Coordinating expectations through central bank projections*

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Abstract

Central banks are increasingly communicating their economic outlook in an effort to manage the public and financial market participants' expectations. We provide original causal evidence that the information communicated and the assumptions underlying a central bank's projection can matter for expectation formation and aggregate stability. Using a between-subject design, we systematically vary the central bank's projected forecasts in an experimental macroeconomy where subjects are incentivized to forecast output and inflation. Without projections, subjects exhibit a wide range of heuristics, with the modal heuristic involving a significant backward-looking component. Ex–ante rational dual projections of output and inflation significantly reduce the number of subjects' using backward-looking heuristics and nudge expectations in the direction of the rational expectations equilibrium. Ex-ante rational interest rate projections are cognitively challenging to employ and have limited effects on the distribution of heuristics. Adaptive dual projections generate unintended inflation volatility by inducing boundedly–rational forecasters to employ the projection and model-consistent forecasters to best-respond to the projection. All projections reduce output gap disagreement but increase inflation disagreement. Central bank credibility is significantly diminished when the central bank makes larger forecast errors when communicating a relatively more complex projection. Our findings suggest that inflation-targeting central banks should strategically ignore agents' irrationalities when constructing their projections and communicate easy-to-process information.

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1. Introduction

The economy is highly complex with many moving parts. It can be very challenging for the average person, with limited cognitive capacity and attention, to accurately forecast how it will evolve. In an effort to ease this cognitive burden, guide expectations, and improve the efficacy of monetary policy which operates largely through the expectations channel, central banks have become increasingly transparent about their objectives, future policies, and the outlook of the future. Many central banks publish a combination of projections about future GDP, GDP growth, CPI and their own policy rates. The Reserve Banks of Australia, New Zealand, and Norges Bank were pioneers in the publication of their inflation projections during the early 1990s. Likewise, the Reserve Bank of New Zealand has communicated their projections for the 90-day bank bill rate via Monetary Policy Statements (MPS) since 1997. Other central banks followed suit with Norway (2005), Sweden (2007) and the FOMC (2012) providing projections of their key policy rates.

Central banks face two critical decisions when constructing and communicating their projections. First, they must make numerous assumptions about how the economy evolves, including how people think about the future. Many central banks' projections are constructed under the assumption that households and firms form rational expectations. While projections based on the assumption of non–rational expectations may be more accurate and may enhance central bank credibility, it is not clear which of many models of non–rational expectations to use. Assumptions about the form of aggregate expectations can have very important implications for aggregate dynamics and optimal monetary policy. Moreover, information has the potential to influence the heuristics individuals use to form their expectations. [1] Second, central banks must decide which of their many projections to communicate to the public given their mandated objectives. Too little information can lead to the central bank insufficiently guiding expectations and coming across as 'opaque'; too much information can result in cognitive overload and audiences not paying sufficient attention to any particular information

The contribution of this paper is to provide empirical insight into these two important policy decisions. Because central banks are not able to do controlled experiments, it can be difficult to disentangle the causal impact of the projections they choose to communicate on the public's expectations and central bank credibility. To circumvent the empirical challenges inherent to observational data, we study individual and aggregate forecasts in 24 multi-period laboratory economies where we can systematically control the information that central banks communicate about their own forecasts in otherwise identical underlying economies. In each period of our experiments, each

[1] Ferrero and Secchi (2010) discuss the widespread strategy of central banks to employ rational expectations into their core macroeconomic DSGE models. As they note, there is an awareness that the general public does not form rational expectations and efforts need to be made to bring this realism into projection models. To date, the Bank of Canada, Bank of Israel, Norges Bank, and Riksbank's main projection models are built around the assumption of rational expectations. The Bank of England's COMPASS, the Reserve Bank of New Zealand's NZSIM, and the ECB's New Multi-Country Model incorporate extensions allowing for adaptive expectations.

subject reports incentivized forecasts of the following period's rate of inflation and output gap. The aggregate expectations and a random disturbance to aggregate demand endogenously determine the current state of the economy.[2]

We study the effects of four different types of central bank projections on individual forecasting heuristics and aggregate dynamics. In our baseline environment, participants observe current and historical information about the economy, as well as full information about the economy's data-generating process. We compare our benchmark economies, where the central bank does not communicate its projections, to compare economies operating under three alternative communication policies. In our Interest Rate Projection treatment, all subjects observe the central bank's projection of future nominal interest rates, derived according to the economy's rational expectations equilibrium (REE) solution. In the Dual Projection treatment, all subjects are instead informed about the central bank's projection of future inflation and output gap, also derived using the REE solution. For a rational subject, the communications in either of these two projection treatments is redundant and should not influence expectations. For boundedly rational subjects, however, such projections provide potentially useful focal information. While both of these REE projections convey the same overall information about the economy, we hypothesized that Dual Projections would be cognitively easier for subjects to apply to their own output and inflation forecasts. Finally, the Adaptive Dual Projection treatment mirrors the Dual Projection treatment except that the central bank's projections follow an adaptive model of expectations that, based on previous work, we expected would better predict aggregate dynamics, and thus, reduce credibility concerns. The purpose of the Adaptive Dual Projection treatment was to address discussions in policy circles as to whether boundedly rational agents should be implemented into central banks' forecasting models.

We find that certain central bank projections can significantly stabilize expectations and the aggregate experimental economy by *nudging* naïve forecasters towards fundamentally–driven rational expectations. Rational projections of future output gap and inflation results in consistently less dispersion in forecasts and significantly forecast errors. By contrast, projections of nominal interest rates lead to mixed results. For relatively low variability in aggregate demand shocks, subjects are willing and able to employ the projections, resulting in significantly more rational forecasts. However, as the variability of shocks increases, the ease and value of using the projection decreases and subjects instead rely on adaptive forecasting heuristics. These results suggest that policy makers cannot take for granted that private agents are able to infer the implied path of inflation and output from an interest rate projection. Rather, central banks concerned about anchoring a specific type of expectation should directly communicate about that variable of interest.

Adaptive dual projections generate significantly greater inflation forecast errors, forecast dispersion, and inflation variability. This is a consequence of a large fraction of subjects directly

[2] See Duffy (2012) for a highly comprehensive survey of macroeconomic experiments, Cornand and Heinemann (2014) for a survey of experiments on central banking, and Amano et al. (2014) for a discussion of how laboratory experiments can help inform monetary policy.

employing the central bank's adaptive projections as their own while others best-respond to their counterparts' adaptive behavior by forecasting even higher inflation. Our paper provides original empirical evidence that inflation–targeting central banks may prefer not communicating a projection than one based on the assumption that agents form adaptive expectations.

Loss of credibility is an important concern central banks face when deciding whether to communicate their own projections. We find that this concern is valid when the central bank communicates either a nominal interest rate projection or an adaptive dual projection. Under both types of projections, the likelihood a subject employs the central bank projection decreases as the central bank makes larger forecast errors in the recent past. Usage of the interest rate projections is consistently very low as it is more challenging to infer what the projection implies about future output and inflation. As the central bank's implied forecast of future output and inflation become increasingly incorrect, the likelihood subjects utilize the projections significantly decreases. By contrast, the central bank's credibility appears to be impervious to its own forecast errors when rational dual projections are communicated.

Our paper complements the existing empirical and theoretical work on the role of central bank communication and projections in shaping expectations. The empirical literature has found mixed evidence on the effectiveness of forward guidance in influencing expectations (Kool and Thornton, 2012; McCaw and Ranchhod, 2002; Goodhart and Lim, 2011; Brubakk et. al. 2017; Turner, 2006) while macroeconomic projections appear to more consistently manage inflation expectations. Hubert (2014) finds a significant positive relationship between projections and forecasters' expectations of inflation in Sweden, UK, Canada, Japan, and Switzerland. In a closely related paper to ours, Jain and Sutherland (2018) construct an original panel data set of twenty-three countries to estimate the effects of numerous central bank projections and forward guidance on private-sector forecast dispersion and accuracy. They find that inflation projections and forward guidance matter primarily for private sector disagreement and accuracy about upcoming rate decisions. Surprisingly, inflation and output gap projections do not consistently reduce forecaster disagreement and errors about current year or next-year inflation rates.

Goy et al. (2016) computationally examine agents' expectations near and at the zero lower bound (ZLB) and find that such forward guidance through output and inflation projections significantly reduces the likelihood of deflationary spirals when the economy is at the ZLB. Likewise, theoretical work by Ferrero and Secchi (2010) highlight that macroeconomic projections are more effective than interest rate projections at stabilizing expectations of recursively learning agents. Our paper provides an experimental validation of these results and additional insight into the consequences of modifying projections in response to the public's backward–looking behavior. Moreover, our findings provide original empirical support for the policy recommendation that strict inflation-targeting central banks disregard the public's adaptive forecasting heuristics when designing their communication strategy.

Learning-to-forecast experiments (LtFEs) have been extensively employed to study how expectations respond to information, policy, and structural features of the economy. In LtFEs, subjects play the roles of forecasters and are tasked to form accurate forecasts for the following period(s) over a long multi–period horizon. Each period, aggregated forecasts are used by computerized households, firms, and banks to make decisions according to a pre-specified data-generating process. In other words, subject-provided aggregate expectations have a direct effect on the macroeconomy. The assumption that expectations influence economic decision making is supported by recent experimental evidence. In a field experiment involving participants in the University of Michigan Survey of Consumers and RAND's American Life Panel, Armantier et al. (2015) find that, on average, participants' expectations and decisions are correlated in a manner consistent with economic theory. Cornand and Hubert (2018) investigate the external validity of expectations elicited in LtFEs. They find that expectations elicited from undergraduate participants in LtFEs are consistent with those formed by households, firms, professional forecasters, financial market participants, and central banks in that forecast errors are large, serially correlated, and predictable indicative of information frictions.[3]

There are a handful of LtFEs that investigate the effect of central bank communication on expectation formation. Kryvtsov and Petersen (2015) study, among many things, the effects of central bank projections of nominal interest rates. They find that focal interest rate projections have an inconsistent effect on forecasting behavior. Many inexperienced subjects incorporate the projections into their forecast and this leads to greater stability in some sessions. However, if only a few subjects initially employ the projections in their forecasts, the announcement creates confusion and expectations become increasingly destabilized. Like Kryvtsov and Petersen, we find that nominal interest rate projections lead to inconsistent heuristics. Our paper extends their findings by providing a more robust study of different types of projections. We additionally consider rationally–and adaptively–formed inflation and output projections to gain insight into the ability of central bank projections to influence expectations and maintain central bank credibility. Communication of inflation targets has also been shown to have mixed effects on the management of expectations. Under a dual mandate to stabilize both inflation and output gap, Cornand and M'baye (2018) find that expectations and inflation are better anchored, while Mirdamadi and Petersen (2018) observe increased heterogeneity in heuristics as forecasters have more information to coordinate on. Arifovic and Petersen (2017) find that communicating a time-varying, history-dependent inflation target can make expectations even more pessimistic at the ZLB when the

[3] The LtFE methodology originates with Marimon and Sunder (1993) who study price forecasting in an overlapping-generations experimental economy. Experiments studying inflation and output expectations in New Keynesian reduced form economies have been developed to study expectation formation and equilibria selection (Adam, 2007); the effects of different monetary policy rules on expectation formation (Pfajfar and Žakelj 2014, 2016; Assenza et al. 2013, Hommes et al. 2015a); expectation formation at the zero lower bound (Arifovic and Petersen 2017, Hommes et al. 2015b). Backward-looking, inattentive forecasting behavior frequently observed in laboratory experiments is also widely found in household and professional forecasts (Malmendier and Nagel 2015; Andrade and LeBihan 2013; Coibion and Gorodnichenko 2015; Cornand and Hubert (2018).

central bank fails to achieve its explicit targets. Ahrens et al. (2016) have extended our paper and Arifovic and Petersen (2017) to study the effects of one-period ahead inflation projections in the presence of both demand and supply shock in the normal times or at the zero lower bound. Similar to our findings, they observe that central bank communication significantly alters how subjects forecast and reduces economic instability at the zero lower bound.

The paper is organized as follows. Section 2 lays out our experimental design, hypotheses, and experimental implementation. Results are discussed in Section 3, namely how participants form expectations and how aggregate variables evolve under different forms of central bank communication, and Section 4 discusses our findings in the context of the learning and inattention literatures.

2. Experimental Design

Our experiment is designed to study how macro-expectations are formed in the presence of central bank projections of key economics variables. Each independent economy involved groups of seven inexperienced subjects playing the role of forecasters who were tasked with submitting incentivized forecasts about two evolving variables: the subsequent period's output gap, x_{t+1}, and inflation, π_{t+1}. The submitted forecasts were aggregated as $\mathbb{E}_t^* x_{t+1}$ and $\mathbb{E}_t^* \pi_{t+1}$ and used by computerized households and firms to form optimal decisions, which in turn influence concurrent inflation and output.

The experimental economy's data–generating process is derived from a log-linear approximation around a deterministic steady state of a standard representative-agent New Keynesian framework. We focus on this specific model for its relative simplicity and because of its ubiquitous use by central banks over the last decade and for the important role expectations play in driving aggregate dynamics. The aggregate economy implemented in our experiment is described by the following system of equations:[4]

$$x_t = \mathbb{E}_t^* x_{t+1} - \sigma^{-1}(i_t - \mathbb{E}_t^* \pi_{t+1} - r_t^n), \tag{1}$$

$$\pi_t = \beta \, \mathbb{E}_t^* \pi_{t+1} + \kappa x_t, \tag{2}$$

$$i_t = \phi_\pi \pi_t + \phi_x x_t, \tag{3}$$

$$r_t^n = \rho_r r_{t-1}^n + \epsilon_{rt}. \tag{4}$$

?? is the Investment–Saving curve and describes the evolution of the output gap or aggregate

[4]See Walsh (2010) for detailed assumptions and derivations in a model with rational expectations. We preferred to implement a linearized version of the homogeneous expectations New Keynesian model to simplify the environment for subjects. This version of the New Keynesian model is arguably the simplest framework where supply and demand interact with monetary policy. For a nonlinear implementation, see Hommes et al. (2015). A heterogenous version of the New Keynesian model has been implemented by Mauersberger (2016) and Kryvtsov and Petersen (2019).

demand. It is derived from a log–linear approximation of households' intertemporal optimization around a deterministic zero inflation and output gap steady state. **??** describes how the current output gap, x_t, depends positively on aggregated expectations of next period's output gap, $\mathbb{E}_t^* x_{t+1}$, and deviations of the real interest rate, $i_t - \mathbb{E}_t^* \pi_{t+1}$, from the natural rate of interest, r_t^n.[5] The quantitative importance of this deviation depends on the elasticity of intertemporal substitution, σ^{-1}.

?? is the New Keynesian Phillips curve (NKPC) which describes the evolution of inflation, π_t, in response to changes in aggregated expectations of future inflation, $\mathbb{E}_t^* \pi_{t+1}$, and the output gap, x_t. The coefficient κ is a function of parameters associated with the frequency and the size of firms' price changes, and governs the sensitivity of prices to aggregate demand, while the coefficient β represents the subjective discount rate. To construct the NKPC, we make the simplifying assumption that households have identical information sets and form expectations using identical functions of the state history.

?? is the central bank's response function and describes the evolution of the nominal interest rate. Under this specification the central bank contemporaneously responds to deviations of output gap and inflation from their steady state values. In each period, the automated central bank increases the nominal interest rate in response to higher current inflation and the output gap. The coefficients ϕ_π and ϕ_x govern the central bank's reaction to inflation and output gap.[6] Note that the implemented environment studies deviations around a constant steady state, ignoring the presence of zero lower bound. That is, i_t was frequently negative in our experiment.[7]

Finally, **??** describes how the natural rate of interest evolves in response to random perturbations. Throughout the paper, we will refer to r_t^n as a *shock* to the demand side of the economy, which follows an *AR(1)* process. The random innovation, ϵ_{rt}, is drawn from an $i.i.d \;\; N(0, \sigma_r)$.[8] The experimental economy's data-generating process is calibrated to match moments of the 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. The environment had a unique steady state where $\pi^* = x^* = i^* = r_t^n = 0$.

?? presents the timing of information, decisions, and outcomes in each round. Before forming their forecasts at the start of a period, subjects had access to the following common information (and all subjects understand that this is common information). First, they observed detailed quantitative and precise qualitative information about the economy's data-generating process.[9]

[5] The natural rate of interest is the equilibrium real rate of interest required to keep aggregate demand equal to the natural rate of output at all times.

[6] We differ from Kryvtsov and Petersen (2015) who implement a policy rule that responds to deviations of past expected inflation and output from the central bank's target policy.

[7] See Arifovic and Petersen (2017), Hommes et al. (2019), and Ahrens et al. (2018) for analysis of expectations in an environment with a binding lower bound on interest rates.

[8] We follow Kryvtsov and Petersen (2015), Arifovic and Petersen (2017), and Pfajfar and Žakelj (2014, 2016) in the implementation of an *AR(1)* shock process.

[9] Mirdamadi and Petersen (2018) demonstrate that precise quantitative information about the data-generating process reduces inflation forecast dispersion and forecast errors.

During the experiment, subjects observed all historical information up to and including the previous period's realized inflation, output, nominal interest rate and shocks, as well as their own personal forecasts (but not other subjects' forecasts or the aggregate forecast).[10] They also observed the current period shock, which allowed them to calculate the expected future shocks for the following periods. Depending on the treatment, participants were also shown a set of projections presented as noisy five–period ahead paths. Forecasts were submitted in basis point measurements and could be positive, zero, or negative. After all subjects submitted their forecasts or time elapsed, the median submitted forecasts for output and inflation were employed as the aggregate forecasts and implemented in the calculation of the current period's output, inflation, and nominal interest rate. We used median forecasts instead of mean forecasts to prevent the influence of extreme entries and minimize subjects' manipulation of the aggregate forecasts.[11]

We incentivized subjects to take seriously their forecasting decisions by rewarding them based on their forecast accuracy. Subject i's score in period t was a function of her inflation and output forecast errors in period t:

$$Score_{i,t} = 0.3(2^{-0.01|E_{i,t-1}\pi_{i,t}-\pi_t|} + 2^{-0.01|E_{i,t-1}x_{i,t}-x_t|}) \ , \tag{5}$$

where $E_{i,t-1}\pi_{i,t} - \pi_t$ and $E_{i,t-1}x_{i,t} - x_t$ are subject i's forecast errors associated with forecasts submitted in period $t-1$ for period t variables. The scoring rule is intuitive and easy to explain to subjects; for every 100 basis point error made for each of inflation and output, a subject's score would decrease by 50%. Thus, there was a very strong incentive to forecast accurately. At the end of the experiment, subjects' points from all periods were converted into dollars and paid out to them in cash.

The dynamics of each economy depend critically on how aggregate expectations are formed. **??** presents simulated impulse responses to a positive 1 s.d. innovation to the r_t^n under alternative forecasting assumptions. Under rational expectations (depicted as a solid blue line), all variables increase on impact of the innovation before monotonically converging back to their steady state values as the shock to the natural rate of interest dissipates.

Kryvtsov and Petersen (2015) observe that aggregate expectations in an identically calibrated experiment can be well-described by an Adaptive(1) heuristic. Under this heuristic, agents place

[10]Current values of output gap, inflation, and interest rates depend on the current aggregate expectations about the subsequent period's outcomes that participants needed to submit.

[11]In each treatment, the median proportion of periods that a participant is the median forecaster ranges between 17-20%. Likewise, the mean proportion ranges from 17-21%. The proportion is slightly higher than 14.3% (1/7), the predicted number of rounds under random assignment to the median. This suggests that there are some participants who are more likely to be "middle" of the road" in their forecasts, and have more influence on the aggregate economy. Put another way, there are participants who are rarely or never the median forecaster, often because of their extreme forecasts Forecasts were submitted on time in 99.7% of the periods(10053 of 10080 opportunities). While this system could be simplified to be written as a function of just one- and two-period ahead inflation forecasts (see Adam, 2007), we preferred to capture the fact that people must form expectations about multiple variables when making economic and financial decisions.

50% weight on period $t-1$ output (inflation) and 50% on the *ex-post* rational forecast of output (inflation) when forecasting period $t+1$ output (inflation). The simulated impulse response functions of the Adaptive(1) heuristic are depicted as red dashed lines. Compared to rational expectations, aggregate forecasts of output and inflation under an Adaptive(1) heuristic under–and over–react to current innovations, respectively. Following the onset of the innovation of the shock, the adaptive heuristics lead to a hump-shaped dynamic for both types of forecasts. While inflation gradually returns back to the steady state, output returns more quickly as a consequence of the relatively high nominal interest rate. Output over-shoots the steady state and becomes depressed before reverting back to zero.

Finally, we consider the possibility that only half of the subjects exhibit an Adaptive(1) forecasting heuristic, while the other half forecast according to the ex-post rational solution. The dynamics associated with this hybrid case are shown as a dotted green line. Compared to the fully Adaptive(1) model, in this hybrid case expectations of output and inflation are considerably more reactive to current innovations as a consequence of "rational" agents best-responding to the Adaptive(1) agents. This leads to considerably greater inflation volatility on impact of the innovation, and simultaneously a significant increase in the nominal interest rate and decrease in the output gap.

Treatments

To investigate the impact of central bank projections on forecasting heuristics and economic stability, we systematically vary the type of projections subjects receive in a between-subject experimental design. A summary of our treatments is presented in **??**.[12]

We conducted four treatments involving different types of communication. In all of our treatments, the central bank is assumed to have the same information about the economy's data-generating process as participants, namely **??** to **??**. The treatments differ in terms of the variable presented to participants and the assumptions underlying the central bank's projections about aggregate expectations. Importantly, in all communication treatments, the central bank assumes that the median agents maintain the same heuristics in response to the economy. i.e. agents do not update the parameters of their forecasting model as new information and projections arrive. These assumptions are consistent with the way central banks assume non–rational expectations to construct their projections.

Our baseline environment, *No Communication (NoComm)*, follows the experimental design described above with no supplementary communication by the central bank.

In the *Interest Rate Projections (IRProj)* and *Dual Projections (DualProj)* treatments, the central bank communicated evolving five-period ahead projection of the nominal interest rate or

[12]We also conducted additional treatments involving individual rational output gap or inflation projections. These results are reported in an earlier versions of this paper found in Mokhtarzadeh and Petersen (2015).

dual projections of output gap and inflation, in which the central bank assumes agents form their expectations according to the unique stationary rational expectations equilibrium solution. That is, the central bank assumed the median agents' expectations were "model consistent" or "Ex–ante Rational". The formulation of ex–ante rational expectations is given by M1 in **??**. The projected values for the current period t were given by

$$x_t = 0.47 \cdot r^n_{t-1} + 0.83 \cdot \epsilon_t,$$
$$\pi_t = 0.14 \cdot r^n_{t-1} + 0.25 \cdot \epsilon_t.$$
$$i_t = 0.45 \cdot r^n_{t-1} + 0.78 \cdot \epsilon_t,$$

while the next five periods were given by

$$\begin{aligned} E^{CB}_t x_{t+s} &= \rho^{s-1} \cdot x_t, \\ E^{CB}_t \pi_{t+s} &= \rho^{s-1} \cdot \pi_t, \\ E^{CB}_t i_{t+s} &= \rho^{s-1} \cdot i_t \end{aligned} \tag{6}$$

for $s = 1, ..., 5$ and $\rho = 0.57$. That is, the projected variable monotonically reverted back toward the steady state. If the median forecaster were to forecast according to the central bank's explicit or implicit projections, the best-response of a subject would be to do the same. That is, a subject's optimal forecasts given the median forecaster's usage of the central bank's projections was given by **??**.

Our fourth treatment, *Adaptive Output and Inflation Projection (ADProj)*, involved providing subjects with five-period ahead projections of output gap and inflation in which the central bank instead assumed that agents form output and inflation expectations as an equally–weighted average of the REE solution and a one-period lag of output or inflation. This assumption is motivated by the findings of Kryvtsov and Petersen (2015) that such an Adaptive(1) forecasting heuristic well describes the median subject's forecasting heuristic. Such a heuristic would generate a unique Adaptive(1) solution for the economy:

$$\begin{aligned} x_t &= 0.30 \cdot x_{t-1} - 0.28 \cdot \pi_{t-1} + 0.39 \cdot r^n_{t-1} + 0.68 \cdot \epsilon_t, \\ \pi_t &= 0.08 \cdot x_{t-1} + 0.67 \cdot \pi_{t-1} + 0.17 \cdot r^n_{t-1} + 0.29 \cdot \epsilon_t. \\ i_t &= 0.27 \cdot x_{t-1} + 0.86 \cdot \pi_{t-1} + 0.45 \cdot r^n_{t-1} + 0.78 \cdot \epsilon_t, \end{aligned} \tag{7}$$

A participant who uses the central bank's ADProj projection to formulate her forecasts would be following a rule given by M5 in **??**. That is, she would behave as if she were using historical inflation and output, as well as current innovations to formulate her forecasts. From the subjects' perspective, adoption of the ADProj projections is a suboptimal strategy as it would lead to, on average, incorrect forecasts. If the median forecaster were to forecast the ADProj projections, a subject's best-response would be to forecast according to M6 in **??** whereby she would react to the relatively volatile median inflation expectations (and consequently inflation) by forming even more volatile inflation expectations. Because interest rates will be rising to stabilize inflation, a best–response to median ADProj expectations would be to form more muted output gap expectations. Subjects in the IRProj and DualProj treatments were informed that the central bank projections were formed by the central bank based on current and expected future shocks as well as the economy's data-generating process. Subjects in the ADProj treatment were informed that the central bank projections were based on a combination of current and expected future shocks as well as the previous period's outcomes. The quantitative models behind the projections were not provided to reduce information overload. We emphasized that the projections were not a promise but simply the central bank's forecast of the future, incorporating all available information. We did not provide any explanation for why the central bank was communicating the projections.

Note that none of these projections are optimal or consistent with the central bank's objectives of zero output gap or inflation.[13] The central bank is not behaving or communicating as an optimal central banker, but rather following an ad-hoc rule. Similar to projections published by real-world central banks, our experimental projections do not assume agents update their expectations in response to the communicated information. There are reasons why the central bank may still prefer to communicate these projections. The projections provide salient information which non-rational participants can base their otherwise potentially unstable expectations on. The ADProj projection, while incorrect even if participants follow it, looks more realistic looking than those in the IRProj and DualProj and may be perceived as more credible. The central bank is better able to achieve its objectives of low inflation and output gap if expectations are better anchored near the steady state.

Experimental Implementation

A total of 168 undergraduate students took part in the experiment at the CRABE lab located at Simon Fraser University from June 2015 to December 2016. Participants were invited randomly to participate in a single session from an inexperienced subject pool consisting of over 2000 subjects from a wide variety of disciplines. For each of our four treatments we collected data from six groups of seven subjects each, for a total of 24 independent observations. To control for learning, subjects participated in two 30-period repetitions with the same group. We describe subjects in Repetition 1 as *inexperienced* and Repetition 2 as *experienced*. Thus, we have a total of 10,080 observations.

[13] An interesting alternative projection would involve the central bank communicating $E_t^{CB}[\pi_{t+1}] = 0$ and $E_t^{CB}[x_{t+1}] = -\frac{1}{\sigma}r_t^n$. If private agents use these forecasts as their own, then $\pi_t = x_t = 0$ at all dates. This would achieve a greater degree of stability than either the REE or the ADProj projection. The projection would, however, lead to systematically erroneous output expectations by both the central bank and private agents. We leave these two types of projections for further research.

Each session began with an instruction phase where we explained the data-generating process both qualitatively and quantitatively.[14] We familiarized subjects with the forecasting task with four trial periods. Subjects had the opportunity to ask questions about the data-generating process and their tasks. No communication between subjects was allowed once they entered the laboratory.[15] As is common in macroeconomics experiments, we provided contextual framing in the instructions and environment (see Duffy and Heinemann (2018) for an example of more neutral framing in a Barro–Gordon monetary policy game). As Alekseev et al. (2018) note, contextual framing encourages participants to bring their own experiences, understanding and context into the lab and has the potential to weaken the experimenter's control over the experimental environment. However, central banks typically communicate about monetary policy and their outlook for the economy using words and concepts that may be unfamiliar to many segments of the population. Given our interest in understanding how *central bank* communication influences expectations, it seemed appropriate to employ more realistic language.

The experiment was conducted in an online interface. **??** presents a representative screenshot of the interface in the IRProj treatment with interest rate projections. In every period the interface of the experiment displayed all information available to the participants throughout the session on a single screen. At the top left corner of the screen, the subject's identification number, current period, time remaining, and total number of points earned were presented. Three history panels were given in each period. The top history panel displayed past interest rates and past and current shocks. The second panel displayed the subject's own past forecasts of inflation and the realized level of inflation. The final panel showed the subject's own forecasts of output and the realized level of output. In treatments with central bank communication, an additional time series graph was added to the history plots to represent the central bank's projection. The central bank's projection of output, inflation, and nominal interest rates were presented as green lines which represented the expected future path of the respective variable. Around each projection was a one standard deviation confidence interval that increased as the projection went further into the future to reinforce that the central bank's projections were noisy predictions.

To ensure consistency across treatments, we preselected the shock sequences and employed them across all treatments.[16] The shocks, r_t^n, while drawn from the same distribution with a standard deviation of 138 basis points, differed in their variability. Shocks ranged from a standard deviation of 125 to 155 basis points. Varying the shock sequences across sessions allowed for a more robust

[14] Mirdamadi and Petersen (2018) show that providing additional precise quantitative information about the economy's DGP leads to lower inflation forecast errors and forecast dispersion. However, such information encourages relatively more backward–looking heuristics as participants have a better sense of how aggregate expectations influence the economy. They speculate that participants use historical outcomes as proxies for aggregate expectations.

[15] A set of instructions is provided in our Online Appendix. At the beginning of every session, we requested subjects not ask questions related to strategy publicly. We explained that such questions have the potential to bias other subjects' behavior, and if such questions should arise, we would have to immediately end the experiment and pay each subject only their show-up fee. Consequently, no subject posed questions publicly about forecasting strategies.

[16] The preselection of shocks was made known to subjects during the instruction phase.

analysis of expectation formation and also provided an additional dimension of exogenous variation.

The experiments lasted for approximately 90 minutes including 35 minutes of instruction and four unpaid practice periods. The maximum possible earnings, including a CDN \$7 show up fee, was \$25. The average payment was CDN \$19 and ranged from CDN \$17 to \$25.

Hypotheses

The experimental design allows us to test a number of hypotheses regarding how subjects form expectations, both with and without projections. The assumption that households and firms have identically rational expectations about the future is widely employed in mainstream macroeconomic models (Lucas, 1972; Fischer, 1977). If subjects formed expectations consistent with the REE solution, they should only need to rely on parameters of the model and the current shock– both of which are common knowledge–to formulate their forecasts.

Hypothesis I: Subjects form expectations consistent with the REE solution.

An implication of Hypothesis I is that there should be no differences across treatments with respect to forecasting heuristics.

Hypothesis II: The IRProj and DualProj rational projections have no effect on forecasting behaviour, forecast errors, and central bank credibility if subjects form expectations according to the REE solutions.

Extensive survey and experimental evidence suggest that individuals do not form macroeconomic expectations rationally but instead heterogeneously weigh historical information in their forecasts (Assenza et al., 2013; Pfajfar and Santoro, 2010; Pfajfar and Žakelj 2014; Coibion and Gorodnichenko, 2015; Malmandier and Nagel, 2016). This suggests a potential role for central bank communication to alleviate information frictions.

Commonly observed projections provide an important focal point for subjects to coordinate their forecasts on. Evidence on the ability of focal information and strategies to coordinate behavior in pure coordination games is mixed. Coordination through focal points can be difficult to achieve unless participants are earning equal payoffs (Schelling, 1960, Mehta et al., 1994a,b, Crawford et al., 2008). [17] Nonetheless, if a subject believes that the majority of participants will utilize the central

[17] In our experiment, participants' private payoffs depend on their own forecast accuracy, and while asymmetric, exhibit rather little heterogeneity. It is unclear how asymmetry in payoffs should matter in our environment where each person's payoffs is kept private. Forecasting heuristics can be manipulated through focal information. Kryvtsov and Petersen (2015) provide nine-period ahead forecasts of future nominal interest rates where the automated central bank assumes agents form expectations according to the REE solution. They find that forecasting heuristics adjust from an Adaptive(1) heuristic where agents place equal weight on lagged information from period $t-1$ and the REE solution to an Adaptive(2) heuristic for inflation forecasts where subjects weight $t-2$ inflation in their forecasts. Petersen (2014) extends the Kryvtsov and Petersen framework to allow for salient forecast error information presented centrally for subjects to observe. She finds that subjects' forecasts of the future are significantly more responsive to forecast errors when presented with such focal auxiliary information.

bank's rational prediction in their forecast, her best response would be to utilize the projection as her forecast.

While both nominal interest rate and dual projections based on the REE solution contain redundant information to a subject that fully understands the economy's data–generating process, they may provide auxiliary assistance in forecasting output and inflation for boundedly rational subjects (Simon, 1959). The ease in effectively using the information in each projection is, however, not the same. Dual projections of output and inflation can be effortlessly employed as subjects' own macroeconomic forecasts. By contrast, subjects must employ significant cognitive effort to correctly infer the intended output and inflation projection from the communicated nominal interest rate projection. Because of subjects' cognitive and time limitations, subjects choose to pay relatively more attention to information that is of higher value to their payoffs and easier to process (see Simon (1959), Mazzotta and Opaluch (1995), Sims (2003), and Gabaix (2014) for models of bounded rationality associated with limited processing).

The success of communication at managing expectations depends on the central bank's credibility in achieving its projections. We measure central bank credibility as the fraction of forecasts that coincide with the central bank's explicit or implicit projected value. In our experiments, the automated central bank constructs its projections assuming that the median subject forms expectations according to either REE or Adaptive(1) solution. The central bank's projections will frequently be incorrect due to the fact that future innovations to the shock process may not be zero (as they are predicted to be) and that subjects may use alternative heuristics to formulate their forecasts. If the central bank is systematically biased in its forecast, an optimizing agent should place less weight on the central bank projections when forming their forecast. As the projections become increasing incorrect, we expect that the central bank will lose credibility.

Hypothesis III: The probability a subject utilizes the central bank's projections decreases with the central bank's past forecast errors.

3. Experimental Results

This section presents our experimental findings. We first consider how central bank (CB henceforth) projections influence subjects' forecasting heuristics, accuracy, dispersion, and usage of the communicated information. We then turn to our aggregate–level data to identify the effects of projections on economic stability and macroeconomic dynamics.

3.1. Individual–level analysis

Forecasting heuristics

We begin by investigating how the various information treatments influence the heuristics participants use to form expectations. **??** lists the eight general classes of heuristics we consider. These heuristics are either commonly observed in laboratory experiments or assumed in theory. Like Pfajfar and Žakelj (2016), we classify a participant as 'using' the model that produces the lowest root-mean-squared error (RMSE) among all competing models. For Constant Gain (M7) and Trend-Chasing (M8), we consider a range of parameters $\gamma, \tau \in [0.1, 1.5]$. The distributions by treatment for Repetitions 1 and 2 forecasts are presented in **??** and **??**. We describe Repetition 1 forecasts as inexperienced and Repetition 2 as experienced. Treatment-level proportions for each heuristic is provided for reference.

NoComm

Consistent with Kryvtsov and Petersen (2015), we observe minimal evidence of ex-ante rational expectations (M1). Only 2.4% of output gap expectations and 12% of inexperienced inflation expectations are best described by M1. These proportions rise to 7% and 14% when participants become experienced. We also observe very few subjects base their forecasts on the central bank's explicitly communicated targets, and this heuristic appears to be less prevalent as participants gain experience.

Rather, we observe that the vast majority of participants rely on heuristics that incorporate historical information. For output gap forecasts, the most frequently observed heuristic is the Adaptive(1) model (M4) where expectations are based on a combination of historical and ex-post rational information. We observe 43% (38%) of inexperienced (experienced) forecasters employ M4. The second most prevalent heuristic is Trend-Chasing (M8), with 17% (19%) of inexperienced (experienced) forecasters extrapolating past trends when forming their forecasts. For inflation forecasts, M8 is the most prevalent heuristic in both repetitions (31-33%). Many experienced forecasters also employ M4 (29%) to forecast inflation. Pfajfar and Žakelj (2016) observe similar proportions of trend-chasing inflation forecasters in their LTF experiments.

A widely assumed heuristic in the learning-in-macroeconomics literature is the Constant Gain model (M7). We find that only a minority of participants employ this heuristic, and its prevalence declines with experience to less than 12%. The simple Naive model (M3) is used for roughly 10% of output gap forecasts and 15% of inflation forecasts. That is, most participants correctly believe that the economy will change over time.

IRProj

Interest rate projections noticeably increase the proportion of inexperienced forecasters who employ the Ex–ante Rational (M1) model by nearly three-fold for output gap forecasts and double for inflation forecasts. By Repetition 2, 12% of output gap forecasts and 36% of inflation forecasts are being formed according to M1. At the same time, we observe a significant reduction in Trend–

Chasing (M8) and Adaptive(1) (M4) expectations.

The IRProj is unable to shift the majority of participants to forecast rationally. Experienced output gap and inflation forecasts become more heterogeneous, with all of the heuristics excluding M4 and M8 weakly increasing in frequency.

DualProj

Rational dual projections of output and inflation substantially increase the prevalence of Ex–ante Rational (M1) forecasting. Among inexperienced forecasters, 31% of output gap forecasts and 64% of inflation forecasts are best described by M1. This comes at a reduction in the prevalence of many backward-looking heuristics (Naive, Adaptive(1), Trend–Chasing, Constant Gain). We do observe an increase in the usage of the ADProj (M5) and BR to ADProj (M6) in inexperienced output gap forecasts. These two heuristics employ a higher order of rationality and require the forecaster to consider the adaptive heuristics of the median forecaster. The shift in the distribution of heuristics continues as participants become experienced. In Repetition 2, we observe 33% of output gap forecasts and 69% of inflation forecasts being formed according to M1.

ADProj

The central bank's adaptive dual projections of output and inflations (M5) are used for 29% of output forecasts and 45% of inflation forecasts in Repetition 1. The ADProj (M5) is the modal heuristic. We also observe a sizeable emergence of the best–response to ADProj (M6) employed by 24% of output forecasters and 19% of inflation forecasters, and Adaptive(1) (M4) for inflation forecasts. Ex–ante rational forecasting (M1) also becomes substantially more prevalent for both types of forecasts. At the same time, we observe a substantial reduction in naive, constant gain, and trend-chasing heuristics. Experience serves to strengthen the usage of the central bank's projections. The proportion of subjects using M5 to form their output forecasts increases to 43% and their inflation forecasts increases to 55%.

We now evaluate the hypotheses advanced in Section 2.

Result I: Subjects expectations are not consistently in line with the ex–ante rational expectations model.

Support for Result I: We compute the proportion of participants who are best described as ex–ante rational at the treatment–session–repetition level for each variable. Wilcoxon signed–rank tests reject the null hypothesis that the proportion of participants that are ex–ante rational is equal to 1 for all treatments and repetitions ($p < 0.05$ in all tests, $N = 6$ for each test). Thus, Hypothesis I is rejected.

We next consider how the different projections influence forecasting heuristics.

Result II: DualProj and ADProj significantly affect the distribution of heuristics for

both experienced and inexperienced participants. IRProj affects the distribution of heuristics for experienced participants.

More precisely, we show that Result II applies to each projection treatment.

Result IIa: IRProj increase the proportion of experienced forecasters using the CB's target to forecast inflation while reducing the proportion that employ an Adaptive(1) model. IRProj also reduces the proportion of trend–chasing output gap forecasters.

Result IIb: DualProj significantly increases the proportion of ex-ante rational forecasters and reduces the proportion of forecasters using Adaptive(1), constant gain, and trend-chasing heuristics to forecast inflation.

Result IIc: ADProj significantly increases the proportion of participants who forecast according to the central bank's projections, as well as best–respond to the projection, while reducing the proportion of participants employing naive, Adaptive(1), constant gain, and trend-chasing heuristics.

Support for Results II, IIa-c: We also compare how the proportion of participants, at the session–repetition level, who exhibit a given heuristic differs from the NoComm treatment using Wilcoxon rank sum tests ($N = 6$ per treatment). Statistically significant differences in proportions is denoted with asterisks in **??** and **??**.

Forecast errors

Central bank projections are meant, among other things, to help forecasters better anticipate the future. Thus, one measure of the success of a CB's projection is its ability to reduce forecast errors. We compute subjects' absolute forecast errors as the absolute difference between their forecasts and the realized outcomes. Distributional plots of all absolute forecast errors by treatment are presented in **??**. We observe that, for experienced subjects in Repetition 2, all three types of projections skew the distribution of absolute output forecast errors down compared to the NoComm treatment. By contrast, the distribution of absolute inflation forecast errors is only noticeably skewed downward in the DualProj treatment. The ADProj treatment is associated with larger absolute inflation forecast errors.

Result III: All types of projections significantly affect participants' forecast accuracy.

Support for Results III: Using a mixed effects panel regression approach, we estimate the effect of the different projections on the log of absolute forecast errors. Our first set of specifications regresses log absolute forecast errors on treatment-specific dummies. We include subject and session random effects, and cluster our standard errors at the session level. The results, by repetition and variable, are presented in the first four columns of **??**.

Forecast errors are large and statistically significant in the NoComm treatment. Mean forecast errors are roughly 60–70 basis points for the output gap, and 19-26 basis points for inflation. Nominal interest rate projections do not have any sizeable or significant effect on output forecast errors, but do increase inexperienced inflation forecast errors by 33% ($e^{0.285}$=1.33). However, with experience, IRProj do not have a consistent or sizeable effect on inflation forecast errors.

Dual rational projections initially increase output forecast errors significantly by roughly 21%, but with experience reduce both output gap and inflation forecast errors. Experienced subjects in the DualProj treatment have output (inflation) forecast errors that are 20% (25%) lower than in the NoComm treatment.

Adaptive dual projections worsen inflation forecasts for both inexperienced and experienced participants. Mean inflation forecast errors are 78% (36%) higher for inexperienced (experienced) participants in the ADProj treatment. We observe the opposite effect for output gap forecast errors, with ADProj significantly reducing experienced output forecast errors by roughly 18%. As we will demonstrate shortly, this is likely a consequence of the decrease (increase) in output gap (inflation) variability associated with participants following the ADProj projection.

Forecast disagreement

We next evaluate whether the central bank projections provided a sufficient common focal piece of information for subjects to coordinate their forecasts on.

Result IV: Rational and adaptive dual projections influence forecast disagreement. Interest rate projections do not have a consistent effect on disagreement.

Support for Results IV: We quantify the degree of disagreement among subjects by calculating the standard deviation of forecasts each period across subjects in a single group. To understand how disagreement is affected by the different projections, we conduct two sets of mixed effects regressions. We include session random effects, and cluster our standard errors at the session level. Our results are presented in columns (5)–(8) of **??**.

We observe that the estimated constant is positive and statistically significant, indicating that there exists significant heterogeneity in NoComm participants' forecasts within a period. This is in spite of having common full information about the economy's data generating process. Interest rate projections do have not a consistent effect on forecast dispersion in either repetition. Likewise, coordination of expectations is not significantly affected by the rational or adaptive dual projections when participants are inexperienced. However, with experience, the treatments diverge. Participants in the DualProj disagree significantly less about future output and inflation, while those in the ADProj disagree significantly less about the future output gap.

Central bank accuracy and credibility

How accurate are the CB forecasts? In the IRProj, DualProj and ADProj treatments, mean CB forecast errors for the output gap range from 77 to 79 basis points, with no significant differences across any treatment-repetition comparisons ($p > 0.50$ in all pairwise rank sum tests). Mean CB inflation forecast errors are the lowest in the DualProj at 24 basis points, followed by 33 basis points in the IRProj, and 56 basis points in the ADProj treatments. The difference between the DualProj and ADProj is statistically significant at the 1% level, while the differences between the IRProj and ADProj are significant at the 5% level.

Credibility is an important concern for the central banks. We next evaluate how participants' credibility in the CB projections varied across treatments and in response to central bank and their own errors.

Result V: Central bank credibility is significantly higher in the DualProj and ADProj treatments than in the IRProj treatment. Credibility in the CB's output projection is also significantly higher in the ADProj treatment than in the DualProj treatment.

Support for Results IV: We describe a CB's projections as credible if subjects utilize it as their own forecast. Our variables of interest are $UtilizedCBxForecast_t$ and $UtilizedCB\pi Forecast_t$ which take the value of 1 if a subject's period t forecast about $t+1$ was less than five basis points from the CB's projection and zero otherwise.[18] **??** plots the distribution of session mean percentages of credible forecast for output gap and inflation. Nominal interest rate projections have little effect on utilization with a mean of 0.07 (s.d. 0.03) for output forecasts and 0.13 (s.d. 0.06) for inflation forecasts. At the session-repetition level, a two–sided Wilcoxon rank–sum test of the null hypothesis that differences in utilization between the NoComm and IRProj treatment follows a symmetric distribution around zero is not rejected (N=6 for each treatment-repetition-variable test, $p > 0.36$ for each test). Rational and dual projections significantly increase utilization of the CB's projection. DualProj utilization increases to means of 0.25 (s.d. 0.06) and 0.38 (s.d. 0.05) for output and inflation forecasts, respectively. Likewise, ADProj utilization increases to means of 0.28 (s.d. 0.11) and 0.45 (s.d. 0.13) for output and inflation forecasts. Two-sided Wilcoxon rank-sum tests significantly reject the null hypothesis that differences in utilization between the NoComm or IRProj and either the DualProj or ADProj follow a symmetric distribution around zero (N=6 for each treatment-repetition-variable test, $p < 0.01$ for each test). Differences in utilization between the DualProj and ADProj treatments are only statistically significant for output forecasts ($p < 0.05$ for both repetitions). **WHERE IS THE OTHER FIGURE?!?**

[18] We are implicitly assuming that subjects fully comprehend how to utilize the CB's interest rate projection to formulate their output and inflation forecasts. For NoComm subjects, we are computing subjects' ability to forecast according to the REE solution.

Result VI: Credibility decreases significantly when the central bank makes larger forecast errors while communicating either an interest rate projection or an adaptive dual projection, but not when it communicating rational dual projections.

Support for Result VI: We employ a series of mixed effects probit models to understand how the probability subjects utilize the CB's projections evolves. Our primary explanatory variables are the CB's absolute forecast error about period $t-1$ output, $|FE^{cb}x_{t-1}| = |E^{cb}_{t-2}x_{t-1} - x_{t-1}|$ and $t-1$ inflation, $|FE^{cb}\pi_{t-1}| = |E^{cb}_{t-2}\pi_{t-1} - \pi_{t-1}|$. We additionally control for whether subjects previously utilized the CB's forecast in period $t-2$ and subjects' own absolute forecast errors $|FEx_{i,t-1}|$ and $|FE\pi_{i,t-1}|$, and interactions of these two variables. We pool together data from both repetitions, as the differences across repetitions are unnoteworthy. Subject and session random effects are included, and standard errors are clustered at the session level. Treatment-specific results are presented in the first six columns of **??**.

We find mixed support for Hypothesis III that larger errors by the CB reduce its credibility. In the IRProj treatment, the probability a subject is willing to use the CB's interest rate projection to forecast output or inflation decreases significantly when the CB makes larger forecast errors. Likewise, in the ADProj treatment, larger CB forecast errors about inflation significantly reduce subjects' utilization of its inflation projections. However, having used the CB's forecast in the previous period does not significantly alter subjects' reaction to the CB's forecast errors. By contrast, CB credibility in the DualProj treatment is impervious to its past forecast errors. We also observe considerable and significant history dependence in credibility in all three projection treatments.

We also estimate the effect of the CB's past forecast errors on the disagreement in subjects' forecasts using a series of mixed effects specification with session random effects. The results are presented in the final six columns of **??**. Larger past CB inflation forecast errors lead to increased disagreement about future inflation in all three projection treatments. Experience significantly reduces disagreement in most specifications consistent with our earlier findings that subjects learn to coordinate on a smaller set of heuristics over time. **CONFIRM!!**

3.2. Aggregate analysis

We begin by presenting representative estimated impulse response functions from our different treatments. Panels A and B of **??** displays the estimated responses of output, inflation and the nominal interest rate to a one-standard deviation innovation to the natural rate of interest in our most stable and volatile sequences in Repetition 2, respectively, while the results from our other sessions can be found in the Online Appendix. The thick solid black line denotes the REE solution. The estimated dynamics of the NoComm treatment are shown as a thin solid black line. Output and inflation in the NoComm treatment deviate considerably from the REE prediction.

Characteristic of an environment with Adaptive(1) aggregate expectations, inflation exhibits a distinct delayed hump-shaped pattern and output exhibits an overshooting of the steady state as the shock dissipates. The dynamics associated with the rational IRProj treatment are presented as the thin dashed blue line while the results from the rational DualProj treatment are presented as a thin dotted red line. In our three most stable sequences, both rational interest rate and dual projections work effectively to nudge expectations, and consequently the aggregate economy, to the REE solution. However, as the variability of the shocks increases in two of our three most volatile sequences, we observe that the macroeconomic dynamics revert back to one consistent with adaptive expectations when the central bank communicates an interest rate projection. That is, the ability for interest rate projections to guide output and inflation expectations to the REE wears off under interest rate projections. Rational dual projections, on the other hand, continue to work effectively even in more unpredictable environments.

The estimated impulse responses from the ADProj treatment are shown as the thin dash-dot green line. Dynamics in the ADProj treatment are consistent with our mixed model of expectations whereby a large fraction of agents place weight on the central bank's adaptive dual projection of output and inflation and the remaining are ex-post rational. The output gap dynamics are slightly more stable than the REE prediction while the inflation dynamics are significantly more volatile on impact of the innovation. Moreover, inflation exhibits a relatively monotonic transition back to the steady state (unlike under adaptive expectations). This pattern consistently appears in all six ADProj sequences.

Result VII: With experience, output and inflation variability in the baseline NoComm treatment are significantly greater than predicted by the REE solution. Introducing rational dual projections lowers macroeconomic variability to the REE predicted levels. Adaptive dual projections reduces output variability significantly below the REE prediction while increases inflation variability significantly above it. Interest rate projections are not consistently effective at reducing macroeconomic variability.

Support for Result VII: Summary statistics of the standard deviation of output and inflation, measured at the session-repetition level and normalized by their rational expectations equilibrium solution's respective standard deviations are presented in **??**.[19] The results are also presented visually in **??** with box plots of the standard deviation of output and inflation relative to the REE solution at the treatment-repetition level. Mean normalized standard deviations of output and inflation in the baseline NoComm treatment exceed one in both repetitions, implying the economies are, on average, more volatile than predicted by the rational expectations model. Two-sided Wilcoxon signed-rank tests are conducted to determine whether the mean results are significantly different from the REE solution, i.e. that the normalized standard deviations are equal to 1. In the first rep-

[19]The normalizing REE solution of output and inflation is calculated for each shock sequence.

etition of the NoComm treatment, we fail to reject the null hypothesis that the standard deviations are consistent with the REE solution. In the second repetition, the standard deviations of output and inflation in the NoComm treatment are 6% and 50% greater than the REE, respectively. This difference is significant at the 5% level. Output and inflation are not significantly different from the REE prediction at the 10% level in either the IRProj or DualProj treatments. In the ADProj treatment, output variability is significantly below the REE prediction while inflation variability is significantly above ($p < 0.05$ for both variables and repetitions).

We find mixed evidence that CB projections improve economic stability. Compared to the NoComm treatment, interest rate projections in the IRProj treatment do not significantly decrease output and inflation variability. There is considerable heterogeneity across IRProj sessions driven by differential responses of expectations to the variability of shocks.

Rational dual projections in the DualProj treatment work effectively when subjects are experienced to significantly reduce output and inflation ($p = 0.01$ and $p = 0.055$, respectively). Dual macroeconomic projections decrease the likelihood of instability. Finally, adaptive dual projections in the ADProj treatment significantly stabilize output variability at the cost of significantly greater inflation variability ($p \leq 0.055$ in Repetition 1, $p < 0.01$ in repetition 2). A detailed discussion of the effects of the projections on aggregate dynamics at the session level can be found in the Online Appendix.**CHECK!!**

4. Discussion

Projections have become an increasingly important instrument that central banks use to guide aggregate expectations. Identifying the effects of projections on expectations is especially challenging because the projections central banks make and the language they employ are a consequence of the effectiveness of past and expected future policies. To gain further insight into how central bank communications are used by ordinary individuals, we conduct a laboratory experiment where projections are varied systematically across independent groups.

Our first key finding is that central bank communication must be easy to understand for subjects to effectively utilize it in their forecast. Rational projections of output and inflation (which subjects are themselves forecasting) reduce subjects' backward–looking forecasting heuristics and refocus their expectations on current fundamentals. Such announcements lead to reduced heterogeneity in forecasts and forecast errors. By contrast, projections of nominal interest rates are inconsistently effective at coordinating expectations and improving forecast accuracy, especially when it comes to inflation forecasts. To make sense of our experimental finding that nominal interest rate projections are more challenging for subjects to utilize than dual macroeconomic projections, we turn our focus to models of recursive learning and noisy information processing.

Recursive learning and projections

Central bank communication in the presence of non-rational subjects can have important consequences for economic stability. Ferrero and Secchi (2010) consider how a central bank announcement of rational interest rate and dual macroeconomic projections in an identical environment to ours influence recursive learning agents' expectations.[20] Employing a recursive learning algorithm to model the expectation formation process (e.g. Marcet and Sargent (1989) and Evans and Honkapohja (2001)), Ferrero and Secchi show that publishing interest rate (output and inflation) projections consistent with the REE can lead to more (less) stringent conditions for stability under learning than under no announcement. These propositions are outlined in detail in our Online Appendix.

Given the data-generating process given by **??** to **??**, where at time t the central bank publishes the time $t+1$ interest rate projection consistent with the REE and recursive learning private agents assign weight $0 \leq (1-\lambda_1) \leq 1$ to these projections[21], revealing the interest rate path makes the condition for stability under learning more stringent than under no announcement. Given the parameterization of our laboratory experiments, the REE is e-unstable when at least a fraction $1-\lambda_1 = 0.703$ of subjects fully employ the interest rate projection as their implicit forecast for interest rates.

On the other hand, if at time t the central bank publishes the time $t+1$ output and inflation projections consistent with the REE and recursive learning private agents assign weight $0 \leq (1-\lambda_2) \leq 1$ to these projections, revealing the projected paths makes the condition for stability under learning less stringent than under no announcement. Given our parameterization, the REE is E-stable under recursive least squares learning irrespective of the number of subjects that employ the central bank's macroeconomic projections.

Compared to those in the NoComm, the median DualProj forecasters formed expectations that were significantly more in line with the REE solution. We observe a similar pattern for the median IRProj forecasters in sequences with less variable shocks. However, in more volatile shock sequences, we do not observe significant improvement in forecasting towards the REE solution.

There are at least two possible explanations for why the IRProj sessions did not experience more severe instability. First, few IRProj subjects paid attention to the interest rate projection. An average of 7–13% of subjects in the IRProj treatment formed expectations that were within five basis points of the intended REE solution. This is far fewer subjects than necessary to generate instability. Under shock sequence 4, where deviation from REE was the greatest, the correlation between the median subject's expectations and the projection was the weakest (Spearman correlation coefficient for output = 0.07 with p=0.71, Spearman correlation coefficient for inflation was 0.47

[20]See Ferrero and Secchi (2010) for details of their model of recursive least squares learning and proofs of their propositions.

[21]Alternatively, it can be assumed that a fraction of agents $1-\lambda_1$ fully internalize the central bank's projection while the remaining agents continue to forecast using their recursive learning model.

with p=0.01). Second, our subjects were more informed about the data-generating process than the recursive learning agents in Ferrero and Secchi's model. The additional quantitative knowledge about the economy's structure may have mitigated the likelihood of instability. As Eusepi and Preston (2010) demonstrate, communicating the precise details of the central bank's policy is sufficient for anchoring private agents' expectations. We conducted a couple of sessions (not reported here) involving interest rate projections where subjects were only provided qualitative information about the economy's data-generating process. We find no noteworthy difference in the stability of our macroeconomic variables when subjects are less informed.

Rational inattention

Rational inattention models developed by Sims (2003) and Mackowiak and Wiederholt (2009) assume that agents, with a limited amount of attention, continuously receive imperfect information in the form of noisy signals about the state of the economy, but must optimally choose which information to pay close attention to and which information to ignore.[22] In the context of our experiment, the subjects' objective is to minimize their forecast errors by choosing the optimal amount of attention to allocate to different continuously updating data sets and the actual data-generating process, given costs associated with utilizing such information.

Rational inattention models predict that the optimal allocation of limited attention to information is decreasing in the marginal cost of processing that information. In our experiment, dual projections of output and inflation involve lower marginal costs to use than nominal interest rate projections. Subjects can effortlessly employ the explicitly communicated output and inflation projection, while nominal interest rate projections would require more time and cognitive effort to translate into output and inflation projections. Our experimental data supports this prediction. We observe that subjects are roughly three times more likely to employ a rational dual projection of output and inflation than nominal interest rate projections as their own forecast.

Second, rational inattention models predict that agents equate the marginal cost of paying attention to projections to the marginal benefit of using such projections. That is, subjects would optimally pay less attention to information that is unlikely to adequately compensate them for the effort of processing such information. To evaluate this prediction, we compute a set of counterfactual

[22] An alternative class of inattention models consider agents that obtain information infrequently due to costly information acquisition (e.g. Mankiw and Reis, 2002; Reis, 2006). We note that our experimental design eliminates economic costs of acquiring information that real-world consumers and firms face. These models assume that when agents do obtain information, they receive perfect information and make optimal decisions. In the context of our experiment, sticky information models would predict that agents infrequently adjust their forecasts, but that their forecast errors would on average equal zero when they do adjust. Sticky information rational inattention models do not appear to describe our data as effectively as its noisy information counterpart. First, we note that all of our subjects update their forecast in at least 50% of the rounds, with the most inattentive subject updating in two-thirds of the rounds. Second, when subjects do adjust their forecast after a period of not updating, their ex-post output and inflation absolute forecast errors exceeds five basis points more than 93% and 85% of the time, respectively. A more detailed discussion on this can be found in our Online Appendix.

payoffs where we assume that the subject either uses the CB's projection or period $t-1$ output and inflation as its forecast. We select period $t-1$ output and inflation as counterfactuals because historical information appears to play a dominant role in subjects' forecasts.[23] For each subject, we compute the root mean squared errors (RMSE) the subject would have incurred had they forecasted under either of these alternative heuristics holding constant other subjects' forecasting behavior. We subtract from the counterfactual RMSE their actual RMSE to compute a relative RMSE. A negative RMSE implies that a subject would have improved her forecasting performance by adopting an alternative forecasting heuristic, and vice versa. **??** plots the cumulative distribution of subjects' relative RMSEs for each of the two counterfactual forecasting heuristics by treatment and repetition. We include counterfactual cumulative distributions for the NoComm treatment assuming they either forecasted according to the REE solution or naïvely.

When forecasting output, the vast majority of the distribution of subjects in all treatments would have improved their payoffs by forecasting according to the CB's projection. The RMSE of the median experienced subject would have been reduced by 21 basis points in the IRProj treatment and by 10 and eight basis points in the DualProj and ADProj treatments, respectively. A naïve forecasting heuristic would have led to lower forecast accuracy for most subjects. Our results suggest that while most subjects are not optimally utilizing the central bank projections, the irrational inattention observed in DualProj and ADProj is rather low. Moreover, subjects rationally avoided using purely naïve strategies that would have decreased their accuracy.

The results for inflation forecasts in the NoComm and IRProj treatments are considerably different. The majority of experienced NoComm subjects would have made larger forecast errors by individually employing the REE solution as their forecast. As we have seen in our earlier analysis, this is because most subjects are significantly under-responsive to random innovations to the natural rate of interest when forecasting inflation. Consequently, a strategy that would have had them respond more to the innovations would have led them to over-react relative to their fellow forecasters and generate larger forecast errors. A similar pattern emerges for 25% of experienced IRProj subjects. Given that most subjects in our sessions with greater shock volatility were not actively employing the *implied* inflation projection as their forecast, responding to the nominal interest rate projection would have led to larger forecast errors. Put another way, these IRProj subjects *rationally* ignored the interest rate projection.

The vast majority of subjects in the DualProj treatment would have formed significantly better inflation projection had they used the central bank's exact projections as their own forecasts. That is, DualProj subjects suboptimally used the central bank's projections. Less than half of subjects used the forecasts as their own, suggesting the central bank's nudge was insufficient.

[23] In the DualProj and ADProj treatments, the marginal cost associated with employing the CB's projection or period $t-1$ output and inflation and output as one's forecast is comparable. Subjects simply have to move their mouse over either value and input those values into the experimental interface. In the IRProj treatment, computing the implied forecast for output and inflation from the CB's interest rate projection is considerably more challenging than using historical values, and would arguably exhibit a larger marginal cost for the subject.

Concluding remarks

Participants in our experiment were tasked with forecasting only the one-period ahead output gap and inflation. In reality, private agents must forecast numerous variables, including nominal and real interest rates, when making economic and financial decisions.

One may that an alternative experimental design, whereby subjects were tasked with forecasting future nominal interest rates, would have led to subjects' expectations to be well–managed by interest rate projections. We speculate that this would likely occur.

Importantly, we are not suggesting that interest rate projections should be avoided in favour of macroeconomic projections. Rather, we emphasize that it is difficult for our subjects to infer information about one macroeconomic variable from another. Our experimental findings suggest that policy makers may wish to exercise caution when assuming that communication about a specific macroeconomic variable implies an understanding about other macroeconomic variables, especially when the intended direction of these variables is not the same. Recent follow-up work by Kryvtsov and Petersen (2019) shows that interest rate projections and time-contingent forward guidance has limited effects on participants' ability to forecast other macroeconomic variables. Rather, simple information such as the direction of the last interest rate change serves as a more effective anchor for participants macroeconomic expectations.

Adaptive dual projections are highly focal and easy to use. Consequently, more subjects adopt the central bank's adaptive dual projection as their own forecast rather than relying on their less responsive forecasting heuristics. Rational subjects best-respond to their counterparts' reliance on the projection by forming more volatile inflation expectations. Overall, we observe significantly greater inflation variability when subjects receive adaptive dual projections than no communication.

Our second key finding relates to the assumptions underlying central bank projections. Central banks are increasingly incorporating household heterogeneity into their forecasting models to better capture realistic aggregate dynamics. While a combination of rational and backward–looking expectations are well-supported by survey and experimental data, our findings suggest that central banks interested in maintaining inflation stability in the presence of demand shocks should strategically communicate projections solely based on rational expectations. This would encourage naïve agents to form more stable inflation expectations and reduce inflation variability.

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5. Tables and Figures

Table 1: Summary of treatments

Treatment	Sessions	Repetitions per session	Periods per repetition	Subjects per session	CB projected variables	CB assumption on aggregate expectations
NoComm	6	2	30	7	none	none
IRProj	6	2	30	7	i_{t+s} for $s = 1, .., 5$	Rational
DualProj	6	2	30	7	x_{t+s}, π_{t+s} for $s = 1, .., 5$	Rational
ADProj	6	2	30	7	x_{t+s}, π_{t+s} for $s = 1, .., 5$	Adaptive(1)

CB Models of Expectations	Output Expectations	Inflation Expectations
Rational	$E_t x_{t+1} = x_{t+1}$	$E_t \pi_{t+1} = \pi_{t+1}$
Adaptive(1)	$E_t x_{t+1} = 0.5x_{t+1} + 0.5x_{t-1}$	$E_t \pi_{t+1} = 0.5\pi_{t+1} + 0.5\pi_{t-1}$

Table 2: Forecasting Heuristics

Model	Heuristic Name	Model
M1	Ex-ante rational	$E_{i,t}x_{t+1} = 0.269r^n_{t-1} + 0.472\epsilon_t$
		$E_{i,t}\pi_{t+1} = 0.08r^n_{t-1} + 0.141\epsilon_t$
M2	Target	$E_{i,t}x_{t+1} = 0$
		$E_{i,t}\pi_{t+1} = 0$
M3	Naive	$E_{i,t}x_{t+1} = x_{t-1}$
		$E_{i,t}\pi_{t+1} = \pi_{t-1}$
M4	Adaptive(1)	$E_{i,t}x_{t+1} = 0.146r^n_{t-1} + 0.536x_{t-1} - 0.138\pi_{t-1} + 0.257\epsilon_t$
		$E_{i,t}\pi_{t+1} = 0.119r^n_{t-1} + 0.037x_{t-1} + 0.711\pi_{t-1} + 0.208\epsilon_t$
M5	ADProj	$E_{i,t}x_{t+1} = 0.293r^n_{t-1} + 0.071x_{t-1} - 0.276\pi_{t-1} + 0.513\epsilon_t$
		$E_{i,t}\pi_{t+1} = 0.237r^n_{t-1} + 0.074x_{t-1} + 0.422\pi_{t-1} + 0.416\epsilon_t$
M6	BR to ADProj	$E_{i,t}x_{t+1} = 0.178r^n_{t-1} - 0.021x_{t-1} - 0.114\pi_{t-1} + 0.312\epsilon_t$
		$E_{i,t}\pi_{t+1} = 0.311r^n_{t-1} + 0.031x_{t-1} + 0.123\pi_{t-1} + 0.546\epsilon_t$
M7	Constant Gain	$E_{i,t}x_{t+1} = x_{t-1} - \gamma(E_{i,t-2}x_{t-1} - x_{t-1})$
		$E_{i,t}\pi_{t+1} = \pi_{t-1} - \gamma(E_{i,t-2}\pi_{t-1} - \pi_{t-1})$
M8	Trend Chasing	$E_{i,t}x_{t+1} = x_{t-1} + \tau(x_{t-1} - x_{t-2})$
		$E_{i,t}\pi_{t+1} = \pi_{t-1} + \tau(\pi_{t-1} - \pi_{t-2})$

Table 3: Effects of central bank projections on absolute forecast errors and disagreement - treatment effects[I]

	ln(Absolute Forecast Errors)				ln(SD of Forecasts)			
	Output Gap		Inflation		Output Gap		Inflation	
	Rep.1	Rep. 2	Rep.1	Rep. 2	Rep.1	Rep. 2	Rep.1	Rep. 2
IRProj	0.037	-0.047	0.285*	-0.091	0.399	-0.181	0.577	0.008
	(0.11)	(0.10)	(0.17)	(0.10)	(0.25)	(0.22)	(0.53)	(0.20)
DualProj	0.194*	-0.222**	0.092	-0.292***	0.332	-0.676***	0.185	-0.334*
	(0.11)	(0.10)	(0.15)	(0.09)	(0.31)	(0.16)	(0.39)	(0.19)
ADProj	-0.116	-0.196**	0.578***	0.305***	-0.028	-0.827***	0.297	-0.080
	(0.09)	(0.09)	(0.12)	(0.09)	(0.32)	(0.15)	(0.37)	(0.16)
α	4.130***	4.269***	2.958***	3.248***	3.747***	4.307***	2.954***	3.153***
	(0.11)	(0.09)	(0.11)	(0.08)	(0.27)	(0.20)	(0.27)	(0.12)
N	4808	4820	4778	4803	719	719	719	719
χ^2	31.67	9.243	34.64	50.29	6.729	35.94	1.295	3.049
Random effects								
subject	✓	✓	✓	✓				
sessions	✓	✓	✓	✓	✓	✓	✓	✓

(I) This table presents results from a series of mixed effects panel regressions. The dependent variables are logs of absolute forecast errors and logs of forecast disagreement, measured as the log standard deviation of forecasts in a given round. IRProj, DualProj, and ADProj are treatment-specific dummies indicating the interest rate, rational dual projection, and adaptive dual projection treatments, respectively. α denotes the estimated constant. Standard errors clustered at the session-level. $*p < 0.10$, $**p < 0.05$, and $***p < 0.01$.

Table 4: Credibility and Disagreement in Central Bank Projections of Output and Inflation - By Treatment[I]

	Dep.Var: Prob(Utilized CB Forecast=1)						ln(SD of Forecasts)					
	IRProj		DualProj		ADProj		IRProj		DualProj		ADProj	
	$E_{i,t}x_{t+1}$	$E_{i,t}\pi_{t+1}$	$E_{i,t}x_{t+1}$	$E_{i,t}\pi_{t+1}$	$E_{i,t}x_{t+1}$	$E_{i,t}\pi_{t+1}$	$E_t x_{t+1}$	$E_t \pi_{t+1}$	$E_t x_{t+1}$	$E_t \pi_{t+1}$	$E_t x_{t+1}$	$E_t \pi_{t+1}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\lvert FE^{cb}x_{t-1}\rvert$	-0.004*		-0.001		-0.002		0.001		0.002		0.000	
	(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)	
$\lvert FE^{cb}x_{t-1}\rvert^2$	0.000		0.000		0.000		0.000		-0.000		0.000	
	(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)	
$UtilizedCBxForecast_{t-1}$	0.072		0.375***		0.220***							
	(0.15)		(0.08)		(0.07)							
$\lvert FEx_{i,t-1}\rvert$	0.001		-0.002**		-0.001							
	(0.00)		(0.00)		(0.00)							
$\lvert FEx_{i,t-1}\rvert \times UtilizedCBxForecast_{t-2}$	0.001		0.002**		0.002***							
	(0.00)		(0.00)		(0.00)							
SD r_t^n	-0.010***	-0.005	0.001	0.003	-0.003	-0.002	0.010***	0.002	0.009***	0.002	-0.000	0.002
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Experienced	0.137*	0.019	0.023	0.068	0.100	-0.025	-0.085*	-0.370***	-0.105	-0.170**	-0.119*	-0.165**
	(0.08)	(0.08)	(0.17)	(0.18)	(0.16)	(0.15)	(0.05)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
$\lvert FE^{cb}\pi_{t-1}\rvert$		-0.011**		-0.004		-0.008***		0.009***		0.011**		0.006**
		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)
$\lvert FE^{cb}\pi_{t-1}\rvert^2$		-0.000		-0.000		0.000***		-0.000		-0.000		-0.000
		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)
$UtilizedCB\pi Forecast_{t-1}$		0.269***		0.450***		0.363***						
		(0.10)		(0.07)		(0.07)						
$\lvert FE\pi_{i,t-1}\rvert$		0.000		-0.004***		-0.003***						
		(0.00)		(0.00)		(0.00)						
$\lvert FE\pi_{i,t-1}\rvert \times UtilizedCB\pi Forecast_{t-2}$		0.001		0.006**		0.001						
		(0.00)		(0.00)		(0.00)						
α	-0.108	-0.300	-0.905	-0.724	-0.062	0.152	2.507***	2.932***	2.365***	2.629***	3.373***	2.787***
	(0.49)	(0.52)	(0.98)	(0.98)	(0.90)	(0.86)	(0.31)	(0.45)	(0.46)	(0.50)	(0.39)	(0.41)
% Observations where Utilized CB Forecast=1	0.07	0.13	0.25	0.38	0.22	0.42						
Average CB Forecast Error (basis points)	77	33	79	24	78	56						
N	2346	2346	2342	2342	2277	2277	336	336	336	336	328	328
χ^2	19.64	50.22	42.07	74.50	27.66	64.46	66.46	54.04	32.50	16.44	19.92	24.06
Random effects												
subject	✓	✓	✓	✓	✓	✓						
sessions	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

(I) This table presents results from a series of mixed effects probit regressions. Standard errors are clustered at the session level in columns (1)-(6) and are robust in (7)-(12). *$p < 0.10$, **$p < 0.05$, and ***$p < 0.01$. $UtilizedCBxForecast_{t-1}$ and $UtilizedCB\pi Forecast_{t-1}$ are dummy variables that take the value of one if a subject's output and inflation forecast in period $t-1$ about period t, respectively, were less than five basis points away from the central bank's projected forecast. $|FE^{cb}x_{t-1}|$ and $|FE^{cb}\pi_{t-1}|$ denote the absolute forecast errors the central bank made in period $t-2$ about period $t-1$ output and inflation, respectively. $|FEx_{i,t-1}|$ and $|FE\pi_{i,t-1}|$ denote subject i's forecast errors formed in period $t-2$ about period $t-1$ output and inflation, respectively. NoComm forecasts are within 5 basis points of the REE solution for 6% of output forecasts and 11% of inflation forecasts.

Table 5: Standard deviations of output and inflation normalized by the REE solution

Treatment		Repetition–1		Repetition–2	
		std.Output	std.Inflation	std.Output	std.Inflation
NoComm					
	Mean	1.02	1.38	1.06**	1.50**
	std.	0.12	0.62	0.07	0.41
IRProj					
	Mean	0.98	1.49	0.99	1.14
	std.	0.13	0.76	0.15	0.48
DualProj					
	Mean	0.96	1.06	0.97	1.04
	std.	0.04	0.20	0.04	0.12
ADProj					
	Mean	0.88**	2.33**	0.88**	2.37**
	std.	0.05	0.22	0.03	0.24
Rank–sum test:		p–value	p–value	p–value	p–value
NoComm–IRProj		0.522	0.749	0.262	0.200
NoComm–DualProj		0.109	0.262	0.010	0.055
NoComm–ADProj		0.055	0.025	0.004	0.004
IRProj–ADProj		0.109	0.037	0.109	0.078
IRProj–DualProj		1.000	0.522	0.522	0.004
DualProj–ADProj		0.025	0.004	0.004	0.004

We report summary statistics on the the standard deviation of output and inflation, measured at the session-repetition level, divided by the rational expectations equilibrium solution's respective standard deviations. N=6 observations are computed per treatment-repetition. The top panel presents means and standard deviations of the variable of interest. Asterisks denote whether the mean result is significantly different from one using a two-sided Wilcoxon signed rank test: $*p < 0.10$, $**p < 0.05$, and $***p < 0.01$. The bottom panel denotes the p-value results from a series of two-sided Wilcoxon rank-sum tests of identical distributions across treatments for different variables and repetitions.

Figure 1: Timing of information, decisions, and outcomes in each round

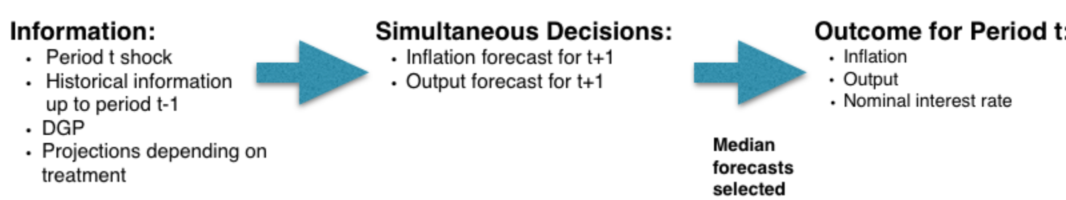


Figure 2: Simulated impulse responses to a 1 s.d. innovation to r_t^n under alternative forecasting assumptions

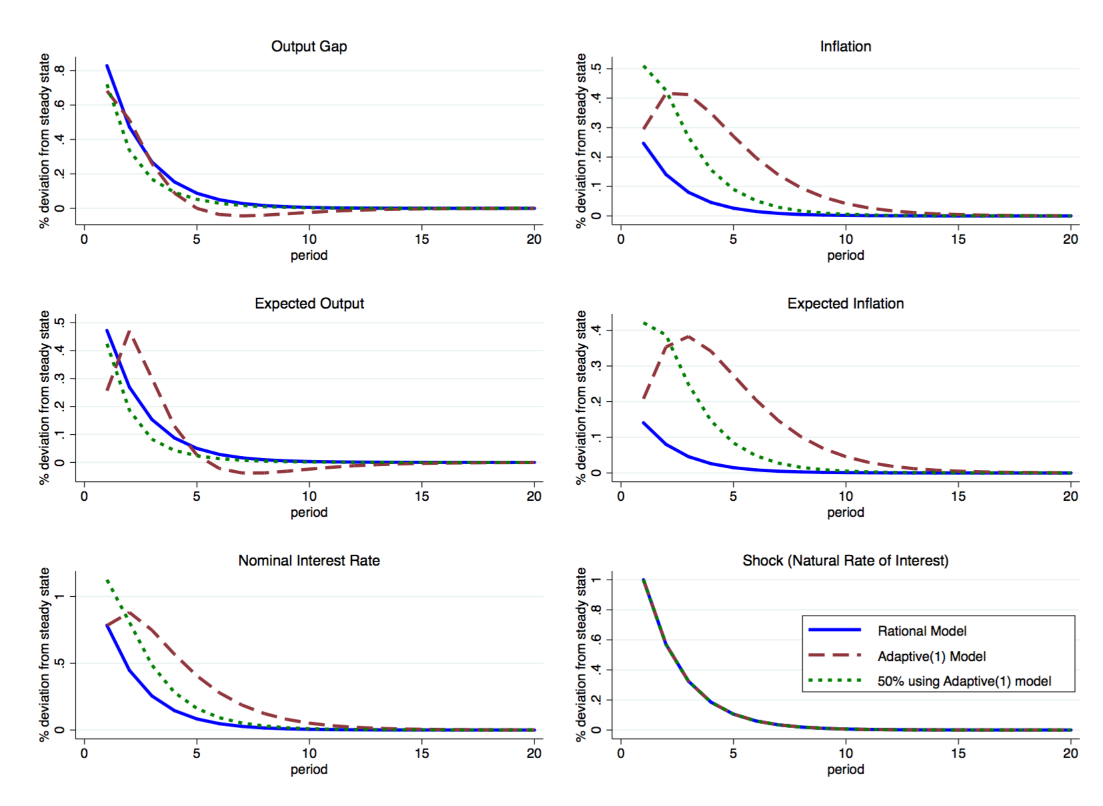


Figure 3: Screenshot from IRProj Treatment

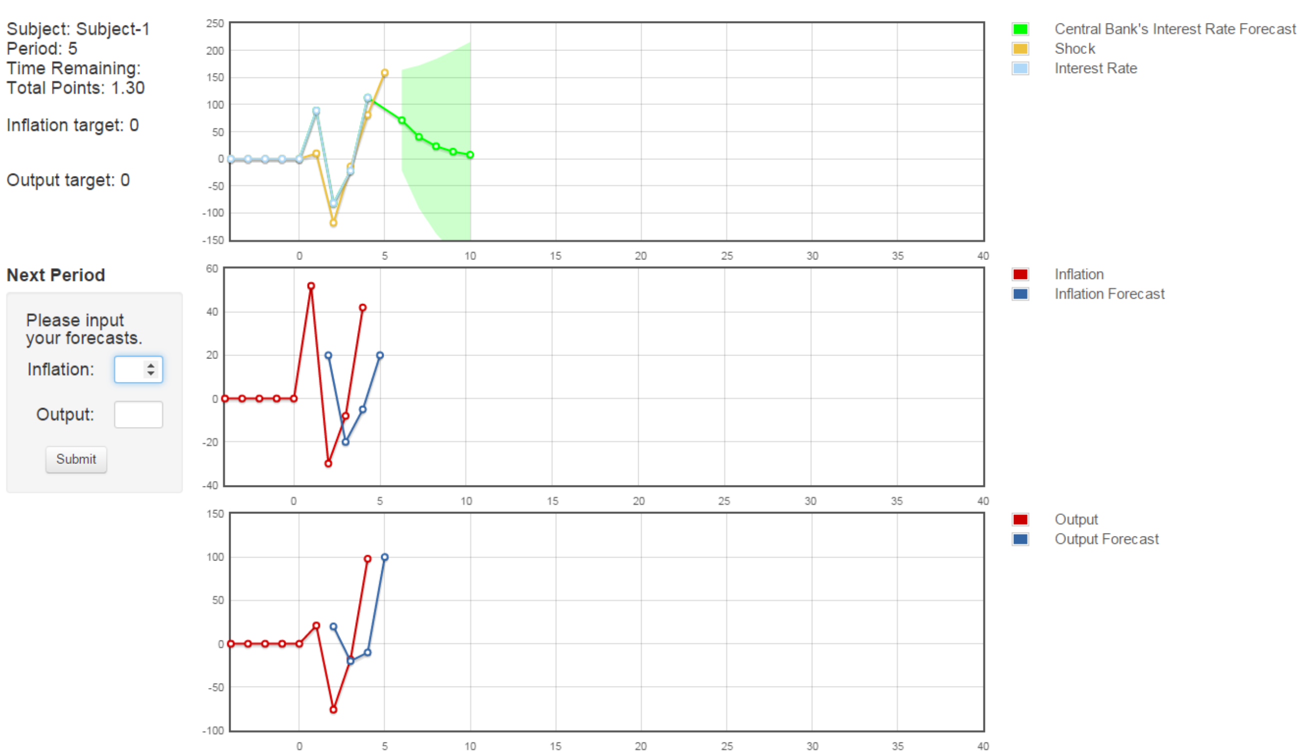
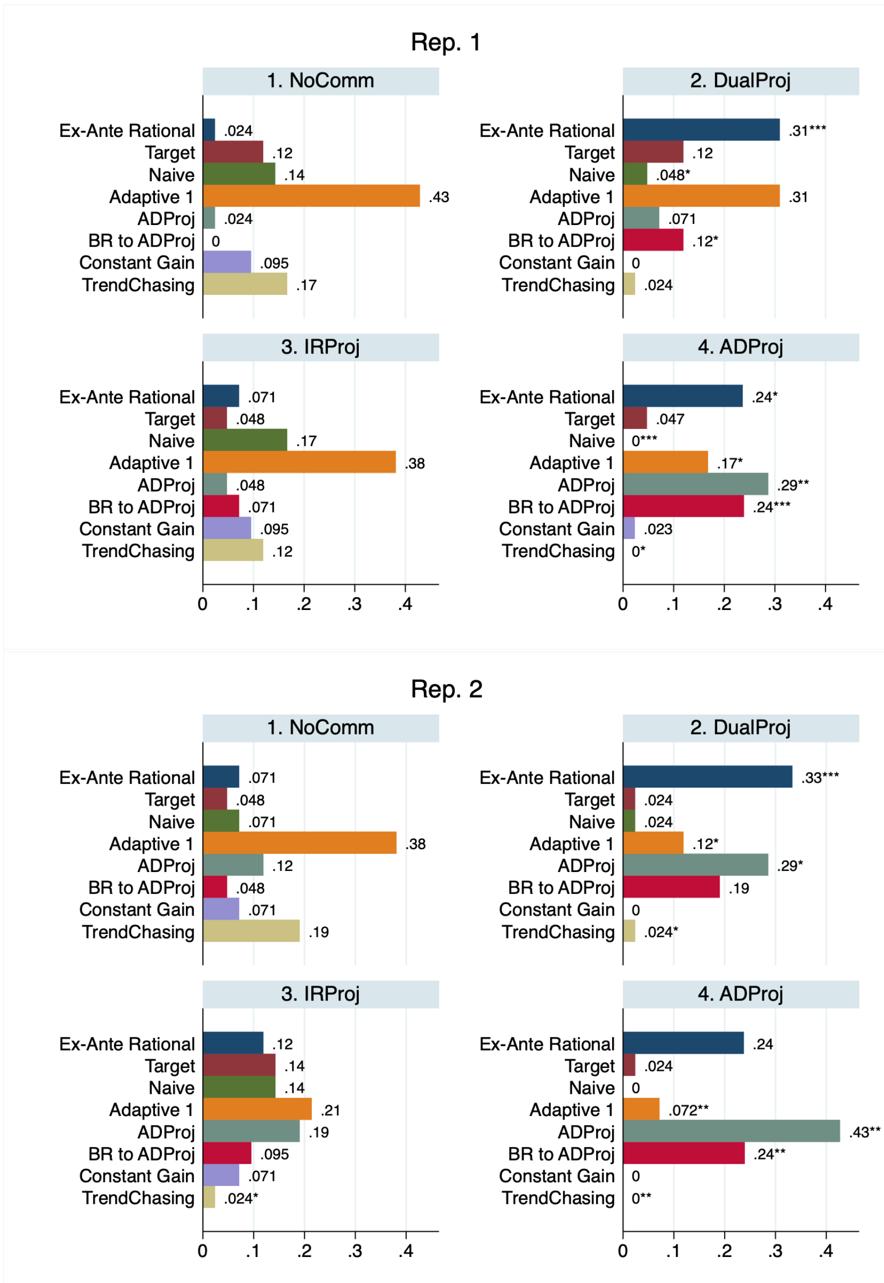
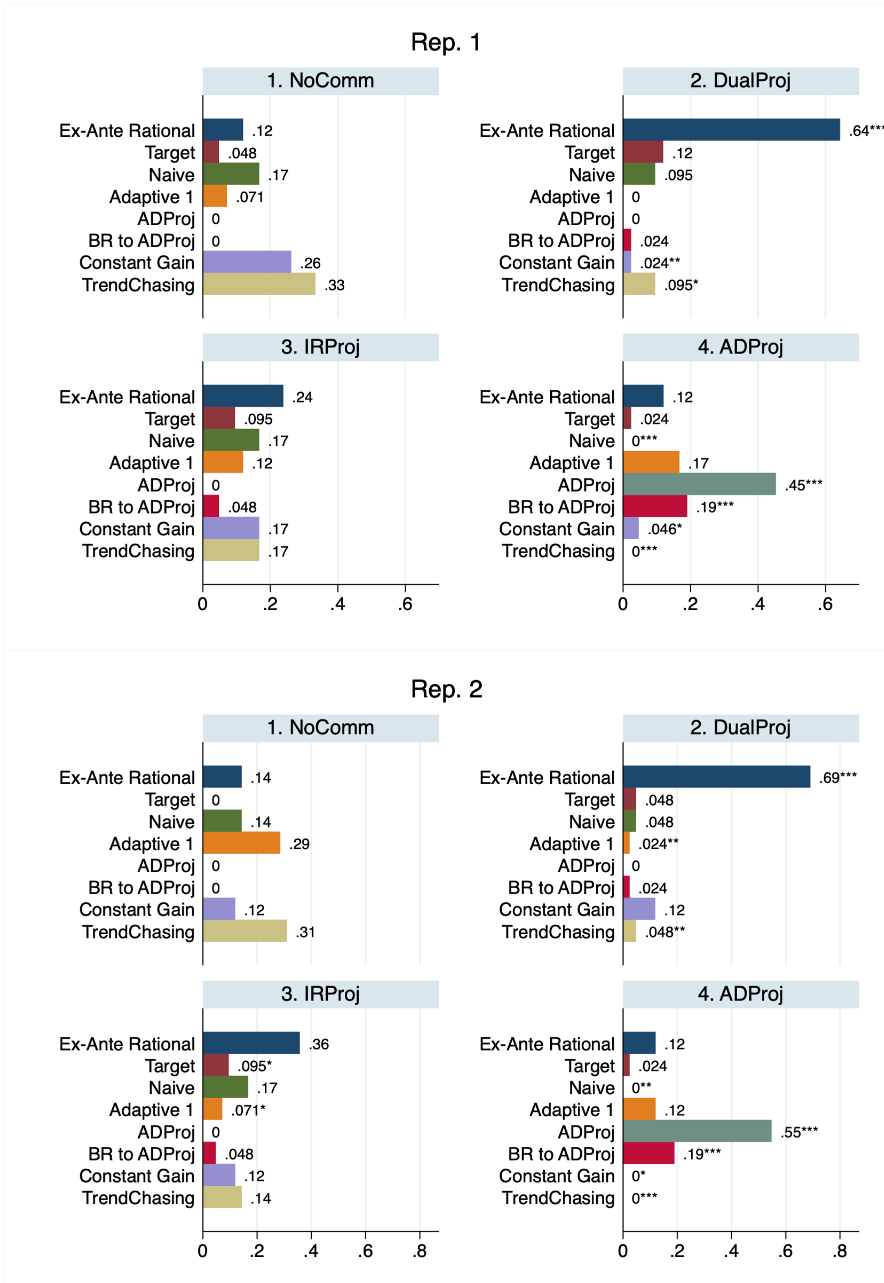


Figure 4: Distribution of forecasting heuristics - Output forecasts



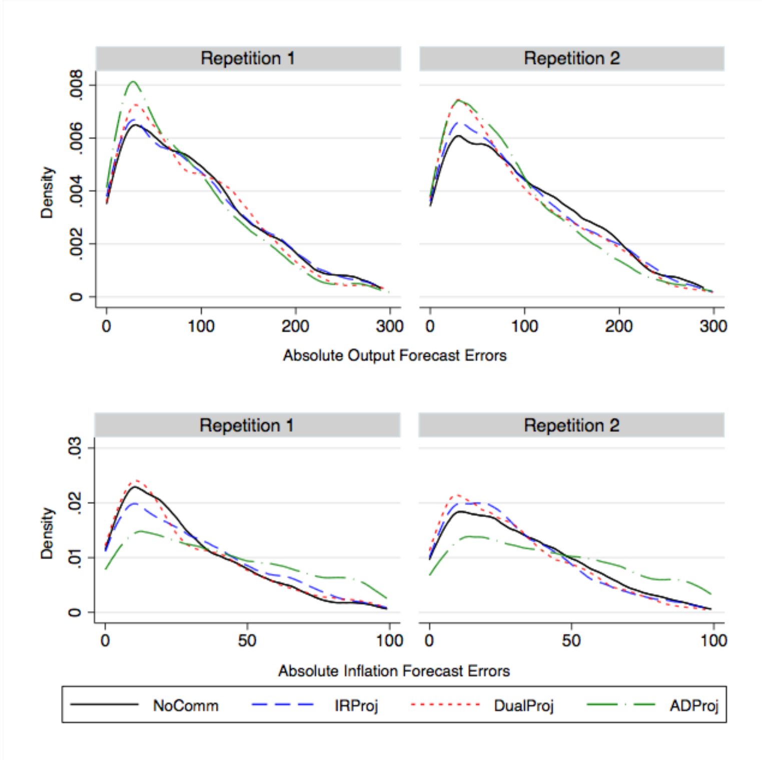
The figure represents the distribution of participants' output forecast heuristics, by repetition.

Figure 5: Distribution of forecasting heuristics - Inflation forecasts



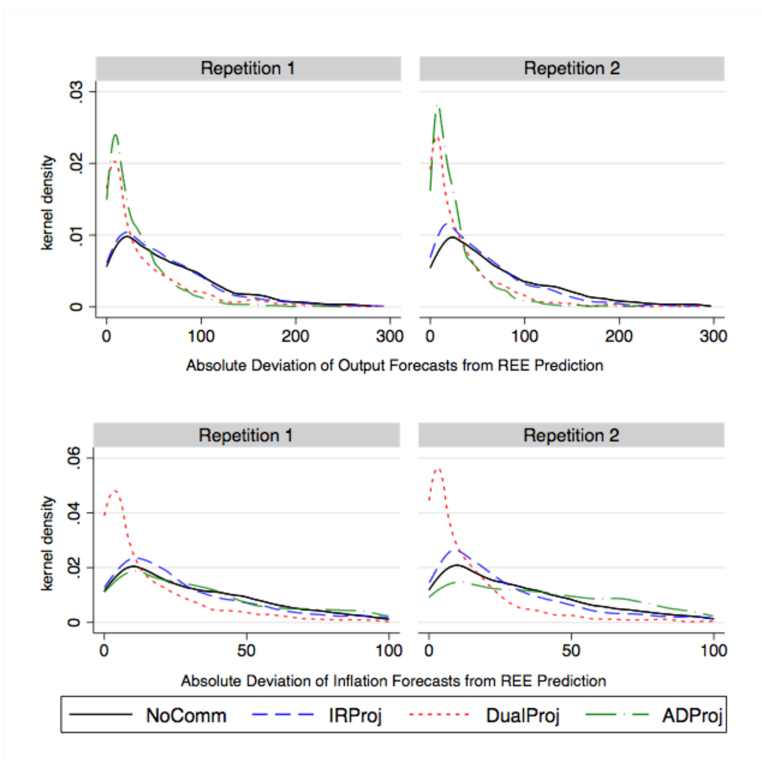
The figure shows the distribution of participants' inflation forecast heuristics, by repetition.

Figure 6: Kernel densities of absolute output and inflation forecast errors



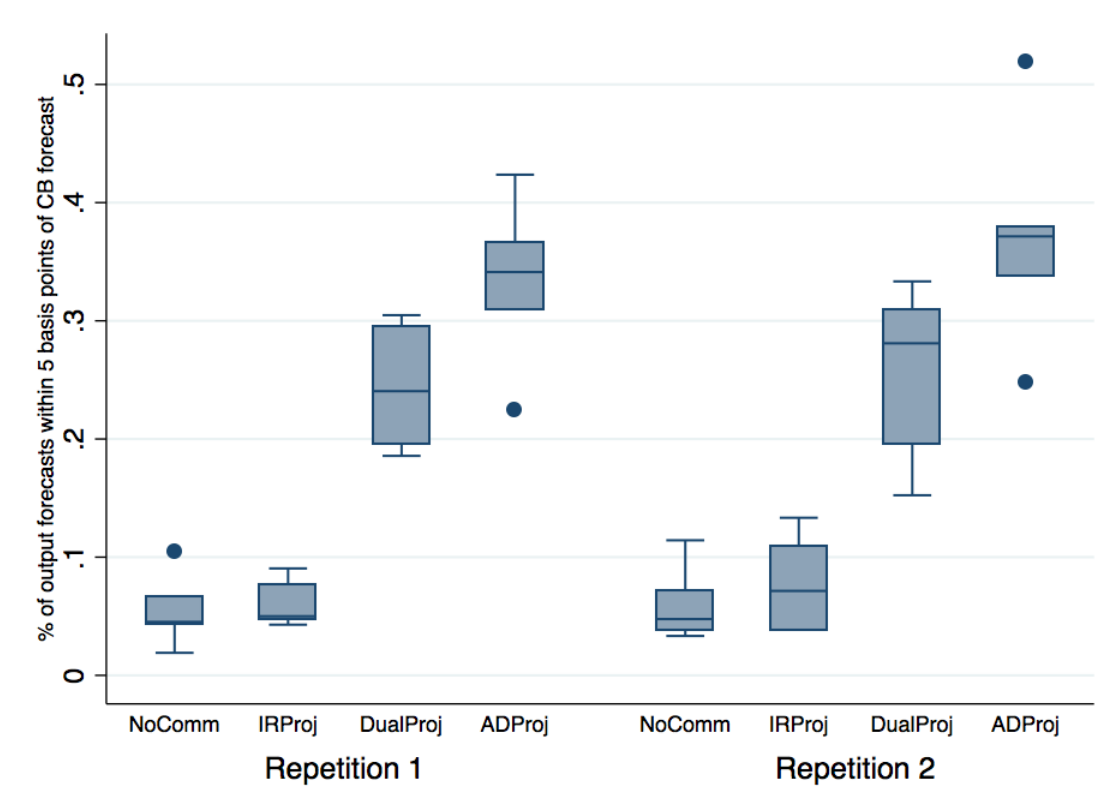
The figure represents the kernel densities associated with individual subject absolute forecast errors from all periods of play.

Figure 7: Kernel densities of absolute deviation of output and inflation forecasts from the REE prediction



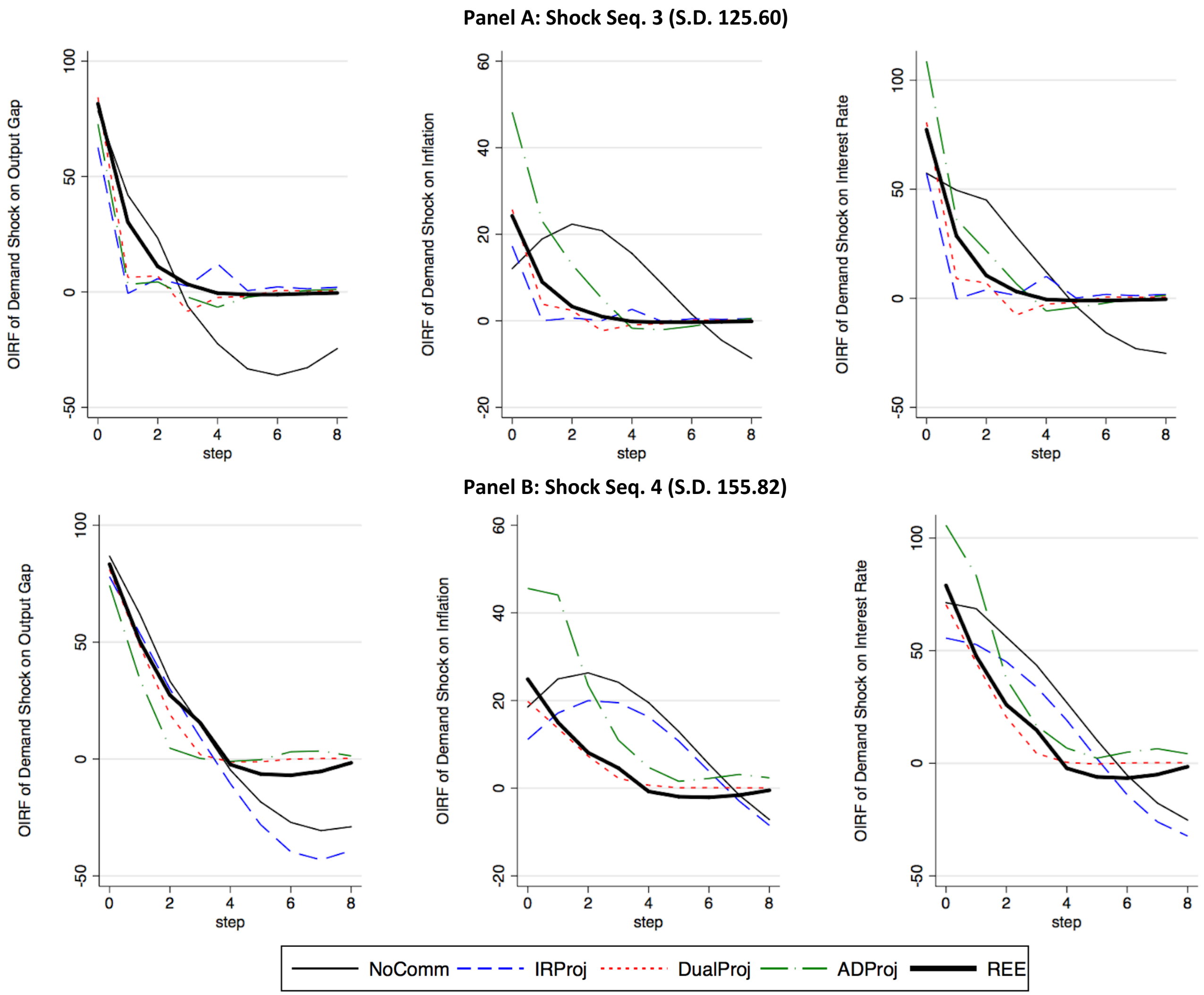
The figure shows the kernel densities associated with all individual absolute deviations of forecasts from the rational expectations equilibrium prediction from all periods of play.

Figure 8: Percentage of output and inflation forecasts within five basis points of the CB's projected value, session means



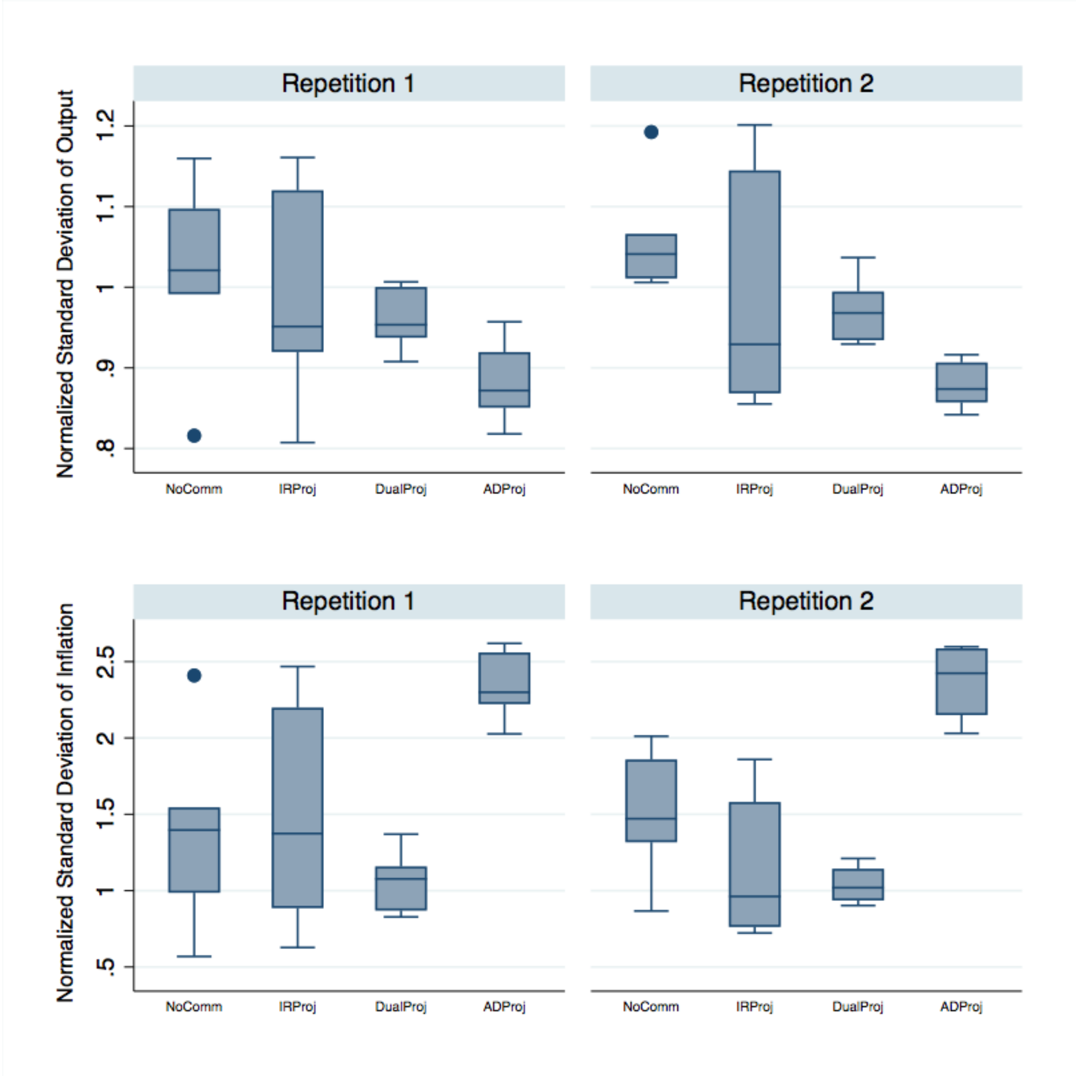
The figure shows the distribution of mean usage of the central bank's projection at the session- and repetition-level, by treatment. Our variables of interest are $UtilizedCBxForecast_t$ and$UtilizedCB\pi Forecast_t$ which take the value of 1 if a subject's period t forecast about $t+1$ was less than five basis points from the CB's projection and zero otherwise. For the NoComm and IRProj treatments, we compare subjects' forecasts to the ex-ante rational output and inflation projections.

Figure 9: Estimated responses to a one-standard deviation innovation to the natural rate of interest



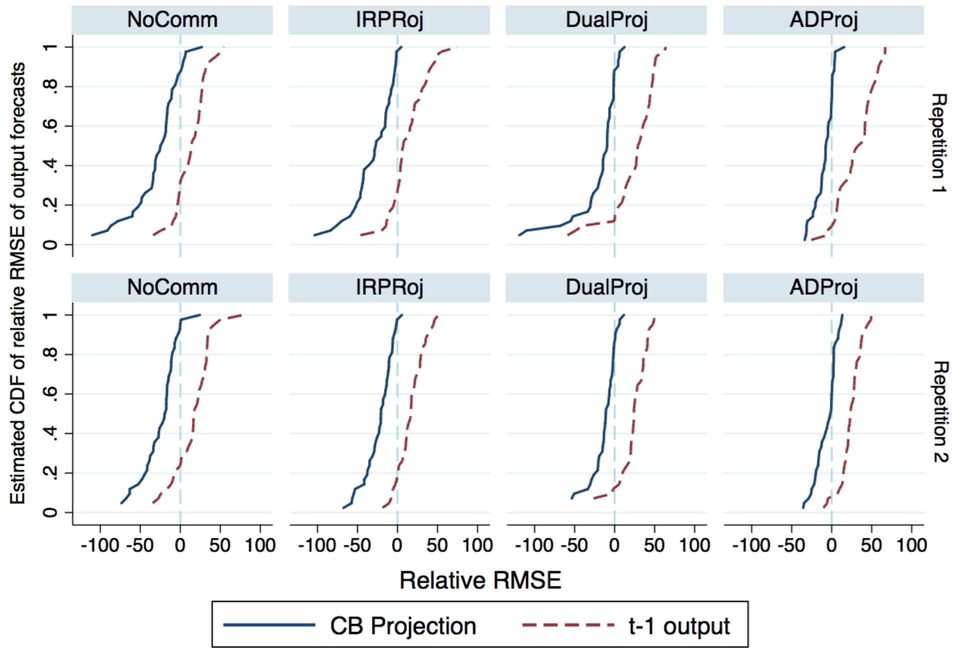
Panels A and B display estimated orthoganlized IRFs associated with the least and most volatile shock sequences, respectively. Data from Repetition 2.

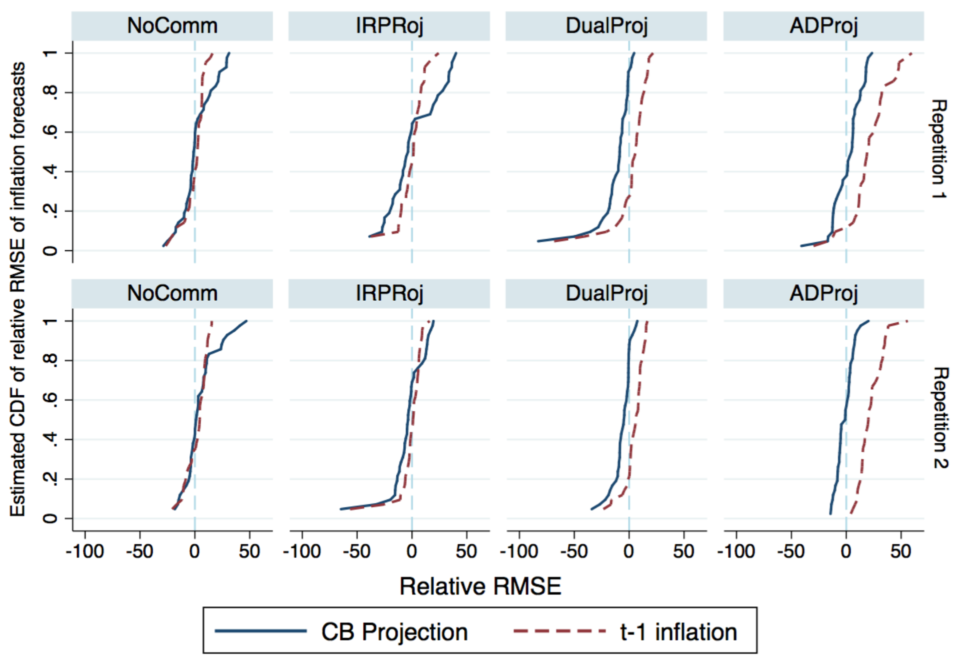
Figure 10: Standard deviation of output and inflation normalized by REE



The figure depicts the standard deviation of output and inflation at the session- and repetition-level, by treatment. The normalizing REE output and inflation is calculated for each shock sequence.

Figure 11: Distribution of adjustment in RMSE under counterfactual forecasting heuristics





The figure depicts the distribution of the change in the RMSE of output and inflation forecasts associated with two counterfactual forecasting heuristics. For each subject in each repetition and treatment, we compute their Relative RMSE $= RMSE^{Hyp.}_{\pi,x} - RMSE^{Actual}_{\pi,x}$ and plot the cumulative distribution for two heuristics. The solid blue line depicts the counterfactual reduction in the RMSE associated with forecasting according to the REE solution. The dashed red line depicts the counterfactual reduction in the RMSE associated with forecasting based on the previous period's output and inflation. Negative values indicate a hypothetical improvement in forecast accuracy associated with the counterfactual heuristic.