# Coordinating expectations through central bank projections*

**Fatemeh Mokhtarzadeh** **Luba Petersen**†

University of Victoria Simon Fraser University

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**Abstract**

Central banks are increasingly communicating to the public about their future outlook in an effort to manage expectations. We provide original causal evidence that the information communicated and the assumptions underlying a central bank's projection 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 adaptive expectations. Ex-ante rational dual projections of output and inflation significantly reduce subjects' 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 in more volatile environments and subjects revert to their backward-looking 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. 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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† Petersen: Department of Economics, Simon Fraser University, 8888 University Drive, Burnaby, BC, V5A 1S6, Canada, lubap@sfu.ca. Moktarhzadeh: Department of Economics, University of Victoria, Victoria, BC, V8P 5C2, Canada

# 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 outlook about the future. Many central banks publish a combination of projections about future GDP, GDP growth, CPI and their own policy rates.

Central banks face two critical decisions when constructing and communicating their projections. First, they must make numerous assumptions about the economy including how people think about the future. Many central banks bank 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 enhance central bank credibility, such information may encourage the public to maintain or adopt backward-looking expectations and de-anchor inflation expectations.[1] Second, central banks must decide which of their many projections to communicate to the public given their mandated objectives.

The contribution of this paper is to provide empirical insight into these two important policy decisions. Because central banks cannot 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 subject reports their forecasts of the following period's rate of inflation and output gap. Aggregate expectations and a random disturbance jointly determine the current state of the economy. Each subject is paid based on the accuracy of their forecasts.

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 comparison economies operating under three alternative communication policies. In our Interest Rate Projection treatment, all subjects observe the central bank's

[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.

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 utilize. Finally, the Adaptive Dual Projection treatment mirrors the Dual Projection treatment except that the central bank's projections follow an adaptive model that, based on previous work, we expected would better predict aggregate dynamics, and thus, reduce credibility concerns.

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 greater coordination of expectations and reduced forecast errors. By contrast, projections of nominal interest rates leads 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 will be 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 variability. This is a consequence of a large fraction of subjects directly 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 shows original empirical evidence that inflation-targeting central banks are better off 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) while macroeconomic projections appear to more consistently manage inflation expectations (Hubert, 2014). 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.

The paper is organized as follows. The next section discusses related literature on central bank communication and expectations from theoretical, policy, and experimental perspectives. Section 3 lays out our experimental design, hypotheses, and laboratory implementation. The experimental results are discussed in Section 4, namely how individuals form expectations and how aggregate variables evolve under different forms of central bank communication, and Section 5 discusses our findings in the context of the learning and inattention literatures.

## 2. Central Bank Communication and Expectations

The growing literature on central bank communication provides a strong body of theoretical and empirical work on the effectiveness of central bank communication on private agents' expectations. Central bank communication has evolved considerably over the last 30 years. The history of central bank communication policy can be roughly divided into three key periods.[2] For decades, central banks were uncommunicative and opaque about their operations to safeguard themselves from political pressure, avoid credibility loss, and to achieve an element of surprise when they did change policy. However, in the early 1990's the Reserve Bank of New Zealand (RBNZ) began to adopt explicit inflation targeting and became more transparent about their inflation objective and mandate. Norway followed suit in 2001 and Sweden in 2007. Central banks' communication of inflation targets led to increased transparency and credibility, and contributed to their ability to achieve low and stable inflation. Most recently, many central banks have moved toward explicit communication of both their targets and forecasts about their future policy rates. Since 1997, the RBNZ has communicated not only their inflation target, but also projections for the 90-day bank bill rate via Monetary Policy Statements (MPS). Norway in 2005, Sweden in 2007, and the U.S. in

[2] See Kang et al. (2013) for a more detailed discussion and Blinder et al. (2008) for a survey of central bank communication strategies.

2012 began to provide projections of key policy variables as a tool to manage market expectations. These types of projections have been used to signal the likely future path of policy rates and the outlook of monetary policy in general.

Central bank transparency is not without its own set of risks and challenges. Mishkin (2004) cautions that transparent central banks expose themselves to an "expectation trap" whereby a central bank may try to sustain a previously projected path for the economy to preserve its credibility when it be suboptimal to do so. The public may misperceive central bank targets or projections as promises. When the central bank fails to live up to its targets or projections, its credibility may be critically compromised. Moreover, central bank communication can induce less clarity due to the limited ability of market agents to process additional information (Winkler, 2002; Kahneman, 2003). Confusion can be further compounded when the central bank does not have better information than private agents (Mishkin, 2004; Archer, 2005; Goodhart, 2009; and Blinder, 2009).

Central bank inflation projections appear to be effective at reducing forecast disagreement and improving forecast accuracy. Hubert (2014) finds a significant positive relationship between projections and forecasters' expectations of inflation in Sweden, UK, Canada, Japan, and Switzerland. The evidence for the effectiveness of interest rate projections and forward guidance is mixed. The RBNZ's interest rate projections do not significantly improve short-term interest rate expectations (McCaw and Ranchhod, 2002; Turner, 2006). More recently, Brubakk et. al. (2017) study high frequency data around announcements of Norwegian and Swedish interest rate projections. They find that surprise revisions in the policy path significantly affect the yield curve in both the short and medium run. Thornton (2012) find that forward guidance is associated with more accurate forecasting in Norway and Sweden but not in the United States or New Zealand. Moreover, forward guidance appears to reduce the cross-sectional standard deviation of forecasts in New Zealand, Norway and Sweden, but not in the United States.

In a closely related paper to ours, Jain and Sutherland (2017) 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 disagreement and accuracy. There are a number of consistent findings in their work and ours. First, Jain and Sutherland find that projections of the central bank's targeted variables, namely output gap and inflation, significantly reduce forecast disagreement about those particular variables. The authors also find that central bank's policy-rate projections do not significantly reduce forecaster disagreement or forecast errors. We differ on our findings regarding forecast accuracy. While Jain and Sutherland find no effects from central bank projections on forecast accuracy, we observe many instances where projections improve forecast accuracy.

While these findings speak to how market and professional forecasts react to central bank projections, no empirical work has identified how the effects of central bank projections alter forecasting heuristics. Our paper contributes to this literature by providing a comprehensive analysis of how

projections alter individual-level expectation formation over a lengthy horizon.

Theoretical and computational work also suggest that central bank projections can be effective at guiding expectations. Ferrero and Secchi (2010) study an environment where agents learn recursively about the economy's data-generating process in the presence of central bank macroeconomic projections. The projections are computed under the assumption that agents form expectations according to the rational expectations equilibrium solution. Ferrero and Secchi find that dual projections about output and inflation increase the set of policy rules that would lead to e-stability and improve the speed of learning and convergence to the steady state. Nominal interest rate projections, in contrast, do the opposite, increasing the space of policy rules under which the economy is e-unstable and reduces the speed of learning. Goy et al. (2016) computationally study agents' expectations near and at the zero lower bound (ZLB). Their agents can endogenously switch their forecasting heuristics based on performance. They consider the effects of publishing central bank projections of macroeconomic projections and future nominal interest rate on agents' learning. Goy et al. find that such forward guidance through output and inflation projections significantly reduces the likelihood of deflationary spirals when the economy is at the ZLB.

Empirical macroeconomists face significant hurdles when it comes to identifying the effects of exogenous disturbances, policies, or communications on expectations and must often make important identifying assumptions about the structure of the economy and agents' information sets. As a consequence of these empirical challenges, controlled laboratory experiments have become an alternative avenue to study how monetary policy influences the expectation formation process.[3] The advantage to laboratory experimentation is that the researcher is able to carefully control for the many factors that might influence individuals' expectations in order to achieve more precise identification. For instance, the experimenter has a high degree of control over subjects' information sets and can control features of the data-generating process including important policy rules and communication strategies while systematically varying features of the economy. Studying expectations in the laboratory does require the researcher to trade off some external validity for experimental control. External validity may be compromised through the choice of the underlying data-generating process or the selection of subjects, though we note that these are two challenges also faced by theory. Given that central banks widely employ variations of the New Keynesian model in their own projections and laboratory subjects have been shown to behave similarly to professionals (e.g. Frechette, 2015), we feel confident that our experimental results can be insightful about real-world expectations.

Learning-to-forecast experiments (LTFEs) have been extensively employed to study how expectations respond to information, policy, and structural features of the economy.[4] In LTFEs,

[3] 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.

[4] 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

subjects play the roles of forecasters and are tasked with forming 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 prespecified 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) compare inflation expectations reported by survey participants with their decisions in a financially incentivized investment experiment. They find that, on average, participants' expectations and decisions are correlated in a manner consistent with economic theory. Inconsistent behavior tends to be associated with lower education and financial literacy.

We focus our discussion of the related experimental literature on LTFEs that investigate the effect of central bank communication on expectation formation. Kryvtsov and Petersen (2013) study the robustness of the strength of the expectations channel of monetary policy to variations in the responsiveness of monetary policy to inflation, persistence of shocks, and central bank projections of future policy rates. Kryvtsov and Petersen find considerable heterogeneity in the degree to which subjects' expectations internalize the stabilizing effects of monetary policy. They also 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.

The nature of communication also matters. Arifovic and Petersen (2017) show that qualitative communication of evolving inflation targets at the zero lower bound tends to be more effective at stabilizing expectations than comparable quantitative communication. Qualitatively announced targets mitigate the credibility loss that occurs the central bank fails to achieve its targets. However, the need to actually communicate the target appears to depend on the mandate of the central bank.

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); and central bank communication (Kryvtsov and Petersen 2013, Cornand and M'Baye 2016). 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).

More recently, 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. Cornand and M'Baye (2016) demonstrate that in normal times (when interest rates are sufficiently above zero) the gains from communicating an inflation target depend on the nature of the central bank's policy rule. Under strict inflation targeting, subjects learn the central bank's target more quickly and additional communication does not have a significant effect on economic stability. By contrast, additional information about the inflation target when the central bank faces a dual mandate to stabilize inflation and output significantly reduces inflation variability.

## 3. Experimental Design, Hypotheses, and Implementation

Our experiment is designed to study how expectations are formed in the presence of central bank projections of key economics variables. The experimental economy's data-generating process is derived from a log-linear approximation around a deterministic steady state of a standard New Keynesian framework. In this framework, private expectations of future aggregate demand and inflation have a direct effect on current outcomes. In our experiment, aggregate expectations are derived from subjects' reported expectations instead of based on an assumed model of expectations. We focus on this general class of models because of its ubiquitous use by central banks over the last decade and for the important role expectations play in driving aggregate dynamics.[5]

Each independent economy involves groups of seven inexperienced subjects playing the role of forecasters who are tasked with submitting incentivized forecasts about the future state of the economy. The submitted forecasts are 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. The aggregate economy implemented in our experiment is described by the following system of equations:

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

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

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

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

[5] 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. For a nonlinear implementation, see Hommes et al. (2015). A heterogenous version of the New Keynesian model has been implemented by Mauersberger (2016).

Equation (1) is the Investment–Saving curve and describes the evolution of the output gap or aggregate demand. It is derived from a log–linear approximation of households' intertemporal optimization around a deterministic zero inflation and output gap steady state. Equation (1) 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, $r_t^n$.[6] The quantitative importance of this deviation depends on the elasticity of intertemporal substitution, $\sigma^{-1}$.

Equation (2) is the New Keynesian Phillips curve (NKPC) which describes the evolution of inflation, $\pi_t$ in response to changes in aggregated expectations of future inflation, $\mathbb{E}_t^* \pi_{t+1}$ and the output gap, $x_t$. The coefficient $\kappa$ 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 $\beta$ represents the subjective discount rate. To construct the NKPC, we assume that households have identical information sets and form expectations using identical functions of the state history.

Equation (3) 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 $\phi_\pi$ and $\phi_x$ govern the central bank's reaction to inflation and output gap.[7] Importantly, subjects are aware of the previous period's interest rate but not the current interest rate when forming their predictions. Note that the implemented environment studies deviations around a constant steady state, ignoring the presence of zero lower bound. That is, the nominal interest rates was frequently negative in our experiment.[8]

Finally, Equation (4) 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, $\epsilon_{rt}$, is drawn from an *i.i.d* $N(0, \sigma_r)$.[9] The experimental economy's data-generating process is calibrated to match moments of the Canadian data following Kryvtsov and Petersen (2013); $\sigma = 1$, $\beta = 0.989$, $\kappa = 0.13$, $\phi_\pi = 1.5$, $\phi_x = 0.5$, $\rho_r = 0.57$, and $\sigma_r = 1.13$. The environment had a unique steady state where $\pi^* = x^* = i^* = r_t^n = 0$.

When forming their forecasts, subjects have access to the following common information (and

[6] 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.

[7] We differ from Kryvtsov and Petersen (2013) who implement a policy rule that responds to deviations of past expected inflation and output from the central bank's target policy.

[8] Two papers explicitly consider expectation formation at the zero lower bound. See Arifovic and Petersen (2017) for expectation formation in a linearized environment and Hommes et al. (2015b) for expectation formation in a nonlinear environment.

[9] We follow Kryvtsov and Petersen (2013), Arifovic and Petersen (2017), and Pfajfar and Žakelj (2014, 2016) in the implementation of an *AR(1)* shock process.

all subjects understand that this is common information). First, they observe detailed quantitative information about the economy's data-generating process. During the experiment, subjects observe 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). They also observe the current period shock, which allows them to calculate the expected future shocks for the following periods. Forecasts are submitted in basis point measurements and could be positive, zero, or negative. After all subjects submit their forecasts or time elapses, the median submitted forecasts for output and inflation are employed as the aggregate forecasts and implemented in the calculation of the current period's output, inflation, and nominal interest rate.[10]

We incentivize subjects to take seriously their forecasting decisions by rewarding them based on their forecast accuracy. Subject $i$'s score in period $t$ is 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%. At the end of the experiment, subjects' points from all periods are converted into dollars and paid out to them in cash.

The dynamics of each economy depend critically on how aggregate expectations are formed. Figure 1 presents simulated impulse responses to a positive 1 s.d. innovation to the $r^n_t$ 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 (2013) observe that aggregate expectations in an identically calibrated experiment can be well-described by an Adaptive(1) heuristic. Under this heuristic, agents place 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

[10] 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.

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 relatively less output volatility and considerably greater inflation volatility on impact of the innovation.

*Treatments and Hypotheses*

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 Table 1.[11] Our baseline environment follows the experiment design described above.

- Treatment I: *No Communication (NoComm)*– There is no supplementary communication by the central bank.

We conduct three additional treatments involving central bank projections. In the next two treatments, central bank projections are presented in the form of five-period ahead projection of the nominal interest rate or dual projections of output gap and inflation, based on Equation (6) in which the central bank assumes agents form their expectations according to the unique REE solution:

$$\begin{aligned} x_t &= 0.47 \cdot r^n_{t-1} + 0.83 \cdot \epsilon_t, \\ \pi_t &= 0.14 \cdot r^n_{t-1} + 0.25 \cdot \epsilon_t. \\ i_t &= 0.45 \cdot r^n_{t-1} + 0.78 \cdot \epsilon_t, \end{aligned} \tag{6}$$

This implies that the central bank's $t+s$ forecasts of the following variables were given by:

$$\begin{aligned} E^{CB}_t x_{t+s} &= \rho^{s-1} \cdot x_t, \\ E^{CB}_t \pi_{t+s} &= \rho^{s-1} \cdot \pi_t, \\ E^{CB}_t i_{t+s} &= \rho^{s-1} \cdot i_t \end{aligned} \tag{7}$$

for $s = 1, ..., 5$.

[11] 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) and Mokhtarzadeh (2016).

- Treatment II: *Interest Rate Projection (IRProj)*–The central bank provides five-period ahead projections of expected future nominal interest rates in each period.

- Treatment III: *Output and Inflation Projection (DualProj)*– The central bank provides five-period ahead projections of expected future output and inflation in each period.

Subjects in the IRProj and DualProj treatment are informed that the central bank projections are forecasts formed by the central bank based on current and expected future shocks as well as the economy's data-generating process. We emphasize that the projections are not a promise but simply the central bank's *best* forecast of the future. Subjects are also reminded that all the projected information is common knowledge among subjects.

Our fourth treatment involves providing subjects with a combination of output gap and inflation projections, in which the central bank instead assumes that subjects 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 (2013) 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:

$$\begin{aligned} x_t &= 0.30 \cdot x_{t-1} - 0.28 \cdot \pi_{t-1} + 0.39 \cdot r^n_{t-1} + 0.68 \cdot \epsilon_t, \\ \pi_t &= 0.08 \cdot x_{t-1} + 0.67 \cdot \pi_{t-1} + 0.17 \cdot r^n_{t-1} + 0.29 \cdot \epsilon_t. \\ i_t &= 0.27 \cdot x_{t-1} + 0.86 \cdot \pi_{t-1} + 0.45 \cdot r^n_{t-1} + 0.78 \cdot \epsilon_t, \end{aligned} \tag{8}$$

- Treatment IV: *Adaptive Output and Inflation Projection (ADProj)*– The central bank provides a five-period ahead projection of expected future output and inflation in each period assuming subjects form their expectations according to an Adaptive(1) heuristic.

Subjects in the ADProj treatment are informed that the central bank projections are based on a combination of current and expected future shocks as well as the previous period's outcomes. The purpose of this treatment is to address discussions in policy circles as to whether boundedly rational agents should be implemented into central banks' forecasting models.[12]

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

[12] In this treatment, the central bank assumes that subjects maintain a static reaction to the state of the economy, ie. subjects do not update the parameters of their forecasting models as new information arrives. It follows that the central bank also does not update the parameters in its projection model. 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.

identically rational expectations about the future is widely employed in mainstream macroeconomic models.[13] If subjects form 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. Extensive survey and experimental evidence suggest that individuals do not form expectations rationally but instead weigh historical information significantly in their forecasts (Pfajfar And Santoro, 2010; Pfajfar and Žakelj 2014; Coibion and Gorodnichenko, 2015; Malmandier and Nagel, 2016). Thus, we test the alternative hypothesis that subjects place significant weight on historical outcomes when forming their forecasts.

**Alternative Hypothesis I:** Subjects' expectations deviate from the REE solution and place significant weight on historical outcomes.

Commonly observed projections provide an important focal point for subjects to coordinate their forecasts on. The ability of focal information and strategies to coordinate behavior has been demonstrated in pure coordination games (Mehta et al., 1994a,b).[14] If a subject believes that the majority of participants will utilize the central bank's rational prediction in their forecast, her best response would be to utilize the projection as her forecast. Therefore, we predict that the IRProj and DualProj communications will have no effect on rational subjects' expectations.

**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.

While both nominal interest rate and dual projections based on the REE solution contain arguably 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.[15] The ease in effectively using the information in each projection is, however, not

[13] Both the New Classical approach beginning with Lucas (1972) and New Keynesian macroeconomics (Fischer, 1977) assume that agents have rational expectations in that they use available information to form expectations about the future.

[14] Forecasting heuristics can be manipulated through focal information. Kryvtsov and Petersen (2013) 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.

[15] See Simon (1959) for a discussion on bounded rationality.

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). We form an alternative hypothesis that rational dual projections are relatively more effective at reducing forecast errors than nominal interest rate projections.

**Alternative Hypothesis IIa:** Rational dual projections are significantly more effective at influencing forecasting behaviour and reducing forecast errors than rational interest rate 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.[16] 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. More precisely, they establish two propositions.

**Proposition 1 (Ferrero and Secchi, 2010).** Let $\sigma\phi_x + \kappa\sigma\phi_\pi + 1 \neq 0$. Given (i) the data-generating process, where (ii) at time $t$ the central bank publishes the time $t+1$ interest rate projection consistent with the REE and (iii) recursive learning private agents assign weight $0 \leq (1-\lambda_1) \leq 1$ to these projections[17], revealing the interest rate path makes the condition for stability under learning more stringent than under no announcement. In particular, the necessary and sufficient conditions for E-stability of the REE is:

$$\phi_\pi > \frac{2}{1+\lambda_1} - \frac{1-\beta}{\kappa}\phi_x.$$

The greater the weight assigned to the interest rate projection, the more the central bank must respond to concurrent inflation and output in order to maintain E-stability of the REE. Figure 2 compares the regions of E-stability in the $(\gamma_x, \gamma_\pi)$ space under communication and no commu-

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

[17] 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.

nication of the central bank's REE interest rate projection assuming full internalization of the projection, $1 - \lambda_1 = 1$. 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.

**Alternative Hypothesis IIb:** Rational nominal interest rate projections increase the likelihood of instability.

**Proposition 2 (Ferrero and Secchi, 2010).** Let $\sigma\phi_x + \kappa\sigma\phi_\pi + 1 \neq 0$. Given (i) the data-generating process, where (ii) at time $t$ the central bank publishes the time $t+1$ output and inflation projections consistent with the REE and (iii) 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. In particular, the necessary and sufficient conditions for E-stability of the REE is:

$$\phi_\pi > \frac{2\lambda_2(\beta\lambda_2 + 1)\kappa\sigma - (\beta^2\lambda_2 - 1)(\lambda_2 - 1)}{(\beta\lambda_2 + 1)(1 + \lambda_2)\kappa\sigma} - \frac{(1 - \beta^2\lambda_2)}{(\beta\lambda_2 + 1)\kappa}\phi_x.$$

The greater the weight assigned to the dual projections, the less the central bank must respond to concurrent inflation and output in order to maintain E-stability of the REE. Figure 3 compares the regions of E-stability in the $(\gamma_x, \gamma_\pi)$ space under communication and no communication of the central bank's REE output and inflation projections assuming minimal internalization of the projection, $1 - \lambda_1 = 0.1$. Given the parameterization of our laboratory experiments, the REE is E-stable under recursive least squares learning irrespective of the number of subjects that employ the central bank's macroeconomic projections.

**Alternative Hypothesis IIc:** Rational dual projections decrease the likelihood of instability.

The success of communication at managing expectations depends on the central bank's credibility in achieving its projections.[18] 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 forms its forecasts assuming that the median subject forms expectations according to either the 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

[18] Preston(2005); Eusepi and Preston(2016); Kocherlakota (2011); De Grauwe (2011); Gali (2009); Park (2016).

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.

*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.

Each session began with an instruction phase where we explained the data-generating process both qualitatively and quantitatively. 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.[19]

We used an online interface programmed in Javascript to implement the experiment. Figure 4 presents a representative screen-shot of the interface in the IRProj treatment with interest rate projections. 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 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 shocks. The second panel displayed subject's past forecasts of inflation and the realized level of inflation. The final panel showed the subject's 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

[19] 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.

them across all treatments.[20] The shocks, 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 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 average payment, including a CDN \$7 show-up fee was CDN \$19 and ranged from CDN \$17 to \$25.

## 4. Experimental Results

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

*Individual-level analysis*

How do subjects form expectations about output and inflation? We can describe a general specification for ex ante one-period ahead forecast errors associated with forecasts $E_t^* x_{t+1}$ and $E_t^* \pi_{t+1}$ as:

$$E_t \left( E_t^* \begin{bmatrix} \pi_{t+1} \\ x_{t+1} \end{bmatrix} - \begin{bmatrix} \pi_{t+1} \\ x_{t+1} \end{bmatrix} \right) = \sigma^{-1} \rho_r \sum_{s=0}^{\infty} \begin{bmatrix} \kappa L_{s\pi} \\ L_{sx} \end{bmatrix} r_{t-s}^n \ , \tag{9}$$

where $E_t$ is the conditional mean on the history of the states through period $t$, and $L_{s\pi}$, $L_{sx}$ represent the sensitivity of ex ante forecast errors of inflation and the output gap with respect to shock realizations in periods $t, t-1, ....$ Assuming rational expectations, $L_{s\pi} = L_{sx} = 0$ for all $t$ since the ex ante forecast errors are always zero. However, under the assumption of non–rational expectations, ex ante forecast errors correlate with both current and lagged innovations.

Experimental evidence from Kryvtsov and Petersen (2013) suggests that aggregate expectations are well described by a range of *Adaptive(l) expectations* models where ex ante forecast errors display the following pattern:

$$E_t \left( E_t^* \begin{bmatrix} \pi_{t+1} \\ x_{t+1} \end{bmatrix} - \begin{bmatrix} \pi_{t+1} \\ x_{t+1} \end{bmatrix} \right) = -\omega \left( \begin{bmatrix} \pi_{t-l} \\ x_{t-l} \end{bmatrix} - E_t \begin{bmatrix} \pi_{t+1} \\ x_{t+1} \end{bmatrix} \right) \ . \tag{10}$$

According to this general adaptive framework, agents in period $t$ employ a period $t-l$ realization of inflation (output gap) to form one-period ahead expectations of inflation (output gap).[21] The ex

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

[21] Note that under Adaptive(l) expectations, agents' forecast errors persist forever. Kryvtsov and Petersen (2013) assume that $\omega = 0.5$ and find that an Adaptive(1) forecasting heuristic well describes the behaviour of subjects in their identically calibrated environment.

ante forecast errors are negative at the time of the shock and are positive thereafter since inflation (output) forecast errors are expected to persist while the forecasted variable slowly returns back to its steady state level.

We construct a series of mixed-effects regression specifications that consider the effects of projections on subjects' ex ante one-period ahead forecast errors. We estimate ex ante forecast errors as functions of the history of innovations to the $r_t^n$ shocks, $\epsilon_t$, where we interact these innovations with treatment–specific dummies:

$$\begin{aligned} E_{i,t}z_{t+1} = \alpha + \beta_1\epsilon_{rt} + \beta_2\epsilon_{rt} \times IRProj + \beta_3\epsilon_{rt} \times DualProj + \beta_4\epsilon_{rt} \times ADProj + ... \\ + \beta_Z\epsilon_{rt-T} \times ADProj + \phi Experienced + \gamma_1 IRProj + \gamma_2 DualProj + \gamma_3 ADProj \\ + \mu_i + \eta_{i,t} \ , \end{aligned} \tag{11}$$

where $E_{i,t}z_{t+1}$ refers to subject $i$'s output or inflation ex ante forecast errors, $Experienced$ is a dummy variable that takes the value of one for repetition 2 data and zero otherwise, $\mu_i$ is a subject-specific effect, $\eta_{it}$ is an idiosyncratic error term, and $T$=6. $IRProj$, $DualProj$, and $ADProj$ are treatment-specific dummy variables.

Under the null hypothesis of rational expectations, ex ante forecast errors should be uncorrelated with shock innovations at any lag, ie. $\hat{\beta}_k = 0$ for all $k$ and $\hat{\alpha} = 0$. In contrast, under Adaptive (l) expectations, ex ante forecast errors would place significant weight on lagged shock innovations, $\hat{\beta}_k \neq 0$ for some $k$. If CB projections are effective at encouraging subjects to form more rational expectations, then we would expect to find that the weight subjects place on current and lagged shock innovations are significantly smaller in absolute terms than in the NoComm treatment. The results of these specifications are presented in Table 2.

Estimated coefficients are plotted for output and inflation forecasts and forecast errors in Figure 5 and Figure 6 respectively. Panels A and B present the theoretical reaction of forecast errors and forecasts to a one-standard deviation (113 bps) shock to the natural rate of interest under three different forecasting models: Rational, Adaptive(1), and a Mixed Model of expectations.[22] Panels C and D plot the estimated responses of the median subjects' forecast errors and forecasts to current and six lags of innovations from repetition 2 data. A two standard deviation confidence interval is plotted around the data.

First, we reject Hypothesis I that subjects form rational expectations in favour of Alternative

[22] The Mixed Model is intended to describe the expectation dynamics observed in the ADProj treatment. Expectations in the Mixed Model depend on a combination of one- and two-period ahead CB projections from the ADProj treatment and the ex-ante rational forecasting solution. The relative weightings of these different factors is selected to match behavior in the ADProj treatment. In particular, the output gap (inflation) expectations are modelled as involving 49% (39%) responding to the CB's one-period ahead projection, 8% (21%) reacting to the CB's two-period ahead projection, and 43% (40%) of subjects over-, under- or nearly perfectly reacting to the ex-ante rational solution.

Hypothesis I. In Table 2 we see that in all treatments subjects' forecast errors assign a significant weight either to current or lagged innovations or the constant. We conclude that subjects' forecast errors are not only described by noise but rely significantly on historical information, indicative of adaptive expectations. This inability to form rational expectations occurs in spite of subjects possessing full information about the economy's data-generating process and the exogenous disturbances influencing the economy.

In the NoComm treatment, output forecasts significantly under-react to current innovations and significantly over-react to one-, two-, three-, and four-period lagged innovations. By contrast, inflation forecasts are significantly under-reactive to current, one- and two-period lagged innovations. Increasing the variability of the shock sequence has a positive but inconsistent effect on forecast errors. We suspect that the under-reaction of inflation forecasts to aggregate demand (i.e. output gap) shocks is a consequence of the increased complexity associated with forecasting inflation. In order to fully account for the effects of shocks on inflation, subjects need to consider the direct effect of the shock on output gap, followed by the effect of the output gap on inflation. In addition to this, subjects need to take into account how aggregate expectations of output and inflation will evolve in response to the shock.

Figure 5D and Figure 6D depict that the path of aggregate output and inflation forecasts track the timing of the Adaptive(1) forecasting model rather well. Output forecasts rise on impact of the innovation and for one additional period before reverting back toward the steady state. Inflation forecasts rise on impact and for two additional periods before reverting back. Compared to the Adaptive(1) model, the reaction of inflation forecasts to innovations is highly muted.

**Observation I: Expectations formed in the NoComm treatment under-react to current innovations and rely significantly on lagged innovations characteristic of adaptive expectations.**

We now turn to forecast errors under different forms of CB projections. Figure 5D and Figure 6D highlight again that forecasts in the IRProj treatment also follow the timing of the Adaptive(1) model. As in the NoComm treatment, subjects significantly under-react to current innovations and over-react to lagged innovations when forming their output forecasts. Table 2 shows that compared to their NoComm counterparts, output forecasts in the IRProj treatment are significantly more responsive to current innovations. The degree of under-reaction to current innovations falls by nearly one-half. IRProj subjects are also significantly less responsive to two-, three-, and four-period lagged innovations than subjects in the NoComm treatments.

Interest rate projections also significantly alter how subjects forecast inflation. Inflation forecasts in the IRProj treatment are significantly less under-reactive to current, one- and two-period lagged innovations.

**Observation II: Nominal interest rate projections increase subjects' reactions to cur-**

**rent innovations when forecasting both output and inflation, and reduce subjects' under-reaction to lagged innovations when forecasting inflation. This nudges expectations in the direction of the REE.**

Expectations in the DualProj treatment track the central bank's forecasts very well, both in terms of timing and magnitude of reactions. This, in turn, nudges expectations towards the REE. Subjects in the DualProj treatment are significantly less under-reactive to current innovations and less over-reactive to lagged innovations when forming their output forecasts. Specifically, output gap forecast errors are significantly less responsive to two- and three-period lagged innovations in both treatments. Inflation forecast errors become significantly more responsive to current, one, two-, and three-period lagged innovations. To summarize, we find ample support from the IRProj and DualProj treatments to reject Hypothesis II.

Under an adaptive dual projection, we observe that aggregate expectations do not blindly follow the CB's projections. Instead, we see that expectations in the ADProj treatment involve a combination of forecasting heuristics: employing the one-period and two-period ahead CB projections, as well as the ex-ante REE solution. Importantly, to generate the overshooting of expectations, it is crucial to have a sizeable proportion of the model overreact to current fundamentals. From Figure 5D and Figure 6D, we see that the Mixed Model model captures the magnitude and timing of aggregate output and inflation expectations rather well.

As in the DualProj treatment, ADProj expectations are highly responsive to the CB's projections, leading to significantly less under-reacting to current innovations and over-reacting to lagged innovations when forming output forecasts. If anything, ADProj subjects significantly over-react to current innovations. We also observe their inflation forecasts to be significantly more backward looking. ADProj subjects place significantly greater weight on one- to four lags of innovations.

**Observation III: DualProj and ADProj projections increase subjects' reactions to current innovations and reduces their reaction to lagged innovations when forming output forecasts. Inflation forecasts become significantly more reactive to both current and lagged innovations, especially under adaptive dual projections.**

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 Figure 7. 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 forecast errors.

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. To capture the possibility of variability of shocks influencing subjects' absolute forecast errors, our second set interacts the treatment dummies with the standard deviation of the shock sequence. The results, by repetition, are presented in Table 3.

In our baseline specification (1), average absolute output forecast errors are significantly reduced by all types of projections. Interest rate and rational dual projections reduce output gap forecast errors by between 8-10%, while adaptive dual projections reduce forecast errors by over 20%. Controlling for the variability of shocks in specification (2) provides additional insight. The efficacy of the different projections depends significantly on the variability of the shocks. As the shocks become more volatile, rational and adaptive dual projections significantly reduce forecast errors compared to the NoComm environment. Interest rate projections do not provide that consistent benefit.

In specification (3) we see that compared to the NoComm treatment, inflation forecast errors are on average 6% higher in the IRProj treatment and a whopping 74% higher in the ADProj treatment. The DualProj treatment has a small negative but statistically insignificant effect on inflation forecast errors. Specification (4) shows that increasing the variability of shocks leads to a significant increase in inflation forecast errors. Higher inflation forecast errors in the IRProj treatment are a consequence of the more variable shock sequences. By contrast, rational dual projections reduce the extent by which inflation forecast errors increase as the variability of shocks increase.

**Observation IV: Average output forecast errors are significantly lower in all three projection treatments. Average inflation forecast errors are significantly higher in the IRProj and ADProj treatments. Absolute forecast errors increase with the variability of shocks.**

Central bank projections provide a common focal piece of information for subjects to coordinate their forecasts on. 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. In our first set, we regress the log of the standard deviation of forecasts on treatment-specific dummy variables and a dummy for whether subjects are experienced. In our second set, we additionally control for the standard deviation of shocks. Our results are presented in columns (5)-(8) of Table 3.

All types of projections significantly reduce disagreement about the output gap. Compared to the NoComm treatment, disagreement is 32% lower in the IRProj, 41% lower in the DualProj, and 59% lower in the ADProj treatment. The degree of disagreement is highly sensitive to the variability of shocks. Disagreement increases significantly for more volatile shock sequences. However, as the

standard deviation of the shock sequence increases, subjects in all three projection treatments exhibit significantly less disagreement than their NoComm counterparts.

Inflation disagreement, in contrast, is significantly increased with all three types of projections. Average disagreement about inflation increases by 15% in DualProj, 22% in the ADProj, and 34% in the IRProj treatment. We speculate that disagreement is lower in the NoComm treatment because of subjects' heavy reliance on the previous period's inflation to form their forecasts. The variability of shocks does not consistently influence disagreement in most treatments. However, in the IRProj treatment, we observe that disagreement about inflation increases significantly as the sequence of shocks becomes more volatile.

Taken together, our findings provide substantial support for Alternative Hypothesis IIa that rational dual projections are more effective at influencing forecasting behavior and forecast errors than rational interest rate projections. Forecasts are better coordinated and errors are generally lower in the DualProj treatment.

**Observation IV: Disagreement about future output decreases with any type of projection. Disagreement about future inflation increases with projections. Interest rate projections create more disagreement about inflation as the economy becomes more unpredictable.**

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 CBs. 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.[23] Figure 9 plots the session mean percentage of subjects' forecast. Utilization is the lowest in the NoComm treatment with a mean of 0.06 (s.d. 0.03) for output forecasts and 0.11 (s.d. 0.06) for inflation forecasts. Nominal interest rate projections have little effect on utilization: utilization marginally increases to 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

[23] 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.

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).

**Observation 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.**

We employ a series of random 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. Treatment-specific results are presented in the first six columns of Table 4.

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. Having used the CB's forecast in the previous period does not significantly alter subjects' reaction to the CB's forecast errors. Likewise, in the ADProj treatment, larger CB forecast errors about inflation significantly reduce subjects' utilization of its inflation projections. By contrast, CB credibility in the DualProj treatment is impervious to its past forecast errors. The errors do not play a quantitatively large or statistically significant role in CB credibility.

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

We also estimate the effect of the CB's past forecast errors on the disagreement in subjects' forecasts. The results are presented in the final six columns of Table 4. Larger CB forecast errors

lead to increased disagreement in all three projection treatments. Larger CB forecast errors increase subjects' disagreement about both output and inflation in the IRProj treatment. DualProj subjects disagree significantly more about output when output projections are more inaccurate but are insensitive to the CB's inflation forecast errors. The opposite is true in the ADProj treatment. Overall, it appears that expectations become more heterogenous when the CB makes larger forecast errors.

*Aggregate analysis*

We begin by presenting representative estimated impulse response functions from our different treatments. Panels A and B of Figure 10 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.

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 Table 5.[24] The results are also presented visually in Figure 11 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 repetition 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. Thus, the evidence for Alternative Hypothesis IIb is limited.

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). This finding is consistent with Alternative Hypothesis IIc that 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.

The central bank's loss function can be simply written as $L_t^{CB} = -\frac{1}{2}\left[\pi_t^2 + \lambda x_t^2\right]$ with $\lambda \geq 0$ the importance the central bank places on minimizing the output gap. The type of projection a central bank would prefer to communicate depends on $\lambda$. For small $\lambda$, inflation stability is a greater priority and it would be in the central bank's interest to communicate output and inflation projections based on the REE solution. If $\lambda$ is high, the central bank would instead prefer to communicate projections based on an Adaptive(1) model.

**Observation VII: With experience, output and inflation variability in the baseline NoComm treatment are significantly greater than predicted by the REE solution.**

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

**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.**

## 5. Discussion

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*

Ferrero and Secchi (2010) consider the impact of the publication of CB projections on the dynamic properties of an economy where private agents have incomplete information and form expectations using recursive learning algorithms (Marcet and Sargent, 1989; and Evans and Honkapohja, 2001). As in our experiment, they assume that the short-term nominal interest rate responds linearly to deviations of inflation and output from their target level, and that the CB assumes agents form expectations according to the REE solution. Ferrero and Secchi find that nominal interest rate projections shrink the set of interest rate rules associated with stable equilibria under learning and slows down learning. This is a consequence of the CB failing to take into account systematic errors private agents form as they are learning, leading to a weak positive feedback of monetary policy, and a system that is more vulnerable to self-fulfilling expectations. By contrast, publication of inflation and output projections reduces the inflationary bias in agents' expectations, expanding the set of policy rules that would allow for stability under learning.

Given our experimental parameterization, the NoComm environment is predicted to be stable under recursive learning. Instability in the IRProj treatment would have occurred had more than 70% of our subjects paid attention to the CB's interest rate projection, while instability was not predicted to occur in our DualProj treatment. 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 less than necessary to obtain 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 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 risk 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.[25]

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 attention 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

[25] 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.

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 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.[26] 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 could have improved its forecasting performance by adopting an alternative forecasting heuristic, and vice versa. Figure 12 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 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

[26] 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.

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. While the aggregate expectations were nudged in the direction of the REE, the nudge was not complete.

## 6. Conclusion

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. We speculate that the inconsistent ability of interest rate projections to influence expectations comes from the additional cognitive challenge of how to employ such projections into one's own forecast. Subjects must consider how nominal interest rates directly influence the output gap and, indirectly, inflation, and this is considerably more difficult.

Subjects in our experiment are only tasked to forecast 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 argue 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 might 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.

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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# 7. 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 | $x_{t+s}$, $\pi_{t+s}$ for $s = 1, .., 5$ | Rational |
| ADProj | 6 | 2 | 30 | 7 | $x_{t+s}$, $\pi_{t+s}$ 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: Effects of central bank projections on forecast errors - treatment effects [I]

| | Output Gap Forecast Errors | | Inflation Forecast Errors | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $\epsilon$ | -0.360*** | -0.357*** | -0.107*** | -0.107*** |
| | (0.09) | (0.09) | (0.01) | (0.01) |
| $\epsilon \times IRProj$ | 0.178** | 0.175* | 0.048*** | 0.049*** |
| | (0.09) | (0.09) | (0.02) | (0.02) |
| $\epsilon \times DualProj$ | 0.331*** | 0.327*** | 0.132*** | 0.131*** |
| | (0.09) | (0.09) | (0.02) | (0.02) |
| $\epsilon \times ADProj$ | 0.512*** | 0.509*** | 0.063*** | 0.063*** |
| | (0.09) | (0.09) | (0.02) | (0.02) |
| $\epsilon_{t-1}$ | 0.210** | 0.215** | -0.084*** | -0.084*** |
| | (0.09) | (0.09) | (0.01) | (0.01) |
| $\epsilon_{t-1} \times IRProj$ | -0.066 | -0.070 | 0.053*** | 0.054*** |
| | (0.10) | (0.09) | (0.02) | (0.02) |
| $\epsilon_{t-1} \times DualProj$ | -0.161* | -0.166* | 0.081*** | 0.079*** |
| | (0.10) | (0.10) | (0.02) | (0.02) |
| $\epsilon_{t-1} \times ADProj$ | -0.048 | -0.052 | 0.164*** | 0.164*** |
| | (0.09) | (0.09) | (0.02) | (0.02) |
| $\epsilon_{t-2}$ | 0.504*** | 0.507*** | -0.031*** | -0.031*** |
| | (0.12) | (0.12) | (0.01) | (0.01) |
| $\epsilon_{t-2} \times IRProj$ | -0.249** | -0.252** | 0.045*** | 0.046*** |
| | (0.13) | (0.12) | (0.02) | (0.02) |
| $\epsilon_{t-2} \times DualProj$ | -0.382*** | -0.387*** | 0.059*** | 0.057*** |
| | (0.13) | (0.13) | (0.01) | (0.01) |
| $\epsilon_{t-2} \times ADProj$ | -0.377*** | -0.381*** | 0.157*** | 0.157*** |
| | (0.12) | (0.12) | (0.01) | (0.01) |
| $\epsilon_{t-3}$ | 0.595*** | 0.599*** | -0.003 | -0.003 |
| | (0.15) | (0.15) | (0.01) | (0.01) |
| $\epsilon_{t-3} \times IRProj$ | -0.427*** | -0.430*** | 0.008 | 0.010 |
| | (0.15) | (0.15) | (0.01) | (0.01) |
| $\epsilon_{t-3} \times DualProj$ | -0.515*** | -0.520*** | 0.014 | 0.012 |
| | (0.15) | (0.15) | (0.01) | (0.01) |
| $\epsilon_{t-3} \times ADProj$ | -0.532*** | -0.536*** | 0.089*** | 0.090*** |
| | (0.15) | (0.15) | (0.01) | (0.01) |
| $\epsilon_{t-4}$ | 0.424** | 0.431*** | 0.005 | 0.005 |
| | (0.17) | (0.17) | (0.01) | (0.01) |
| $\epsilon_{t-4} \times IRProj$ | -0.287* | -0.293* | 0.012 | 0.014 |
| | (0.17) | (0.17) | (0.01) | (0.01) |
| $\epsilon_{t-4} \times DualProj$ | -0.380** | -0.388** | 0.003 | 0.000 |
| | (0.17) | (0.17) | (0.02) | (0.01) |
| $\epsilon_{t-4} \times ADProj$ | -0.400** | -0.406** | 0.032** | 0.032** |
| | (0.17) | (0.17) | (0.01) | (0.01) |
| $\epsilon_{t-5}$ | 0.252* | 0.254* | -0.000 | -0.000 |
| | (0.14) | (0.14) | (0.01) | (0.01) |
| $\epsilon_{t-5} \times IRProj$ | -0.184 | -0.186 | 0.001 | 0.002 |
| | (0.14) | (0.14) | (0.01) | (0.01) |
| $\epsilon_{t-5} \times DualProj$ | -0.272* | -0.275** | -0.005 | -0.007 |
| | (0.14) | (0.14) | (0.01) | (0.01) |
| $\epsilon_{t-5} \times ADProj$ | -0.266* | -0.268* | 0.011 | 0.011 |
| | (0.14) | (0.14) | (0.01) | (0.01) |
| $\epsilon_{t-6}$ | 0.265** | 0.266** | 0.023*** | 0.023*** |
| | (0.11) | (0.11) | (0.01) | (0.01) |
| $\epsilon_{t-6} \times IRProj$ | -0.119 | -0.120 | 0.017 | 0.017 |
| | (0.12) | (0.12) | (0.02) | (0.02) |
| $\epsilon_{t-6} \times DualProj$ | -0.177 | -0.177 | -0.015 | -0.015 |
| | (0.12) | (0.12) | (0.01) | (0.01) |
| $\epsilon_{t-6} \times ADProj$ | -0.160 | -0.161 | 0.043*** | 0.043*** |
| | (0.12) | (0.12) | (0.01) | (0.01) |
| Experienced | -19.325*** | -18.871*** | -7.189*** | -7.243*** |
| | (7.16) | (6.83) | (1.77) | (1.83) |
| $IRProj$ | -57.245*** | 87.243 | -0.171 | -43.041** |
| | (14.04) | (172.92) | (1.68) | (21.62) |
| $DualProj$ | -44.405*** | 148.292 | 9.025*** | 86.087** |
| | (14.46) | (177.00) | (2.54) | (41.14) |
| $ADProj$ | -54.837*** | 99.083 | 4.967*** | -2.754 |
| | (13.98) | (173.90) | (1.88) | (19.71) |
| $\alpha$ | 79.113*** | -86.736 | 6.311*** | 6.113 |
| | (15.10) | (165.64) | (1.25) | (9.23) |
| S.D. $r_t^n$ | | 1.195 | | 0.002 |
| | | (1.27) | | (0.07) |
| S.D. $r_t^n \times IRProj$ | | -1.043 | | 0.310* |
| | | (1.30) | | (0.16) |
| S.D. $r_t^n \times DualProj$ | | -1.391 | | -0.556* |
| | | (1.32) | | (0.29) |
| S.D. $r_t^n \times ADProj$ | | -1.111 | | 0.056 |
| | | (1.30) | | (0.14) |
| $N$ | 7563 | 7563 | 7563 | 7563 |
| $\chi^2$ | 534.6 | 576.1 | 591.1 | 593.4 |

(I) This table presents results from a series of mixed effects panel regressions. The dependent variables are individual-level output and inflation forecast errors from all relevant periods of play, measured as $E_{i,t}x_{t+1} - x_{t+1}$ and $E_{i,t}\pi_{t+1} - \pi_{t+1}$ . $\epsilon_t$ denotes the random innovation that occurs in period $t$. IRProj, DualProj, and ADProj are treatment-specific dummies indicating the interest rate, rational dual projection, and adaptive dual projection treatments. $\alpha$ denotes the estimated constant. Robust standard errors are employed. $^*p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

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 | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| IRProj | -0.084** | 0.355 | 0.060** | -0.544* | -0.394*** | 1.976*** | 0.295*** | -1.517** |
| | (0.03) | (0.37) | (0.03) | (0.33) | (0.07) | (0.74) | (0.05) | (0.62) |
| DualProj | -0.106*** | 1.316*** | -0.032 | 0.715** | -0.531*** | 3.098*** | 0.138** | 0.616 |
| | (0.03) | (0.37) | (0.03) | (0.35) | (0.08) | (0.85) | (0.06) | (0.74) |
| ADProj | -0.226*** | 1.092*** | 0.551*** | 0.073 | -0.899*** | 3.397*** | 0.199*** | -0.443 |
| | (0.03) | (0.37) | (0.03) | (0.34) | (0.07) | (0.77) | (0.05) | (0.58) |
| Experienced | 0.005 | 0.024 | 0.042* | 0.054** | -0.021 | -0.001 | -0.151*** | -0.149*** |
| | (0.02) | (0.02) | (0.02) | (0.02) | (0.04) | (0.04) | (0.04) | (0.04) |
| SD $r_t^n$ | | 0.017*** | | 0.006*** | | 0.030*** | | -0.003 |
| | | (0.00) | | (0.00) | | (0.00) | | (0.00) |
| SD $r_t^n \times IRProj$ | | -0.003 | | 0.004* | | -0.017*** | | 0.013*** |
| | | (0.00) | | (0.00) | | (0.01) | | (0.00) |
| SD $r_t^n \times DualProj$ | | -0.010*** | | -0.005** | | -0.026*** | | -0.003 |
| | | (0.00) | | (0.00) | | (0.01) | | (0.01) |
| SD $r_t^n \times ADProj$ | | -0.010*** | | 0.003 | | -0.031*** | | 0.005 |
| | | (0.00) | | (0.00) | | (0.01) | | (0.00) |
| $\alpha$ | 4.254*** | 1.912*** | 3.066*** | 2.174*** | 4.317*** | 0.097 | 3.050*** | 3.402*** |
| | (0.03) | (0.27) | (0.02) | (0.23) | (0.07) | (0.66) | (0.04) | (0.39) |
| $N$ | 9628 | 9628 | 9581 | 9581 | 1438 | 1438 | 1438 | 1438 |
| $\chi^2$ | 49.48 | 209.9 | 468.6 | 571.3 | 213.9 | 273.5 | 49.79 | 58.87 |

(I) This table presents results from a series of mixed effects panel regressions The dependent variables are absolute forecast errors and 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. SD $r_t^n$ is the standard deviation of the shock sequence for a given repetition. *Experienced* is a dummy variable that takes the value of 1 for repetition 2 data. $\alpha$ denotes the estimated constant. Robust standard errors are employed. $^*p < 0.10$, $^{**}p < 0.05$, 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 | | 0.004* | | 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) | |
| $UtilizedCBxForecast_{t-1}$ | 0.093 | | 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 $r_t^n$ | -0.011*** | -0.004 | 0.001 | 0.003 | -0.003 | -0.002 | 0.013*** | 0.010*** | 0.003 | -0.007 | -0.001 | 0.001 |
| | (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 | 0.147* | 0.032 | 0.023 | 0.068 | 0.100 | -0.025 | -0.079 | -0.355*** | -0.115 | -0.179* | -0.122* | -0.169** |
| | (0.08) | (0.09) | (0.17) | (0.18) | (0.16) | (0.15) | (0.05) | (0.08) | (0.09) | (0.10) | (0.07) | (0.07) |
| $\lvert FE^{cb}\pi_{t-1}\rvert$ | | -0.012** | | -0.004 | | -0.008*** | | 0.005* | | 0.007 | | 0.006** |
| | | (0.00) | | (0.00) | | (0.00) | | (0.00) | | (0.01) | | (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) |
| $UtilizedCB\pi Forecast_{t-1}$ | | 0.274*** | | 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) | | | | | | |
| $\lvert FE\pi_{i,t-1}\rvert \times UtilizedCB\pi Forecast_{t-2}$ | | 0.002 | | 0.006** | | 0.001 | | | | | | |
| | | (0.00) | | (0.00) | | (0.00) | | | | | | |
| $\alpha$ | -0.004 | -0.312 | -0.905 | -0.723 | -0.063 | 0.152 | 2.023*** | 1.889*** | 3.161*** | 3.950*** | 3.522*** | 2.936*** |
| | (0.46) | (0.50) | (0.98) | (0.98) | (0.90) | (0.86) | (0.31) | (0.51) | (0.57) | (0.71) | (0.38) | (0.43) |
| % 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 |
| $\chi^2$ | 23.37 | 60.23 | 42.07 | 74.49 | 27.66 | 64.45 | 75.71 | 56.70 | 11.48 | 5.204 | 26.82 | 20.96 |

(I) This table presents results from a series of random effects probit regressions. $^*p < 0.10$, $^{**}p < 0.05$, 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. $\lvert FE^{cb}x_{t-1}\rvert$ and $\lvert FE^{cb}\pi_{t-1}\rvert$ denote the absolute forecast errors the central bank made in period $t-2$ about period $t-1$ output and inflation, respectively. $\lvert FEx_{i,t-1}\rvert$ and $\lvert FE\pi_{i,t-1}\rvert$ 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: Simulated impulse responses to a 1 s.d. innovation to $r_t^n$ under alternative forecasting assumptions

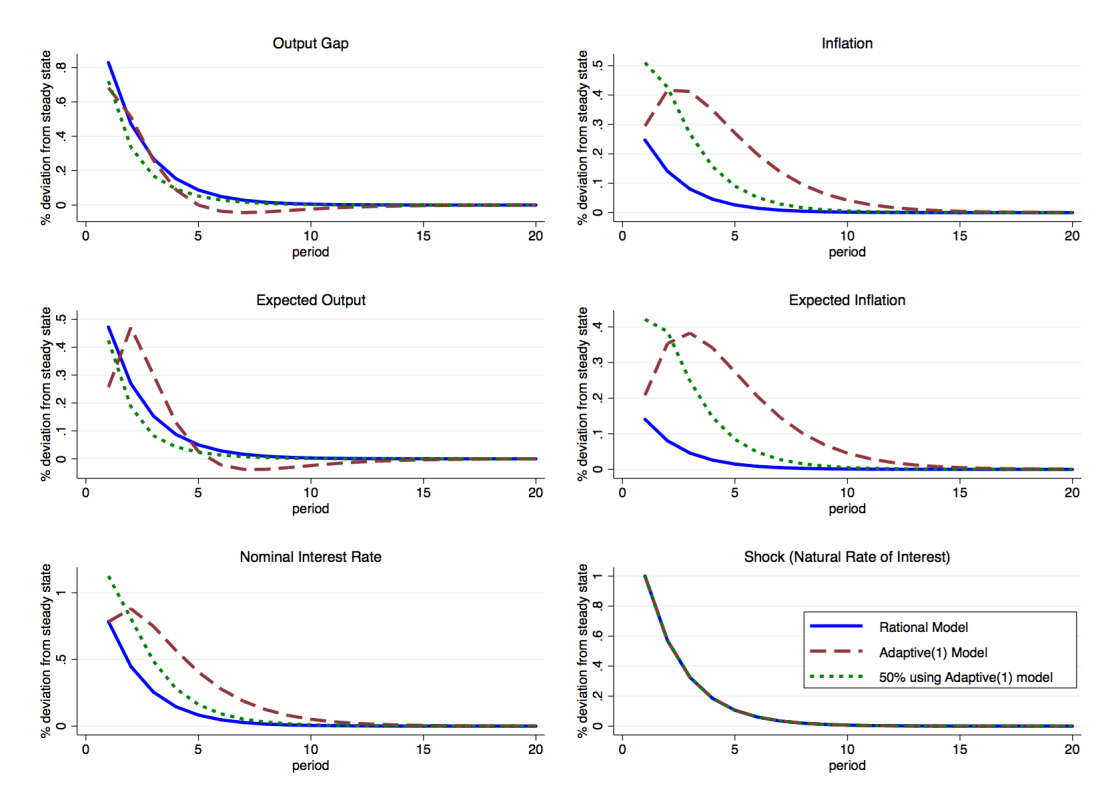


Figure 2: E-stability under recursive learning and no-announcement $(1 - \lambda_1) = 0$ and under a fully-internalized announcement of the interest rate path, $(1 - \lambda_1) = 1$.

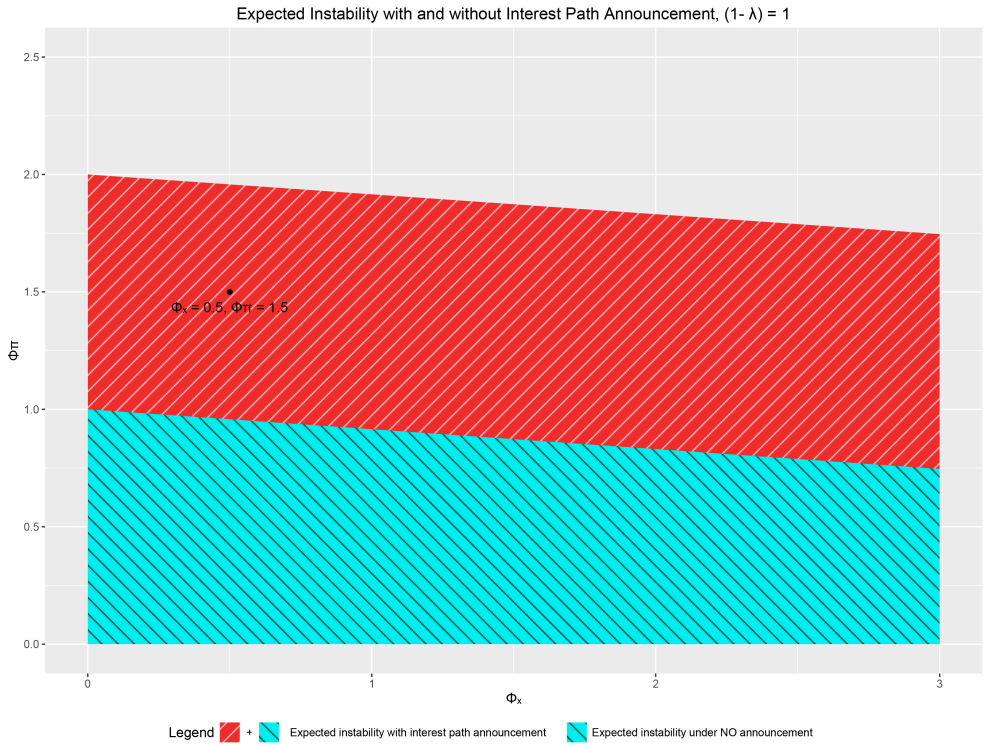



Figure 3: E-stability under recursive learning and no-announcement $(1-\lambda_2) = 0$ and under a minimally-internalized announcement of the interest rate path, $(1 - \lambda_2) = 0.1$.

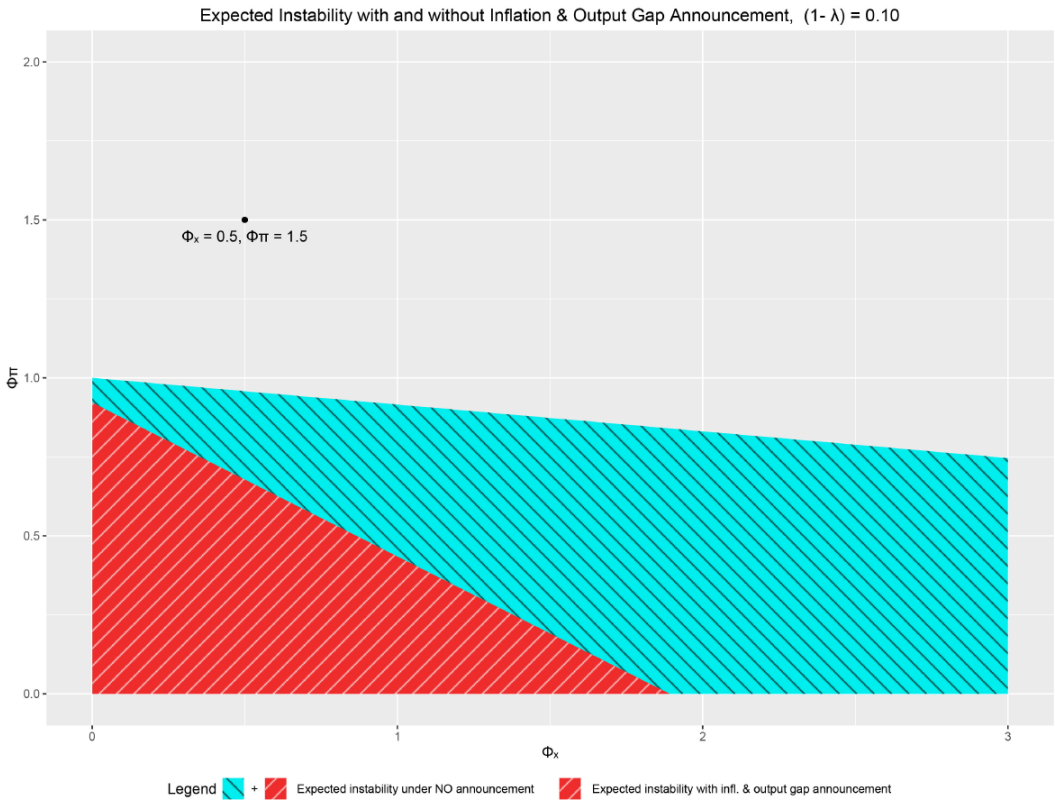


Figure 4: Screenshot from IRProj Treatment

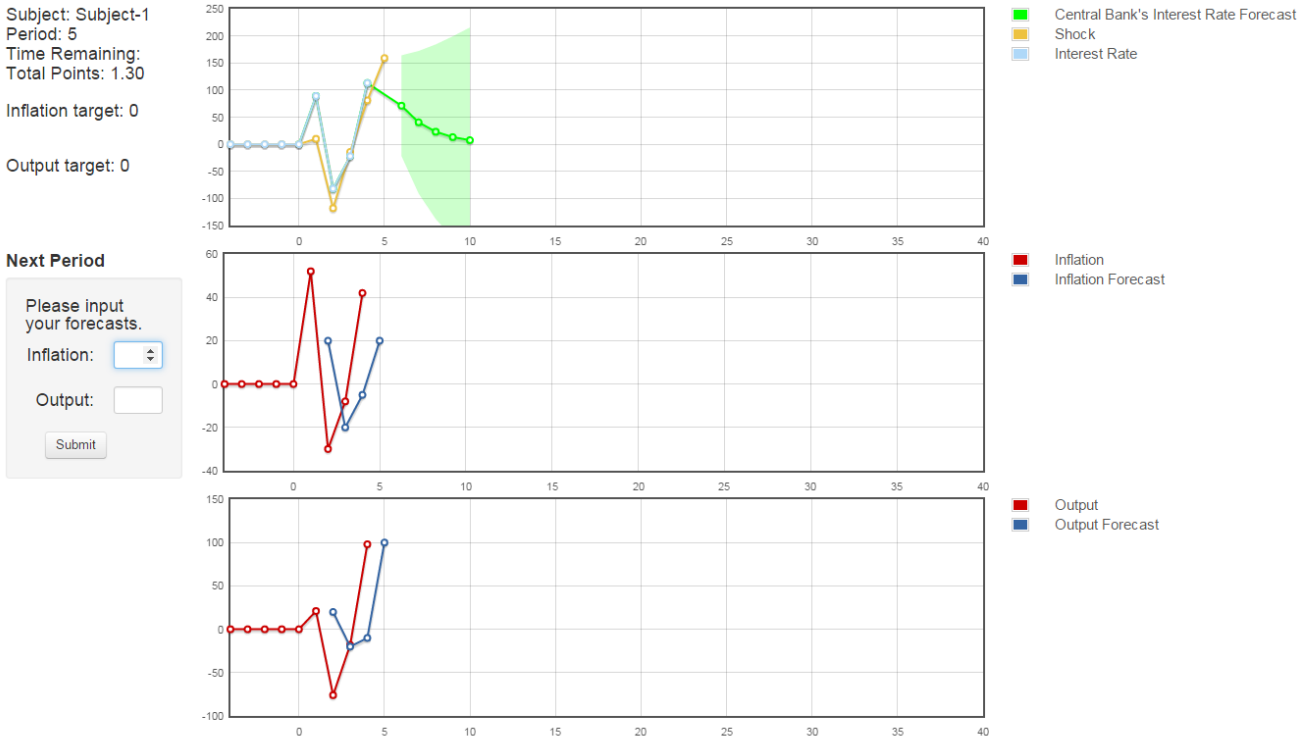
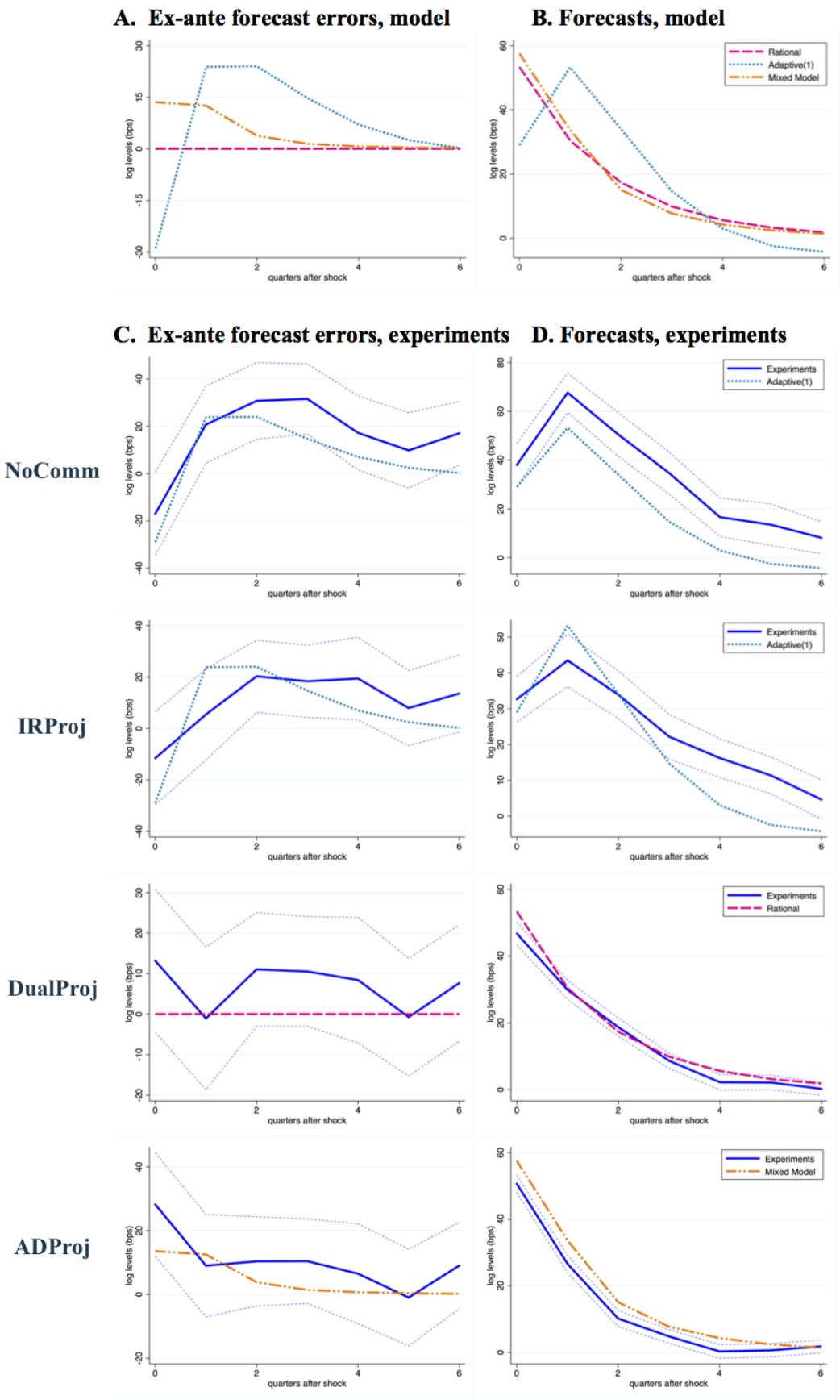
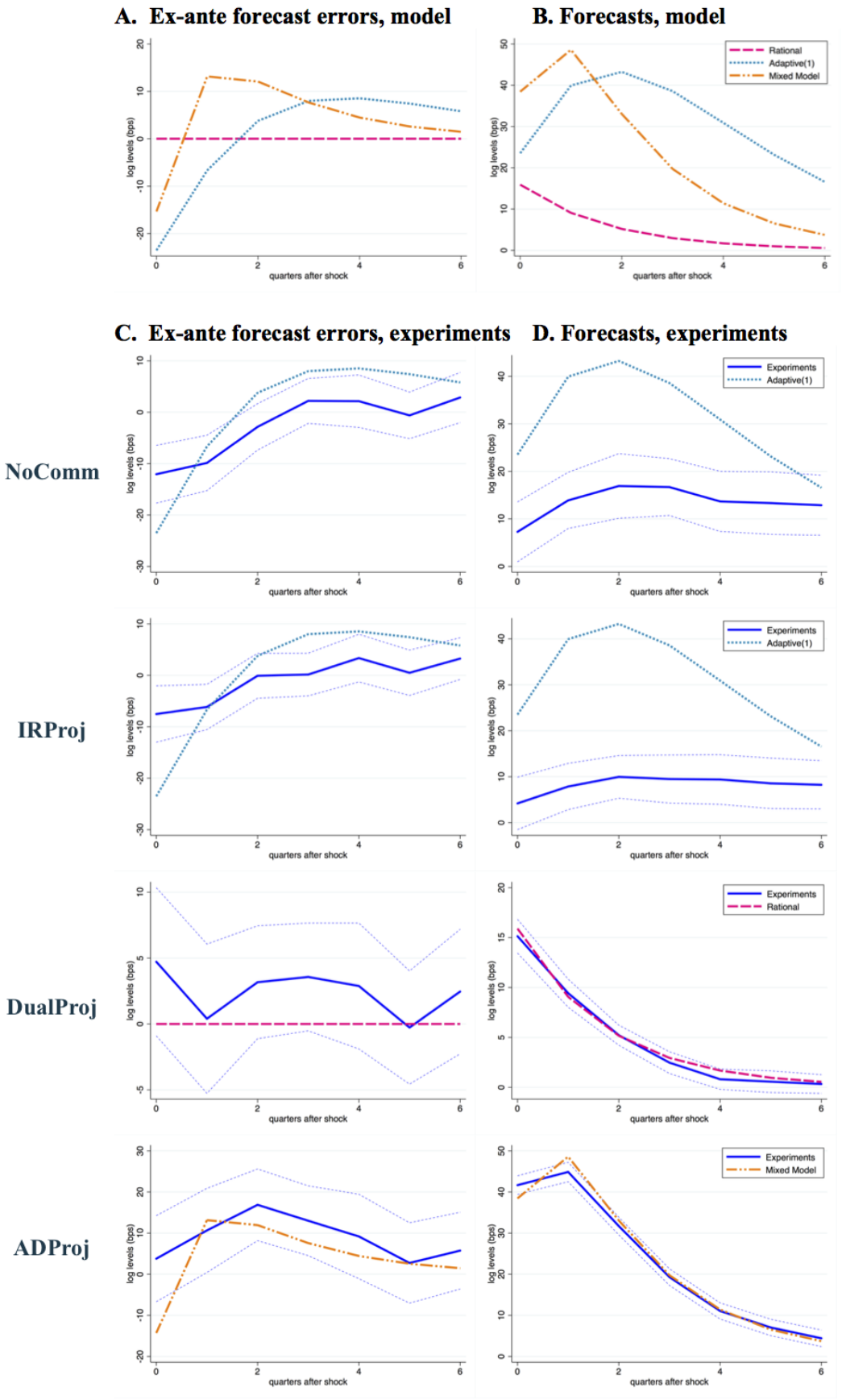


Figure 5: Estimated coefficient plots of output gap forecasts and forecast errors, by treatment



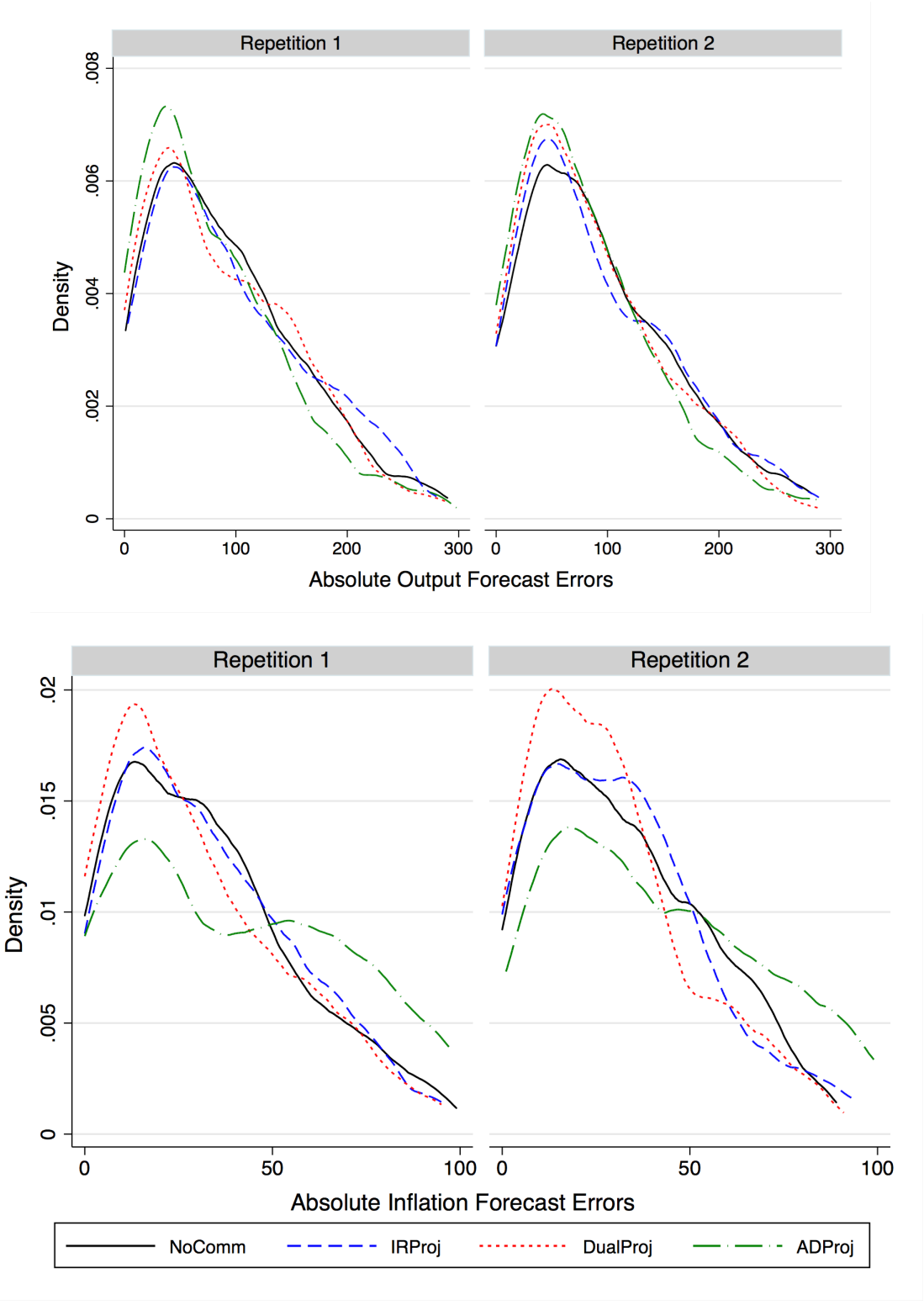

The figure shows the estimated coefficients associated with regressing current output forecast errors and forecasts on current and lagged innovations to the natural rate of interest. Data from repetition 2.

Figure 6: Estimated coefficient plots of inflation forecasts and forecast errors, by treatment



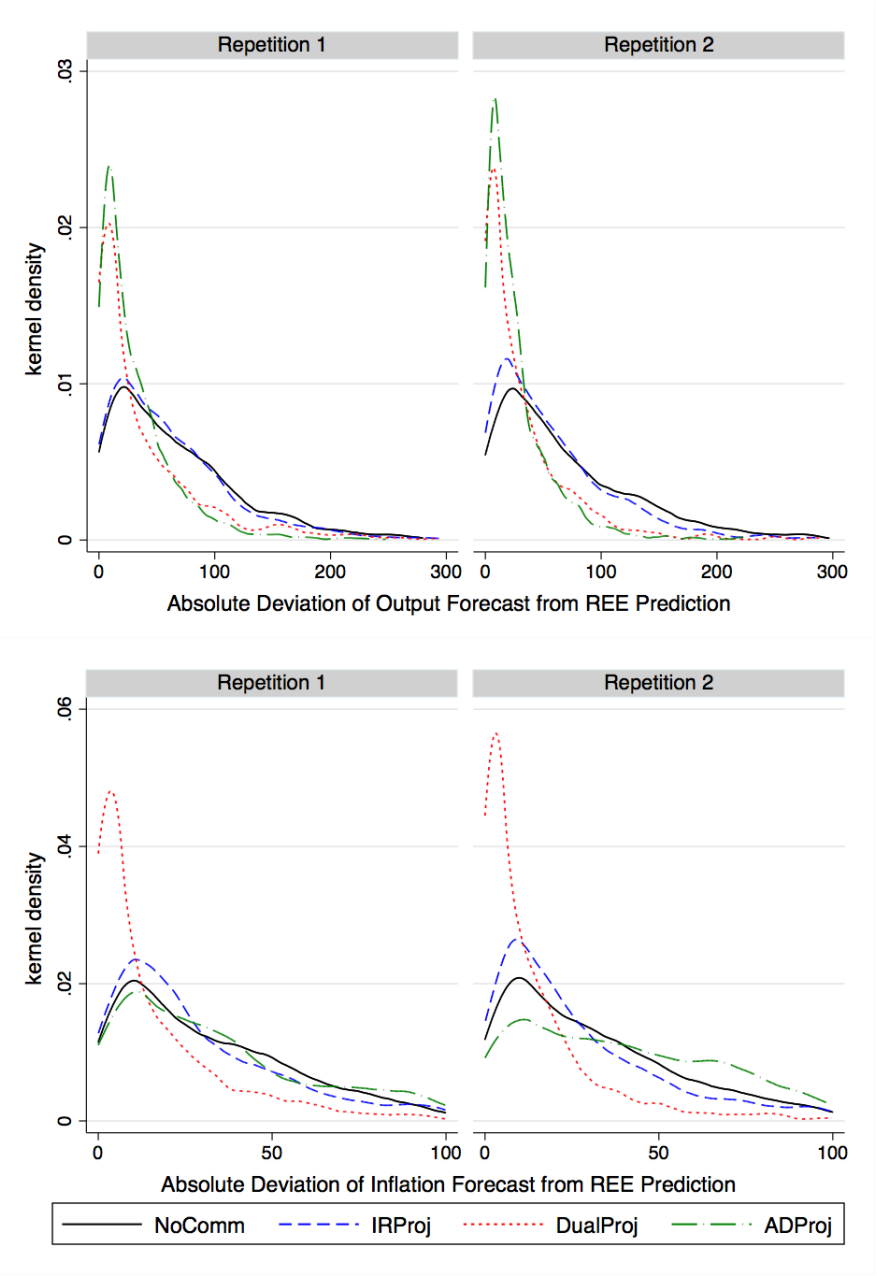

The figure shows the estimated coefficients associated with regressing current inflation forecast errors and forecasts on current and lagged innovations to the natural rate of interest. Data from repetition 2.

Figure 7: Kernel densities of absolute output and inflation forecast errors



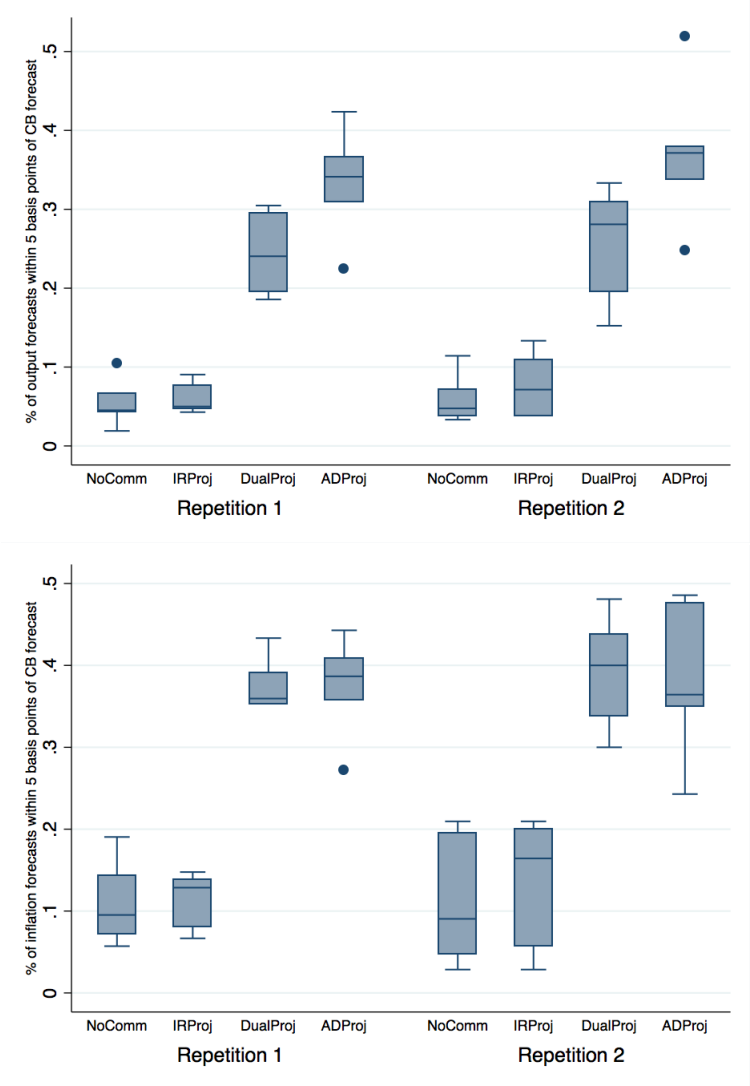

The figure shows the kernel densities associated with individual subject absolute forecast errors from all periods of play.

Figure 8: Kernel densities of absolute deviation of output and inflation forecasts from the REE prediction



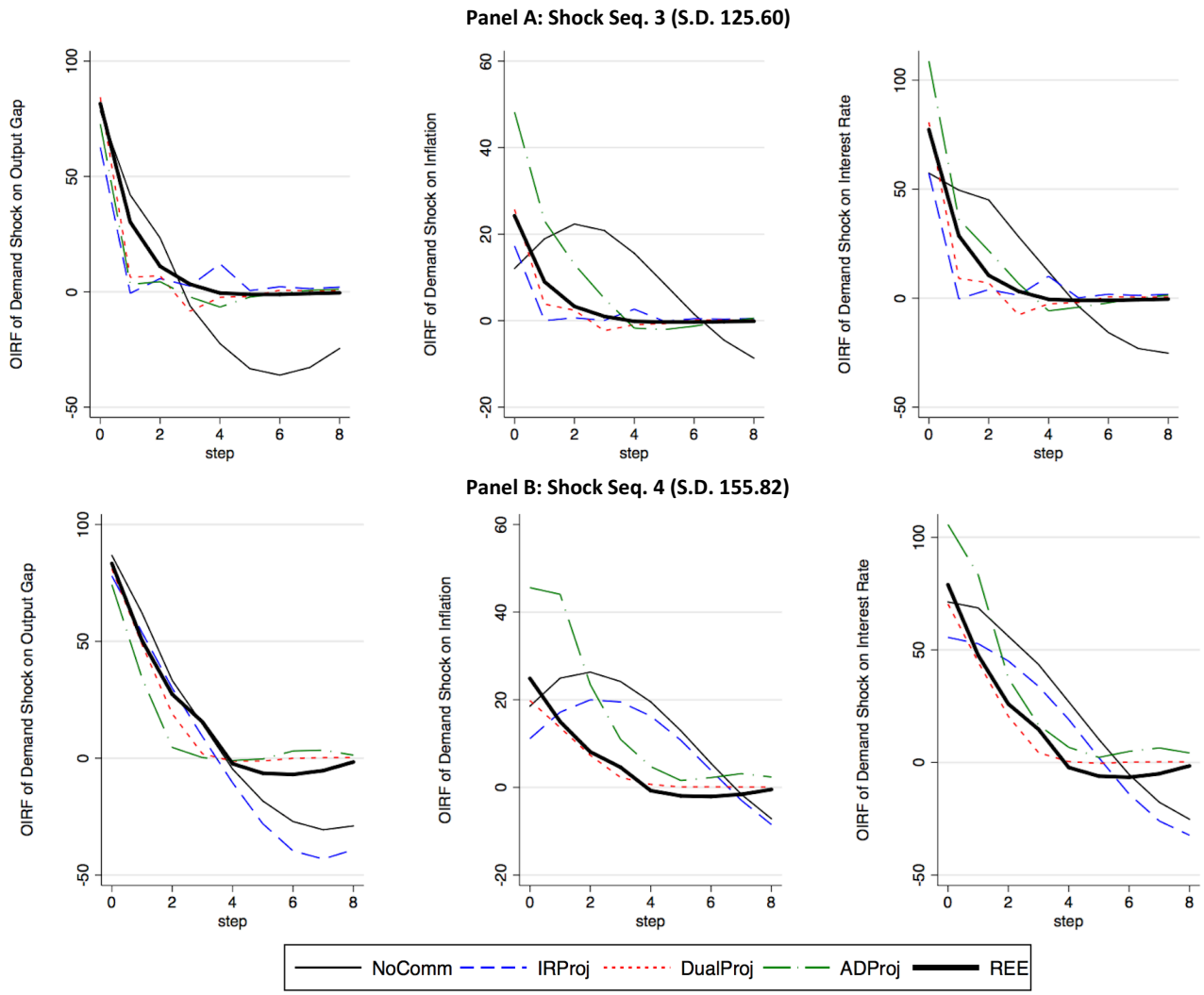

The figure shows the kernel densities associated with all individual absolute deviations of forecasts from the rational expectations equilibrium prediction from all periods of play.

Figure 9: Percentage of output and inflation forecasts within five basis points of the CB's projected value, session means



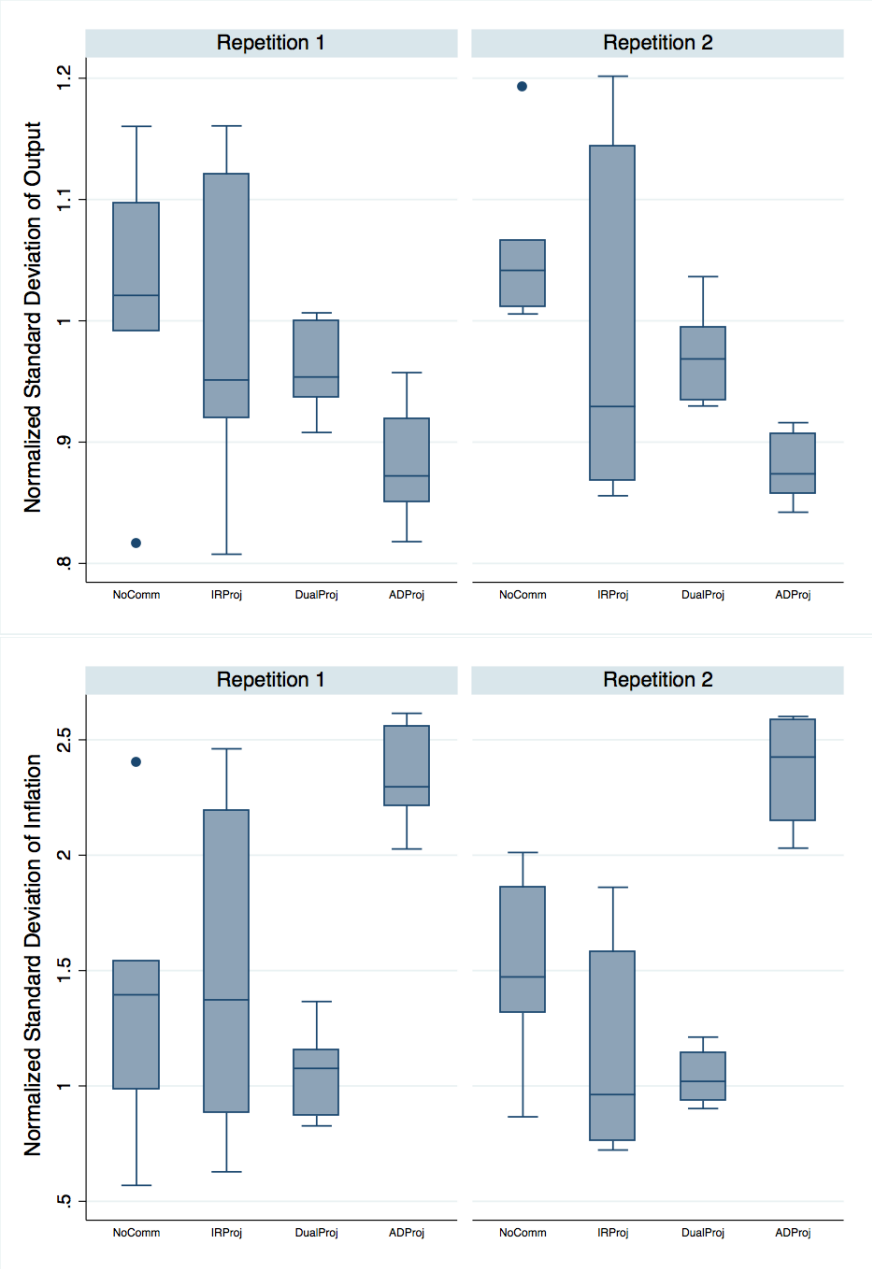

The figure shows the distribution of mean usage of the central bank's projection at the session- and repetition-level, by treatment. Our variables of interest are $UtilizedCBxForecast_t$ and$UtilizedCB\pi Forecast_t$ which take the value of 1 if a subject's period $t$ forecast about $t+1$ was less than 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 10: Estimated responses to a one-standard deviation innovation to the natural rate of interest



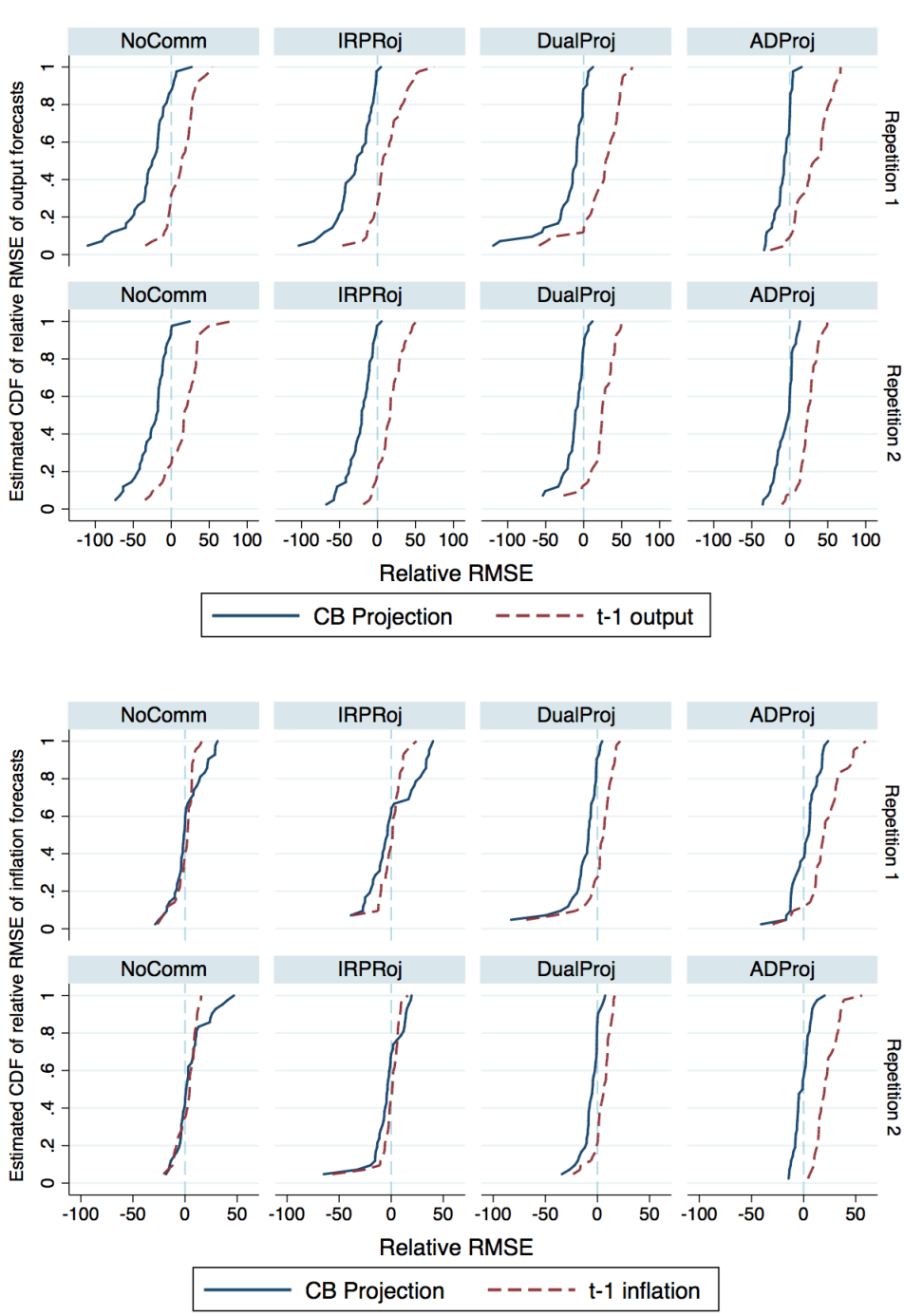

Panels A and B display estimated orthoganlized IRFs associated with the least and most volatile shock sequences, respectively. Data from Repetition 2.

Figure 11: 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 12: 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.