$

The payoff that participants receive for their error forecast decreases in the level of their forecasted error. Because we incentivize uncertainty measures for each forecast horizon, a subject could earn a total of three points in each period for her uncertainty measures. This scoring rule is similar to the rule used in Pfajfar and Žakelj (2016), which studied the effect of various monetary policy rules on individual uncertainty.[4] To address the possibility of hedging, we randomly selected at the session level in each period whether to pay F or $U_{t+1} + U_{t+2}$. However, we never paid both in the same period.

2.3 Treatments

We used a 3x2 between-subject experimental design to study the effects of central bank communication and strategic motives on expectation formation and aggregate dynamics. Table 1 summarizes the treatments.

Subjects formed forecasts under one of three information conditions: a baseline where a mechanistic central bank provided no projections (NoComm), a projection-only treatment where the central bank provided an evolving five-period-ahead point forecast of inflation (Point), and a density forecast treatment where the central bank provided both an evolving five-period-ahead point forecast point and density forecast of inflation (Point&Density).

We also varied the environment along a coordination dimension. Subjects either participated in a Group treatment, where they interacted in an experimental economy with six other subjects, or an Individual treatment, where each subject served as the sole forecaster in her experimental economy. In other words, subjects in Individual treatments played an individual choice game; their expectations alone, coupled with the demand shock, drove the dynamics of their economies. Subjects in Individual treatments understood that they each inhabited a unique economy.

Insert Table 1

Participants interacted in an online platform. See Figure 2 for an example of the NoComm interface, Figure 3 for the Point interface, and Figure 4 for the Point&Density interface. Subjects in all treatments always interacted with the same screen in each decision period.

[4] Pfajfar and Žakelj (2016) elicit participants' own 95% confidence intervals around their point forecasts.

The screen updated to display new information as that information became available.

Aside from the communications from the central bank, all participants received common information. The top left corner of a subject's screen showed the subject's identification number, the current decision period, time remaining to make a decision, and the total number of points earned through the end of the previous period. The interface also featured three history plots. The top history panel displayed past interest rates, and both past and current shocks. The second panel displayed the subject's one-period-ahead inflation forecast (blue dots), the subject's uncertainty surrounding this one-period-ahead forecast (blue shading), and all realized values of inflation (red dots). The third history panel displayed the subject's two-period-ahead inflation forecast (orange dots), the subject's uncertainty surrounding this two-period-ahead forecast (orange shading), and all realized values of inflation (red dots).

Treatment variation appeared in the second and third history panels. Notice in Figure 2 (NoComm) that the central bank provided neither point nor density forecasts. In Figure 3 (Point) the second and third history plots displayed the central bank's evolving, five-period-ahead point forecast (green dots). Finally, the second and third history plots in Figure 4 (Point&Density) contained the central bank's evolving five-period-ahead point forecast (green dots) with its corresponding level of uncertainty (green shading).

We explained to subjects in both Point and Point&Density treatments that the central bank's projections were not a guarantee, thus indicating that there is some level of uncertainty surrounding the central bank's projections. We also explained to subjects that the central bank's forecasts are based on the DGP and all available information to emphasize the potential errors in the central bank's projection model.

We further indicate in Point&Density treatments that the density forecast represents the central bank's own uncertainty about its point projections. Our exact phrasing was: "These forecasts also include green shading, which represents the Central Bank's level of uncertainty for its corresponding point projections. These bands will contain the correct realization of inflation about 66% of the time."

The level of fundamental uncertainty is always the same because it is driven by the shock process, which is quantitatively conveyed to participants in the instructions. The density treatment does not provide any new information in this regard. It only changes the salience of the uncertainty in the environment.

The mechanistic central bank in our experiment always used a symmetric density forecast. However, this is not always true of density forecasts provided by real-world central banks. An interesting extension to this project would be studying how forecasters react to asymmetric density forecasts. This is akin to studying how forecasters incorporate information contained in the skewness (third central moment) of a central bank density forecasts, which we can think of intuitively as a bank's outlook on economic risks. Finally, we note that the mechanistic central bank assumed that the aggregate expectation in each experimental economy was ex-ante rational. The central bank's density forecast was simply a one standard-deviation band centered around its point forecast.[5]

We conducted six independent sessions of each of the six treatments for a total of 36 experimental sessions. Each session consisted of two, 30-period repetitions (decision blocks). For a given session, we randomly drew a shock sequence for two repetitions from our theoretical distribution of shocks. Within a treatment, we drew six different shock sequences (or 12 if you count each repetition). We then used the same shock sequences across treatments for comparability. Usage of different shock sequences allows for a more robust analysis of expectation formation.

Finally, we initialized each experimental economy at the zero–inflation steady state. We showed subjects five preceding periods of the economy operating along this steady state before introducing a demand shock in period one. Note that it would not be rational, given that shocks evolve according to an autoregressive process, to forecast zero inflation for periods two or three.

2.4 Procedures

The experiments were conducted at Simon Fraser University from October 2019 to January 2020. We began each session by reading aloud from paper instructions that included detailed information about subjects' forecasting task, the uncertainty measurement task, how we incentivize forecasts and uncertainty, and how the experimental economy evolved in response to expectations and aggregate shocks. Participants knew they could use the computer's calculator or spreadsheets if desired.

[5] Mokhtarzadeh and Petersen (2020) show experimentally that both the assumptions underlying central bank projections and the information communicated alongside projects matter for expectations formations and aggregate stability. Thus, it seems reasonable that additional information about perceived risk could change how agents incorporate information contained in other forecast moments.

Following the instructions, subjects played four unpaid practice periods during which they could ask questions. Following the practice periods, subjects played through the two incentivized sequences. Each sequence employed a different variation of the shock sequence so that subjects did not repeat an identical game in the second block of decisions. We paid subjects in cash immediately following each experimental session. Payoffs, including a CDN$7 show–up fee, ranged from CDN$12-25, and were on average CDN$21.

2.5 Hypotheses

Our experimental design allows us to test several hypotheses regarding differences in how point and density forecasts impact aggregate dynamics and individual behavior. Further, we are able to test hypotheses regarding how subjects use information differently when they face the strategic considerations present in a coordination setting.

If all subjects in our experiment are model–consistent and have full information about the data–generating process (as they do), then we should observe that neither projection (Point or Point&Density) changes aggregate dynamics or individual behavior relative to one another or the NoComm setting. The projections would be irrelevant because they would neither increase the information set of agents (as the mechanistic central bank does not have more information than our subjects) nor impact how agents use available information. Further, model-consistent subjects would behave equivalently when forming expectations in both individual-choice and coordination settings since they possess the same information.

However, ample laboratory and survey evidence demonstrate that individuals, rather than conforming to rational expectations, form expectations in a backward-looking manner (See Assenza et al., 2013; Pfajfar and Santoro, 2010; Pfajfar and Žakelj 2014; Coibion and Gorodnichenko, 2015; Malmandier and Nagel, 2016). In a closely related experiment, Mokhtarzadeh and Petersen (2020) show that, in the absence of central bank forecasts, most subjects follow either a Constant Gain Learning model or an Adaptive(1) heuristic, whereby they equally weight historical information and the ex-ante rational forecast when forming expectations. Backward-looking heuristics also explain behavior in Pfajfar and Žakelj (2016), Cornand and M'Baye (2018b), and Hommes et al. (2019).

Further, extensive empirical and experimental evidence supports the notion that central bank forecasts have effectively coordinated private-sector expectations and stabilized markets (Hubert 2014, 2015, Jain and Sutherland, 2018, Mokhtarzadeh and Petersen, 2018, Ahrens et al. 2018, Kryvtsov and Petersen, 2020).

Figure 5 presents simulated standard deviations of inflation and mean absolute forecast errors under various forecasting heuristics and parameterizations. See Table 7 for the underlying models and the Online Appendix Section B for a comparison of statistics under the one-period and two-period ahead version of the linearized New Keynesian model under alternative heuristics.

Simulations show that inflation variability and forecast errors are strongly positively correlated. Variability and errors are high when the representative agent adopts simple heuristics such as trend-chasing, Adaptive(1), naive, and constant gain learning. Under all these heuristics, the agent uses a misspecified model that relies on historical data, which introduces persistence into the economy. Further, these heuristics yield relatively unstable dynamics because ad-hoc monetary policy is unable to compensate for the agents non-rational expectations.[6] We expect simple heuristics such as naive, trend-chasing, and constant gain learning models to dominate given past experimental findings in similar experiments (Cornand and MBaye, 2018a; Pfajfar and Zakelj, 2014 and 2016; Petersen and Rholes, 2020).

While forecasting the inflation target for one- and two-period-ahead inflation would produce the lowest volatility and the smallest forecast errors of any of the non-rational alternatives we consider, we believe it is unlikely that subjects will adopt this heuristic. This is because participants have full information about the economys data-generating process and know that monetary policy is unable to perfectly offset the exogenous demand shocks.

Heuristics that employ some degree of rational expectations (e.g. Adaptive(1) and ex-ante rational) are considerably more sophisticated and unlikely to be used by most subjects. However, both inflation variability and forecast errors are substantially lower if agents form ex-ante rational expectations. Thus, there is value in easy-to-understand central bank communication that can guide boundedly-rational agents to forecast rationally.

Insert Figure 5 here

To illustrate how projections can manage expectations and uncertainty, we consider the beliefs of a Bayesian-updating agent. We suppose there is some true state of the world π_{t+s}

[6] Note that under optimal monetary policy, the central bank would be able to offset the demand shock and perfectly stabilize inflation given the agents expectations.

and that both our economic agent i and our central bank form beliefs about π_{t+s} equal to the state of the world plus some error,

$$\mathcal{B}_i \equiv \mathbb{B}_{i,t}\{\pi_{t+s}\} = \pi_{t+s} + \delta_{i,t}, \quad \delta_{i,t} \sim \mathcal{N}\left(0, \frac{1}{\psi}\right), \tag{13}$$

$$\mathcal{B}_{CB} \equiv \mathbb{B}_{CB,t}\{\pi_{t+s}\} = \pi_{t+s} + \nu_t, \quad \nu_t \sim \mathcal{N}\left(0, \frac{1}{\omega}\right). \tag{14}$$

$\mathcal{B}_i$ is the ex-ante expectation of agent i about π_{t+s} given complete knowledge about the economy's data-generating process, historical economic information, and the realized shock in period t. $\mathcal{B}_{CB}$ is the central bank's inflation point projection based on an identical information set. Parameters ψ and ω denote the precision (or the reciprocal of the variance) of the distributions of δ and ν, respectively.

Agent i updates her prior of π_{t+s} with the central bank's communicated projection. Her posterior expectation is a linear combination of her private belief and the central bank's public belief,

$$\mathbb{E}_{i,t}\{\pi_{t+s} \mid \mathcal{B}_{CB}, \mathcal{B}_i\} = \frac{\psi\mathcal{B}_i + \omega\mathcal{B}_{CB}}{\psi + \omega}. \tag{15}$$

This Bayseian updating exercise reveals that increasing the precision of the central bank's inflation projection, ω, leads an agent to more heavily weight that projection when forming expectations. This implies that we should see more ex-ante rational forecasters in the Point treatment where the central banks ex-ante rational projections are more precise than in the Point+Density treatment. We show in Figure 5 using simulations that shifting boundedly-rational subjects toward ex-ante rationality will always reduce forecaster errors and, for all but inflation targeters, reduce price volatility. Thus, we hypothesise that surrounding point forecasts with uncertainty will lead to larger forecast errors and more price volatility.

Less sophisticated agents may not fully internalize the uncertainty present in the environment. If so, then communicating uncertainty alongside the central bank's point projection can make the uncertainty salient. Depending on how the central bank communicates its projection, it may influence the perceived value of ω to boundedly-rational agents. For such agents, density projections make salient the model uncertainty surrounding the central bank's point forecast, while point-only projections may obscure the degree of uncertainty in the central bank's outlook.

This framework yields insight into how central bank communicated uncertainty influences private agents' uncertainty, measured as the conditional variance of agent i's forecast of π_{t+s},

$$Var_{i,t}(\pi_{t+s}|\ \mathcal{B}_{CB}, \mathcal{B}_i) = \frac{1}{\frac{1}{\omega} + \frac{1}{\psi}}. \tag{16}$$

Agent i's conditional variance about π_{t+s} is decreasing in her perception of the precision of the central bank's forecast. Thus, for a boundedly-rational agent who conflates the absence of communicated uncertainty with the absence of uncertainty surrounding the central bank's projection, providing a density forecast alongside a point forecast ought to increase individual–level uncertainty.

We also predict that central bank projections will influence the level of disagreement across forecasters. With NoComm, participants have various pieces of information at their disposal to formulate their forecasts: the DGP, historical information, and the current shock. There is no obvious focal point for coordination. By contrast, both Point and Point&Density projections provide a salient focal point projection to coordinate forecasts. Point projections provide a unique single focal point on the rational expectations equilibrium forecast and should lead to the lowest levels of disagreement. Point&Density also provides a greater focus on a one-standard-deviation range of predicted inflation values. Group treatments have a high degree of strategic complementarities; improved coordination due to the projections is also predicted to lower forecast errors.

The effects of communicating uncertainty in central bank projections on central bank credibility will depend on how credibility is measured. We can measure a participant's credibility in the forecast as their willingness to use the communicated point projection. A density forecast would 'wash out' the focal power of point projections, which undermines the ability of point projections to coordinate expectations. In this case, we would expect credibility to be higher in Point than Point&Density. Alternatively, in Point&Density, we can calculate credibility as a participant's willingness to forecast within the central bank's forecasted one-standard deviation range. With this broader definition of credibility, there is more scope for the Point&Density projection to be perceived as credible.

Projections serve two purposes to our subjects in our experiment. The projections reduce the cognitive burden associated with correctly forecasting future inflation (*information motive*). In Group treatments, aggregate expectations are the predominant driver of inflation dynamics, and a subject who aligns her expectations with aggregate (median) expectations is likely to form more accurate expectations. That is, in the Group treatments, inflation projections also provide a salient focal point to coordinate forecasts (*strategic motive*). From this perspective, we expect that projections will be more widely used and be more effective at managing and coordinating expectations in the Group treatments than Individual treatments. This logic aligns with the idea that agents react strongly to public information in environments featuring strategic complementarities, since public signals in these settings are information of the actions of others (i.e. they reduce strategic uncertainty).

On the other hand, the strategic motive to use the projections may be absent in Group treatments if participants do not believe the median forecaster(s) will incorporate the communication into their private forecasts. Participants' best response would be to incorporate their perception of aggregate expectations into their forecast. Furthermore, any increase in central bank uncertainty should make Group participants less confident that the median forecaster will adhere to the central bank's forecast. In this case, projections may be more effective at managing expectations in the Individual treatments than Group treatments.

It is not immediately apparent whether strategic considerations present in the Group treatments will lead to an increased usage of the central bank projections. However, given past experimental evidence that central bank communication can be a useful coordination device (Cornand and Heinemann, 2014; Mokhtarzadeh and Petersen, 2020), we expect the strategic motive to be sufficiently powerful. Increased credibility in the projections in the Group treatments should then lead to more ex-ante rational forecasting, less inflation volatility, and lower forecast errors.

There are some key differences between Individual and Group hypotheses, specifically in the NoComm treatment. Without strategic concerns or an obvious focal point, Individual participants are likely to exhibit more heterogeneity in their inflation forecasts. This, in turn, can lead to higher mean inflation variability if some participants employ more extreme extrapolative forecasting heuristics in Individual than Group. At the same time, participants in Individual have full information about the aggregate forecasts influencing inflation (as it is their own forecasts) and, consequently, should form smaller forecast errors and be more confident about their own expectations than Group participants.

Furthermore, we predict that private uncertainty will be lower in the Individual than in the Group treatments. This is because Individual participants face no uncertainty about the aggregate forecast and thus the expected path of inflation. Similarly, in the absence of strategic complementarities, Individual participants are less likely to be coordinated in their forecasts and so should exhibit more disagreement.

We summarize these aggregate and individual-level predictions in the following hypotheses:

H1.a Inflation volatility$_{NoComm}$ > Inflation volatility$_{Point\&Density}$ > Inflation volatility$_{Point}$

H1.b Inflation volatility$_{Group,NoComm}$ > Inflation volatility$_{Individual,NoComm}$

H1.c Inflation volatility$_{Individual,Point,Point\&Density}$ > Inflation volatility$_{Group,Point,Point\&Density}$

H2.a Forecast errors$_{NoComm}$ > Forecast errors$_{Point\&Density}$ > Forecast errors$_{Point}$

H2.b Forecast errors$_{Group,NoComm}$ > Forecast errors$_{Individual,NoComm}$

H2.c Forecast errors$_{Individual,Point,Point\&Density}$ > Forecast errors$_{Group,Point,Point\&Density}$

H3.a Disagreement$_{NoComm}$ > Disagreement$_{Point\&Density}$ > Disagreement$_{Point}$

H3.b Disagreement$_{Individual}$ > Disagreement$_{Group}$

H4.a Uncertainty$_{NoComm}$ > Uncertainty$_{Point\&Density}$ > Uncertainty$_{Point}$

H4.b Uncertainty$_{Group}$ > Uncertainty$_{Individual}$

H5.a $Credibility_{Point} > Credibility_{Point\&Density}$

H5.b $Credibility_{Group}$ > Credibility$_{Individual}$

3 Results

We begin by describing how point and density projections influence aggregate dynamics. We then explore how the projections influence individual forecasting behavior.

3.1 Aggregate results

Figure 6 and Figure 7 compare the time series of inflation for groups and individuals, respectively, across our three information treatments by sequence and repetition.[7] Time series comparing Group and Individual treatments can be found in the Online Appendix Section C. While the variability of inflation certainly differs across treatments, impressive is the contemporaneous correlation of inflation across treatments across independent groups of participants who face the same shock sequence.

Insert Figure 6
Insert Figure 7

We consider two measures of macroeconomic stability at the session-repetition level. First, we compute the mean deviation of inflation from the central bank's target of zero. Second, we compute the standard deviation of inflation. The mean values of both measures are presented in the first two columns of Table 2. Both metrics indicate that inflation variability is greatest in NoComm, followed by Point&Density, and lowest in Point. A series of Wilcoxon rank-sum tests fails to reject the null hypothesis that the distributions of these statistics are not different across treatments ($N = 6$ per treatment; $p > 0.12$ in all treatment-repetition pairwise comparisons). Our results remain qualitatively similar when we instead normalize the session-level standard deviation measures by the standard deviation of the realized shocks, which differ across sessions. Overall, we are unable to find support for Hypothesis 1a that either type of projection reduces inflation variability in Group settings.

In the Individual sessions, we obtain the same ordering of treatments with NoComm exhibiting the most inflation volatility (71 bps), followed by Point&Density (62 bps) and Point (59 bps). The differences between NoComm and Point are statistically significant in Rep. 2 ($N = 39$ in NoComm, $N = 42$ in Point; $p = 0.02$ for both the raw and normalized standard deviation measures). All other treatment-repetition differences are not statistically significant ($p > 0.12$). We find minimal support for Hypothesis 1a that either type of projection reduces inflation variability in Individual settings.

We do not find significant support for Hypothesis 1b and 1c that inflation volatility is significantly different across Group and Individual treatments. While mean inflation variability is more than 50% greater in Individual treatments than Group treatments, there is considerable variance across Individual subjects within any given treatment. The differences

[7] We use the terms sequence and session interchangeably.

between Group and Individual treatments for a given information set are not statistically significant ($N = 6$ in Group treatments and $N \geq 34$ in Individual treatments; $p > 0.17$ in all treatment-repetition comparisons).

Result 1: In Group settings, projections do not significantly improve inflation stability.

Result 2: In Individual settings, only point projections significantly reduce inflation variability for experienced participants.

3.2 Individual results

We now turn to our individual–level forecast data to identify participants' ability and forecasting strategies. We keep data only from those participants whose forecasts are within ±1500 bps. This excludes five participants from each of the Point–Indiv. and Point&Density–Indiv. treatments.

Forecast Errors

Distributions of the forecast errors are presented in Figure 8 by repetition and coordination type, with the densities truncated at 600 for better clarity. Given the minimal differences in the distribution of forecast errors across treatments, we henceforth pool data from the two repetitions together. Forecast summary statistics of individual inflation forecasts are presented in Table 2. The third and fourth columns present the mean and standard deviation of absolute forecast errors of $t + 1$ and $t + 2$ inflation by treatment.

Insert Figure 8

Insert Table 2

We find mixed support for Hypothesis 2a that projections reduce forecast errors, with Point projections more effective than Point&Density projections at improving forecast accuracy. Consistent across both groups and individuals, as well as one- and two-period-ahead forecasts, we find that absolute forecast errors are largest in the NoComm, followed by Point&Density, and lowest in the Point treatments.

Insert Table 3

To evaluate whether the differences are statistically significant, we conduct a series of random effects panel regressions where we regress absolute forecast errors on treatment-specific dummy variables. Table 3 Panel A presents the results for Group treatments in columns (1) to (4) and Individual treatments in columns (5) to (8). Odd columns compare the two projection treatments to the NoComm treatment (denoted by α). The even columns compare forecast errors in Point&Density to Point. While forecast errors do decline with projections, the effect is not statistically significant in the Group treatments for one-period-ahead forecasts. Two-period-ahead inflation forecast errors are significantly lower when a Point projection is communicated. Columns (2) and (4) show that adding a density forecast to an existing point forecast can lead to a small but statistically significant increase in both one- and two-period-ahead forecast errors. In the Individual treatments, point projections significantly decrease two-period-ahead forecast errors by roughly 14 bps. Overall, however, the projections do not have a consistent effect on one-period-ahead forecasts.

Table 3 Panel B presents the estimated effects of eliminating strategic motives on absolute forecast errors, by treatment. *Individual* is a dummy variable that takes the value of one if participants are in the Individual treatment, with the Group treatment taken as the baseline. Consistently, two-period-ahead forecast errors are more extreme in Individual treatments than in Group treatments. This difference is statistically significant at the 5% level in the NoComm and Point&Density treatments, and 10% level in the Point treatment. On average, one-period-ahead forecast errors are also larger in the Individual treatments, but the effect is not statistically significant. Thus, we reject Hypothesis 2b that forecast errors in NoComm-Indiv. are lower than in No-Comm Group, and find some support for Hypothesis 2c that errors are smaller in Group treatments with central bank projections.

Result 3: Point projections significantly reduce $t + 2$ ahead forecast errors, and are significantly more effective than Point&Density projections in Group treatments.

Result 4: Participants in Individual treatments form significantly larger forecast errors about $t + 2$ inflation than their Group counterparts.

Results 3 and 4 coincide with our hypotheses. The fact that projections are more effective at reducing forecast errors for $t + 2$ than $t + 1$ is likely due to the additional cognitive complexity associated with forecasting further into the future. Regarding Result 4, we note that there are more outlier forecasts, fewer ex-ante rational subjects and considerably more trend-chasing heuristics in Individual than Group treatments. Thus, it is not surprising that the forecast errors are larger in Individual treatments.

Disagreement

We next consider how forecast disagreement is affected by the communication of projections. We measure forecast disagreement at the session-period level as the standard deviation of inflation forecasts across subjects. Mean and standard deviations of forecast disagreement are presented in the third and fourth columns of Table 2. Table 4 provides estimates of the treatment differences in disagreement.

Insert Table 4

We find mixed support for Hypothesis 3a that Point and Point&Density projections reduce disagreement. Within Group treatments, we find that Point projections significantly reduce both one- and two-period-ahead disagreement ($p < 0.05$ in both cases). We also find that the additional inclusion of densities around a point projection leads to a small but significant increase in disagreement in two-period-ahead disagreement. Point&Density projections, when compared to NoComm, do not significantly reduce disagreement. Within Individual treatments, the two types of projections reduce disagreement across subjects by roughly ten bps, but the differences across Communication treatments are not statistically significant at the 10% level.

Disagreement across subjects is significantly higher in the Individual treatments when no strategic coordination motive is present ($p < 0.001$ in all communication treatments). Disagreement falls by more than 50% in NoComm Groups, by 74% in Point Groups, and by roughly 65% in Point+Density Groups. Thus, we fail to reject Hypothesis 3b that disagreement is higher in Individual treatments.

Result 5: Point projections significantly reduce disagreement about future inflation, but Point&Density projections are not consistently effective.

Result 6: Disagreement is significantly lower in the Group treatment than in the Individual treatment, i.e. when participants have a strategic motive to coordinate their forecasts.

Uncertainty

Subjects provided predictions of their forecast errors, which we take as a measure of uncertainty. Mean and standard deviations of expected forecast errors are presented in the final two columns of Table 2. Table 5 provides estimates of the treatment differences in participants' conveyed uncertainty.

Insert Table 5

Immediately striking is the high level of confidence participants convey alongside their point forecasts. The average uncertainty is approximately 30 bps in NoComm, 20 bps in Point, and 33 bps in Point&Density in Group settings and slightly lower in Individual. A rational agent asked to convey a one-standard deviation forecast would predict an expected error of 113 bps. Our participants are much more confident in their forecasts, conveying only one–quarter of one–standard–deviation of a rational level of uncertainty.[8]
We predicted in Hypothesis 4a that uncertainty would be the highest in the NoComm treatment, followed by Point& Density, and lowest in the Point treatment. We find significant support for this hypothesis in both the Group and Individual treatments. Within Group treatments, one- and two-period-ahead uncertainty decreases by approximately ten bps when the central bank communicates a Point projection. This effect is significant at the 1% (5%) level for one- (two-) period ahead forecasts. Communicating an auxiliary density around the point projection significantly increases both forecast uncertainties by approximately 14 bps. This effect is significant at the 1% level. We obtain qualitatively similar effects from projections in the Individual treatments, though the effects are smaller and not statistically significant.

In Hypothesis 4b we predicted that introducing strategic considerations would increase participants' uncertainty about future inflation. We find mixed evidence to support this. Only in the Point&Density treatment are subjects significantly more unsure about their personal forecasts when dealing with other participants. In Point and, especially, NoComm, strategic coordination leads to less uncertainty about future inflation.

Result 7: Point projections significantly reduce individual-level uncertainty about forecasts of future inflation in Group treatments, but Point&Density projections are not consistently effective.

Result 8: Individuals exhibit less uncertainty about their private forecasts than Groups when presented with Point&Density projections.

[8]Pfajfar and Žakelj (2016) also observe a high level of overconfidence in related LtF New Keynesian experiments. Uncertainty declines as the central bank pursues a more aggressive reaction to deviations of inflation from target and induces more stable inflation dynamics.

Credibility

Credibility is an important concern for central banks who communicate their projections to the public. We denote a participant as perceiving the central bank's projection as credible if she uses its projected point forecast to formulate her private expectations. Given the potential for rounding errors, we assume a participant uses the projected value if their forecast is within five basis points of the projection. Table 6 provides estimates of the treatment differences in participants' credibility in the central bank's projections.

Insert Table 6

Without any communication, roughly 15% (11%) of one- and two-period-ahead forecasts in NoComm-Group (NoComm-Indiv.) are within five basis points of the rational expectations equilibrium forecast. Point projections are used by 41% (36%) of Group (Indiv.) subjects to formulate their one- and two-period-ahead forecasts. Communicating a density decreases the usage of the point projection. Credibility in the actual point prediction decreases to 34% (23%) for one-period-ahead forecasts and 37% (24%) for two-period-ahead forecasts in the Group (Indiv.) treatments.

We can alternatively consider credibility in the Point&Density treatment to include any forecast in the central bank's communicated density forecast. Credibility according to this definition is 99% for both one- and two-period ahead forecasts in the Group treatments, and between 86% and 91% in the Individual treatments. For reference, NoComm and Point also exhibit nearly identical levels of credibility for both forecasted variables. This high degree of similarly across information treatments indicates that the density projection is not improving credibility, and, if anything, is reducing credibility in the central bank's *point* projections.

For both Group and Individual treatments, communicating either a Point or Point&Density projection significantly increases the share of participants forecasting the REE solution for $t+1$ inflation. Consistent with Hypothesis 5a, credibility in the central bank's point projection is significantly lower, however, when the projection includes a density forecast for both $t+1$ and $t+2$ forecasts in Group and Individual treatments.

We also observe a small but significant increase in credibility in the projections when participants face strategic considerations. The effect is roughly four percentage points in the Point treatments, and between 6-9 percentage points in the Point&Density treatments. Thus, we find support for Hypothesis 5b that Group settings improve credibility in projections.

Result 9: Credibility in the central bank's point forecast is significantly lower when the central bank communicates a density around its point projection.

Result 10: Credibility in projections is higher when participants interact in Group treatments.

Heuristics

Finally, we consider how the projections and strategic considerations alter the heuristics subjects use to formulate their forecasts. This exercise not only provides insight into whether projections have the intended impact on expectations, but also highlights which types of heuristics become more or less prevalent in the presence of central bank communication. Table 7 presents the six general classes of heuristics we consider. The heuristics have been previously identified by theory and experiments as describing forecasters' expectation formation process.

Insert Table 7

Following Mokhtarzadeh and Petersen (2020), we classify each participant into one of six heuristics that most closely matches their own submitted expectations. Specifically, we identify the heuristic that produces the lowest absolute mean-squared error among all competing models. For the Constant Gain and Trend Chasing heuristics, we consider a range of parameters $\gamma, \tau \in [0.1, 1.5]$ with 0.1 increments. The distribution of $t+1$ inflation forecasting heuristics are presented in Figure 10 by treatment.

Insert Figure 10

There are many interesting results to be taken away from these analyses. Without any auxiliary communication, between 10 and 20% of participants in both Group and Individual treatments formulate ex-ante rational expectations. Importantly, after controlling for experience, there is little difference in the prevalence of rational agents in strategic and individual environments. This is noteworthy as one might assume that participants' potential irrationality in NoComm may be due to the perceived irrationality of their counterparts. Rather, it is in the NoComm-Individual treatment that we observe a greater frequency of highly irrational heuristics such as Trend Chasing.

Communicating a Point projection is very effective at guiding participants to forecasting the REE solution. Roughly 80% of Group participants and 48% of Individual participants behave as if they were forming ex-ante rational expectations when they receive Point projections. In Point-Individual, the inflation projection effectively nudges subjects away from using Adaptive and Trend-Chasing heuristics toward both Rational and Constant Gain. The point projection is noticeably less effective in the Individual treatment, likely because Individual participants who do not initially utilize the projection to formulate their forecast observe dynamics that look different from the projected values. They subsequently lose credibility in the projections.

Density projections also increase the proportion of subjects who forecast as if they were Ex-ante Rational and reduces the proportion of Adaptive forecasters. However, for inexperienced Group participants and both inexperienced and experienced Individual participants, the inclusion of the density projection mutes the effects of the point projection. In addition to the previously noted heterogeneity in forecasts, we also observe considerably greater heterogeneity in heuristics in Point&Density compared to Point.

Between 76 and 87% of participants use the same heuristic to forecast one- and two-period-ahead inflation, without much difference across treatments. For those that exhibit differences, a few consistencies emerge. Adaptive forecasters of $t+1$ inflation tend to be Rational for their $t+2$ forecasts in projection treatments. Rational forecasters of $t+1$ inflation tend to be primarily split between Target and Trend-Chasing for their subsequent forecast. Finally, those that forecast $t+1$ inflation with a Trend Chasing heuristic use predominantly a Rational heuristic to forecast their subsequent forecast, in treatments with projections.

Result 11: Ex-ante rational projections reduce the prevalence of backward-looking forecasting heuristics and encourage more rational forecasting.

Result 12: Point projections are more effective at guiding expectations to the REE than Point&Density projections.

Result 13: The majority of participants use the same heuristics to formulate both their one- and two-period-ahead forecasts.

4 Conclusion

As more central banks publish forecasts about their outlook, they face the dilemma as to whether to communicate their own uncertainty. To the best of our knowledge, there has been no work evaluating the impact of publishing density forecasts in addition to point projections on market expectations.

Our work aims to fill this gap by providing original evidence on the effects of communicating uncertainty on expectation formation. First, we study the introduction of a measure of a central bank's forecast uncertainty into central bank projections (i.e. the publication of density rather than point forecasts). Our interest is in how this affects aggregate dynamics and how forecasters incorporate information in the first and second central moments into their own expectations and perceptions of future uncertainty. Second, this paper studies behavior in individual-choice and coordination settings to understand the extent to which strategic concerns influence how agents use information when forming expectations.

We find that both point and density projections significantly improve forecast accuracy and decrease cross-sectional disagreement relative to an environment with no auxiliary central bank communication. This is consistent with empirical evidence that central bank projections coordinate expectations and reduce forecast errors. Furthermore, projections increase the proportion of participants who form ex-ante rational expectations. We provide new evidence showing that a large majority of participants use the same heuristics to formulate both their one- and two-period-ahead forecasts. However, roughly 20% of participants employ different heuristics when forecasting at different horizons. These subjects tend to use more irrational heuristics for their further ahead forecasts. However, projections nudge more distant forecasts toward the ex-ante rational prediction.

These results are in line with Mokhtarzadeh and Petersen (2020) who find inflation projections works effectively to guide expectations in the absence of a zero lower bound (ZLB). Inflation expectations are not as well managed by rationally–constructed inflation projections in the presence of ZLB. See Arifovic and Petersen (2017), Ahrens et al. (2018), and Kryvtsov and Petersen (2020) for examples of relatively poorer management of inflation expectations through projections at ZLB. In particular, more simplistic communications are more effective to guide expectations. Kryvtsov and Petersen note that simple, relatable information about past interest rates work more effectively to manage expectations than forward-looking projections about policy rates and forward guidance. Ahrens et al. find that gradual adjustment of inflation projections by human central bankers can more effectively build up credibility and manage expectations at the ZLB. Arifovic and Petersen find that qualitative rather than quantitative communication can work somewhat better to reduce pessimism.

Communicating an additional density forecast around a point projection mutes the positive effects of publishing point projections. Compared to point projections, density projections significantly increase forecast errors and disagreement. The central bank transmits their uncertainty to forecasters, leading to higher levels of private forecast uncertainty. Moreover, fewer subjects form ex-ante rational expectations at both forecasting horizons.

Credibility in the central bank's projections significantly decreases when participants are presented with a less precise projection. This result is in line with Baeriswyl and Cornand (2016) who show in a Keynesian beauty contest environment that subjects place more weight on public signals the more precise is the signal. Their results are more nuanced. Subjects overreact relative to theoretical predictions when the public signal is imprecise, and underreact when it is more precise.

A notable finding in our experiment is that inflation volatility and the heterogeneity in forecasts and heuristics increases when participants have more market power in the Individual treatments. Other LTF experiments have also explored the effects of individual subjects' market size on system stability. Kopányi et al. (2019) show in an asset market LTF that increasing the market power of more accurate forecasters can lead to greater instability. Bao et al. (2020), on the other hand, find that asset price bubbles grow even faster with larger group sizes (where individuals have less market power) and participants are more likely to coordinate on trend-chasing strategies. The differences in our experimental findings and Bao et al. likely are driven by the relatively greater negative feedback present in our data-generating process, that encourage coordination on more stable heuristics (see Heemeijer et al. 2009 for evidence on the effects of positive and negative feedback in LTF experiments).

We show that central bank projections both provide valuable information to reduce forecasters' confusion and can alleviate some strategic uncertainty. Our results line up with Akiyama et al. (2017) who show that mispricing commonly observed in experimental asset markets is driven at least in part by strategic uncertainty. In fact, they show that strategic uncertainty explains at least as much of median initial forecast deviation from the fundamental value as does confusion. Our results are consistent with the broader literature that shows individuals will anchor on simple and salient information when facing cognitive overload (Deck and Jahedi, 2015, Kryvtsov and Petersen, 2020).

Much of the macroeconomic literature uses a notion of rational expectations that focuses on an agents' point forecast of some future event. There is scope in learning-to-forecast experiments to better understand participants' subjective uncertainty, how it relates to rationality, and how the relationship between rationality and uncertainty can be influenced by monetary policy and central bank communication. We find that participants exhibit an unusually high level of confidence in their own forecasts, and this confidence can be better strengthened through more precise information. An important avenue of future study is whether participants would act on expectations given their level of confidence.

References

[1] Ahrens, S., Lustenhouwer, J., & Tettamanzi, M. (2018). The Stabilizing Role of Forward Guidance: A Macro Experiment. BERG Working Paper 137.

[2] Akiyama, E., Hanaki, N., & Ishikawa, R. (2017). It is Not Just Confusion! Strategic Uncertainty in An Experimental Asset Market. Economic Journal, 127(605), 563-580.

[3] Arifovic, J., & Petersen, L. (2017). Stabilizing expectations at the zero lower bound: Experimental evidence. Journal of Economic Dynamics and Control, 82, 21-43.

[4] Assenza, T., Heemeijer, P., Hommes, C. H., & Massaro, D. (2013). Individual expectations and aggregate macro behavior.

[5] Baeriswyl, R., & Cornand, C. (2016). The predominant role of signal precision in experimental beauty contests. The BE Journal of Theoretical Economics, 16(1), 267-301.

[6] Bao, T., Duffy, J., & Hommes, C. (2013). Learning, forecasting and optimizing: An experimental study. European Economic Review, 61, 186-204.

[7] Bao, T., Hennequin, M., Hommes, C., & Massaro, D. (2020). Coordination on bubbles in large-group asset pricing experiments. Journal of Economic Dynamics and Control, 110, 103702.

[8] Bauer, M. D. (2012). Monetary policy and interest rate uncertainty. FRBSF Economic Letter, 38, 1-5.

[9] Blinder, A. S., Ehrmann, M., Fratzscher, M., De Haan, J., & Jansen, D. J. (2008). Central bank communication and monetary policy: A survey of theory and evidence. Journal of Economic Literature, 46(4), 910-45.

[10] Brubakk, L., Ter Ellen, S., & Xu, H. (2017). Forward guidance through interest rate projections: does it work? Norges Bank Working Paper 6/2017.

[11] Coibion, O., & Gorodnichenko, Y. (2015). Information rigidity and the expectations formation process: A simple framework and new facts. American Economic Review, 105(8), 2644-78.

[12] Cornand, C., & Heinemann, F. (2008). Optimal degree of public information dissemination. The Economic Journal, 118(528), 718-742.

[13] Cornand, C., & Hubert, P. (2019). On the external validity of experimental inflation forecasts: A comparison with five categories of field expectations. Journal of Economic Dynamics and Control, 103746.

[14] Cornand, C., & M'baye, C. K. (2018a). Does inflation targeting matter? An experimental investigation. Macroeconomic Dynamics, 22(2), 362-401.

[15] Cornand C. & M'baye C. K. (2018b), "Band or Point Inflation Targeting? An Experimental Approach", Journal of Economic Interaction and Coordination, 13(2) : 283-309.

[16] Deck, C., & Jahedi, S. (2015). The effect of cognitive load on economic decision making: A survey and new experiments. European Economic Review, 78, 97-119.

[17] Geraats, P. M. (2002). Central bank transparency. The Economic Journal, 112(483), F532-F565.

[18] Gosselin, P., Lotz, A., & Wyplosz, C. (2008). The Expected Interest Rate Path: Alignment of Expectations vs. Creative Opacity. International Journal of Central Banking, 4(3), 145-185.

[19] Greenspan, A. (2004). Risk and uncertainty in monetary policy. American Economic Review, 94(2), 33-40.

[20] Heemeijer, P., Hommes, C., Sonnemans, J., Tuinstra, J. (2009). Price stability and volatility in markets with positive and negative expectations feedback: An experimental investigation. Journal of Economic dynamics and control, 33(5), 1052-1072.

[21] Hommes, C., Massaro, D., & Weber, M. (2019a). Monetary policy under behavioral expectations: Theory and experiment. European Economic Review, 118, 193-212.

[22] Hommes, C., Massaro, D., & Salle, I. (2019b). Monetary and fiscal policy design at the zero lower bound: Evidence from the lab. Economic Inquiry, 57(2), 1120-1140.

[23] Hubert, P. (2014). FOMC forecasts as a focal point for private expectations. Journal of Money, Credit and Banking, 46(7), 1381-1420.

[24] Hubert, P. (2015). Do central bank forecasts influence private agents? Forecasting performance versus signals. Journal of Money, Credit and Banking, 47(4), 771-789.

[25] Husted, L., Rogers, J., & Sun, B. (2018). Uncertainty, currency excess returns, and risk reversals. Journal of International Money and Finance, 88, 228-241.

[26] Husted, L., Rogers, J., & Sun, B. (2019). Monetary policy uncertainty. Journal of Monetary Economics.

[27] Jain, M., & Sutherland, C. S. (2018). How do central bank projections and forward guidance influence private-sector forecasts? (No. 2018-2). Bank of Canada Staff Working Paper.

[28] Kool, C. J., & Thornton, D. L. (2015). How effective is central bank forward guidance?.

[29] Kopányi, D., Rabanal, J. P., Rud, O. A., & Tuinstra, J. (2019). Can competition between forecasters stabilize asset prices in learning to forecast experiments?. Journal of Economic Dynamics and Control, 109, 103770.

[30] Kryvtsov, O., & Petersen, L. (2013). Expectations and monetary policy: experimental evidence (No. 2013-44). Bank of Canada.

[31] Kryvtsov, O., & Petersen, L. (2020). Central bank communication that works: Lessons from lab experiments. Journal of Monetary Economics. Forthcoming.

[32] Malmendier, U., & Nagel, S. (2016). Learning from inflation experiences. The Quarterly Journal of Economics, 131(1), 53-87.

[33] Mokhtarzadeh, F., & Petersen, L. (2020). Coordinating expectations through central bank projections. Experimental Economics. Forthcoming.

[34] Mitchell, J., & Weale, M. (2019). Forecasting with Unknown Unknowns: Censoring and Fat Tails on the Bank of Englands Monetary Policy Committee (No. 27). Economic Modelling and Forecasting Group.

[35] Neely, C. (2005). Using implied volatility to measure uncertainty about interest rates. Federal Reserve Bank of St. Louis Review, 87(3), 407-25.

[36] Petersen, L. & Rholes, R. (2020). Escaping Secular Stagnation with Unconventional Policy.

[37] Pfajfar, D., & Santoro, E. (2010). Heterogeneity, learning and information stickiness in inflation expectations. Journal of Economic Behavior & Organization, 75(3), 426-444.

[38] Pfajfar, D., & Žakelj, B. (2014). Experimental evidence on inflation expectation formation. Journal of Economic Dynamics and Control, 44, 147-168.

[39] Pfajfar, D., & Žakelj, B. (2016). Uncertainty in forecasting inflation and monetary policy design: Evidence from the laboratory. International Journal of Forecasting, 32(3), 849-864.

[40] Pfajfar, D., & Žakelj, B. (2018). Inflation expectations and monetary policy design: Evidence from the laboratory. Macroeconomic Dynamics, 22(4), 1035-1075.

[41] Rholes, R. & Sekhposyan, T. (2019). Central Bank Density Forecasts and Asset Prices: Do Revisions to Higher-order Moments Matter?

[42] Rudebusch, G. D., & Williams, J. C. (2008). Revealing the secrets of the temple: The value of publishing central bank interest rate projections. In Asset Prices and Monetary Policy (pp. 247-289). University of Chicago Press.

[43] Swanson, E. T. (2006). Have increases in Federal Reserve transparency improved private sector interest rate forecasts?. Journal of Money, Credit, and Banking, 38(3), 791-819.

[44] Woodford, M. (2005). Central bank communication and policy effectiveness (No. w11898). National Bureau of Economic Research.

5 Figures and Tables

Figure 1: Flow of information, decisions, and outcomes

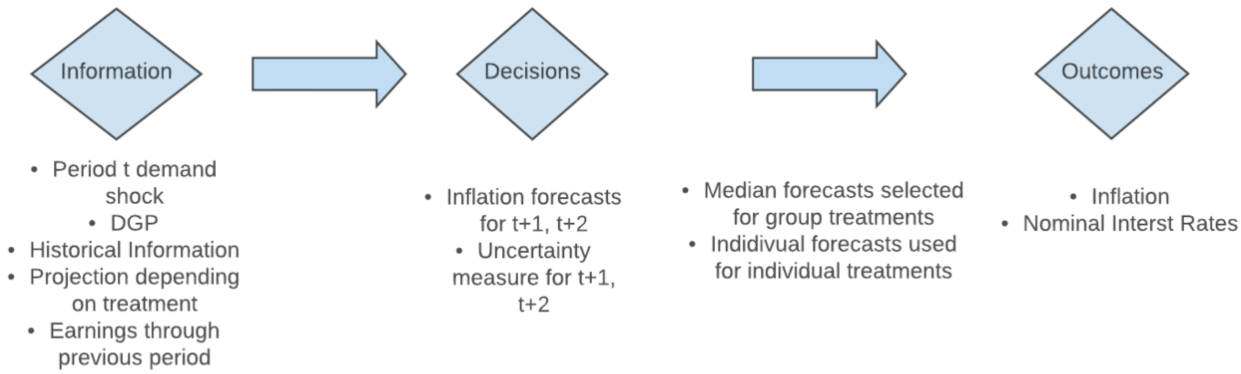

Figure 2: NoComm screenshot

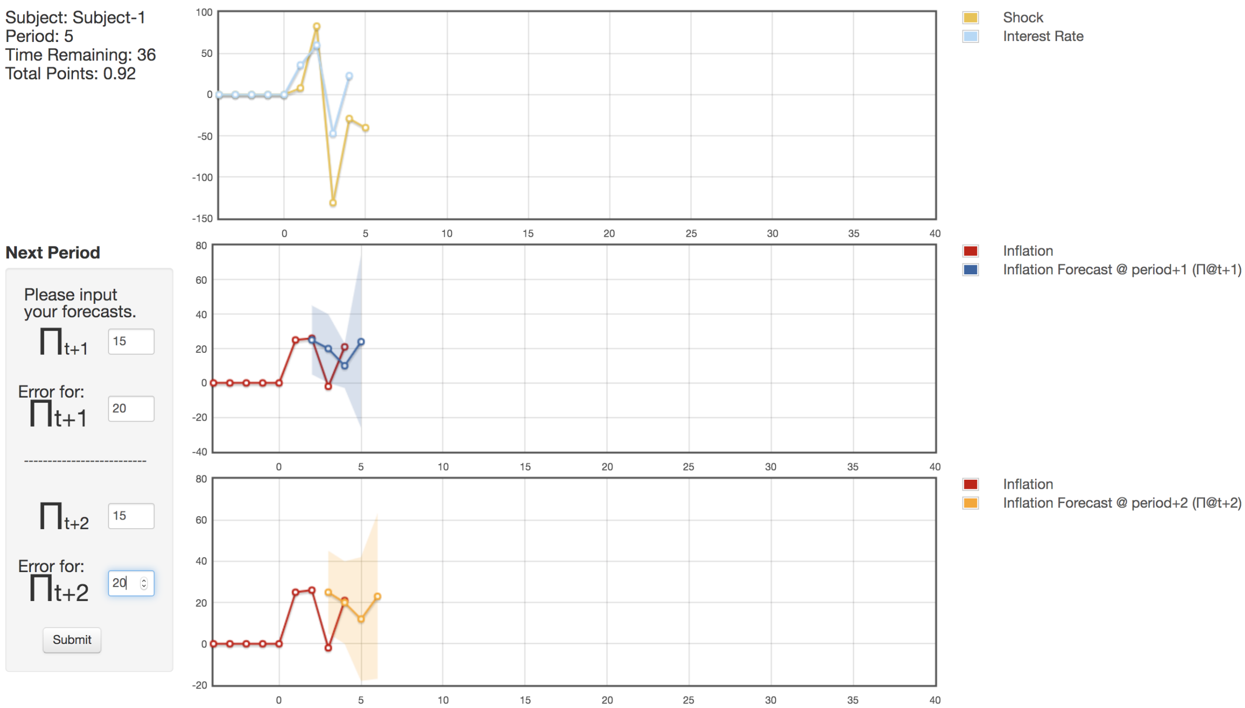

Figure 3: Point screenshot

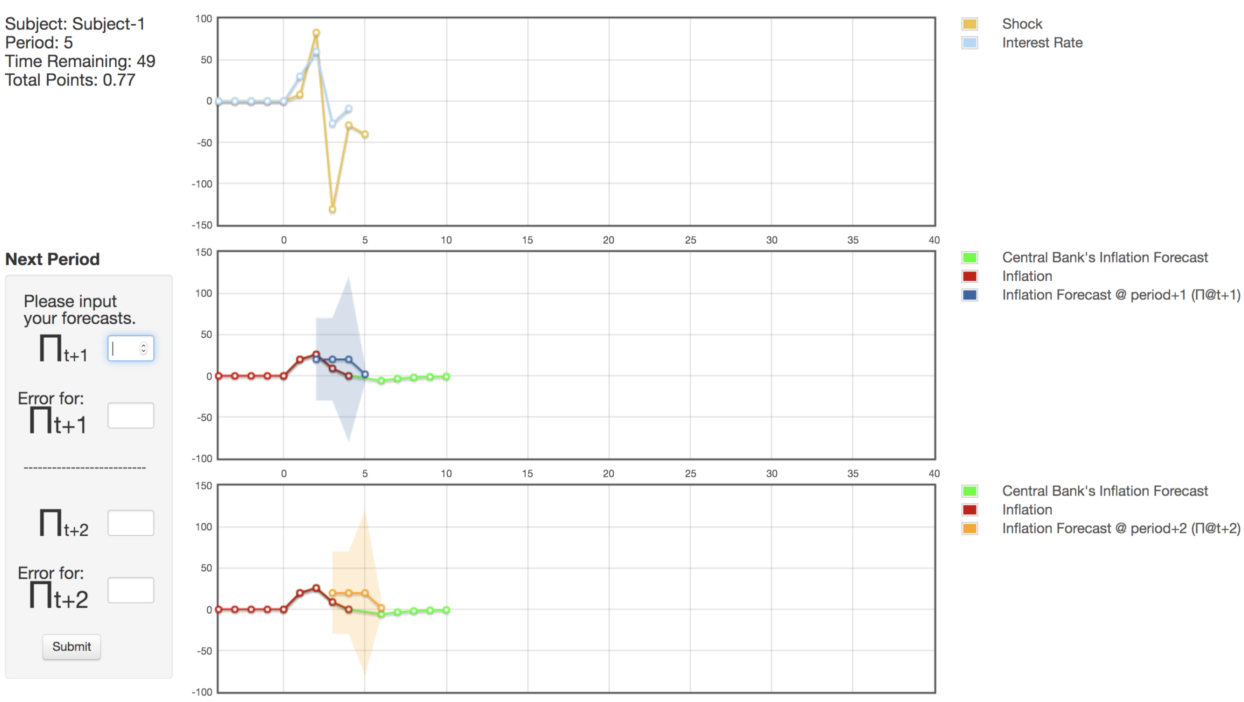

Figure 4: Point&Density screenshot

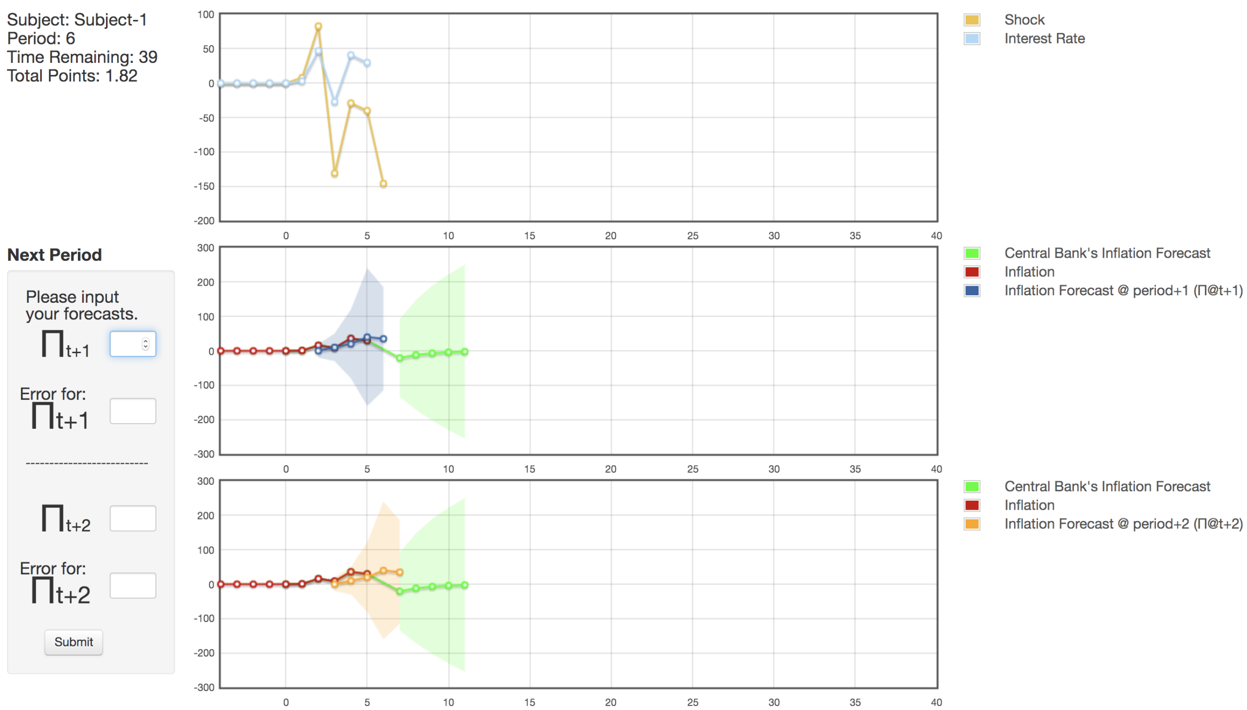

Figure 5: Simulated statistics under alternative forecasting heuristics

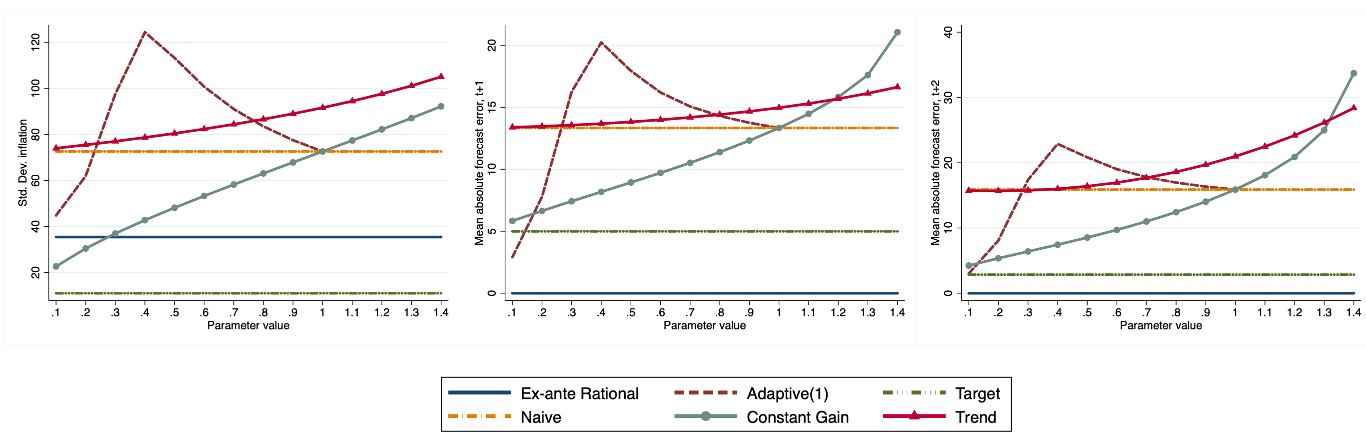

Figure 6: Time series of Group treatments

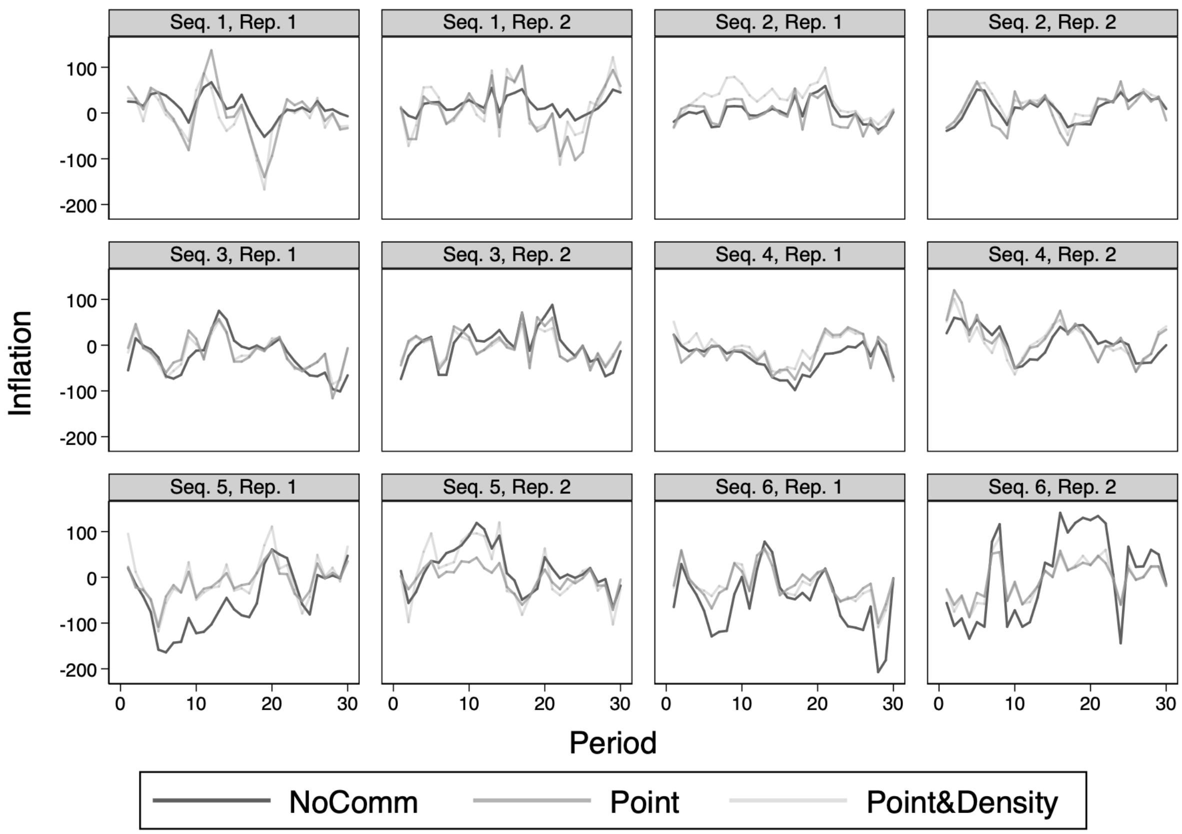

Figure 7: Time series of Individual treatments

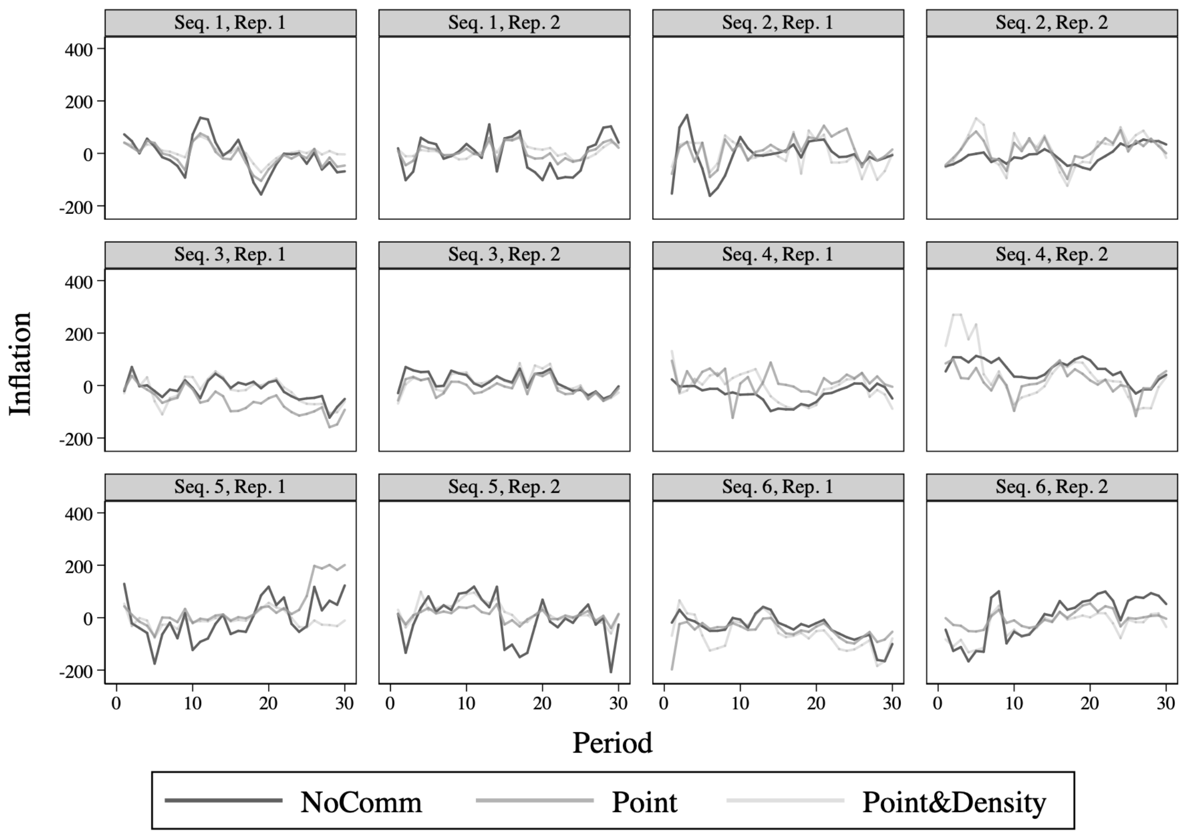

Figure 8: Distributions of absolute forecast errors

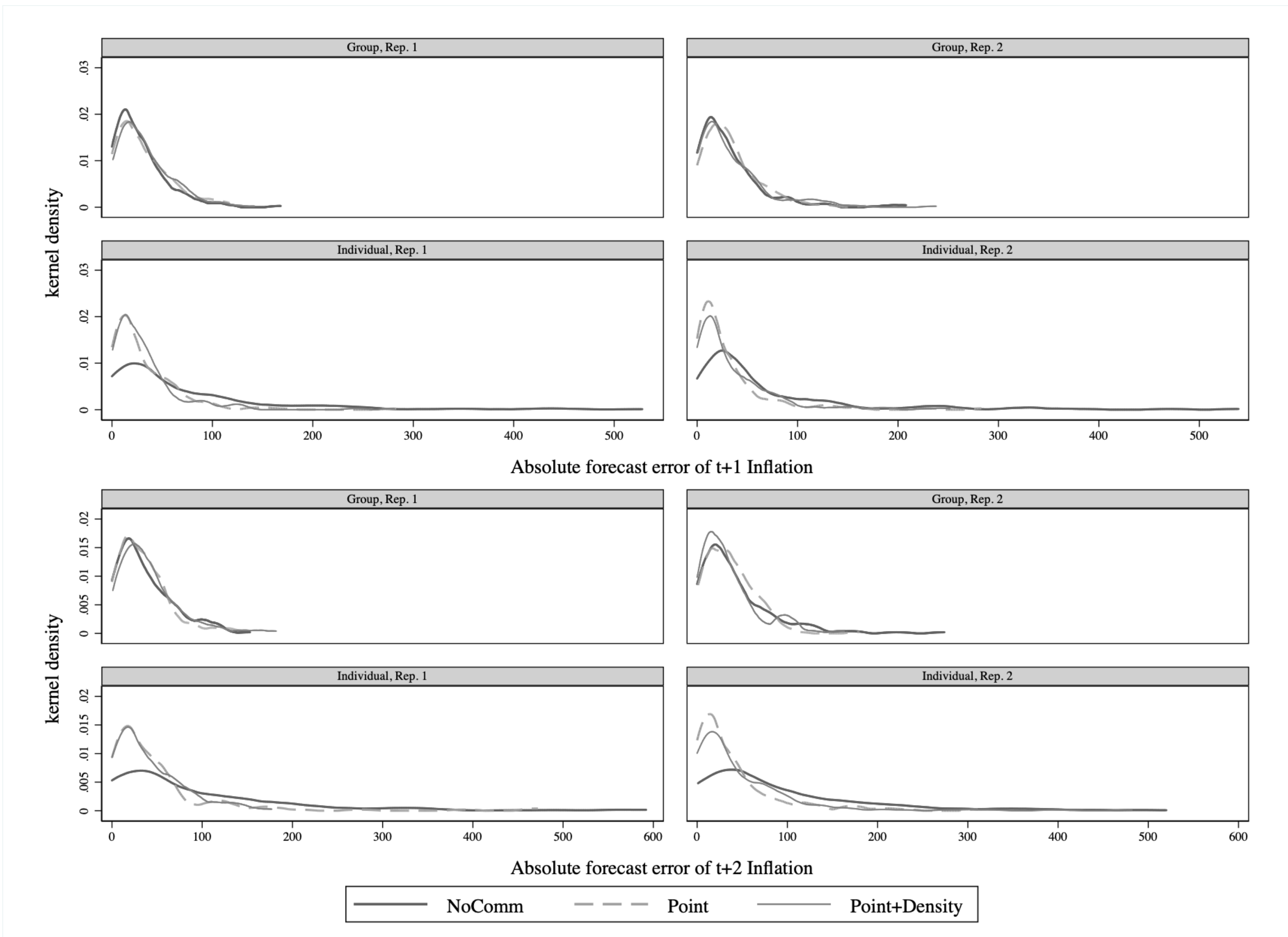

Figure 9: Distribution of forecasting heuristics for $t+1$ inflation, by treatment

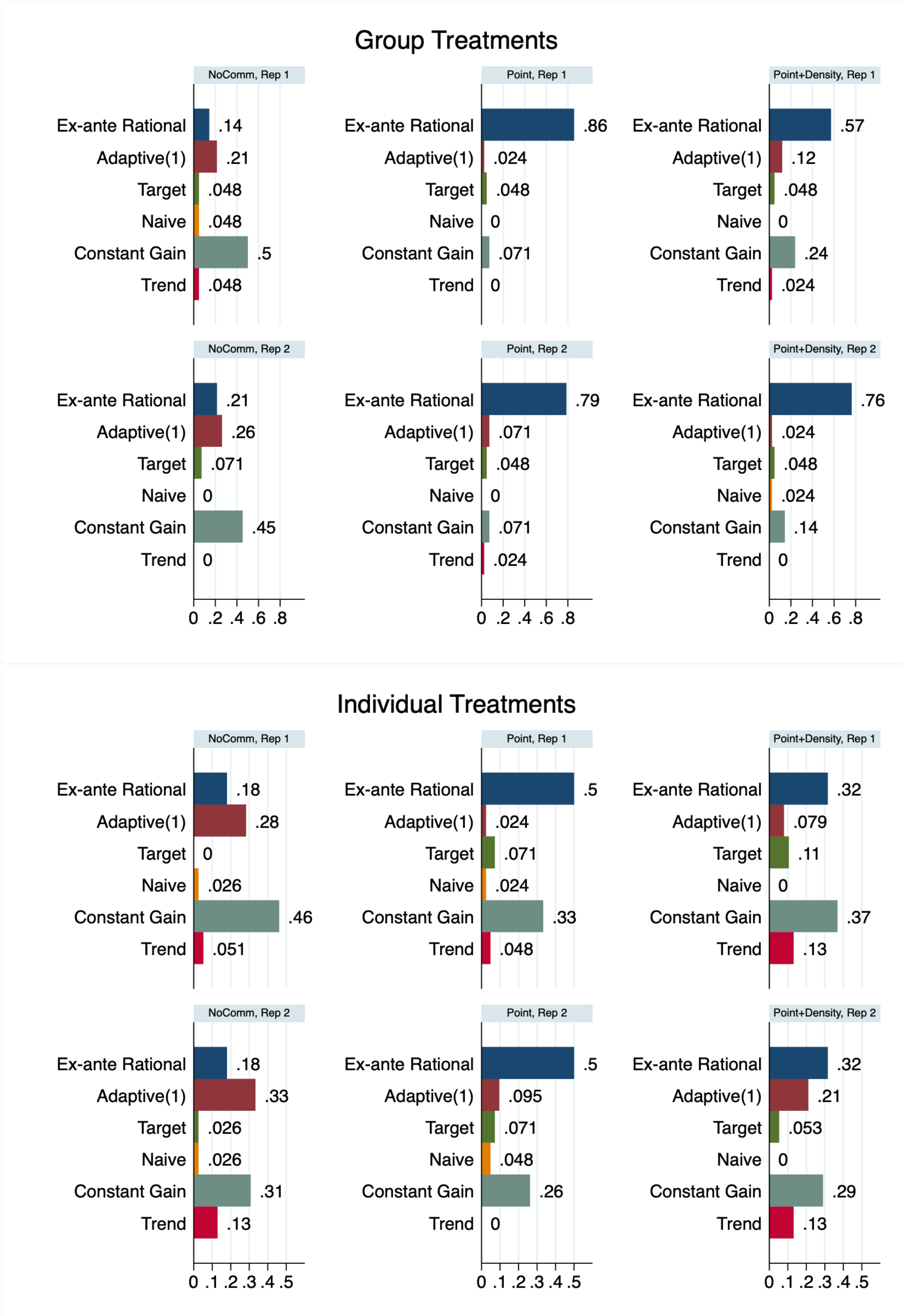

Figure 10: Distribution of forecasting heuristics for $t+2$ inflation, by treatment

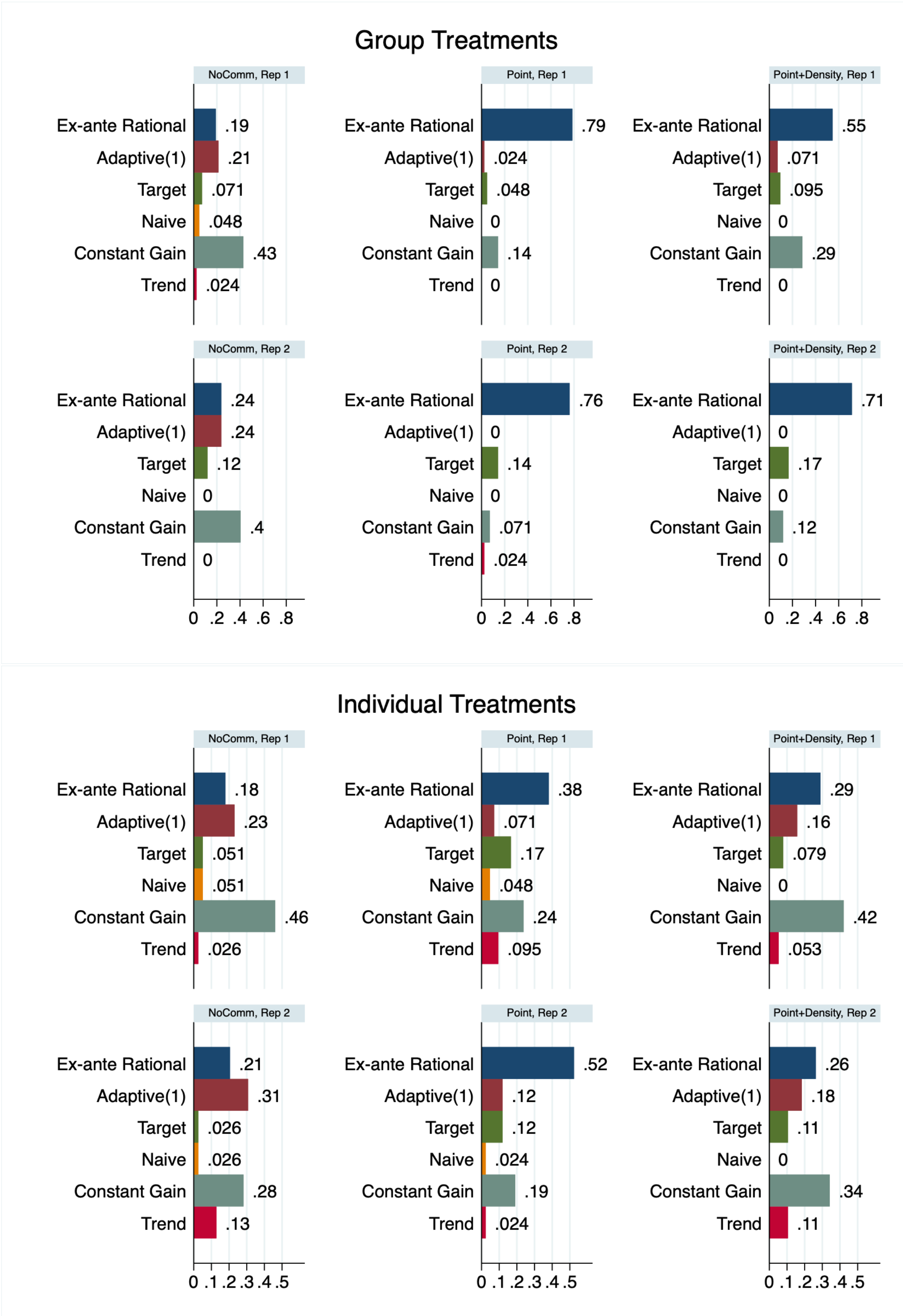

Table 1: Treatments summary

Group				
CB Projection	**Sequences**	**Total Subjects**	**Periods**	**Aggregate Expectations**
NoComm	6	42	30 x 2	median of group
Point	6	42	30 x 2	median of group
PointDensity	6	42	30 x 2	median of group
Individual				
CB Projection	**Sequences**	**Total Subjects**	**Periods**	**Aggregate Expectations**
NoComm	6	39	30 x 2	own
Point	6	42	30 x 2	own
Point&Density	6	38	30 x 2	own

Table 2: Summary statistics of aggregate and individual forecast variables

Group										
CB Projection	**Deviation from Target**	**Std. Dev. Inflation**	**Abs.FE** π_{t+1}	**Abs.FE** π_{t+2}	**Disagreement** π_{t+1}	**Disagreement** π_{t+2}	**Uncertainty** π_{t+1}	**Uncertainty** π_{t+2}	**Credibility** π_{t+1}	**Credibility** π_{t+2}
NoComm	39	43	36	43	32	31	27	32	15%	16%
	(37)	(22)	(56)	(55)	(46)	(40)	(37)	(92)	(0.35)	(0.36)
Point	32	38	31	35	17	16	17	21	41%	41%
	(24)	(9)	(28)	(27)	(14)	(10)	(17)	(24)	(0.49)	(0.49)
Point&Density	34	40	34	38	21	21	30	35	34%	37%
	(26)	(11)	(31)	(35)	(17)	(20)	(29)	(32)	(0.47)	(0.48)
									99%†	99%†
									(0.08)	(0.05)
Individual										
CB Projection	**Deviation from Target**	**Std. Dev. Inflation**	**Abs.FE** π_{t+1}	**Abs.FE** π_{t+2}	**Disagreement** π_{t+1}	**Disagreement** π_{t+2}	**Uncertainty** π_{t+1}	**Uncertainty** π_{t+2}	**Credibility** π_{t+1}	**Credibility** π_{t+2}
NoComm	66	117	43	57	74	73	23	26	11%	11%
	(79)	(89)	(68)	(80)	(44)	(45)	(45)	(35)	(0.11)	(0.32)
Point	51	53	37	43	66	62	19	21	36%	35%
	(93)	(41)	(68)	(82)	(70)	(68)	(29)	(29)	(0.48)	(0.48)
Point&Density	58	65	36	47	65	61	24	26	23%	24%
	(73)	(60)	(51)	(62)	(45)	(45)	(28)	(30)	(0.42)	(0.43)
									86%†	91%†
									(0.35)	(0.28)

This table presents means and standard deviation for each variable by treatment. Units are given in basis points, except for Credibility which is the percentage of participants who forecast the central bank's projected value within 5 bps. † denotes the percentage of forecasts that fall within the central bank's projected range in the PointDensity treatment.

Table 3: Absolute forecast errors

Panel A: Information comparisons

	Group				Individual			
	$t+1$		$t+2$		$t+1$		$t+2$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Point	-5.057		-7.829**		-6.460		-13.082*	
	(3.37)		(3.32)		(5.71)		(6.99)	
Point&Density	-2.155	2.902*	-4.795	3.034*	-7.376	-0.916	-9.759	3.322
	(3.51)	(1.52)	(3.47)	(1.72)	(4.94)	(4.93)	(6.61)	(6.04)
α	35.901***	30.844***	42.690***	34.862***	43.161***	36.701***	56.678***	43.596***
	(3.26)	(0.82)	(3.17)	(1.00)	(4.05)	(4.03)	(5.30)	(4.56)
N	7306	4872	7054	4704	6604	4343	6377	4194
χ^2	5.237	3.629	7.437	3.094	2.336	0.0346	3.684	0.303

Panel B: Group vs. Individual comparisons

	NoComm		Point		Point&Density	
	$t+1$	$t+2$	$t+1$	$t+2$	$t+1$	$t+2$
	(1)	(2)	(3)	(4)	(5)	(6)
Individual	7.260	13.986**	5.858	8.735*	2.040	9.023**
	(5.21)	(6.18)	(4.11)	(4.67)	(3.11)	(4.20)
α	35.901***	42.691***	30.844***	34.862***	33.746***	37.896***
	(3.27)	(3.17)	(0.82)	(1.00)	(1.29)	(1.41)
N	4695	4533	4720	4558	4495	4340
χ^2	1.946	5.120	2.028	3.500	0.430	4.623

This table presents results from a series of random effects panel regressions. Units are given in basis points. The dependent variables are the absolute one- and two-period-ahead absolute forecast errors of inflation. Point, Point&Density, and Individual are treatment-specific dummy variables. α denotes the estimated constant. Robust standard errors are given in parentheses. $*p < 0.10$, $**p < 0.05$, and $***p < 0.01$.

Table 4: Disagreement in inflation forecasts

	Panel A: Information comparisons							
	Group				Individual			
	$t+1$		$t+2$		$t+1$		$t+2$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Point	-14.937**		-15.685**		-8.346		-11.102	
	(7.16)		(6.31)		(11.41)		(9.96)	
Point&Density	-10.616	4.321	-10.038	5.647*	-9.342	-0.997	-11.406	-0.304
	(7.29)	(2.83)	(6.63)	(3.13)	(10.80)	(12.50)	(10.45)	(11.37)
α	31.634***	16.697***	31.259***	15.574***	74.220***	65.875***	72.889***	61.787***
	(6.95)	(1.76)	(6.08)	(1.68)	(6.80)	(9.22)	(6.36)	(7.72)
N	1080	720	1080	720	1080	720	1080	720
χ^2	5.877	2.335	8.368	3.245	0.941	0.00635	1.753	0.000716

	Panel B: Group vs. Individual comparisons					
	NoComm		Point		Point&Density	
	$t+1$	$t+2$	$t+1$	$t+2$	$t+1$	$t+2$
	(1)	(2)	(3)	(4)	(5)	(6)
Individual	42.586***	41.630***	49.178***	46.213***	43.860***	40.262***
	(9.79)	(8.86)	(9.38)	(7.90)	(8.73)	(8.76)
α	31.634***	31.259***	16.697***	15.574***	21.017***	21.221***
	(7.00)	(6.13)	(1.76)	(1.68)	(2.21)	(2.65)
N	720	720	720	720	720	720
χ^2	18.91	22.07	27.46	34.22	25.22	21.13

This table presents results from a series of random effects panel regressions. Units are given in basis points. The dependent variables are the per-period standard deviations of one- and two-period-ahead forecasts of inflation, computed at the session level. Point, Point&Density, and Individual are treatment-specific dummy variables. α denotes the estimated constant. Robust standard errors are given in parentheses. $^*p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

Table 5: Uncertainty in inflation forecasts

Panel A: Information comparisons

	Group				Individual			
	$t+1$		$t+2$		$t+1$		$t+2$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Point	-9.377***		-11.790**		-3.858		-5.129	
	(3.53)		(4.70)		(3.26)		(3.61)	
Point&Density	3.650	13.027***	1.938	13.728***	0.305	4.163	0.089	5.218
	(4.06)	(2.92)	(4.98)	(3.52)	(3.47)	(3.09)	(3.82)	(3.39)
α	26.703***	17.326***	32.894***	21.105***	23.339***	19.482***	26.047***	20.918***
	(3.20)	(1.49)	(4.15)	(2.19)	(2.56)	(2.02)	(2.85)	(2.22)
N	7559	5040	7559	5040	6840	4500	6840	4500
χ^2	22.96	19.92	17.30	15.20	2.301	1.811	3.142	2.376

Panel B: Group vs. Individual comparisons

	NoComm		Point		Point&Density	
	$t+1$	$t+2$	$t+1$	$t+2$	$t+1$	$t+2$
	(1)	(2)	(3)	(4)	(5)	(6)
Individual	27.817**	19.853*	1.017	0.656	-10.045*	-13.212*
	(11.53)	(10.35)	(8.68)	(9.47)	(6.08)	(7.57)
α	18.392***	23.639***	20.903***	22.889***	29.136***	34.122***
	(1.81)	(3.47)	(4.90)	(5.68)	(4.92)	(6.39)
N	720	720	720	720	720	720
χ^2	5.822	3.681	0.0137	0.00479	2.732	3.042

This table presents results from a series of random effects panel regressions. Units are given in basis points. The dependent variables are the participants' expected errors in their one- and two-period-ahead forecasts of inflation. Point, Point&Density, and Individual are treatment-specific dummy variables. α denotes the estimated constant. Robust standard errors are given in parentheses. *$p < 0.10$, **$p < 0.05$, and ***$p < 0.01$.

Table 6: Credibility of central bank projectionsI

Panel A: Information comparisons

	Group				Individual			
	$t+1$		$t+2$		$t+1$		$t+2$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Point	0.267***		0.156***		0.270***		0.146***	
	(0.03)		(0.02)		(0.03)		(0.02)	
Point&Density	0.196***	-0.071*	0.082***	-0.074***	0.140***	-0.130***	0.059***	-0.087***
	(0.03)	(0.04)	(0.02)	(0.02)	(0.03)	(0.05)	(0.02)	(0.03)
α	0.147***	0.413***	0.152***	0.308***	0.109***	0.378***	0.114***	0.260***
	(0.01)	(0.03)	(0.01)	(0.02)	(0.01)	(0.03)	(0.01)	(0.02)
N	7559	5040	7559	5040	6840	4500	6840	4500
χ^2	98.30	2.812	62.74	10.05	72.07	7.668	42.92	10.13

Panel B: Group vs. Individual comparisons

	NoComm		Point		Point&Density	
	$t+1$	$t+2$	$t+1$	$t+2$	$t+1$	$t+2$
	(1)	(2)	(3)	(4)	(5)	(6)
Individual	-0.038**	-0.038**	-0.035	-0.048*	-0.094**	-0.061**
	(0.01)	(0.02)	(0.04)	(0.03)	(0.05)	(0.02)
α	0.147***	0.152***	0.413***	0.308***	0.342***	0.234***
	(0.01)	(0.01)	(0.03)	(0.02)	(0.03)	(0.01)
N	4859	4859	4890	4890	4650	4650
χ^2	6.549	6.196	0.627	3.190	4.325	6.614

This table presents results from a series of random effects panel regressions. The dependent variables are dummy variables that take the value of one if one- and two-period-ahead forecasts of inflation are less than five basis points from the central banks point projection. Point, Point&Density, and Individual are treatment-specific dummy variables. α denotes the estimated constant. Robust standard errors are given in parentheses. *$p < 0.10$, **$p < 0.05$, and ***$p < 0.01$.

Table 7: Forecasting heuristics

Model	Heuristic Name	Model
M1	Ex-ante rational	$E_{i,t}\pi_{t+1} = 0.08r^n_{t-1} + 0.14\epsilon_t$
		$E_{i,t}\pi_{t+2} = 0.05r^n_{t-1} + 0.08\epsilon_t$
M2	Adaptive(1)	$E_{i,t}\pi_{t+1} = 0.09r_{t-1} + 0.88\pi_{t-1} + 0.17\epsilon_t$
		$E_{i,t}\pi_{t+2} = 0.10r_{t-1} + 0.84\pi_{t-1} + 0.18\epsilon_t$
M3	Target	$E_{i,t}\pi_{t+1} = 0$
		$E_{i,t}\pi_{t+2} = 0$
M4	Naive	$E_{i,t}\pi_{t+1} = \pi_{t-1}$
		$E_{i,t}\pi_{t+2} = \pi_{t-1}$
M5	Constant Gain	$E_{i,t}\pi_{t+1} = E_{i,t-2}\pi_{t-1} - \gamma(E_{i,t-2}\pi_{t-1} - \pi_{t-1})$
		$E_{i,t}\pi_{t+2} = E_{i,t-3}\pi_{t-1} - \gamma(E_{i,t-2}\pi_{t-1} - \pi_{t-1})$
M6	Trend Chasing	$E_{i,t}\pi_{t+1} = \pi_{t-1} + \tau(\pi_{t-1} - \pi_{t-2})$
		$E_{i,t}\pi_{t+2} = \pi_{t-1} + 2\tau(\pi_{t-1} - \pi_{t-2})$

Models of expectations as functions of exogenous or historical data. γ and $\tau \in [0.1, 1.5]$ in increments of 0.1.