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.

JEL classifications: C9, D84, E52, E58

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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 preserve credibility. Density forecasts typically covey 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 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. [Neely (2005), Swanson (2006), Bauer (2012), Husted, Rogers, and Sun (2018, 2019)].

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. 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. This suggest 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 point and density projections influence aggregate dynamics and individual expectations. To this end, we build an experimental macroeconomy that allows expectations provided by either groups or 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, 2018), 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). We are also interested in understanding how subjects' own uncertainty about future inflation responds to both precise and noisy projections. Pfajfar and Žakelj (2016) also explore uncertainty in response to different inflation targeting regimes. 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 begin by describing the design of our baseline environment which involves groups of 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

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

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 forecasts with a precision of $\frac{1}{100}$th of 1%.

After expectations were submitted or time elapsed, participants moved onto the next period. The economy's data-generating process, which will be described in the next section, relies on aggregate one- and two-period-ahead expectations about inflation. Aggregate one- and two-period-ahead expectations are median expectation from both distributions into our data generating process. We use the median forecast, rather than the average, 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 a 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.

We begin with a standard 3-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.

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 of this problem by allowing subjects to focus on forecasting a single time series. Second, it allows us to understand how these information conditions effect 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 see, perhaps 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 puts upward pressure on prices today, leading to higher inflation today. If an agent also expects inflation two days from now, then I will want to have a bit more money to spend tomorrow than otherwise so that an agent can similarly avoid paying higher prices two days from now.

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 $u_{i,t+1}, u_{i,t+2}$. This measure of uncertainty creates a subject-level density forecast in each period for both forecast horizons. To do this, we assume a subject's forecast uncertainty is symmetric around her point forecast, which is similar to our assumption about the central bank's forecast uncertainty. This means that subjects could submit values for $u_{i,t+1}, u_{i,t+2} \in \mathbb{N}_0$. We incentive this uncertainty measure using a piece-wise scoring rule.[3] A subject earned nothing if actual inflation fell outside of her density forecast (i.e. her uncertainty bands). Otherwise, a subject earns $U_{i,t+k}$, where $k = \{1, 2\}$:

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

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. 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.

[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-adverse agent may slightly over-report uncertainty. However, we can distinguish neither risk-loving behavior from over confidence nor risk-adverse behavior from under-confidence.

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 own experimental economy. This means that subjects in individual treatments played an individual choice game; their expectations alone, coupled with the demand shock, drove the dynamics of their economy. 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. 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 screen displayed in the top left corner a subjects identification number, the current decision period, time remaining to make a decision, and total number of points earned through the end of the previous period. The interface also features three horizontal 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).

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.[4] 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.

We conducted six sessions of each our six treatments for a total of 36 experimental sessions. Each session consisted of two, 30-period repetitions (decision blocks). We pre-drew shock sequences so that we can hold these constant across treatments. We drew all sequences from a mean-zero normal distribution with the same standard deviation. We selected sequences so that there was variation in the sample standard deviation. This allows for a more robust understanding of forecasting under different information and strategic conditions.

2.4 Procedures

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.

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.

[4] Petersen and Mokhtarzadeh (2018) 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.

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 subjects in our experiment form rational expectations, then we should observe that neither projection (Point or Point&Density) changes aggregate dynamics or individual behavior. This is because providing these projections would neither increase the information set of agents nor impact how they use available information. Further, subjects would behave equivalently when forming expectations in both individual-choice and coordination settings. This is because rational subjects would behave identically in our experiment since they all access the same information.

However, ample laboratory and survey evidence indicates 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). Mokhtarzadeh and Petersen (2018) also implement a reduced-form New Keynseian data generating process to study expectations coordination in the lab and find that most subjects follow a constant gains heuristic when forming expectations in the absence of central bank forecasts. Backward-looking heuristics also explain behavior in Kryvtsov and Petersen (2015), Pfajfar and Žakelj (2016), and Petersen and Rholes (2020).

Further, extensive 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). Moreover, simulations (not reported here) show that increasing the share of agents forming model-consistent expectations (and reducing those adhering to a constant-gains heuristic) leads to more stable aggregate dynamics. This leads us to believe that both density and point forecasts can alleviate information frictions to yield more stable aggregate dynamics and improve forecast accuracy.

It is possible that including uncertainty bands in central bank projections will cause agents to place less weight onto the point projections when forming their own expectations. This might be because density forecasts make salient the imprecision of point projections. It could also cause subjects to update their prior on exactly how much uncertainty surrounds these point forecasts. Further, the uncertainty communicated by the central bank in a density forecast may transmit to forecaster, increasing the uncertainty s about their own forecasts.

To illustrate this idea, suppose a boundedly-rational agent i forms inflation expectations as a linear combination of some adaptive process, $\mathbb{E}_i, t_t^A\{\pi_{t+s}\}$, and the central bank's inflation projections, $\mathbb{E}_t^{CB}{}_t\{\pi_{t+s}\}$. Then we have

$$\mathbb{E}_{i,t}\{\pi_{t+s}\} = \alpha_i(\mathbb{E}_{i,t}^A\{\pi_{t+s}\}) + (1-\alpha_i)(\mathbb{E}_t^{CB}\{\pi_{t+s}\}) \tag{13}$$

where $\alpha \in [0,1]$ governs the weight agent i places on the central bank's forecast in her expectations. Denote the total degree of uncertainty conveyed by the central bank at time t in a density forecast of period $t+s$ as $U_{t,t+s}$. If we suppose that $\alpha_i(\cdot)$ depends on $U_{t,t+s}$ so that $\alpha_i'(U_{t,t+s}) > 0$ then $U_{t,t+s} > 0$ ought to yield 'more adaptive' aggregate expectations than otherwise. However, unless the uncertainty completely undermines the central bank's projection (i.e. there is enough uncertainty surrounding the point projection so that i chooses $\alpha_i = 1$), providing a point forecast along with a measure of uncertainty should be better than providing no forecast at all.

Thus, including some positive measure of uncertainty ought to lead to more heterogeneity in expectations[5] and higher average forecast errors than point projections alone but not more so than providing no projections. Also, since this means that more agents rely on (or agents rely more heavily on) an heuristic, this should yield less stable dynamics, as discussed above.

Finally, we can consider differences in how subjects incorporate information when forming expectations in either a coordination or an individual-choice setting. Since aggregate expectations are the predominant driver of inflation dynamics, a subject who aligns her expectations with aggregate (median) expectations is likely to form more accurate expectations.

If participants in Group treatments believe the median subject will use the projections, it is rational for them to do so as well. Otherwise, their best response would be to incorporate their perception of aggregate expectations into their own forecast. The incentive to ignore the projections is absent in the Individual treatments. Furthermore, any increase in central bank uncertainty should make a forecaster less certain that other subjects will adhere to the central banks forecast. Thus, we expect the benefits of projections to be more pronounced

[5] Since it is not likely that $\alpha_i(U_{t,t+s}) \equiv \alpha_j, (U_{t,t+s}), \forall i \neq j$

in the Individual treatments than Group treatments.

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

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

H1.b Inflation $\text{volatility}_{Group}$ > Inflation $\text{volatility}_{Individual}$

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

H2.b Forecast errors_{Group} > Forecast $\text{errors}_{Individual}$

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

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

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

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

H5.a $\text{Credibility}_{Point\&Density}$ < $\text{Credibility}_{Point}$

H5.b $\text{Credibility}_{Group}$ < $\text{Credibility}_{Individual}$

3 Results

We first describe how point and density projections influence aggregate dynamics and then how they influence individual forecasting behavior.

3.1 Aggregate results

Figure 5 and Figure 6 compare the time series of inflation for groups and individuals, respectively, across our three information treatments by sequence and repetition.[6] Time series comparing Group and Individual treatments can be found in the Appendix. 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.

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

Insert Figure 5
Insert Figure 6

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 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 are unable to find significant support for Hypothesis 1b that inflation volatility is higher in Group treatments than 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 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 next turn to our individual forecast data to identify participants' ability and strategies for forecasting. We only participants whose forecasts are within ±1500 bps. This excludes five participants from each of the Point-Indiv. and Point&Density-Indiv. treatments.

Forecast Errors

The distribution of the forecast errors are presented in Figure 7 by repetition and group 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 7

Insert Table 2

We find mixed support for Hypothesis 2a that projections reduce forecast errors, with Point projections more effective than Point&Density projections. 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. We reject Hypothesis 2b that forecast errors are smaller in Individual treatments than Group treatments. Consistently, two-period-ahead forecast errors are more extreme in the 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.

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.

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 the 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 10 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 reject Hypothesis 3b that disagreement is lower 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 when participants interact in the Group treatments than in the Individual treatments.

Uncertainty

Subjects provided their own 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

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 10 bps when participants are provided 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 own forecasts when dealing with other human participants. In Point and, especially, NoComm, strategic coordination actually leads to less uncertainty about future inflation.

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

Result 8: Individuals are less uncertainty about future inflation than Groups when presented with presented with Point&Density projections.

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 own expectations. Given the potential for rounding errors, we assume a participant is using the projected value if their forecast is within 5 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, 15% (11%) of one- and two-period-ahead forecasts in NoComm-Group (NoComm-Indiv.) are within 5 basis points of the rational expectations equilibrium forecast. Point projections are used by 41% (38%) of Group (Indiv.) subjects to formulate their one-period-ahead forecasts. Subjects use projections a bit less to formulate two-period-ahead projections: 31% (26%) of Group (Indiv.) participants. Communicating a density decreases usage of the projection. Credibility decreases to 34% (25%) for one-period-ahead forecasts and 23% (17%) for two-period-ahead forecasts in the Group (Indiv.) treatments.

For both Group and Individual treatments, communicating either a Point or Point&Density projection significantly increases the ability of participants to forecast the REE solution for $t+1$ inflation. Consistent with Hypothesis 5a, credibility in the projections is significantly lower, however, when the projection includes a density forecast for both $t+1$ and $t+2$ forecasts. This is true in both 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 4 percentage points in the Point treatments, and between 6-9 percentage points in the Point&Density treatments. Thus, we reject Hypothesis 5b that Individual-choice settings improve credibility in projections.

Result 9: Credibility 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 (Mokhtarzadeh and Petersen, 2018).

Insert Table 7

Following Mokhtarzadeh and Petersen, we classify each participant into one of the six heuristics according to the heuristic 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 9 by treatment.

Insert Figure 9

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 is effective at nudging subjects away from using Adaptive and Trend-Chasing heuristics toward both Rational and Constant Gain. The projection is noticeably less effective in the Individual treatment. This is likely because Individual participants who have initially not utilized 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 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 general 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. This occurs in the 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 heuristics.

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 market dynamics and how market participants incorporate information in the first and second central moments into their own expectations and perceptions of future uncertainty. Second, this paper studies the difference in how economic agents use information 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.

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 higher levels of private forecast uncertainty. Moreover, we observe fewer subjects classified as ex-ante rational.

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5 Figures and Tables

Figure 1: Flow of information, decisions, and outcomes

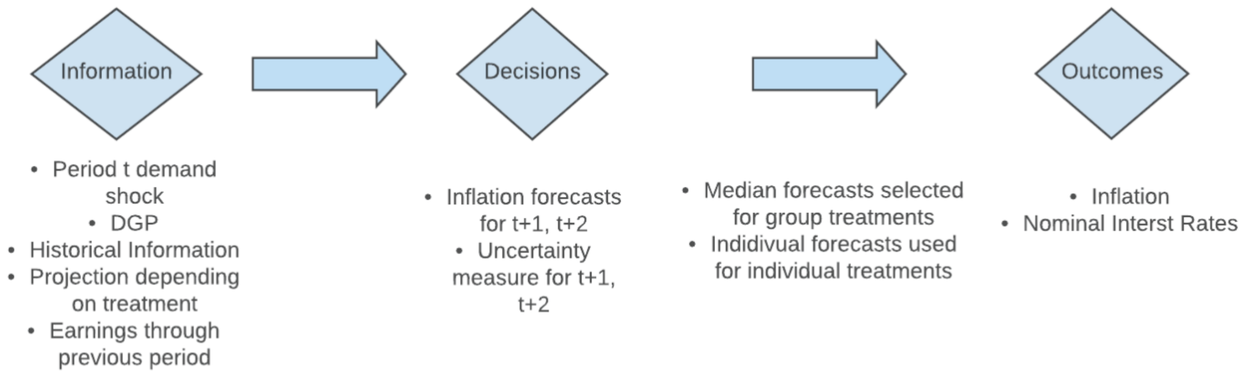

Figure 2: NoComm screenshot

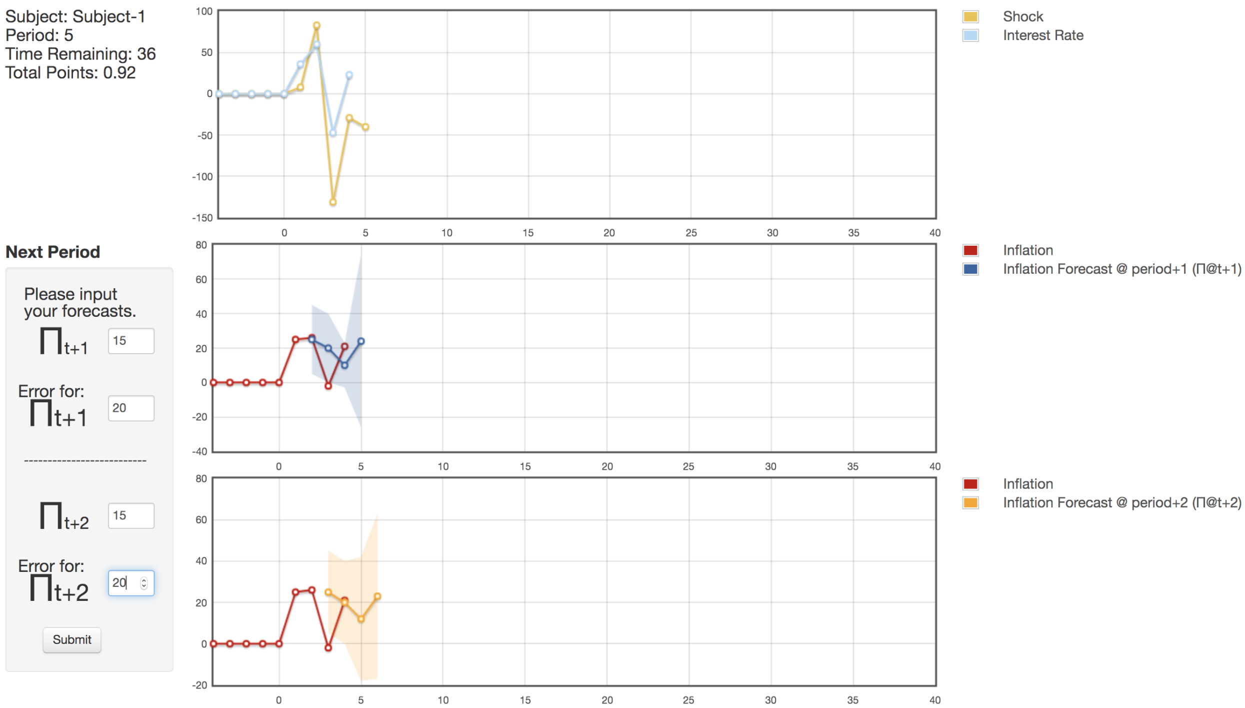

Figure 3: Point screenshot

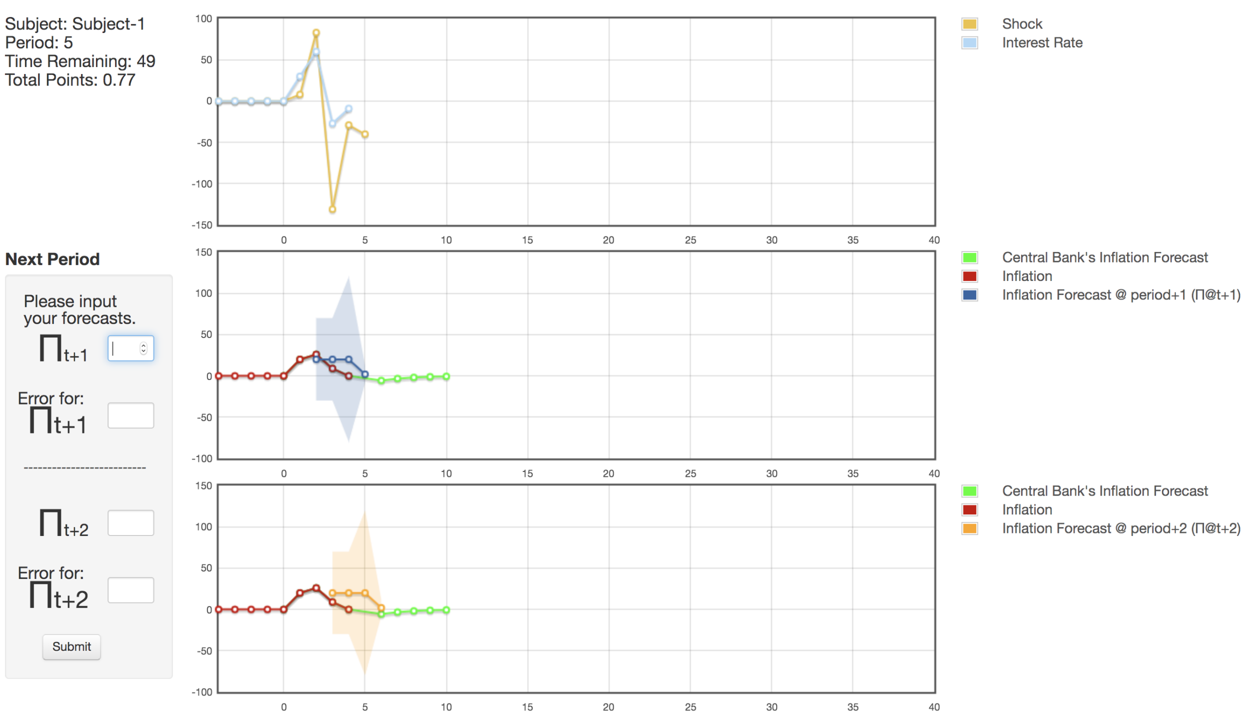

Figure 4: Point&Density screenshot

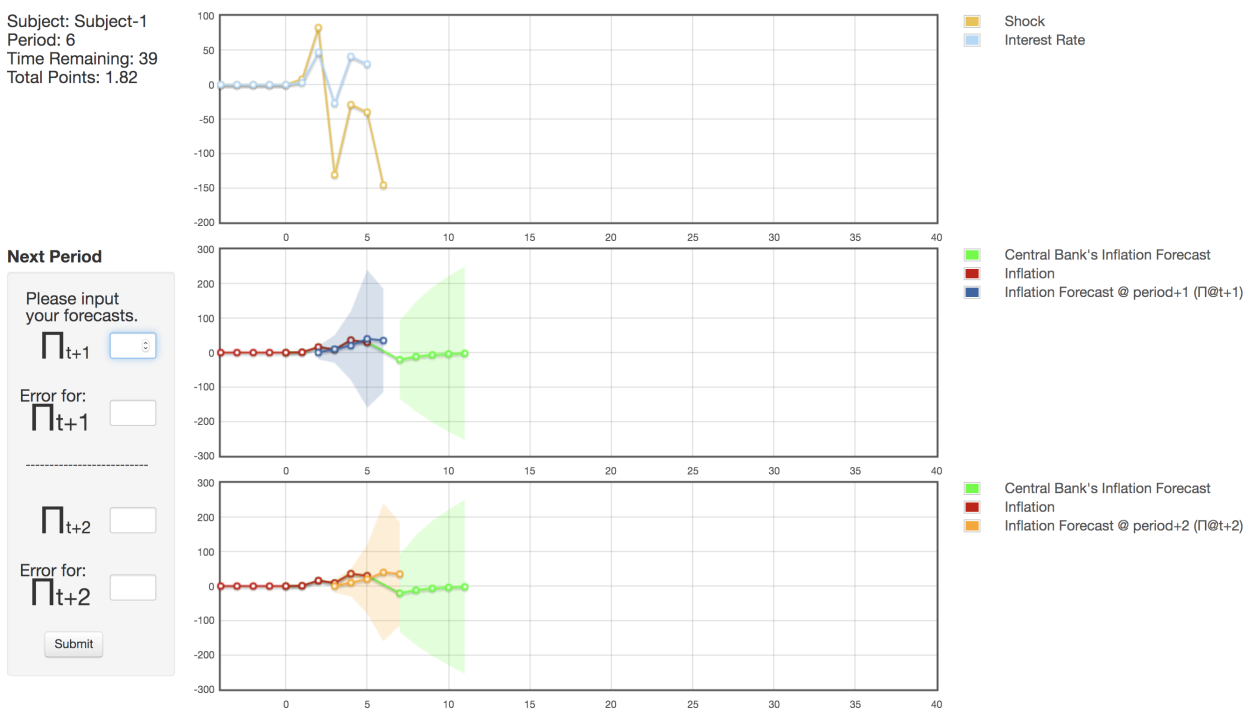

Figure 5: Time series of Group treatments

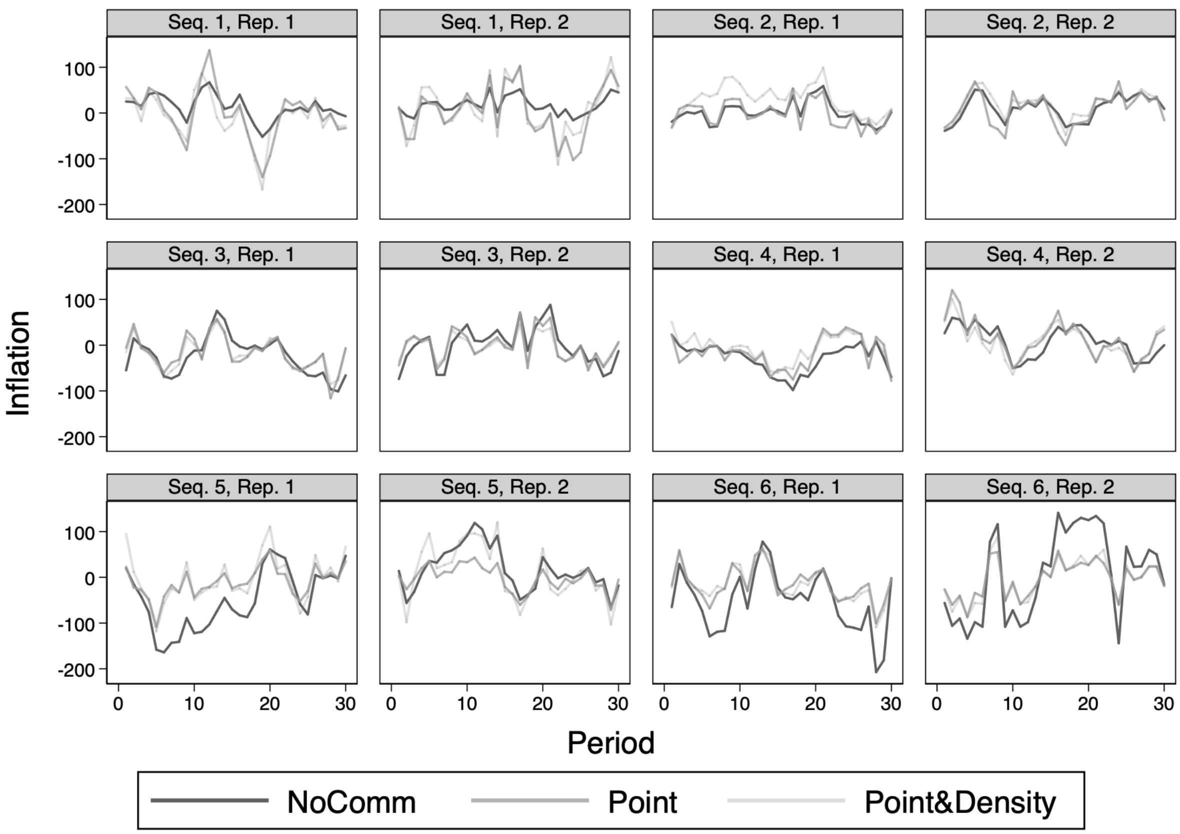

Figure 6: Time series of Individual treatments

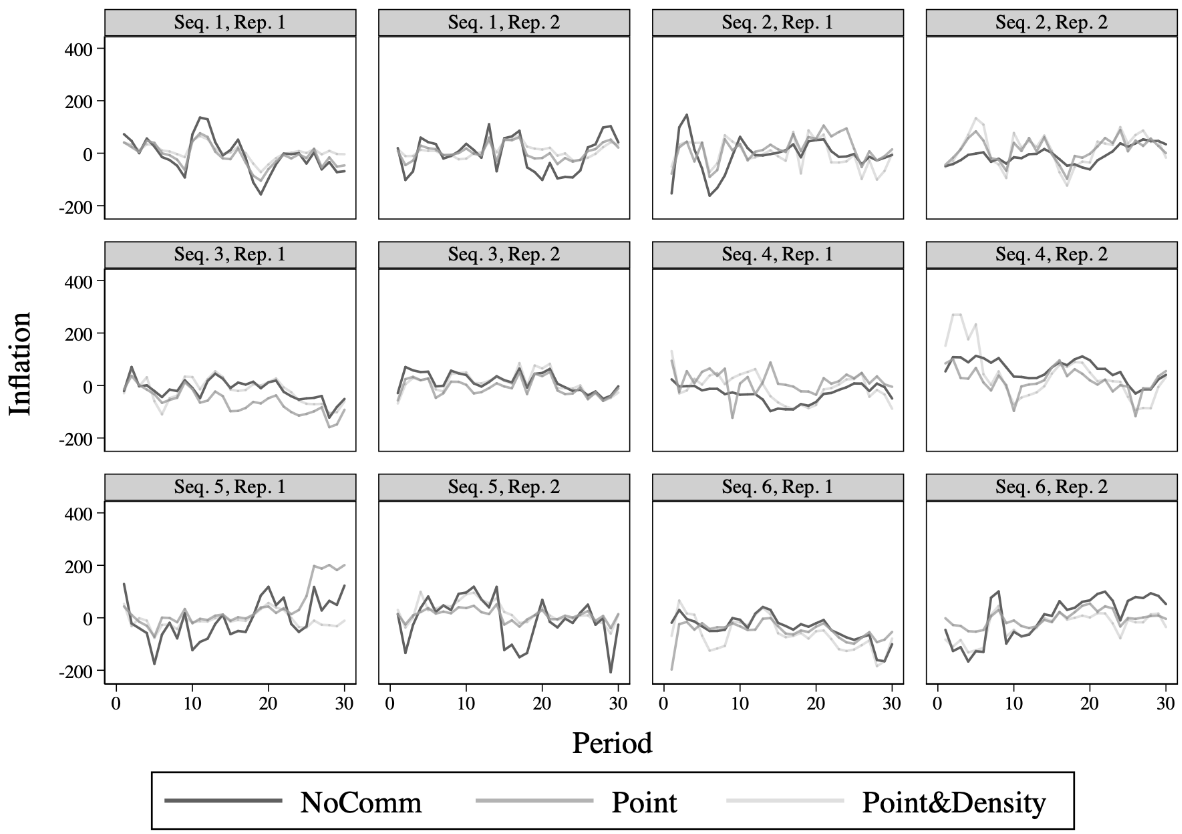

Figure 7: Distributions of absolute forecast errors

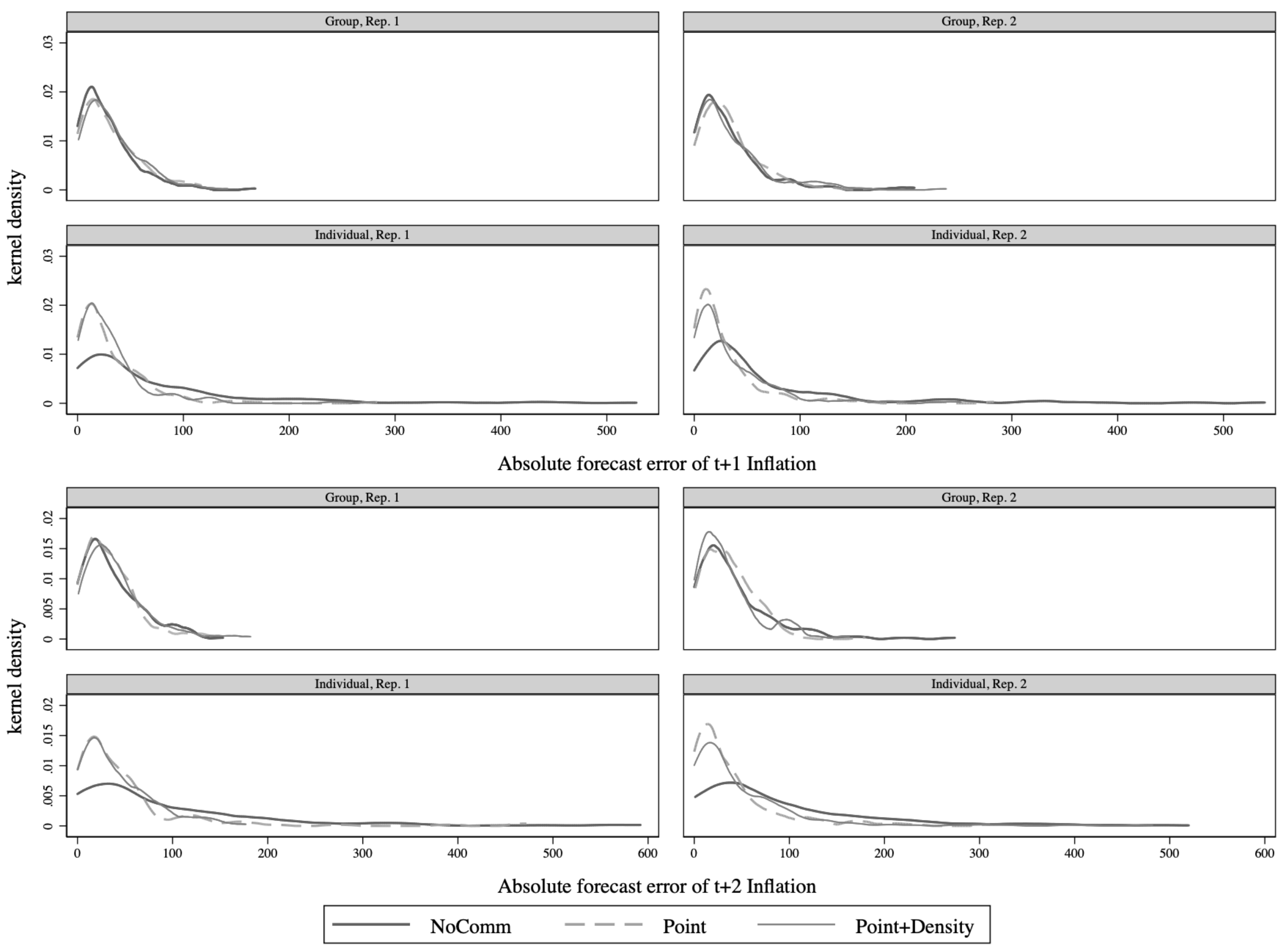

Figure 8: Distribution of forecasting heuristics for $t+1$ inflation, by treatment

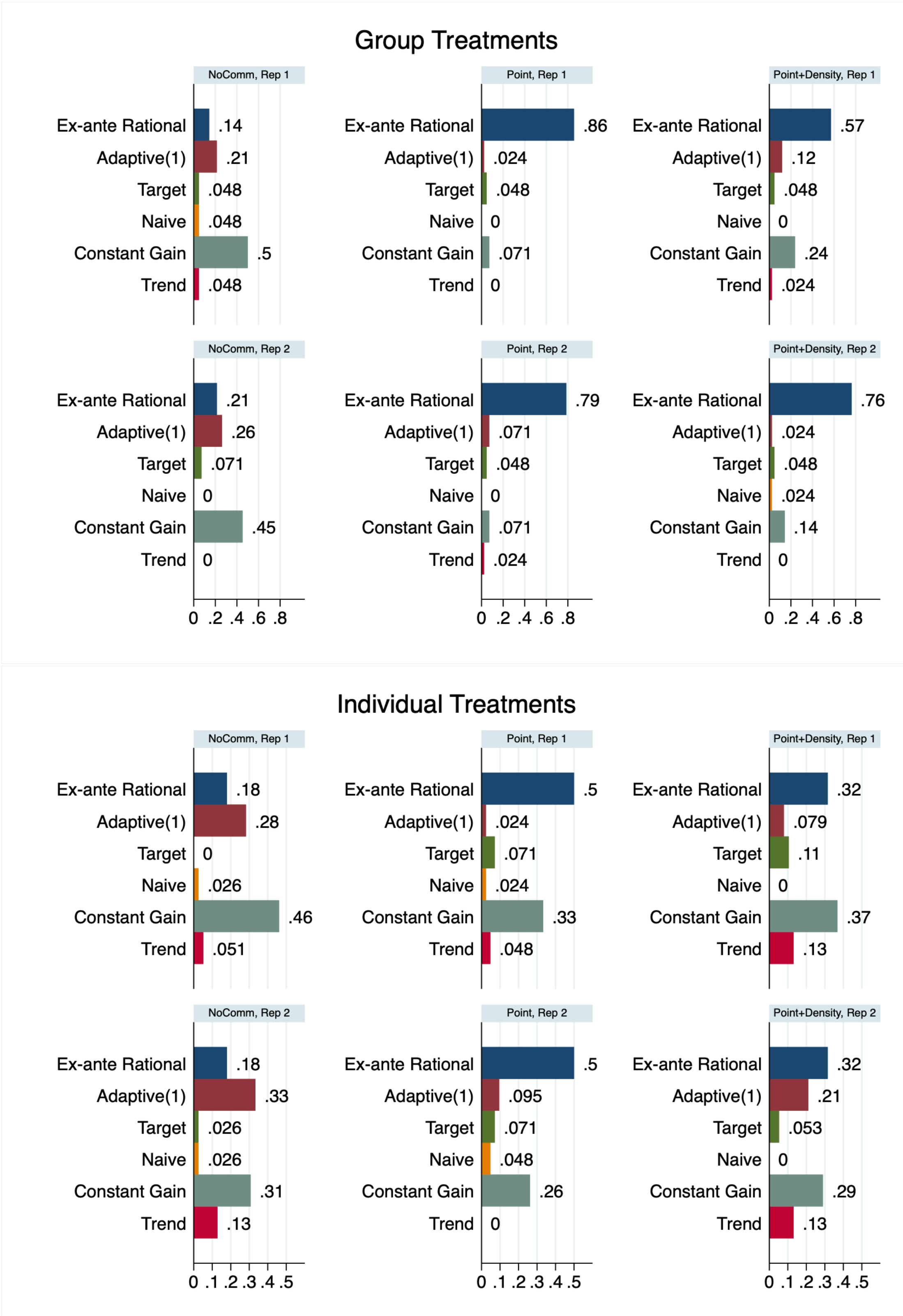

Figure 9: Distribution of forecasting heuristics for $t + 2$ inflation, by treatment

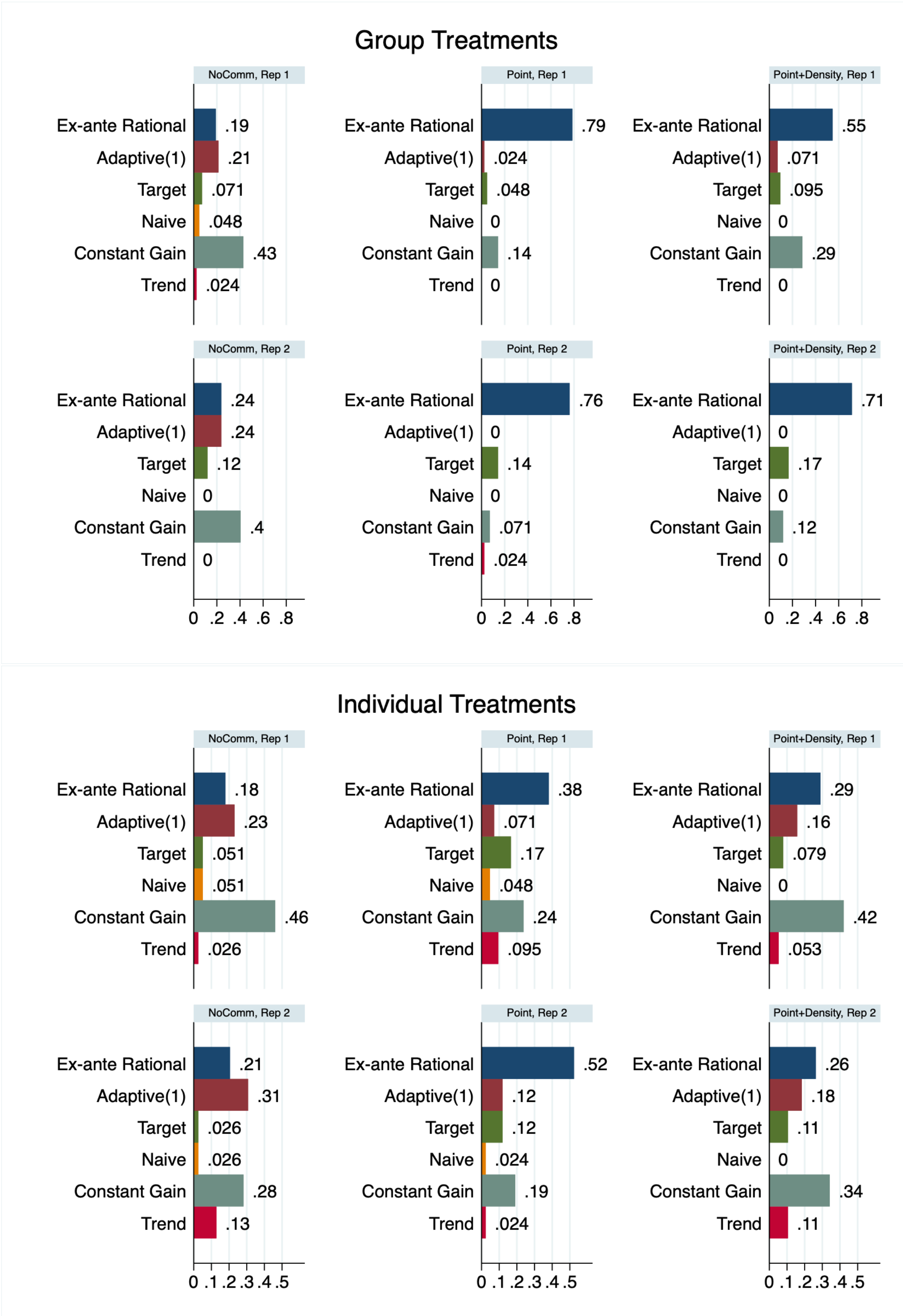

Table 1: Treatments summary

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
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
Point&Density	6	42	30 x 2	median of group

Table 2: Summary statistics of aggregate and individual forecast variables

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}
Group										
NoComm	39	43	36	43	32	31	27	32	15%	15%
	(37)	(22)	(56)	(55)	(46)	(40)	(37)	(92)	(0.35)	(0.36)
Point	32	38	31	35	17	16	17	21	41%	31%
	(24)	(9)	(28)	(27)	(14)	(10)	(17)	(24)	(0.49)	(0.46)
Point&Density	34	40	34	38	21	21	30	35	35%	23%
	(26)	(11)	(31)	(35)	(17)	(20)	(29)	(32)	(0.47)	(0.42)
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	38%	26%
	(93)	(41)	(68)	(82)	(70)	(68)	(29)	(29)	(0.48)	(0.44)
Point&Density	58	65	36	47	65	61	24	26	25%	17%
	(73)	(60)	(51)	(62)	(45)	(45)	(28)	(30)	(0.43)	(0.38)

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.

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	$E_{i,t}\pi_{t+1} = \pi_{t-1} - \gamma(E_{i,t-2}\pi_{t-1} - \pi_{t-1})$
		$E_{i,t}\pi_{t+2} = \pi_{t-1} - \gamma(E_{i,t-2}\pi_{t-1} - \pi_{t-1})$
M6	Trend Chasing	$E_{i,t}\pi_{t+1} = \pi_{t-1} + \tau(\pi_{t-1} - \pi_{t-2})$
		$E_{i,t}\pi_{t+2} = \pi_{t-1} + 2\tau(\pi_{t-1} - \pi_{t-2})$