Coordinating expectations through central bank projections*

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Abstract

This paper explores how expectations of inflation and output are influenced by central bank projections within a learning-to-forecast laboratory macroeconomy. Subjects are incentivized to forecast the output gap and inflation in a laboratory macroeconomy where their aggregated expectations directly influence macroeconomic dynamics. An automated central bank forms projections about the economy assuming subjects form expectations either following rational or adaptive expectations. Using a between-subject design, we vary whether the central bank communicates no information, rational nominal interest rate projections, or rational or adaptive dual projections of output and inflation. Communicating about future output and inflation generally reduces the degree to which subjects rely on lagged information and increase their reliance on the central bank's projection. Interest rate projections, by contrast, do not consistently alter subjects' forecast accuracy, disagreements, and heuristics used, due to the significant heterogeneity in how subjects utilize the information. Central bank credibility is only significantly lost when the central bank makes larger forecast errors when communicating interest rate or adaptive dual projections. Our experimental findings suggest that expectations are best coordinated and stabilized by communicating rational output and inflation forecasts simultaneously.

JEL classifications: C9, D84, E52, E43, G12, G14

Keywords: expectations, monetary policy, projections, communication, credibility, laboratory experiment, experimental macroeconomics

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1. Introduction

Expectations are a key factor in the decisions of households and firms and, consequently, the economy. But 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 and guide expectations, 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/or their own policy rates.[1] An important drawback of publishing forecasts is that the central bank risks losing credibility when the economy deviates from its predicted path.

A central bank looking to design an effective communication strategy faces two questions: what forecasts should it communicate to best guide cognitively-limited people and is its credibility lost when projections are ex-post incorrect? Because central banks cannot do controlled experiments, it can be challenging to disentangle the causal impact of the projections they communicate on the public's expectations and central bank credibility.

To circumvent the empirical challenges inherent to observational data, we study individual and group forecasts in 24 multi-period laboratory economies where we systematically control the information that central banks communicate about their own forecasts. In each period of our experiments, each subject reports their forecasts of the following period's rate of inflation and output gap. The aggregate of subjects' 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 effect of four different types of central bank communication policies on the accuracy of subjects' forecasts. In our benchmark environment, participants only observe current and historical information about the economy. 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 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. While both of these projections convey the same overall information about the economy, we expected that Dual Projections would be cognitively easier for subjects to utilize. Finally, the Adaptive Dual Projection treatment mirrors the Dual Projection treatment except that central bank projections follow an adaptive model that, based on previous work, we

[1] The Reserve Bank of New Zealand (RBNZ), Norges Bank, Czech National Bank, Riksbank, and the Bank of Israel provide the public with a projected future path of nominal interest rates. The RBNZ and Norges Bank have gone even further to publish central bank projections of their economies' inflation rates and output gap. As interest rates have crept toward the zero lower bound since the start of the Great Recession, the Federal Reserve, ECB and Bank of England have experimented with a variety of forms of forward guidance about the direction of their future policy rates.

expect will better predict aggregate dynamics, and thus, reduce credibility concerns.

We find that central bank projections can significantly stabilize expectations and the aggregate experimental economy by *nudging* naïve forecasters towards fundamentally-driven rational expectations. Projections of future output gap and inflation results in consistently greater coordination of expectations and reduced forecast errors associated with the communicated variable. By contrast, projections of nominal interest rates leads to mixed results. For relatively low variability in aggregate demand shocks, nominal interest rate projections are relatively accurate and result in significantly more *rational* forecasts. However, as the variability of shocks increases, the benefits of such projections weaken and subjects continue to rely on an adaptive forecasting heuristic.

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 projections, the likelihood a subject employ 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, central bank credibility under rational and adaptive dual projections is significantly higher and is impervious to its own forecast errors when rational dual projections are communicated.

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 concludes.

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

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

of inflation targets led to increased transparency and credibility and also allowed the markets 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 inflation projections for the 90-day bank bill rate via Monetary Policy Statements (MPS). Norway in 2005, Sweden in 2007, Canada in 2009, and the U.S. in 2012 began to provide projections of key policy variables as a tool to manage market expectations (Woodford 2012). These types of projections have been used to signal the likely future path of policy rates and the outlook of monetary policy in general.

Evidence on the effects of central bank projections on expectations is rather limited. Hubert (2014) employs a linear regression approach to identify the effects of central bank inflation projections in Sweden, UK, Canada, Japan and Switzerland on private inflation forecasts collected by Consensus Forecasts' surveys. Hubert finds a significant positive relationship between central bank projections of inflation and forecasters' expectations of inflation. Kool and Thornton (2012) find mixed evidences of the ability of forward guidance of future nominal interest rates to improve private agents' ability to forecast future short- and long-term rates. 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. McCaw and Ranchhod (2002) and Turner (2006) in different studies provide evidence that the RBNZ's interest rate projection path does not significantly improve short-term future expectations. Finally, Goodhart and Lim (2011) report that the projected future path of interest rate by the RBNZ is significant for 1-quarter ahead and slightly for 2-quarter ahead money market rate. While these findings speak to how market forecasts react to central bank projections, no empirical work identifies how the effects of central bank projections alter forecasting. Identifying forecasting behavior at the individual level is difficult due to the limited availability of long panel datasets of expectations.[3]

Theoretical and computational work also suggest that central bank projections can be effective at guiding expectations. Ferrero and Secchi (2010) study an 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

[3]Malmendier and Nagel (2015) identify a decreasing gain forecasting heuristics using cross-sectional data from the U.S. households in the Michigan Survey of Consumers. Andrade and LeBihan (2013) utilize the panel dimension of the European Survey of Professional Forecasters and find evidence of rational inattention in sticky and noisy information models.

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 future nominal interest rate on agents' learning. Goy et al. find that such *delphic* forward guidance of future interest rates significantly reduces the likelihood of deflationary spirals when the economy is at the ZLB.

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 more critically lost (Woodford, 2005). 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. For these reasons, Mishkin (2004), Goodhart (2009), Archer (2005) and Blinder (2009) assert that too much transparency can become counterproductive.

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, laboratory experiments have increasing been conducted to study how monetary policy can influence the expectation formation process.[4] 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 can control features of the data-generating process including important policy rules and communication strategies while systematically varying features of the economy.

Learning-to-forecast experiments (LTFEs) have been extensively employed to study how expectations respond to information, policy, and structural features of the economy. In LTFEs, subjects play the roles of professional 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.[5]

[4] 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.

[5] The LTFE methodology originates with Marimon and Sunder (1993) who study price forecasting in an overlapping-generations experimental economy. Experiments studying inflation and output expectations in New Keynesian reduced form economies have been developed to study expectation formation and equilibria selection (Adam, 2007); the effects of different monetary policy rules on expectation formation (Pfajfar and Zakelj (2014, 2016)); Assenza et al. (2013), Hommes et al. (2015a)); expectation formation at the zero lower bound (Arifovic and Petersen (2015), Hommes et al. (2015b); and central bank communication (Kryvtsov and Petersen (2013), Cornand and M'Baye

We focus our discussion of the 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 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 that providing focal central bank forecasts of the path of future interest rates leads to inconsistent 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. Arifovic and Petersen (2015) show that, at the zero lower bound, qualitative communication of evolving inflation targets tends to be more effective at stabilizing expectations than comparable qualitative communication. Qualitatively announced targets mitigate the credibility loss that occurs the central bank fails to achieve its targets. Cornand and M'Baye (2016) consider the effectiveness of announcing the central bank's constant inflation target when a central bank follows strict or flexible inflation targeting. They find that the gains from communicating the 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. More recently, Ahrens et al. (2016) have extended this work and Arifovic and Petersen (2015) to study the effect 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.

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 experiment closely follows the design of Kryvtsov and Petersen (2013). The experimental economy's data-generating process is derived from a linearized version of a standard New Keynesian framework in which 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.[6]

(2016)).

[6]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

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 $E_t^* x_{t+1}$ and $E_t^* \pi_{t+1}$ 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:

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

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

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

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

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, $E_t^* x_{t+1}$, and deviations of the real interest rate, $i_t - E_t^* \pi_{t+1}$ from the natural rate of interest, r_t^n.[7] The quantitative importance of this deviation depends on the elasticity of intertemporal substitution, σ^{-1}.

Equation (2) is the New Keynesian Phillips curve which describes the evolution of inflation, π_t in response to changes in aggregated expectations of future inflation, $E_t^* \pi_{t+1}$ and the output gap, x_t. The coefficient κ is a function of parameters associated with the frequency and the size of firms' price changes, and governs the sensitivity of prices to aggregate demand, while the coefficient β represents the subjective discount rate.

Equation (3) is the central bank's response function and describes the evolution of nominal interest rates. Under this specification the central bank contemporaneously responds to deviations of output gap and inflation from their steady state values. In each period, the automated central bank increases the nominal interest rate in response to higher current inflation and the output gap. The coefficients ϕ_π and ϕ_x govern the central bank's reaction to inflation and output gap.[8] 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, negative

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).

[7]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.

[8]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.

nominal interest rates were possible in our experiment.[9]

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, ϵ_{rt}, is drawn from an $i.i.d$ $N(0, \sigma_r)$.[10] 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 $\pi^* = x^* = i^* = 0$.

When forming forecasts, subjects have access to the following common information (and 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.[11]

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 intuitively 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%. Another convenient feature of this payoff function is that it incentivizes subjects even as forecast errors grow large. At the end of the experiment, subjects' points from all periods are converted into dollars and paid out to them in cash.

To ensure consistency across treatments, we preselect the shock sequences and employ them

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

[10]Fluctuations in the natural rate of interest may originate from disturbances to government purchases, households propensity to consume or willingness to work, and to firms' productivity. See Woodford (2003, Chapter 4) for details. We follow Kryvtsov and Petersen (2013), Arifovic and Petersen (2015), and Pfajfar and Zakelj (2014, 2016) in the implementation of a *AR(1)* shock process.

[11]Forecasts were submitted on time in 99.7% of the periods(10053 of 10080 opportunities).

across all treatments. 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 extra dimension of exogenous variation.

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

Kryvtsov and Petersen (2015) observe that aggregate expectations in an identically calibrated experiment can be well-described by an Adaptive(1) heuristic. Under this heuristic, agents place 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 the rational forecasters, aggregate forecasts of output and inflation under an Adaptive(1) heuristic under- and over-react to current innovations, respectively. Following the onset of the innovation of the shock, the adaptive heuristics lead to a hump-shaped dynamic for both types of forecasts. While inflation gradually returns back to the steady state, output returns more quickly as a consequence of the relatively high nominal interest rate. Output over-shoots the steady state and becomes depressed before reverting back to zero.

Finally, we consider the possibility that only half of the subjects exhibit an Adaptive(1) forecasting heuristic, while the other half forecast according to the ex-post rational solution. The dynamics associated with this hybrid case are shown as a dotted green line in **??**. 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 the increased rationality of agents. This leads to relatively more output volatility and much higher inflation volatility. All variables monotonically revert back to the steady state.

Treatments and Hypotheses

To investigate the impact of central bank projections on economic stability and forecasting heuristics, we systematically vary the type of projections subjects receive in a between-subject experimental design. In our baseline environment, we provide no additional information to subjects.

- 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:

$$\begin{aligned} x_t &= 0.472198 \cdot r^n_{t-1} + 0.82847 \cdot \epsilon_t, \\ \pi_t &= 0.140706 \cdot r^n_{t-1} + 0.246852 \cdot \epsilon_t. \\ i_t &= 0.447157 \cdot r^n_{t-1} + 0.784487 \cdot \epsilon_t, \end{aligned} \tag{6}$$

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

- 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 simply forecasts formed by the central bank based on current and expected future shocks. 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 a 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:

$$\begin{aligned} x_t &= 0.305505 \cdot x_{t-1} - 0.284377 \cdot \pi_{t-1} + 0.388763 \cdot r^n_{t-1} + 0.682040 \cdot \epsilon_t, \\ \pi_t &= 0.076461 \cdot x_{t-1} + 0.666343 \cdot \pi_{t-1} + 0.167868 \cdot r^n_{t-1} + 0.294506 \cdot \epsilon_t. \\ i_t &= 0.267444 \cdot x_{t-1} + 0.857326 \cdot \pi_{t-1} + 0.446184 \cdot r^n_{t-1} + 0.782779 \cdot \epsilon_t, \end{aligned} \tag{8}$$

- 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 experimental design allows us to test a number of hypotheses regarding how subjects form expectations, both with and without projections. Standard New Keynesian models assume that agents form identically rational expectations of future output and inflation. 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 1 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. Thus, we test the alternative hypothesis that subjects place significant weight on historical information when forming their forecasts.

Commonly observed projections provide an important focal point for subjects to coordinate their forecasts on.[c0] 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 communications will reduce subjects' usage of non-fundamental information in their forecasts in favor of the fundamentally-driven central bank projections. This in turn should reduce subjects' forecast errors.

Hypothesis II: Rational projections reduce subjects' reliance on historical information and increase their reliance on current fundamentals when forming expectations.

Hypothesis III: Rational projections reduce subjects' forecast errors.

While nominal interest rate and dual projections based on the REE solution contain arguably irrelevant 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. But the ability to effectively use the information is not the same. Dual projections of output and inflation could arguably be effortlessly employed as subjects' forecasts. By contrast,

[c0] 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, with experience, subjects' forecasts of the future are significantly more responsive to forecast errors when presented with such focal auxiliary information.

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

The success of communication in managing expectations depends on the central bank's credibility in achieving its projections. We measure central bank credibility as the fraction of forecasts that coincide with the central bank's explicit or implicit projected value. In our experiments, the automated central bank forms forecasts following an ad hoc Taylor rule and assumes 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. As the projections become increasing incorrect, we expect that the central bank will lose credibility and subjects will reduce their willingness to utilize the central bank projection as their own forecast.

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

Given that an Adaptive(1) forecasting heuristic has well-described subjects' behavior in related experiments, we speculate it will continue to be effective in this experiment. In this case, we alternatively hypothesize that the central bank's forecast errors in the ADProj treatment will be lower than in the DualProj treatment, and its credibility will be higher. Likewise, nominal interest rate projections are likely to be more incorrect as subjects face more cognitive challenge employing them in their forecasts. We further hypothesize that central bank credibility will be lower in the IRProj treatment.

Hypothesis V: The percentage of expectations that coincide with the central bank's explicit or implicit projections is the highest in the ADProj treatment, followed by the DualProj, and lowest in the IRProj treatment.

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 February 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. 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.[c0]

We used *Redwood*, an open source software (Pettit et al., 2013), to implement the experiment. 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. Figure 2 presents a representative screen-shot of the interface in the DualProj treatment with output and inflation projections. 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 confidence interval that increased as the projection went further into the future to reinforce the point that the central bank's projections were noisy predictions.

The experiments lasted for approximately 90 minutes including 35 minutes of instruction and four unpaid practice periods to familiarize themselves with the software and task. The average payment, including a CDN $7 show-up fee was CDN $25 and ranged from CDN $17 to $32.

4. Experimental Results

This section summarizes our experimental findings. We first consider how central bank 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:

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

[c0]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.

where E_t denotes the mean conditional on state history through period t, and $L_{s\pi}$, L_{sx} are real numbers representing the elasticity of ex ante forecast errors for inflation and the output gap with respect to shock realizations in periods $t, t-1, \ldots$. A standard assumption is that subjects form rational expectations. That is, ex ante forecast errors are always zero. This would imply that $L_{s\pi} = L_{sx} = 0$ for all s. According to Equation (9), non–rational expectations imply that ex ante forecast errors correlate with the current or past shock realizations.[c0]

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 use a period $t-l$ realization of inflation (output gap) to form expectations of period-$(t+1)$ inflation (output gap).[c0] The ex ante forecast errors are negative at the time of the shock and are positive thereafter since inflation (output) forecasts are expected to persist while the forecasted variable slowly returns back to its steady state level.

We construct a series of 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, ϵ_t, where we interact these innovations with treatment–specific dummies:

$$\begin{aligned}E_{i,t}z_{t+1} &= \alpha+\beta_1\epsilon_{rt}+\beta_2\epsilon_{rt}\times IRProj+\beta_3\epsilon_{rt}\times DualProj+\beta_4\epsilon_{rt}\times ADProj+\ldots \\ &\quad+\beta_Z\epsilon_{rt-T}\times ADProj+u_{it},\end{aligned} \tag{11}$$

and where $E_{i,t}z_{t+1}$ refers to subject i's output or inflation ex ante forecast errors, u_{it} is an idiosyncratic error term, and T=4. A series of Hausman tests indicate that the random effects model is preferred for all treatments. 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 an Adaptive (l) expectations, ex ante forecast errors would place significant weight on lagged shock innovations, $\hat{\beta}_k \neq 0$ for some k. If central bank projections are effective at encouraging subjects to form more rational expectations, then we would expect to find that the weight

[c0]Under non–rational expectations as defined above, the law of iterated expectations, in general, does not hold; e.g., $E_t^*E_{t+s}^*\pi_{t+1+s} \neq E_t^*\pi_{t+s+1}$ for a given $s = 1, 2, \ldots$.

[c0]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.

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 1. For reference, a comparison of the lowest and highest shock volatility sessions are presented in Table 2. The appendix includes additional specifications run at the repetition level, where we interact each current and lagged innovation with a measure of the standard-deviation of the shock sequence.

First, we reject Hypothesis I that subjects form rational expectations. In Table 1 we see that in all treatments subjects' forecast errors assign a significant weight either on 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, subjects forecasting output place significant negative weight on current innovations and large positive weight on one-, two-, three-, and four-period lagged innovations. That is, output forecasts in the NoComm treatment are under-responsive to current innovations while over-responsive to 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 results in significantly greater under-reaction to current innovations and over-reaction to one-period lagged innovations.

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 central bank projections. We begin first with nominal interest rate projections. As in the NoComm treatment, subjects significantly under-react to current innovations and over-react to lagged innovations when forming their output forecasts, with the under- and over-reaction increasing with more variable shock sequences. 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, on average, less responsive to lagged innovations but the effect is not statistically significant.

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. Subjects become increasingly more responsive to lagged innovations as the variability of shocks increases. This means that for high variability shocks, subjects observing an interest rate projection become more reliant on historical information to formulate their inflation forecasts.

Observation II: Nominal interest rate projections increase subjects' reaction to current

innovations when forecasting both output and inflation, and reduce subjects' under-reaction to lagged innovations when forecasting inflation. The ability of interest rate projections to reduce forecast errors decreases as the standard deviation of shocks increases.

Expectations in the DualProj and ADProj treatments are highly responsive to the central bank's projections of output and inflation. Consequently, subjects in these treatments 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. As in the NoComm treatment, increasing the variability of shocks leads to a more pronounced adaptive forecasting heuristic. Rational and adaptive dual projections of output and inflation are both effective at nudging output forecast errors toward rationality.

When it comes to inflation forecasts, subjects in the DualProj and ADProj are both significantly more responsive to current and lagged innovations than their NoComm counterparts. While both types of dual projections increase subjects' backward-looking behavior, adaptive dual projections induce significantly greater responsiveness to lagged innovations. To summarize, we find mixed support for hypothesis II.

Observation III: Rational and adaptive dual projections increase subjects' reaction 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 central bank'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 5. We observe that, for experienced subjects in Repetition 2, all three types of projections skew the distribution of absolute 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 IRProj treatment and, especially, the ADProj treatment are associated with larger absolute forecast errors.

Using a population-averaged generalized estimating equation panel regression approach with a log link, we estimate the effect of the different projections on absolute forecast errors. We employ a log link because of our nonnegative skewed dependent values. Our first set of specifications regresses absolute forecast errors on treatment-specific dummies. To capture the possibility of variability of shocks influencing subjects' absolute forecast errors, our second interacts the treatment dummies with the standard deviation of the shock sequence. The results, by repetition, are presented in

Table 3.

We find mixed support for Hypothesis III that rational forecasts reduce subjects' forecast errors. In our baseline specifications, average absolute output forecast errors are significantly reduced by all rational and adaptive dual projections for both inexperienced and experienced subjects. Interest rate projections increase output gap forecast errors on average, but the effect is highly heterogeneous across subjects. When we control for the variability of shocks, the differences across treatments is mostly insignificant. The exception is that, for inexperienced subjects, interest rate projections lead to increasingly larger forecast errors as the variability of the shock sequences increases.

Turning to absolute inflation forecast errors, we observe that interest rate projections significantly increase inexperienced subjects' forecast errors while rational dual projections do the opposite. On average, adaptive dual projections do not significantly affect inexperienced inflation forecast errors. Controlling for the variability of shocks, we observe that inexperienced subjects' forecast errors increases significantly with the variability of the shock sequences in the IRProj and ADProj treatments. Experienced subjects' inflation forecast errors are only consistently lower in the DualProj treatment, but after controlling for shock variability, we find no significant differences in forecast accuracy across our projection treatments.

Observation IV: Inexperienced and experienced subjects' forecast errors for both output and inflation are significantly reduced in the DualProj treatment. Adaptive dual projections decrease only output forecast errors while interest rate projections increase inexperienced subjects' inflation forecast errors. With experience, 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 coordination by calculating the standard deviation of forecasts each period across subjects in a single group. We calculate the median disagreement at the session-repetition level. Summary statistics of median disagreement are reported in Table 4.[c0] Central bank communication does not consistently lead to a statistically significant improvement in the coordination of expectations for inexperienced subjects. Rank-sum tests comparing session-repetition median disagreements across treatments fail to reject that the distributions of median disagreements are identical across most pairwise comparisons ($p > 0.20$). There are but a few key exceptions. Interest rate projections significantly increase disagreements about future inflation compared to the NoComm treatment ($p = 0.025$). Adaptive dual projections significantly decrease disagreement about output while significantly increasing disagreement about inflation ($p = 0.05$ and $p = 0.037$, respectively).

With experience, central bank projections considerably improve the coordination of output

[c0]Normalizing median disagreement by the standard deviation of the shock does not alter the significance of our results.

gap expectations. The average session-level disagreement in Repetition 2 falls from 175.15 bps in the NoComm treatment to under 50 bps when subjects receive some form of central bank communication. The reduction in disagreement about future output is highly significant in the DualProj and ADProj treatments ($p = 0.055$ and $p = 0.004$ respectively), while less consistently effective in the IRProj ($p = 0.109$). Average disagreement about inflation increases insignificantly in all three projection treatments ($p > 0.20$).

The extent to which subjects' forecasts deviate from the REE solution is depicted in Figure 6. The figure presents kernel densities of the absolute deviation of output and inflation forecasts from the REE solution's predicted forecasts by treatment and repetition. Compared to the NoComm treatment, rational dual projections dramatically improve coordination of both types of forecasts to the REE solution. Interest rate projections also improve coordination of forecasts to the REE solution, but the effect is less pronounced. Finally, adaptive dual projections work effectively in coordinating output forecasts but poorly at coordinating inflation forecasts. In fact, adaptive dual projections increase experienced subjects' deviation of inflation forecasts from the REE prediction.

These findings provide further support for Hypothesis II.

Observation IV: Central bank projections generally have minimal effects on coordinating expectations for inexperienced subjects. Experienced subjects exhibit considerably less disagreement about future output when they observe any type of projections. Coordination on the REE solution is improved with rational and adaptive dual projections.

Finally, we consider how central bank forecast errors influence subjects' willingness to utilize the publicly announced projections as their own forecasts. In the IRProj, DualProj and ADProj treatments, mean central bank 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 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.

We now focus on subjects' likelihood of utilizing central bank projections in the IRProj, DualProj and ADProj treatments. 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 central bank's projection and zero otherwise.[c0] Figure 7 plots the session mean percentage of subjects forecast. Utilization is the lowest in the NoComm treatment with a mean of

[c0] We are implicitly assuming that subjects fully comprehend how to utilize the central bank's interest rate projection to formulate their output and inflation forecasts.

0.06 (s.d. 0.03) for output forecasts and 0.11 (s.d. 0.06) for inflation forecasts. Nominal interest rates 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 Wilcoxon rank-sum test of the null hypothesis that differences in utilization between the NoComm and IRProj treatment follows a symmetric distribution around zero is not rejected (N=6 for each treatment-repetition-variable test, $p > 0.36$ for each test). Rational and dual projections significantly increase utilization of the central bank'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. Wilcoxon rank-sum tests significantly reject the null hypothesis that differences in utilization between the NoComm 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) Thus, we find considerable support for Hypothesis V.

Observation V: Central bank credibility is significantly higher in the DualProj and ADProj treatments than in the IRProj treatment. Credibility in the central bank'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 central bank's projections evolves. Our primary explanatory variables are the central bank'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 central bank'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 treatments are unnoteworthy. Treatment-specific results are presented in Table 5.

We begin with central bank credibility under interest rate projections. We find that the probability a subject is willing to use the central bank's interest rate projection to forecast output or inflation decreases significantly when the bank makes larger forecast errors. Having used the central bank's forecast in the previous period, a larger forecast error does not significantly alter subjects' willingness to continue to use the projection in their own forecast. This finding in the IRProj treatment supports Hypothesis IV.

In the DualProj treatment, past forecast errors of the central bank do not play a quantitatively large or statistically significant role in central bank credibility. In fact, subjects in the DualProj are more willing to continue to utilize the central bank's projections when the central bank's projections are more inaccurate. By contrast, in the ADProj treatment, larger central bank forecast errors about inflation significantly reduce subjects' utilization of the projections.

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.

Aggregate Analysis

We now consider the effects of central bank projections on aggregate macroeconomic variables. Our analysis begins by considering how the dynamics of output, inflation, and nominal interest rates respond to different forms of communication. We estimate the orthogonalized impulse responses of output, inflation, and nominal interest rates to a one-standard deviation shock to aggregate demand. The results for Repetition 2 are presented in Figure 8 by shock sequence, ordered from least to most volatile sequences. The heavy solid lines indicate the estimated REE predictions, while the thin solid lines denote the estimated impulse response functions in the NoComm treatment. The initial response of output to the demand shock in the NoComm treatment is rather consistent with the REE prediction. In the periods that follow, we observe a consistently sluggish decline in output. By the fourth period following the initial shock, the output gap becomes negative before returning to the steady state.

Inflation follows a noticeably different transition path from the REE prediction. On impact of the aggregate demand shock, inflation in the NoComm treatment exhibits a relatively muted response in most sessions. In those sessions, inflation then rises for two additional periods before beginning to trend back toward the steady state. The hump-shaped pattern of inflation is indicative of an Adaptive(2) forecasting model where the aggregate expectation of $t+1$ places significant positive weight on inflation from period $t-2$. Such inflation forecasting behavior is also observed in Kryvtsov and Petersen (2013).

Introducing central bank projections has varying effects on the transition paths of output and inflation. The estimated impulse response functions are presented for the IRProj as blue dashed lines, the DualProj as short red dashed lines, and the ADProj as green long dash–dot–long dash lines. Generally, all three types of projections have a similar effect on output dynamics for low variability shocks. As the shocks become more variable, nominal interest rate and adaptive dual projections are associated with a greater contractionary overshooting effect of output, suggestive of a larger backward-looking nature of forecasts consistent with behavior in the NoComm treatment.

The effects of central bank communication are more stark when we consider the estimated responses of inflation. Rational projections lead to a response of inflation that is considerably more inline with the REE prediction. Inflation is more consistently monotonically converging back to the steady state, and the hump-shaped pattern observed in the NoComm treatment is largely eliminated. We observe noticeable heterogeneity across sequences in the estimated impulse response functions of IRProj sessions. The impulse response functions tend to track the timing of the REE prediction better when the shock volatility is relatively low. However, for relatively more volatile shock sequences such as Sequences 4 and 6, the reactions of inflation under IRProj are more sluggish and exhibit timing similar to that of the NoComm treatment. In other words, for greater shock volatility, central bank projections of nominal interest rates do not considerably alter forecasting heuristics and inflation dynamics.

The dynamics of inflation in the ADProj treatment are rather unusual. In all sequences, inflation significantly overshoots the REE prediction, and remains high thereafter as the shocks dissipate. The persistently high inflation is associated with ADProj subjects' over-reaction to lagged innovations. In half of the sessions, inflation becomes negative as a consequence of subjects' backward-looking forecasting heuristics combined with an aggressive response of monetary policy to high inflation.

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 6.[c0] The results are also presented visually in Figure 9 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. Wilcoxon signed-rank tests are conducted to determine whether the mean results are significantly different from the REE solution, ie. 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. By the second repetition, output and inflation in the NoComm treatment are 6% and 50%, respectively, more volatile than predicted by the model. 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).

The ability of central bank projections to enhance economic stability is mixed. Compared to the NoComm treatment, interest rate projections in the IRProj treatment do not significantly decrease output and inflation variability. 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). Finally, adaptive dual projections in the ADProj treatment significantly

[c0]The normalizing REE solution of output and inflation is calculated for each shock sequence.

stabilize output variability at the cost of significantly greater inflation variability ($p \leq 0.055$ in Repetition 1, $p < 0.01$ in repetition 2).

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

5. Discussion

To make sense of our experimental finding that nominal interest rate projections are more challenging for subjects to utilize than dual 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 central bank 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 central bank 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 central bank 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 central bank's 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. We conducted a couple of sessions (not reported here) 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.[c0]

Limited attention models predict that the optimal allocation of 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.

[c0] An alternative class of inattention models consider agents that obtain information infrequently due to costly information acquisition (e.g. Mankiw and Reis, 2002; Reis, 2003). 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.

Second, rational inattention models predict that agents equate the marginal cost of paying attention to projections to the marginal benefit of using such projections. That is, subjects would optimally pay less attention to information that is unlikely to adequately compensate them for the effort of processing such information. We compute a set of counterfactual payoffs where we assume that the subject either uses the central bank'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.[c0] 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 10 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 central bank'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 information, 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 projection information.

[c0]In the DualProj and ADProj treatments, the marginal cost associated with employing the central bank's projection or period $t-1$ output and inflation and output as one's forecast is comparable. Subjects simply have to 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 central bank's interest rate projection is considerably more challenging than using historical values, and would arguably exhibit a larger marginal cost for the subject.

6. Conclusion

Central bank 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 central bank projections are varied systematically across independent groups.

Our 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, central bank projections of nominal interest rates are not consistently 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.

Adaptive dual projections bring about increased inflation instability. The projection is 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, considerably less responsive, forecasting heuristics. This predictably leads to increased inflation variability. Thus, our findings suggest that central banks interested in maintaining inflation stability should strategically communicate rational projections rather than adaptive projections.

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7. Tables and Figures

Table 1: Effects of central bank projections on forecast errors - treatment effects [I]

	Output Gap Forecast Errors		Inflation Forecast Errors	
ϵ_t	-0.361***	-0.360***	-0.108***	-0.109***
	(0.10)	(0.10)	(0.01)	(0.01)
$\epsilon_t \times IRProj$	0.201*	0.200*	0.059**	0.059**
	(0.11)	(0.10)	(0.03)	(0.03)
$\epsilon_t \times DualProj$	0.352***	0.353***	0.133***	0.136***
	(0.11)	(0.10)	(0.02)	(0.02)
$\epsilon_t \times ADProj$	0.526***	0.525***	0.076***	0.077***
	(0.10)	(0.10)	(0.02)	(0.02)
ϵ_{t-1}	0.166***	0.167***	-0.078***	-0.078***
	(0.05)	(0.05)	(0.01)	(0.01)
$\epsilon_{t-1} \times IRProj$	-0.013	-0.014	0.050**	0.050**
	(0.05)	(0.06)	(0.02)	(0.02)
$\epsilon_{t-1} \times DualProj$	-0.088*	-0.087	0.082***	0.085***
	(0.05)	(0.05)	(0.02)	(0.02)
$\epsilon_{t-1} \times ADProj$	0.012	0.011	0.165***	0.166***
	(0.05)	(0.05)	(0.02)	(0.02)
ϵ_{t-2}	0.464***	0.465***	-0.027***	-0.027***
	(0.17)	(0.17)	(0.01)	(0.01)
$\epsilon_{t-2} \times IRProj$	-0.206	-0.207	0.043*	0.043*
	(0.17)	(0.17)	(0.02)	(0.02)
$\epsilon_{t-2} \times DualProj$	-0.315*	-0.313*	0.064***	0.067***
	(0.17)	(0.17)	(0.01)	(0.01)
$\epsilon_{t-2} \times ADProj$	-0.331**	-0.332**	0.155***	0.156***
	(0.17)	(0.17)	(0.02)	(0.02)
ϵ_{t-3}	0.552**	0.553**	-0.000	-0.001
	(0.24)	(0.24)	(0.01)	(0.01)
$\epsilon_{t-3} \times IRProj$	-0.374	-0.375	0.005	0.005
	(0.24)	(0.24)	(0.02)	(0.02)
$\epsilon_{t-3} \times DualProj$	-0.448*	-0.447*	0.021**	0.024***
	(0.24)	(0.24)	(0.01)	(0.01)
$\epsilon_{t-3} \times ADProj$	-0.478**	-0.479**	0.092***	0.093***
	(0.24)	(0.24)	(0.01)	(0.01)
ϵ_{t-4}	0.392*	0.393*	0.009	0.008
	(0.22)	(0.22)	(0.01)	(0.01)
$\epsilon_{t-4} \times IRProj$	-0.255	-0.256	0.005	0.005
	(0.22)	(0.22)	(0.01)	(0.01)
$\epsilon_{t-4} \times DualProj$	-0.330	-0.329	0.008	0.009
	(0.22)	(0.22)	(0.01)	(0.01)
$\epsilon_{t-4} \times ADProj$	-0.355	-0.356	0.034***	0.036***
	(0.22)	(0.22)	(0.01)	(0.01)
α	30.076***	84.207*	7.097***	4.397***
	(9.18)	(48.22)	(1.54)	(1.43)
Session FE		✓		✓
N	8263	8263	8263	8263
χ^2	381.8	498.8	335.8	506.6

(I) This table presents results from a series of random effects panel regressions. The dependent variables are individual-level output and inflation forecast errors from all relevant periods of play. ϵ_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. α denotes the estimated constant. Robust standard errors are employed. $*p < 0.10$, $**p < 0.05$, and $***p < 0.01$.

Table 2: Effects of central bank projections on forecast errors, by shock sequence - treatment effects - Repetition 2 - Comparison[I]

	Lowest Variability Shocks		Highest Variability Shocks	
	fe_output	fe_inflation	fe_output	fe_inflation
	(1)	(2)	(3)	(4)
ϵ_t	-0.213**	-0.191**	-0.428***	-0.263***
	(0.09)	(0.07)	(0.11)	(0.03)
$\epsilon_t \times IRProj$	0.278**	0.249***	-0.097	0.057
	(0.12)	(0.08)	(0.14)	(0.04)
$\epsilon_t \times DualProj$	0.419***	0.295***	0.181	0.256***
	(0.12)	(0.10)	(0.14)	(0.07)
$\epsilon_t \times ADProj$	0.587***	0.362***	0.273**	0.086*
	(0.13)	(0.08)	(0.11)	(0.05)
ϵ_{t-1}	0.185**	-0.176***	0.299***	-0.059
	(0.07)	(0.03)	(0.08)	(0.04)
$\epsilon_{t-1} \times IRProj$	-0.095	0.195***	-0.058	-0.092**
	(0.11)	(0.04)	(0.10)	(0.04)
$\epsilon_{t-1} \times DualProj$	-0.059	0.231***	-0.171	0.060
	(0.09)	(0.04)	(0.11)	(0.05)
$\epsilon_{t-1} \times ADProj$	-0.028	0.333***	-0.102	0.161***
	(0.09)	(0.04)	(0.10)	(0.06)
ϵ_{t-2}	0.402***	-0.129***	0.259***	-0.060
	(0.07)	(0.04)	(0.07)	(0.04)
$\epsilon_{t-2} \times IRProj$	-0.226**	0.169***	-0.079	-0.064
	(0.10)	(0.04)	(0.08)	(0.04)
$\epsilon_{t-2} \times DualProj$	-0.198**	0.219***	-0.400***	0.081*
	(0.09)	(0.04)	(0.12)	(0.04)
$\epsilon_{t-2} \times ADProj$	-0.225***	0.315***	-0.332***	0.047
	(0.07)	(0.04)	(0.08)	(0.05)
ϵ_{t-3}	0.233***	-0.092**	0.427***	0.040*
	(0.05)	(0.04)	(0.04)	(0.02)
$\epsilon_{t-3} \times IRProj$	-0.306***	0.092**	-0.016	-0.065**
	(0.07)	(0.04)	(0.05)	(0.03)
$\epsilon_{t-3} \times DualProj$	-0.212***	0.118***	-0.327***	-0.033
	(0.07)	(0.04)	(0.10)	(0.05)
$\epsilon_{t-3} \times ADProj$	-0.223***	0.150***	-0.225***	0.115***
	(0.05)	(0.04)	(0.05)	(0.03)
ϵ_{t-4}	0.095***	-0.014	0.322***	0.018
	(0.03)	(0.06)	(0.05)	(0.01)
$\epsilon_{t-4} \times IRProj$	-0.184***	-0.022	0.021	-0.019
	(0.03)	(0.06)	(0.05)	(0.02)
$\epsilon_{t-4} \times DualProj$	-0.199***	-0.015	-0.129**	0.025
	(0.04)	(0.06)	(0.06)	(0.02)
$\epsilon_{t-4} \times ADProj$	-0.156***	0.000	-0.225***	0.103***
	(0.03)	(0.06)	(0.05)	(0.02)
α	11.438***	4.000***	19.659*	12.824*
	(1.61)	(1.34)	(10.47)	(6.97)
SD r_t^n	125.60	125.60	155.82	155.82
N	699	699	697	697
χ^2	18393.8	1831.3	7927.4	11898.8

(I) This table presents results from a series of random effects panel regressions. The dependent variables are individual-level output and inflation forecast errors from all relevant periods of play. ϵ_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. α 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 - treatment effects[I]

	Absolute Forecast Errors							
	Output Gap Forecast Errors				Inflation Forecast Errors			
	Repetition 1		Repetition 2		Repetition 1		Repetition 2	
IRProj	0.346	-3.479	0.130	1.806	0.714*	-7.109*	-0.256	-1.416
	(0.30)	(2.18)	(0.15)	(1.53)	(0.43)	(3.73)	(0.25)	(2.33)
DualProj	-0.609***	0.331	-0.541***	-0.045	-0.604*	1.839	-1.039***	-1.035
	(0.23)	(2.31)	(0.21)	(2.61)	(0.33)	(2.63)	(0.22)	(2.71)
ADProj	-0.888***	-0.207	-0.779***	-0.823	0.052	-2.266*	-0.053	0.509
	(0.18)	(1.31)	(0.21)	(1.92)	(0.13)	(1.18)	(0.21)	(2.25)
SD r_t^n		0.006		0.019***		-0.007		0.024*
		(0.00)		(0.01)		(0.01)		(0.01)
SD $r_t^n \times IRProj$		0.027*		-0.012		0.055**		0.008
		(0.02)		(0.01)		(0.03)		(0.02)
SD$r_t^n \times DualProj$		-0.007		-0.004		-0.018		-0.000
		(0.02)		(0.02)		(0.02)		(0.02)
SD $r_t^n \times ADProj$		-0.005		0.000		0.017*		-0.004
		(0.01)		(0.01)		(0.01)		(0.02)
α	4.235***	3.419***	4.064***	1.387	3.687***	4.667***	3.802***	0.422
	(0.07)	(0.53)	(0.12)	(1.01)	(0.09)	(0.82)	(0.16)	(1.99)
N	718	718	718	718	718	718	718	718
χ^2	33.07	42.21	31.43	110.1	6.617	29.41	30.82	138.0

(I) This table presents results from a series of population-averaged panel model with a log link. The dependent variables are individual-level absolute output and inflation forecast errors from all relevant periods of play. 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. α denotes the estimated constant. Robust standard errors are employed. $^*p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

Table 4: Median forecast disagreement by treatment and repetition

Treatment		Repetition–1		Repetition–2	
		Output	Inflation	Output	Inflation
NoComm					
	Mean	196.98	19.31	175.15	19.59
	std.	375.47	3.27	280.30	3.03
IRProj					
	Mean	55.65	35.06	49.60	20.84
	std.	29.89	21.85	8.05	9.56
DualProj					
	Mean	50.37	29.75	47.71	22.36
	std.	24.85	24.41	32.90	15.07
ADProj					
	Mean	32.91	26.40	30.07	21.91
	std.	4.06	6.22	3.95	5.30
Rank–sum test:		p–value	p–value	p–value	p–value
NoComm–IRProj		0.873	0.025	0.109	0.749
NoComm–DualProj		0.522	0.631	0.055	0.262
NoComm–ADProj		0.055	0.037	0.004	0.200
IRProj–DualProj		0.522	0.262	0.078	0.522
IRProj–ADProj		0.025	0.749	0.004	0.631
DualProj–ADProj		0.149	0.749	0.078	0.262

The entries are the average and the standard deviation of the session-level median disagreement of output and inflation forecasts at the session-repetition level. Disagreement is measured as the within-period standard deviation of a particular forecasted variable. N=6 observations per treatment. Signed rank tests reject the null hypothesis that the session-level median disagreements are equal to zero for all treatments and repetitions ($p = 0.028$ in all cases).

Table 5: Credibility of Central Bank Projections of Output and Inflation - By Treatment[I]

	IRProj		DualProj		ADProj	
Dep.Var: Prob(Utilized CB Forecast=1)	$E_{i,t}x_{t+1}$	$E_{i,t}\pi_{t+1}$	$E_{i,t}x_{t+1}$	$E_{i,t}\pi_{t+1}$	$E_{i,t}x_{t+1}$	$E_{i,t}\pi_{t+1}$
$\lvert FE^{cb}x_{t-1}\rvert$	-0.004*		-0.001		-0.002	
	(0.00)		(0.00)		(0.00)	
$\lvert FE^{cb}x_{t-1}\rvert^2$	0.000		0.000		0.000	
	(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
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
Experienced	0.147*	0.032	0.023	0.068	0.100	-0.025
	(0.08)	(0.09)	(0.17)	(0.18)	(0.16)	(0.15)
$\lvert FE^{cb}\pi_{t-1}\rvert$		-0.012**		-0.004		-0.008***
		(0.00)		(0.00)		(0.00)
$\lvert FE^{cb}\pi_{t-1}\rvert^2$		-0.000		-0.000		0.000***
		(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)
α	-0.004	-0.312	-0.905	-0.723	-0.063	0.152
	(0.46)	(0.50)	(0.98)	(0.98)	(0.90)	(0.86)
% 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
χ^2	23.37	60.23	42.07	74.49	27.66	64.45

(I) This table presents results from a series of random effects probit regressions. $*p < 0.10$, $**p < 0.05$, and $***p < 0.01$. $UtilizedCBxForecast_t$ and $UtilizedCB\pi Forecast_t$ are dummy variables that take the value of one if a subject's output and inflation forecast in period t about period $t+1$, respectively, were less than five basis points away from the central bank's projected forecast. $\lvert FE^{cb}x_{t-2}\rvert$ and $\lvert FE^{cb}\pi_{t-2}\rvert$ denote the absolute forecast errors the central bank made in period $t-2$ about period $t-1$ output and inflation, respectively. $\lvert FEx_{i,t-2}\rvert$ and $\lvert FE\pi_{i,t-2}\rvert$ 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 6: 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 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 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

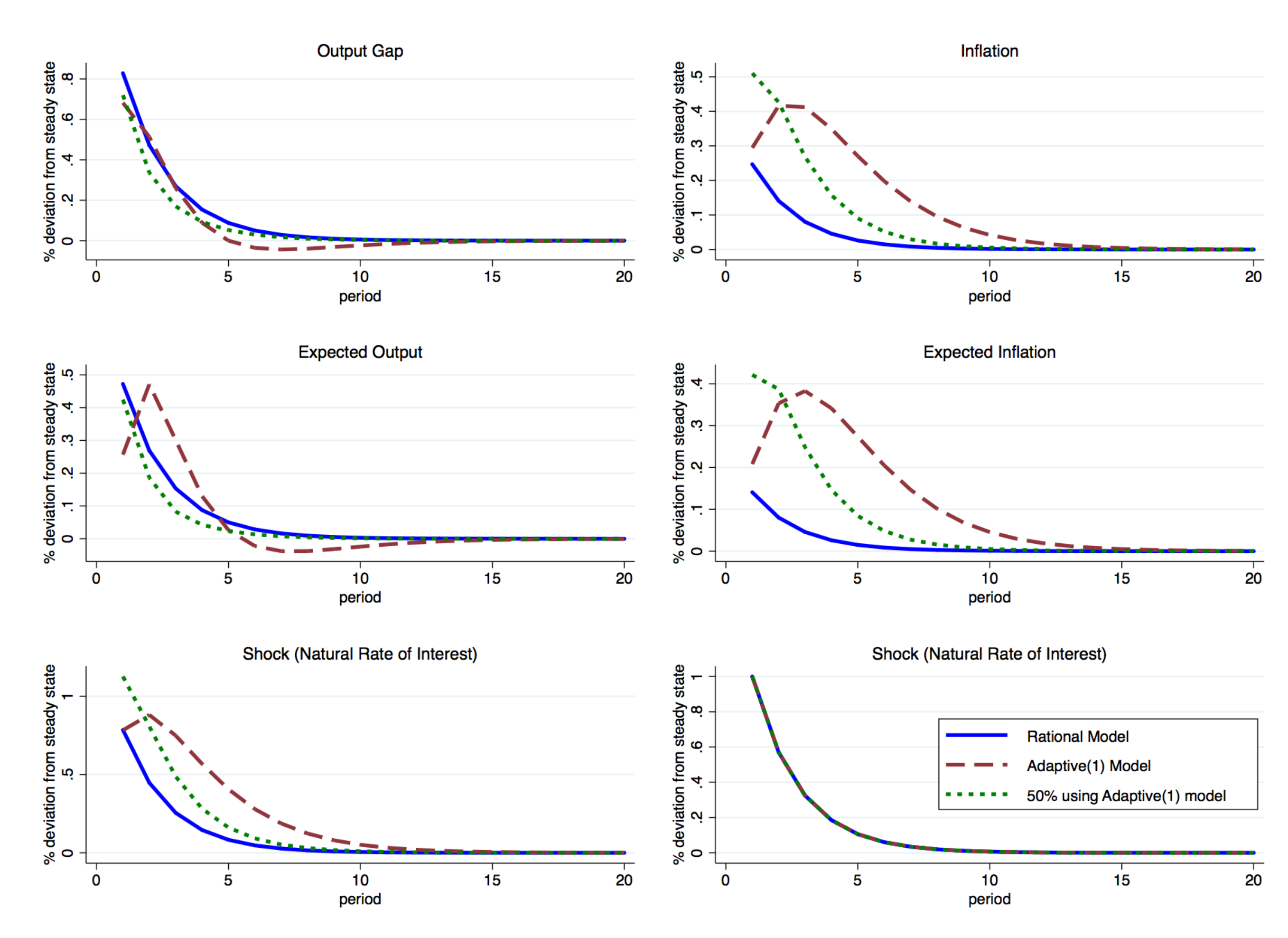


Figure 2: Screenshot from DualProj Treatment

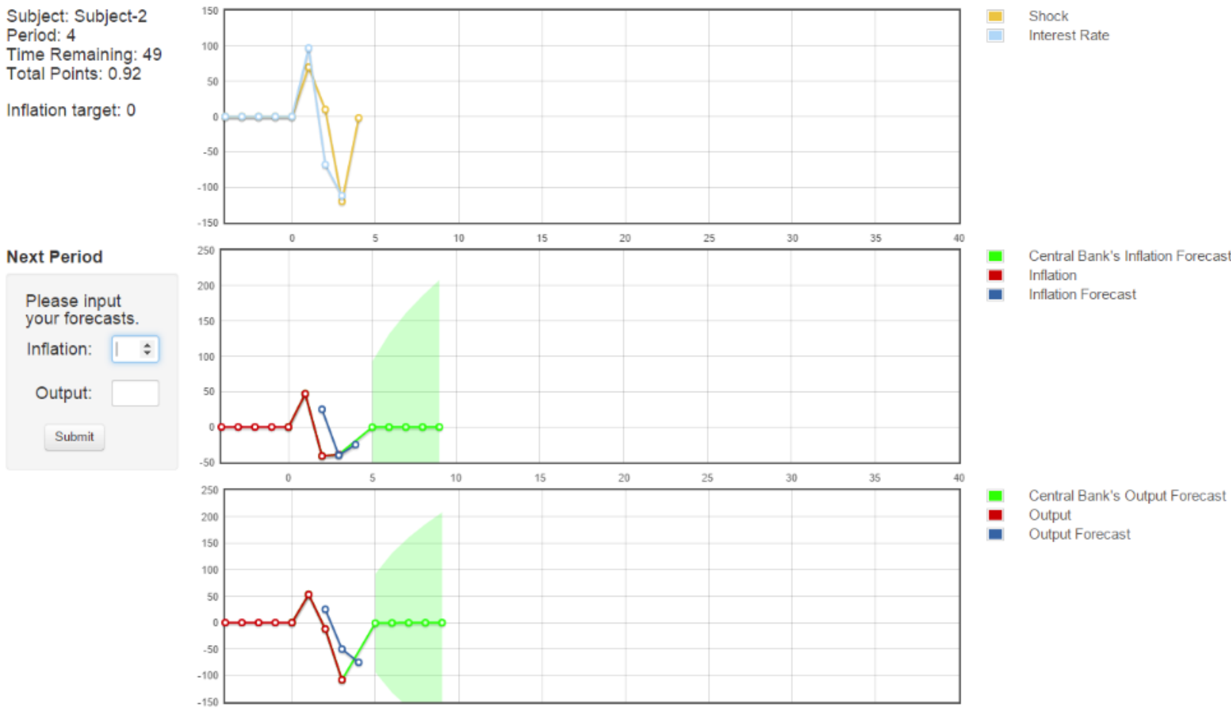
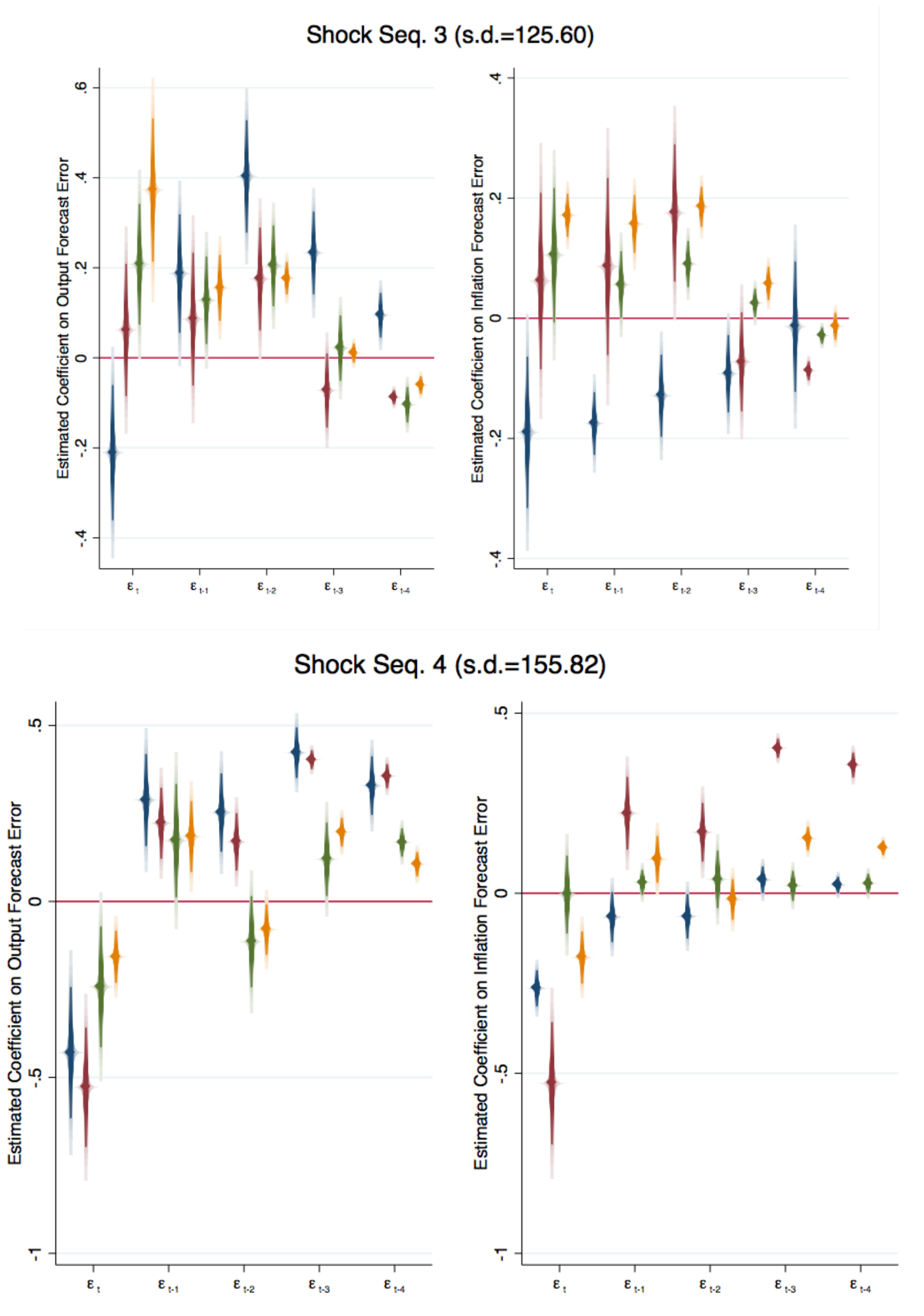
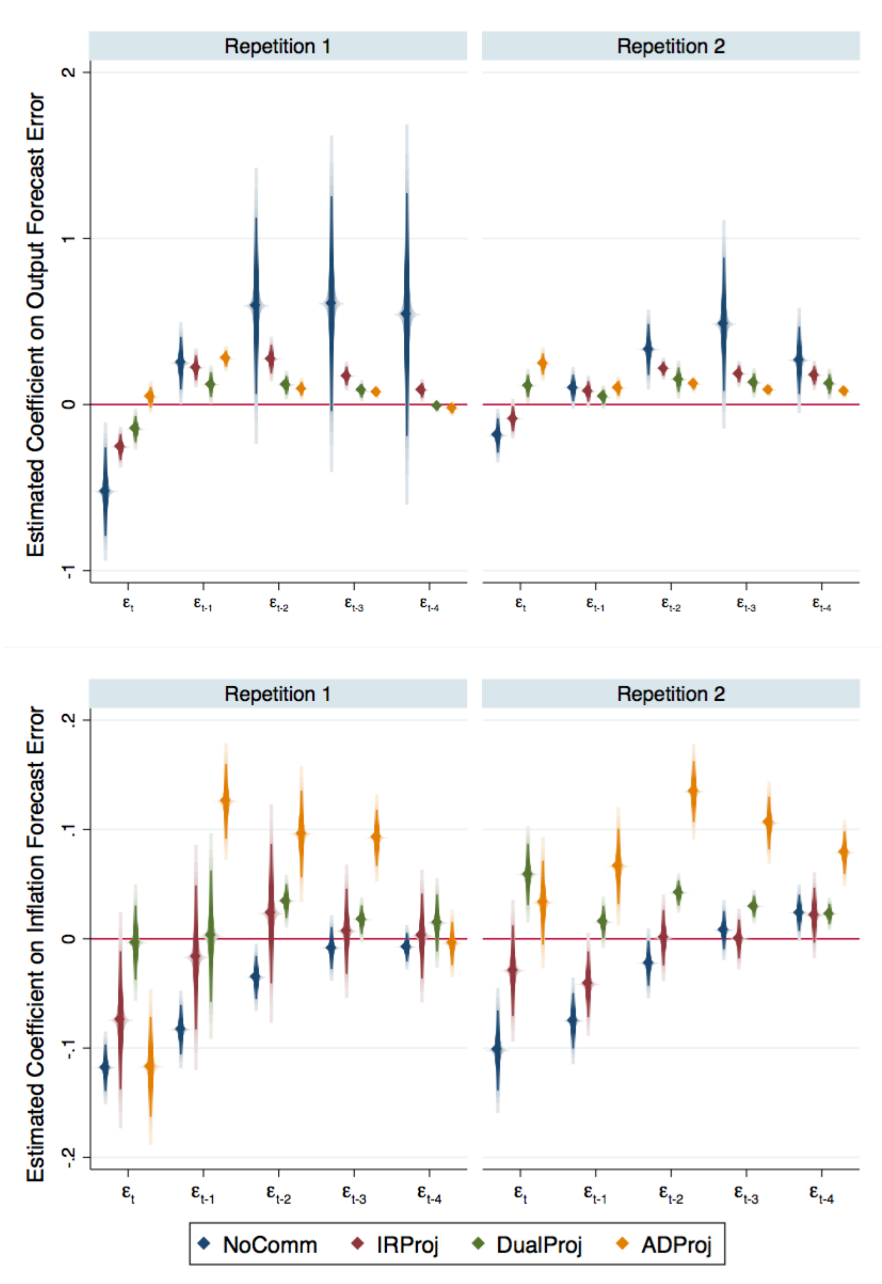


Figure 3: Coefficient plots - Output and inflation forecast errors - Least and most volatile experienced shock sequences



The figure shows the estimated coefficients associated with regressing current output and inflation forecast errors on current and lagged innovations to the natural rate of interest. Sequences 3 and 4 involve the least and most volatility to the natural rate of interest.

Figure 4: Coefficient plots - Output and inflation forecast errors



The figure shows the estimated coefficients associated with regressing current output and inflation forecast errors on current and lagged innovations to the natural rate of interest.

Figure 5: Kernel densities of absolute output and inflation forecast errors

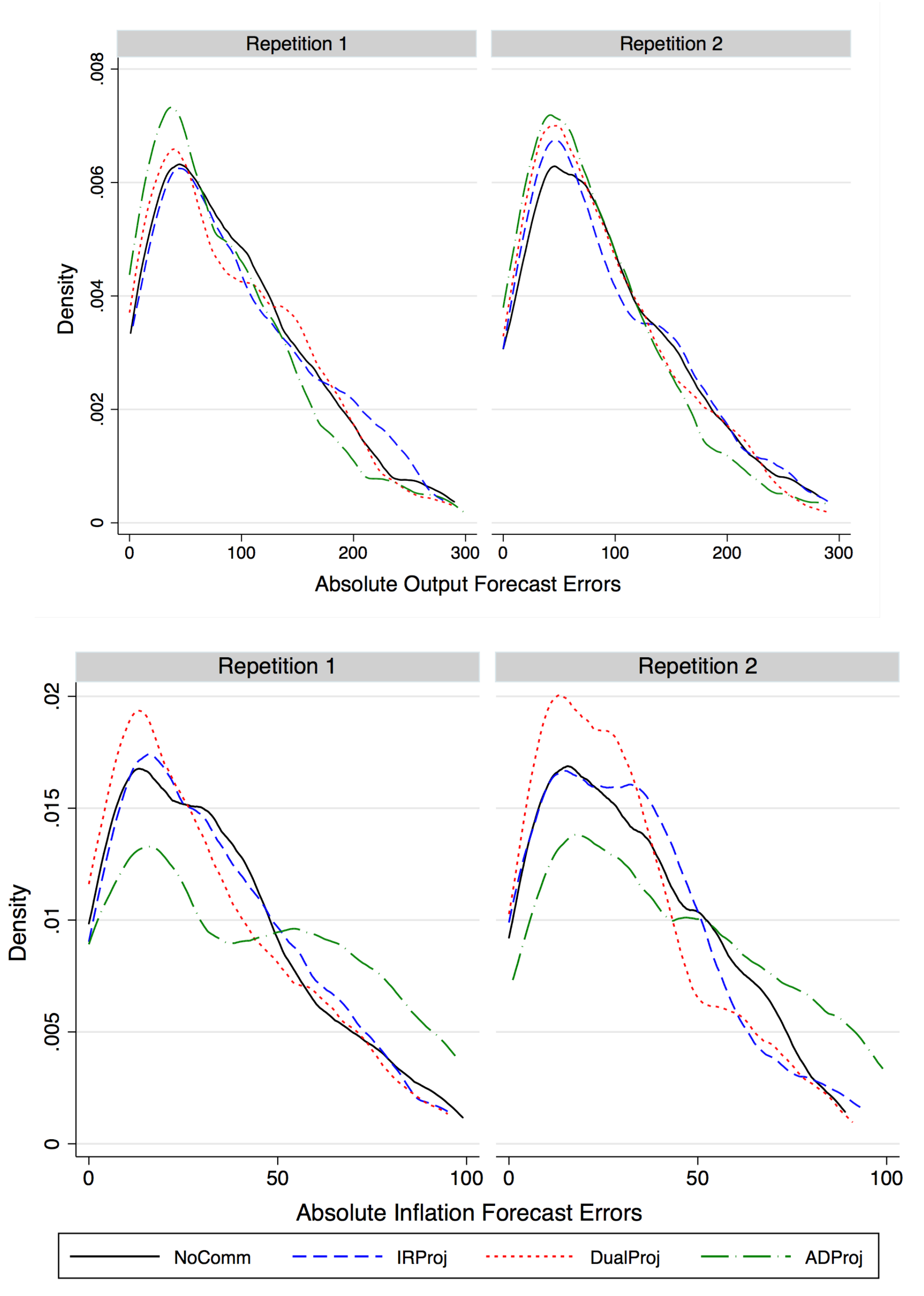


Figure 6: Kernel densities of absolute deviation of output and inflation forecasts from the REE prediction

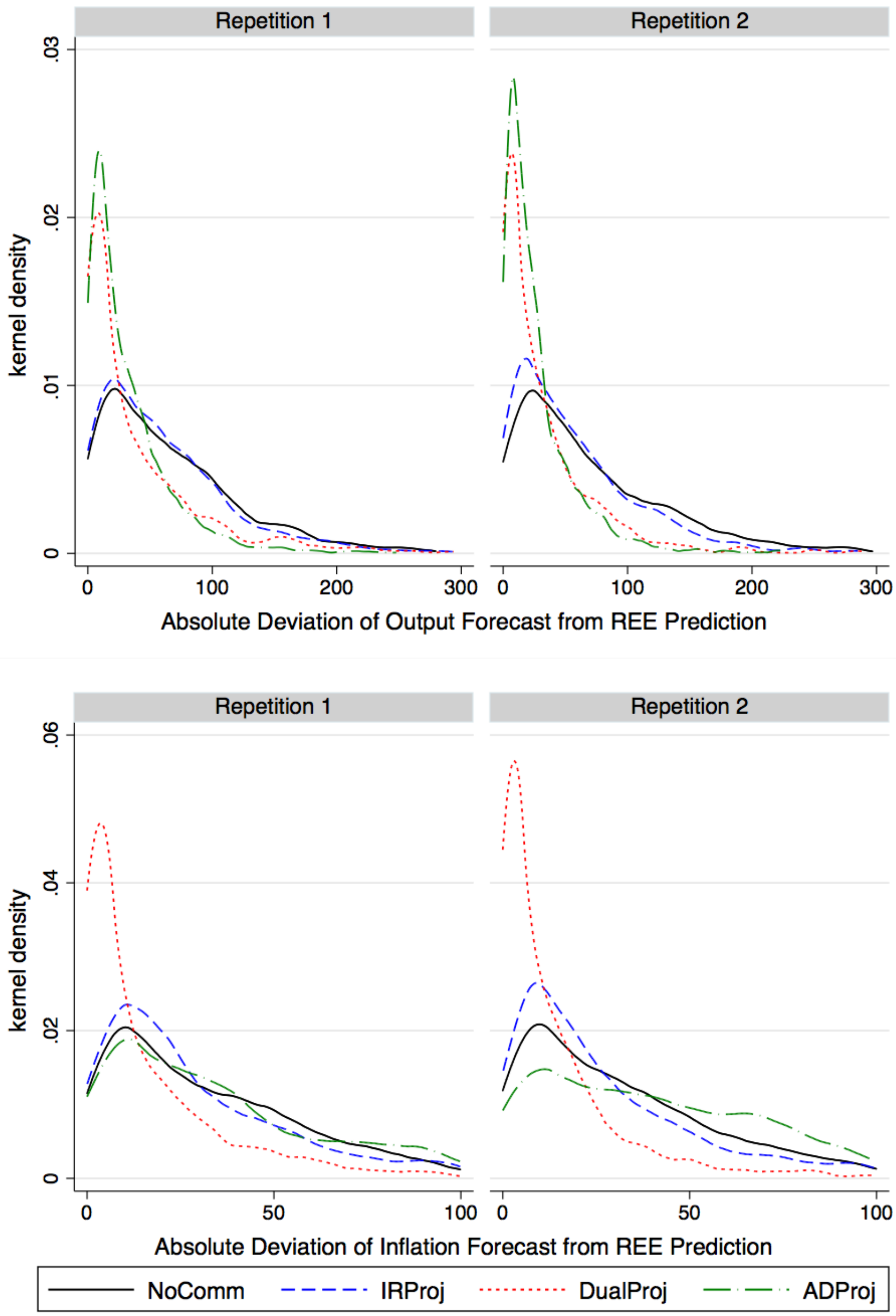


Figure 7: Percentage of output and inflation forecasts within five basis points of the CB's projected value, session means

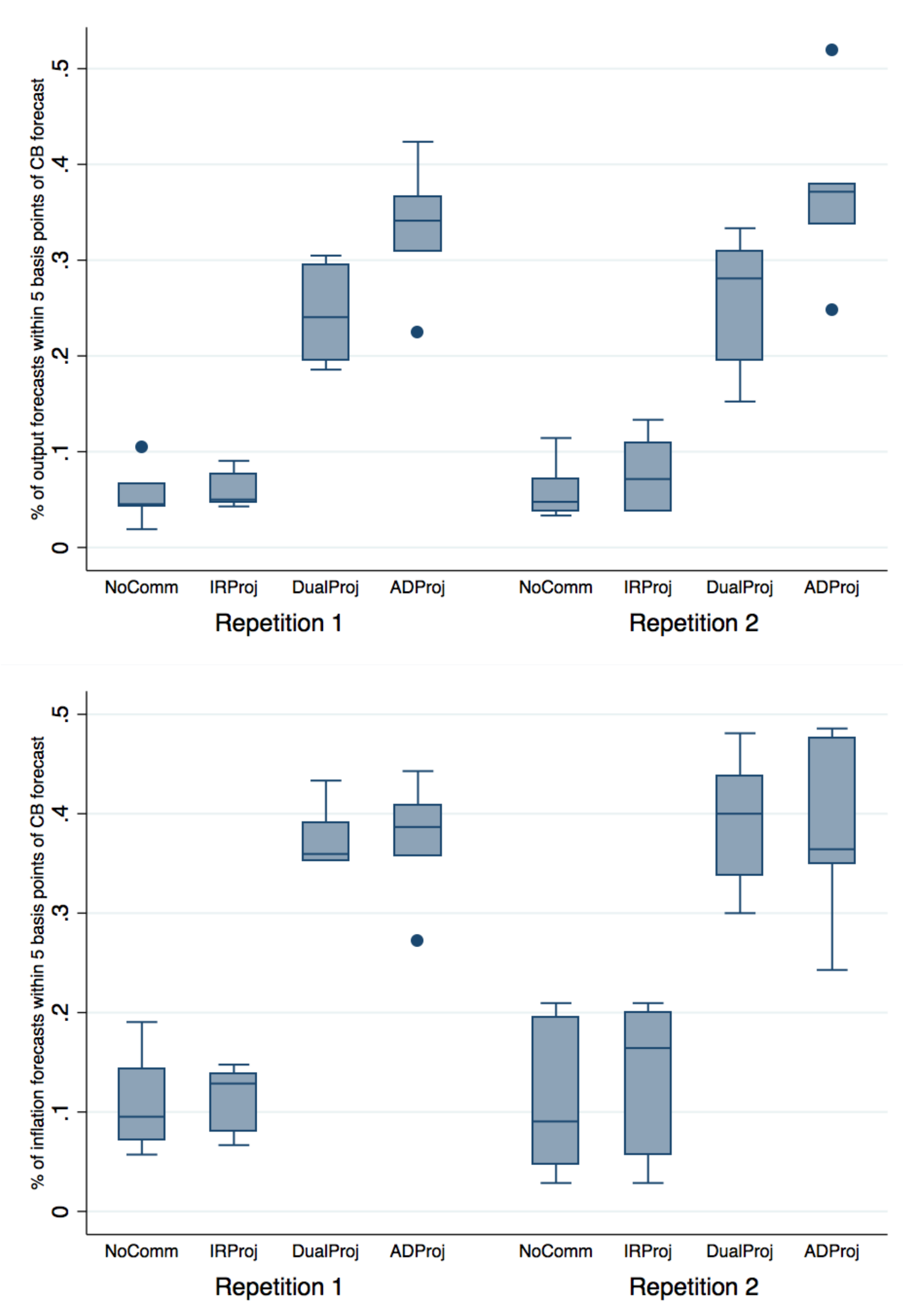


Figure 8: Estimated Impulse Responses of Endogenous Variables to 113 basis points shock

The figure shows the impulse responses of the variables to one standard deviation of the shock in basis points.

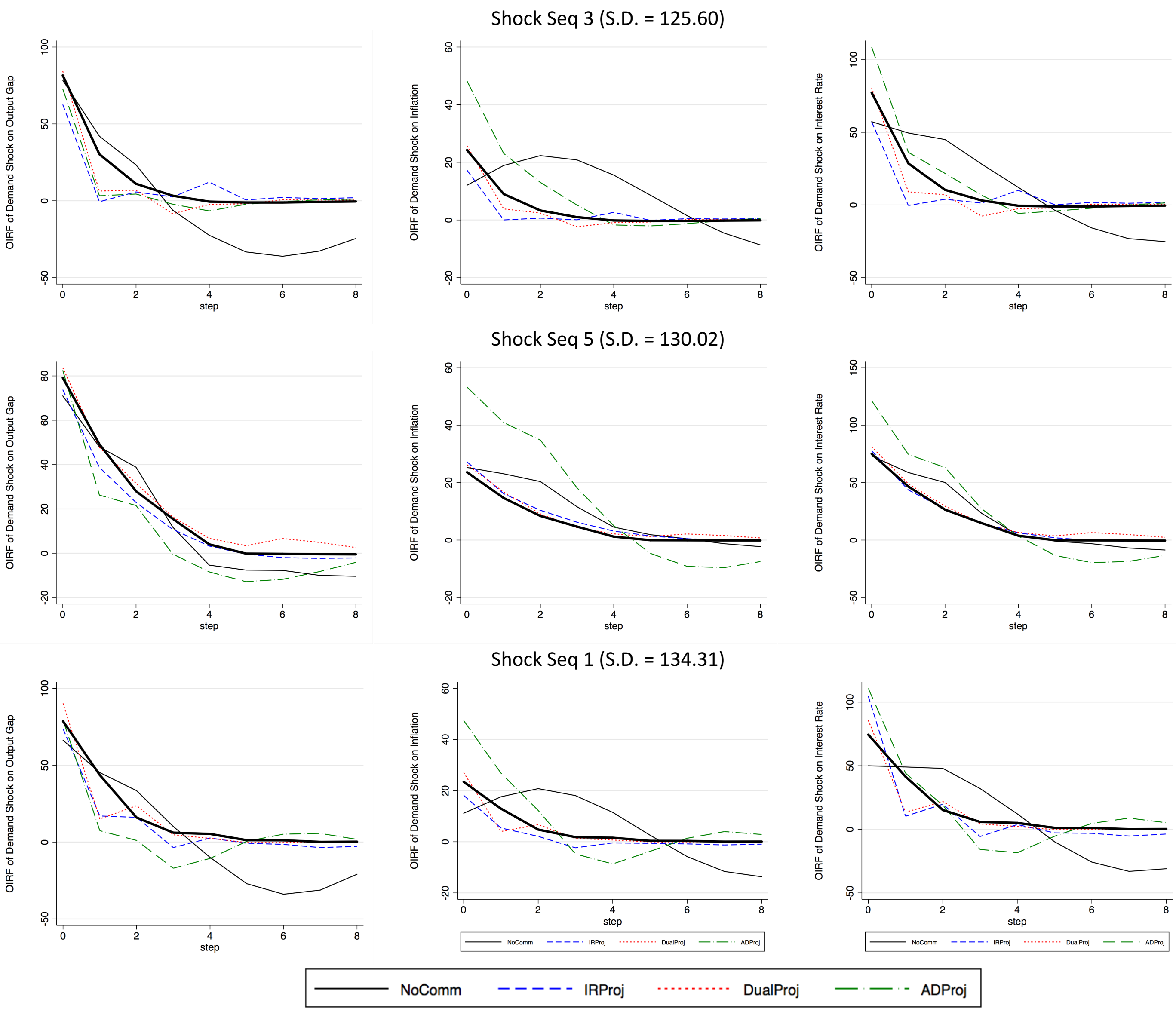


Figure 8: Estimated impulse responses of endogenous variables to 113 basis point shock

The figure shows the impulse responses of the variables to one standard deviation of the shock in basis points.

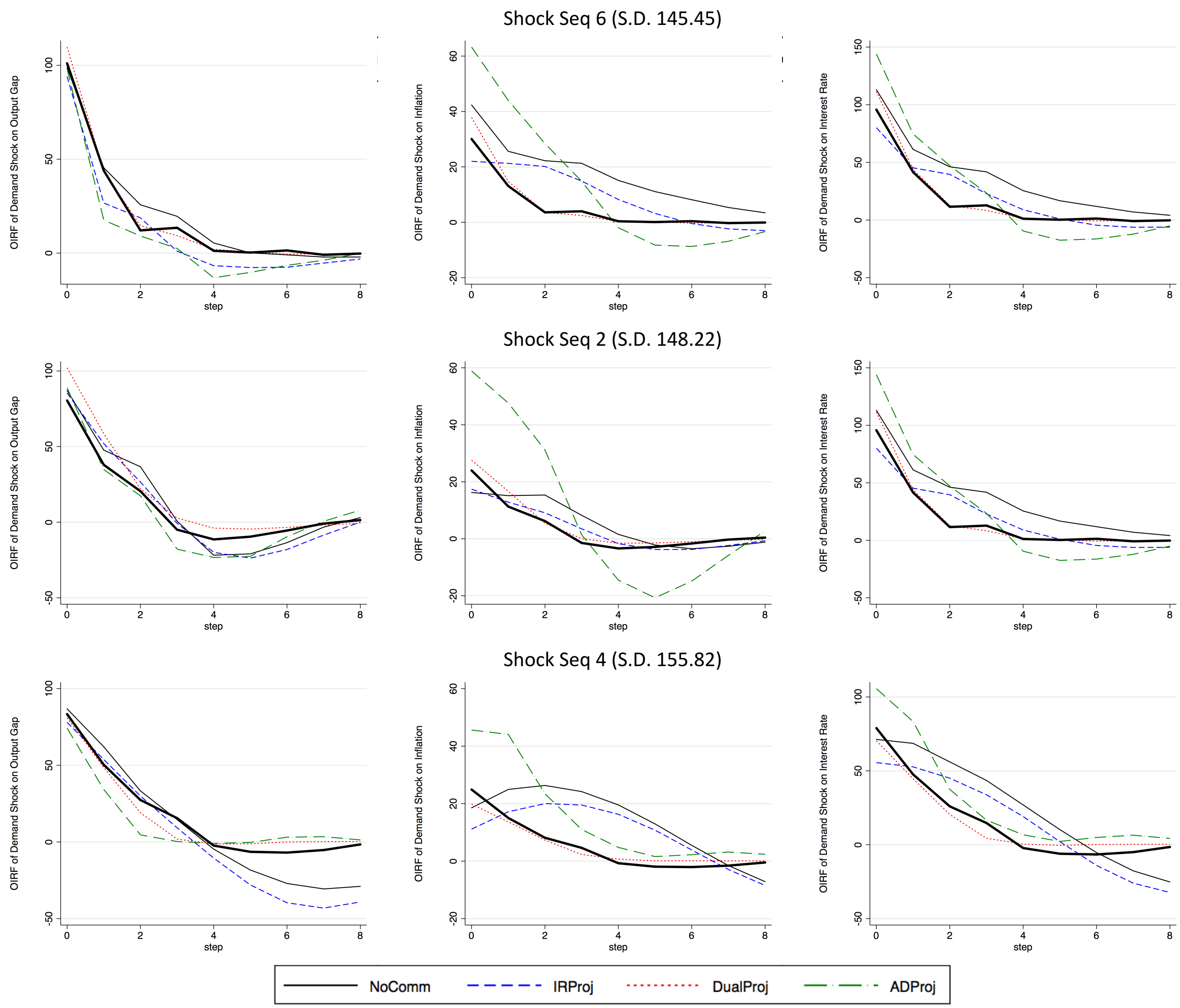
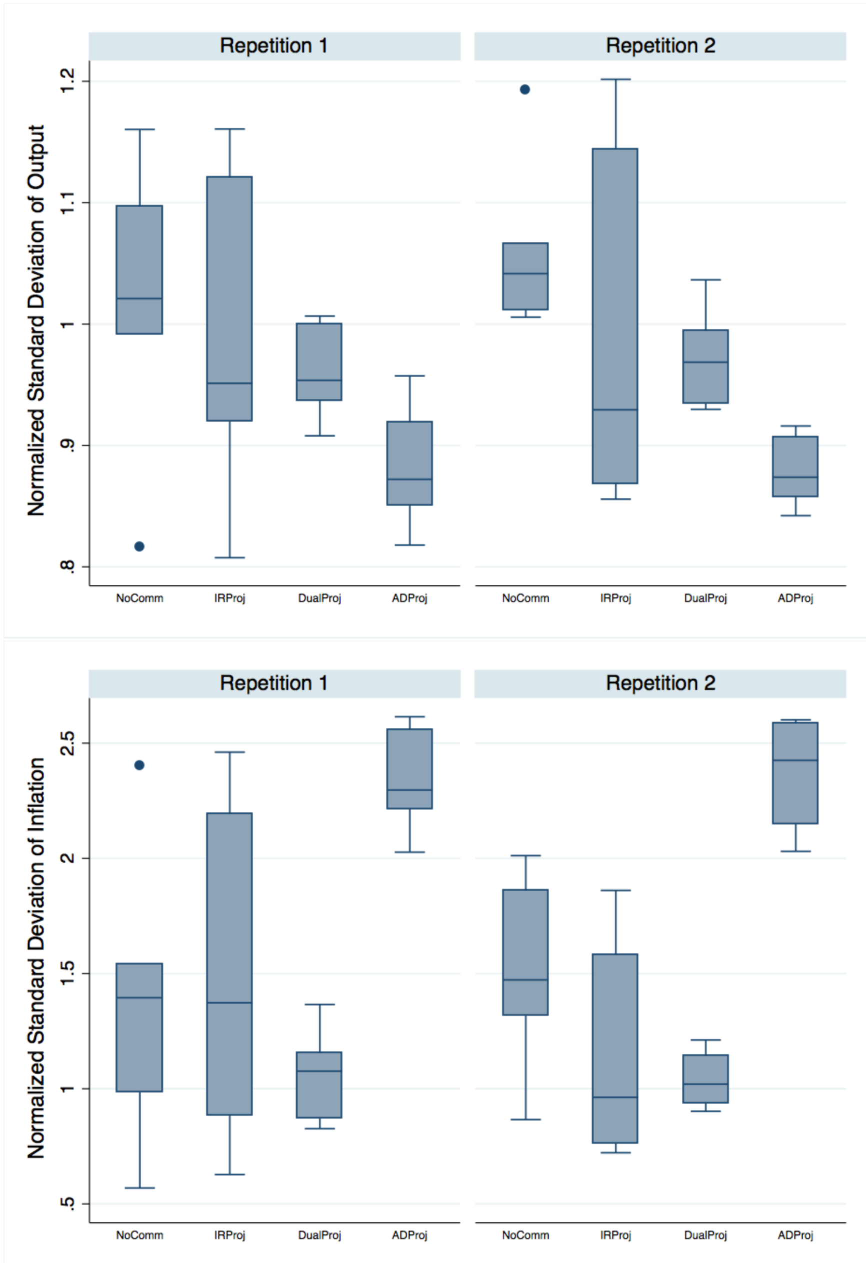
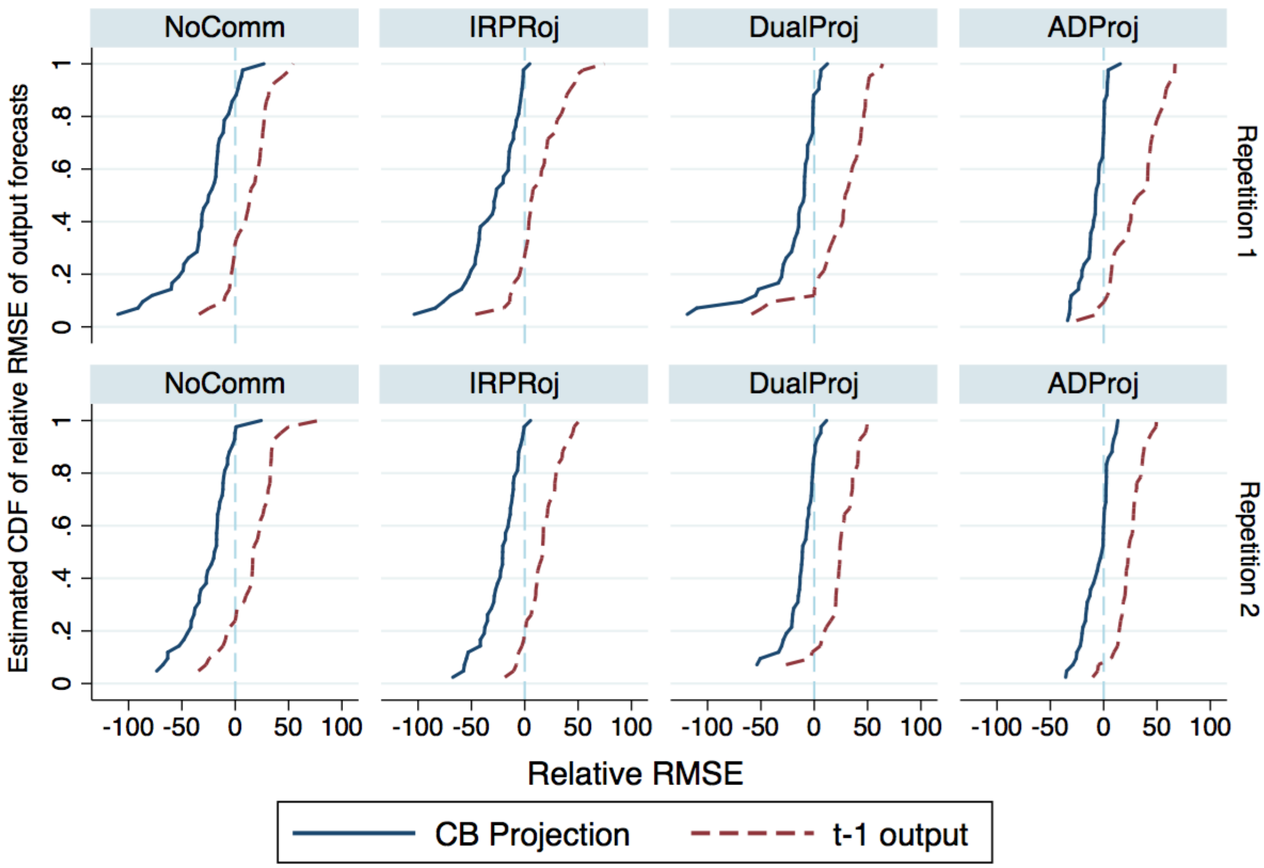


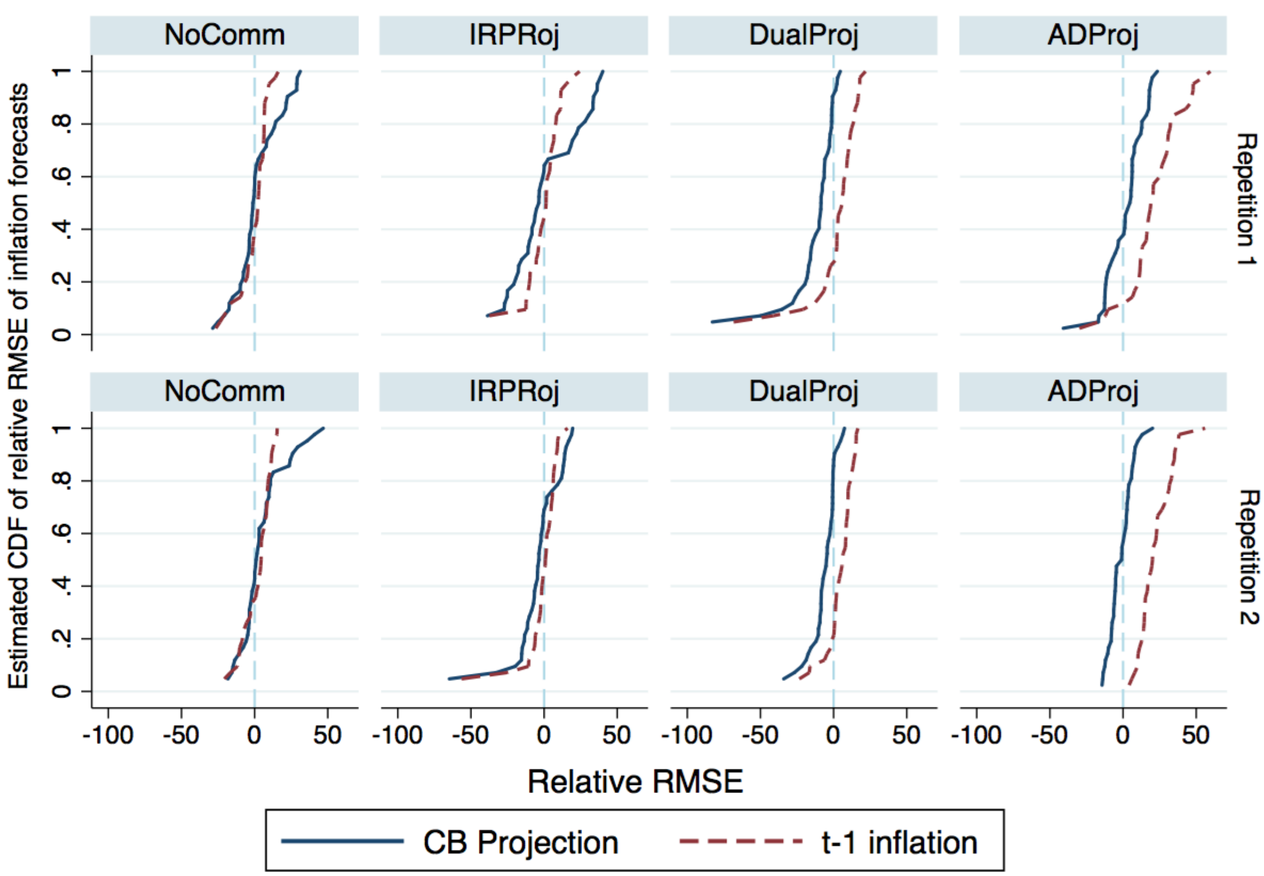
Figure 9: Standard deviation of output and inflation normalized by REE



The figure represents the standard deviation of output and inflation at the treatment-repetition level.

Figure 10: Distribution of adjustment in RMSE under counterfactual forecasting heuristics, by repetition





8. Appendix A–Solving the model under rational expectations

Replace equation (2) and (3) into (1):

$$x_t = E_t x_{t+1} - \sigma^{-1}\{\phi_\pi(\kappa x_t + \beta E_t \pi_{t+1}) + \phi_x x_t - E_t \pi_{t+1} - r_t^n\} \tag{12}$$

Rearrange the equation:

$$x_t = E_t x_{t+1} - \sigma^{-1}(\phi_\pi \kappa + \phi_x) x_t - \sigma^{-1}(\phi_\pi \beta - 1) E_t \pi_{t+1} + \sigma^{-1} r_t^n \tag{13}$$

$$[1 + \sigma^{-1}(\phi_\pi \kappa + \phi_x)] x_t = E_t x_{t+1} - \sigma^{-1}(\phi_\pi \beta - 1) E_t \pi_{t+1} + \sigma^{-1} r_t^n \tag{14}$$

We get:

$$x_t = \frac{1}{1 + \sigma^{-1}(\phi_\pi \kappa + \phi_x)} E_t x_{t+1} - \frac{\sigma^{-1}(\phi_\pi \beta - 1)}{1 + \sigma^{-1}(\phi_\pi \kappa + \phi_x)} E_t \pi_{t+1} + \frac{\sigma^{-1}}{1 + \sigma^{-1}(\phi_\pi \kappa + \phi_x)} r_t^n \tag{15}$$

Replace equation(8) into (2):

$$\pi_t = \kappa x_t + \beta E_t \pi_{t+1}, \tag{16}$$

$$\begin{aligned} \pi_t = \kappa\{ & \frac{1}{1 + \sigma^{-1}(\phi_\pi \kappa + \phi_x)} E_t x_{t+1} - \frac{\sigma^{-1}(\phi_\pi \beta - 1)}{1 + \sigma^{-1}(\phi_\pi \kappa + \phi_x)} E_t \pi_{t+1} + \\ & \frac{\sigma^{-1}}{1 + \sigma^{-1}(\phi_\pi \kappa + \phi_x)} r_t^n\} + \beta E_t \pi_{t+1} \end{aligned} \tag{17}$$

We get:

$$\begin{aligned} \pi_t = & \frac{\kappa}{1 + \sigma^{-1}(\phi_\pi \kappa + \phi_x)} E_t x_{t+1} + (\frac{\beta + \beta \sigma^{-1} \phi_x + \kappa \sigma^{-1}}{1 + \sigma^{-1}(\phi_\pi \kappa + \phi_x)}) E_t \pi_{t+1} \\ & + \frac{\kappa \sigma^{-1}}{1 + \sigma^{-1}(\phi_\pi \kappa + \phi_x)} r_t^n \end{aligned} \tag{18}$$

Solve for i_t:
Using equations 8 and 11 we get:

$$i_t = \frac{\phi_x + \phi_\pi \kappa}{1 + \sigma^{-1}(\phi_\pi \kappa + \phi_x)} E_t x_{t+1} + \frac{\phi_x \sigma^{-1} + \phi_\pi(\beta + \kappa \sigma^{-1})}{1 + \sigma^{-1}(\phi_\pi \kappa + \phi_x)} E_t \pi_{t+1} + \frac{\kappa \sigma^{-1} \phi_\pi + \sigma^{-1} \phi_x}{1 + \sigma^{-1}(\phi_\pi \kappa + \phi_x)} r_t^n \tag{19}$$

$$
\begin{aligned}
x_t &= \frac{1}{1+\sigma^{-1}(\phi_\pi\kappa+\phi_x)}E_t x_{t+1} - \frac{\sigma^{-1}(\phi_\pi\beta-1)}{1+\sigma^{-1}(\phi_\pi\kappa+\phi_x)}E_t\pi_{t+1} + \frac{\sigma^{-1}}{1+\sigma^{-1}(\phi_\pi\kappa+\phi_x)}r_t^n, \\
\pi_t &= \frac{\kappa}{1+\sigma^{-1}(\phi_\pi\kappa+\phi_x)}E_t x_{t+1} + \frac{\beta+\beta\sigma^{-1}\phi_x+\kappa\sigma^{-1}}{1+\sigma^{-1}(\phi_\pi\kappa+\phi_x)}E_t\pi_{t+1} + \frac{\kappa\sigma^{-1}}{1+\sigma^{-1}(\phi_\pi\kappa+\phi_x)}r_t^n, \\
i_t &= \frac{\phi_x+\phi_\pi\kappa}{1+\sigma^{-1}(\phi_\pi\kappa+\phi_x)}E_t x_{t+1} + \frac{\phi_x\sigma^{-1}+\phi_\pi(\beta+\kappa\sigma^{-1})}{1+\sigma^{-1}(\phi_\pi\kappa+\phi_x)}E_t\pi_{t+1} + \frac{\kappa\sigma^{-1}\phi_\pi+\sigma^{-1}\phi_x}{1+\sigma^{-1}(\phi_\pi\kappa+\phi_x)}r_t^n
\end{aligned}
$$

Results:

$$
\begin{aligned}
x_t &= 0.58997 \times E_t x_{t+1} - 0.28525 \times E_t\pi_{t+1} + 0.58997 \times r_t^n, \\
\pi_t &= 0.076696 \times E_t x_{t+1} + 0.95192 \times E_t\pi_{t+1} + 0.076696 \times r_t^n, \\
i_t &= 0.41004 \times E_t x_{t+1} + 1.2853 \times E_t\pi_{t+1} + 0.41003 \times r_t^n
\end{aligned}
$$

Under rational expectation, the transition path of interested variables are as the following:

$$
\begin{aligned}
x_t &= 0.472198 \times r_{t-1}^n + 0.82847 \times \epsilon_t, \\
\pi_t &= 0.140706 \times r_{t-1}^n + 0.246852 \times \epsilon_t, \\
i_t &= 0.447157 \times r_{t-1}^n + 0.784487 \times \epsilon_t, \\
E_{t-1}x_t &= 0.269153 \times r_{t-1}^n + 0.472198 \times \epsilon_t, \\
E_{t-1}\pi_t &= 0.080202 \times r_{t-1}^n + 0.140706 \times \epsilon_t
\end{aligned}
$$

9. Appendix B–Additional Results

Table 7: Effects of central bank projections on forecast errors[I]

	Output Forecast Errors								Inflation Forecast Errors							
	NoComm		IRProj		DualProj		ADProj		NoComm		IRProj		DualProj		ADProj	
ϵ_t	-0.356***	2.491	-0.177***	1.184***	-0.013	1.525***	0.080**	2.334***	-0.111***	0.162	-0.053**	0.421	0.028**	0.566***	0.010	0.696***
	(0.10)	(1.63)	(0.03)	(0.35)	(0.03)	(0.40)	(0.04)	(0.35)	(0.01)	(0.15)	(0.02)	(0.31)	(0.01)	(0.13)	(0.02)	(0.12)
ϵ_{t-1}	0.170***	-1.154*	0.136***	-1.227***	0.074***	-0.594*	0.078***	-0.644***	-0.081***	-0.086	-0.031	-0.250	0.007	-0.505	0.005	-0.128*
	(0.05)	(0.67)	(0.03)	(0.30)	(0.03)	(0.34)	(0.03)	(0.23)	(0.01)	(0.13)	(0.02)	(0.32)	(0.02)	(0.42)	(0.01)	(0.07)
ϵ_{t-2}	0.468***	-2.367	0.245***	-0.776**	0.145***	-0.175	0.143***	-0.296	-0.029***	-0.034	0.013	-0.348	0.039***	-0.137	0.031***	-0.041
	(0.17)	(2.51)	(0.03)	(0.33)	(0.03)	(0.45)	(0.02)	(0.32)	(0.01)	(0.11)	(0.02)	(0.29)	(0.01)	(0.15)	(0.01)	(0.11)
ϵ_{t-3}	0.556**	-2.293	0.168***	-0.558**	0.100***	-0.197	0.075***	-0.281*	-0.002	-0.119	0.002	-0.171	0.023***	-0.050	0.023***	-0.109**
	(0.24)	(3.10)	(0.02)	(0.25)	(0.02)	(0.29)	(0.02)	(0.15)	(0.01)	(0.08)	(0.01)	(0.16)	(0.00)	(0.05)	(0.01)	(0.06)
ϵ_{t-4}	0.396*	-3.209	0.126***	-0.447*	0.059***	-0.188	0.029**	-0.049	0.008	-0.116	0.011	-0.329**	0.019***	0.026	0.005	-0.012
	(0.22)	(3.49)	(0.02)	(0.23)	(0.02)	(0.28)	(0.01)	(0.16)	(0.01)	(0.10)	(0.01)	(0.14)	(0.01)	(0.15)	(0.01)	(0.06)
$\epsilon_t \times SDshock$		-0.020*		-0.010***		-0.011***		-0.016***		-0.002*		-0.003		-0.004***		-0.005***
		(0.01)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)
$\epsilon_{t-1} \times SDshock$		0.010*		0.010***		0.005**		0.005***		0.000		0.002		0.004		0.001*
		(0.01)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)
$\epsilon_{t-2} \times SDshock$		0.020		0.007***		0.002		0.003		0.000		0.002		0.001		0.000
		(0.02)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)
$\epsilon_{t-3} \times SDshock$		0.019		0.005***		0.002		0.002**		0.001		0.001		0.001		0.001**
		(0.02)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)
$\epsilon_{t-4} \times SDshock$		0.025		0.004**		0.002		0.000		0.001		0.002**		-0.000		0.000
		(0.03)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)
α	64.549*	64.555*	12.049***	11.969***	26.961***	26.725***	15.687***	15.452***	3.034***	2.991***	3.279	3.285	12.557**	12.461**	5.895***	5.811***
	(35.75)	(35.91)	(2.88)	(2.89)	(6.49)	(6.53)	(2.15)	(2.08)	(0.92)	(0.92)	(2.14)	(2.18)	(5.57)	(5.57)	(1.04)	(1.02)
N	2096	2096	2094	2094	2091	2091	2098	2098	2096	2096	2094	2094	2091	2091	2098	2098
χ^2	68.89	96.01	132.8	194.2	34.29	141.6	58.07	163.8	137.8	203.8	25.52	103.8	72.90	104.2	30.06	111.4

(I) This table presents results from a series of random effects panel regressions. The dependent variables are individual-level output and inflation forecast errors from all relevant periods of play. ϵ_t denotes the random innovation that occurs in period t. α denotes the estimated constant. Robust standard errors are employed. $^*p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

Table 8: Effects of central bank projections on forecast errors[I]

	Output Forecast Errors								Inflation Forecast Errors							
	NoComm		IRProj		DualProj		ADProj		NoComm		IRProj		DualProj		ADProj	
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
ϵ_t	-0.524***	4.512*	-0.256***	0.781*	-0.148***	1.660***	-0.019	1.694***	-0.118***	0.308***	-0.075*	-0.047	-0.004	0.614***	-0.015	0.505***
	(0.16)	(2.40)	(0.05)	(0.46)	(0.05)	(0.49)	(0.05)	(0.36)	(0.01)	(0.12)	(0.04)	(0.42)	(0.02)	(0.12)	(0.01)	(0.12)
ϵ_{t-1}	0.250***	-1.086	0.221***	-1.361***	0.120***	-0.710	0.173***	-0.797**	-0.083***	0.071	-0.017	-0.733*	0.002	-0.946	0.039***	-0.161*
	(0.10)	(0.77)	(0.05)	(0.35)	(0.04)	(0.49)	(0.04)	(0.33)	(0.01)	(0.14)	(0.04)	(0.42)	(0.04)	(0.79)	(0.01)	(0.09)
ϵ_{t-2}	0.594*	-4.257	0.274***	-1.252***	0.117***	-1.009**	0.165***	-0.877**	-0.035***	0.018	0.023	-0.898**	0.034***	-0.375	0.036***	-0.271*
	(0.32)	(3.22)	(0.05)	(0.43)	(0.03)	(0.50)	(0.04)	(0.42)	(0.01)	(0.11)	(0.04)	(0.36)	(0.01)	(0.25)	(0.01)	(0.14)
ϵ_{t-3}	0.607	-4.428	0.172***	0.140	0.083***	-0.292	0.081***	-0.004	-0.008	-0.096	0.007	-0.310	0.017**	0.030	0.017*	-0.003
	(0.39)	(3.68)	(0.03)	(0.34)	(0.02)	(0.24)	(0.02)	(0.19)	(0.01)	(0.07)	(0.02)	(0.21)	(0.01)	(0.14)	(0.01)	(0.06)
ϵ_{t-4}	0.542	-5.134	0.086***	0.169	-0.010	-0.051	-0.020	0.210	-0.008	-0.134	0.002	-0.419*	0.014	0.237	0.002	0.044
	(0.44)	(4.98)	(0.03)	(0.32)	(0.02)	(0.21)	(0.02)	(0.18)	(0.01)	(0.08)	(0.02)	(0.22)	(0.02)	(0.35)	(0.01)	(0.06)
$\epsilon_t \times SDshock$		-0.035**		-0.007**		-0.013***		-0.012***		-0.003***		-0.000		-0.004***		-0.004***
		(0.02)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)
$\epsilon_{t-1} \times SDshock$		0.010		0.011***		0.006*		0.007***		-0.001		0.005		0.007		0.001**
		(0.01)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.01)		(0.00)
$\epsilon_{t-2} \times SDshock$		0.033		0.010***		0.007**		0.007**		-0.000		0.006**		0.003		0.002**
		(0.02)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)
$\epsilon_{t-3} \times SDshock$		0.034		0.000		0.002		0.000		0.001		0.002		-0.000		0.000
		(0.03)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)
$\epsilon_{t-4} \times SDshock$		0.039		-0.000		0.000		-0.002		0.001		0.003*		-0.001		-0.000
		(0.04)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)
α	74.933	72.470	20.865***	19.681***	34.123***	32.704***	25.022***	23.728***	2.814**	2.682**	5.571	5.367	16.961*	16.073*	8.282***	7.952***
	(55.52)	(54.50)	(5.80)	(5.81)	(8.42)	(8.46)	(2.15)	(2.14)	(1.30)	(1.27)	(5.38)	(5.37)	(10.09)	(9.67)	(1.42)	(1.43)
N	1048	1048	1047	1047	1043	1043	1048	1048	1048	1048	1047	1047	1043	1043	1048	1048
χ^2	74.99	151.4	77.88	129.1	37.04	109.6	50.99	180.9	129.1	255.9	13.61	78.14	19.38	66.73	24.66	87.67

	Output Forecast Errors								Inflation Forecast Errors							
	NoComm		IRProj		DualProj		ADProj		NoComm		IRProj		DualProj		ADProj	
ϵ_t	-0.187***	-0.788	-0.086*	1.532***	0.112***	0.957*	0.187***	3.250***	-0.102***	-0.054	-0.029	1.169***	0.059***	0.400	0.037	1.045***
	(0.06)	(0.71)	(0.05)	(0.57)	(0.04)	(0.53)	(0.06)	(0.58)	(0.02)	(0.35)	(0.03)	(0.26)	(0.02)	(0.26)	(0.03)	(0.32)
ϵ_{t-1}	0.100**	-0.249	0.079**	-0.795*	0.044	-0.076	0.012	0.206	-0.075***	-0.309	-0.042**	0.761***	0.015*	0.143	-0.021	0.132
	(0.05)	(0.52)	(0.04)	(0.43)	(0.03)	(0.40)	(0.04)	(0.39)	(0.02)	(0.23)	(0.02)	(0.24)	(0.01)	(0.13)	(0.03)	(0.26)
ϵ_{t-2}	0.331***	1.889	0.216***	0.046	0.150***	1.464**	0.115***	1.044***	-0.022*	-0.164	0.001	0.770***	0.042***	0.292***	0.026*	0.395***
	(0.09)	(1.24)	(0.03)	(0.29)	(0.04)	(0.72)	(0.02)	(0.26)	(0.01)	(0.22)	(0.02)	(0.19)	(0.01)	(0.10)	(0.01)	(0.15)
ϵ_{t-3}	0.483**	2.354	0.184***	-1.666***	0.130***	0.243	0.091***	-0.564**	0.008	-0.239	-0.000	0.249*	0.030***	0.000	0.035***	-0.274*
	(0.24)	(2.66)	(0.03)	(0.23)	(0.03)	(0.61)	(0.02)	(0.22)	(0.01)	(0.16)	(0.01)	(0.13)	(0.01)	(0.09)	(0.01)	(0.14)
ϵ_{t-4}	0.266**	0.344	0.176***	-1.920***	0.123***	-0.708	0.087***	-0.890***	0.024**	-0.170	0.022	-0.182	0.023***	-0.252***	0.012	-0.218**
	(0.12)	(1.69)	(0.03)	(0.17)	(0.04)	(0.62)	(0.02)	(0.21)	(0.01)	(0.20)	(0.02)	(0.11)	(0.01)	(0.06)	(0.01)	(0.09)
$\epsilon_t \times SDshock$		0.004		-0.012***		-0.006		-0.022***		-0.000		-0.009***		-0.002		-0.007***
		(0.01)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)
$\epsilon_{t-1} \times SDshock$		0.003		0.006**		0.001		-0.001		0.002		-0.006***		-0.001		-0.001
		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)
$\epsilon_{t-2} \times SDshock$		-0.011		0.001		-0.009*		-0.007***		0.001		-0.005***		-0.002***		-0.003**
		(0.01)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)
$\epsilon_{t-3} \times SDshock$		-0.013		0.013***		-0.001		0.005***		0.002		-0.002*		0.000		0.002**
		(0.02)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)
$\epsilon_{t-4} \times SDshock$	-0.000		0.015***		0.006		0.007***		0.001		0.001*		0.002***		0.002**	
		(0.01)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)		(0.00)
α	58.380	57.919	3.193	3.515	15.000*	15.019*	5.776*	6.788**	2.397*	2.400	0.939	1.313	6.884	6.844	3.617*	3.961*
	(52.66)	(52.82)	(2.48)	(2.49)	(8.65)	(8.52)	(3.02)	(3.19)	(1.45)	(1.46)	(1.65)	(1.60)	(4.62)	(4.47)	(2.12)	(2.25)
N	1048	1048	1047	1047	1048	1048	1050	1050	1048	1048	1047	1047	1048	1048	1050	1050
χ^2	32.47	218.8	169.6	395.2	28.48	542.7	155.3	305.6	45.76	100.0	19.77	148.0	125.1	171.2	85.75	186.7

(I) This table presents results from a series of random effects panel regressions. The dependent variables are individual-level output and inflation forecast errors from all relevant periods of play. ϵ_t denotes the random innovation that occurs in period t. α denotes the estimated constant. Robust standard errors are employed. $^*p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

Table 9: Effects of central bank projections on forecast errors, by shock sequence - Treatment Effects - Repetition 2[I]

	Panel A: Low variability shocks					
	Output F.E.	Inflation F.E.	Output F.E.	Inflation F.E.	Output F.E.	Inflation F.E.
	(1)	(2)	(3)	(4)	(5)	(6)
$epsilon_t$	-0.211***	-0.190***	-0.047	-0.041	-0.578*	-0.176***
	(0.07)	(0.03)	(0.13)	(0.03)	(0.35)	(0.02)
$\epsilon_t \times IRProj$	0.278***	0.249***	-0.065	0.121***	0.572	0.215***
	(0.10)	(0.04)	(0.19)	(0.04)	(0.49)	(0.03)
$\epsilon_t \times DualProj$	0.419***	0.295***	0.023	0.058	0.705	0.268***
	(0.10)	(0.04)	(0.19)	(0.04)	(0.49)	(0.03)
$\epsilon_t \times ADProj$	0.735***	0.336***	0.360*	0.135***	0.875*	0.258***
	(0.10)	(0.04)	(0.19)	(0.04)	(0.49)	(0.03)
ϵ_{t-1}	0.187**	-0.176***	0.112	-0.013	0.197	-0.187***
	(0.07)	(0.03)	(0.15)	(0.03)	(0.36)	(0.02)
$\epsilon_{t-1} \times IRProj$	-0.096	0.195***	-0.208	0.030	-0.300	0.179***
	(0.11)	(0.05)	(0.21)	(0.05)	(0.51)	(0.03)
$\epsilon_{t-1} \times DualProj$	-0.059	0.231***	-0.138	0.037	-0.385	0.169***
	(0.11)	(0.05)	(0.21)	(0.05)	(0.51)	(0.03)
$\epsilon_{t-1} \times ADProj$	-0.019	0.231***	-0.182	-0.060	-0.256	0.181***
	(0.11)	(0.05)	(0.21)	(0.05)	(0.51)	(0.03)
ϵ_{t-2}	0.403***	-0.129***	0.214	0.059*	1.276***	-0.085***
	(0.08)	(0.03)	(0.15)	(0.03)	(0.37)	(0.02)
$\epsilon_{t-2} \times IRProj$	-0.226**	0.169***	-0.030	0.033	-1.156**	0.102***
	(0.11)	(0.05)	(0.21)	(0.05)	(0.53)	(0.03)
$\epsilon_{t-2} \times DualProj$	-0.198*	0.219***	0.187	-0.014	-1.232**	0.100***
	(0.11)	(0.05)	(0.21)	(0.05)	(0.53)	(0.03)
$\epsilon_{t-2} \times ADProj$	-0.178*	0.202***	-0.064	-0.011	-1.186**	0.120***
	(0.11)	(0.05)	(0.21)	(0.05)	(0.53)	(0.03)
ϵ_{t-3}	0.233***	-0.092***	0.170	0.037	1.956***	-0.035
	(0.07)	(0.03)	(0.15)	(0.03)	(0.36)	(0.02)
$\epsilon_{t-3} \times IRProj$	-0.306***	0.092**	-0.054	0.018	-1.914***	0.013
	(0.11)	(0.05)	(0.21)	(0.05)	(0.51)	(0.03)
$\epsilon_{t-3} \times DualProj$	-0.212**	0.118**	0.098	-0.021	-1.929***	0.035
	(0.11)	(0.05)	(0.21)	(0.05)	(0.51)	(0.03)
$\epsilon_{t-3} \times ADProj$	-0.219**	0.101**	-0.007	0.015	-1.930***	0.036
	(0.11)	(0.05)	(0.21)	(0.05)	(0.51)	(0.03)
ϵ_{t-4}	0.095	-0.014	-0.040	-0.036	1.092***	0.001
	(0.07)	(0.03)	(0.15)	(0.03)	(0.34)	(0.02)
$\epsilon_{t-4} \times IRProj$	-0.184*	-0.022	0.041	0.050	-1.081**	-0.014
	(0.10)	(0.04)	(0.21)	(0.05)	(0.48)	(0.03)
$\epsilon_{t-4} \times DualProj$	-0.199**	-0.015	0.285	0.062	-1.042**	-0.004
	(0.10)	(0.04)	(0.21)	(0.05)	(0.48)	(0.03)
$\epsilon_{t-4} \times ADProj$	-0.176*	-0.008	0.044	0.018	-1.026**	0.000
	(0.10)	(0.04)	(0.21)	(0.05)	(0.48)	(0.03)
α	13.763***	4.133**	23.978***	4.719***	81.299***	-0.711
	(4.32)	(1.89)	(7.50)	(1.69)	(21.82)	(1.30)
SD r_t^n	125.60	125.60	130.02	130.02	134.31	134.31
N	699	699	700	700	699	699
χ^2	156.8	117.8	29.87	50.79	39.64	192.9

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

Table 9: Effects of central bank projections on forecast errors, by shock sequence - Treatment Effects - Repetition 2 - Continued[I]

	Panel A: High variability shocks					
	Output F.E.	Inflation F.E.	Output F.E.	Inflation F.E.	Output F.E.	Inflation F.E.
	(1)	(2)	(3)	(4)	(5)	(6)
$epsilon_t$	0.156**	0.065**	-0.081	-0.084*	-0.428***	-0.263***
	(0.07)	(0.03)	(0.08)	(0.05)	(0.08)	(0.04)
$\epsilon_t \times IRProj$	-0.068	-0.147***	-0.075	0.031	-0.097	0.057
	(0.10)	(0.05)	(0.12)	(0.07)	(0.12)	(0.06)
$\epsilon_t \times DualProj$	0.269***	0.077	0.093	0.085	0.181	0.256***
	(0.10)	(0.05)	(0.12)	(0.07)	(0.12)	(0.06)
$\epsilon_t \times ADProj$	0.113	0.028	-0.010	-0.024	0.161	0.185***
	(0.10)	(0.05)	(0.12)	(0.07)	(0.12)	(0.06)
ϵ_{t-1}	0.179***	0.011	0.045	-0.056	0.297***	-0.061
	(0.07)	(0.03)	(0.08)	(0.05)	(0.09)	(0.05)
$\epsilon_{t-1} \times IRProj$	0.177*	-0.097**	-0.077	0.044	-0.058	-0.092
	(0.10)	(0.05)	(0.11)	(0.07)	(0.13)	(0.07)
$\epsilon_{t-1} \times DualProj$	0.045	0.064	-0.071	0.038	-0.171	0.060
	(0.09)	(0.05)	(0.11)	(0.07)	(0.12)	(0.07)
$\epsilon_{t-1} \times ADProj$	0.037	0.066	-0.249**	-0.099	-0.149	0.107
	(0.09)	(0.05)	(0.11)	(0.07)	(0.12)	(0.07)
ϵ_{t-2}	0.167**	0.010	0.230***	0.013	0.258***	-0.061
	(0.07)	(0.03)	(0.08)	(0.05)	(0.09)	(0.04)
$\epsilon_{t-2} \times IRProj$	0.152	-0.053	-0.057	-0.015	-0.079	-0.064
	(0.09)	(0.05)	(0.11)	(0.06)	(0.12)	(0.06)
$\epsilon_{t-2} \times DualProj$	-0.027	0.037	-0.018	0.018	-0.400***	0.081
	(0.09)	(0.05)	(0.11)	(0.06)	(0.12)	(0.06)
$\epsilon_{t-2} \times ADProj$	-0.081	0.026	-0.130	-0.019	-0.295**	0.050
	(0.09)	(0.05)	(0.11)	(0.06)	(0.12)	(0.06)
ϵ_{t-3}	0.272***	0.055*	0.152*	0.026	0.427***	0.039
	(0.06)	(0.03)	(0.08)	(0.05)	(0.08)	(0.04)
$\epsilon_{t-3} \times IRProj$	0.135	-0.027	0.055	-0.014	-0.016	-0.066
	(0.09)	(0.04)	(0.11)	(0.07)	(0.11)	(0.06)
$\epsilon_{t-3} \times DualProj$	-0.046	0.020	0.042	0.010	-0.327***	-0.033
	(0.09)	(0.04)	(0.11)	(0.07)	(0.11)	(0.06)
$\epsilon_{t-3} \times ADProj$	-0.126	-0.018	0.047	0.081	-0.231**	0.030
	(0.09)	(0.04)	(0.11)	(0.07)	(0.11)	(0.06)
ϵ_{t-4}	0.228***	0.077**	0.127	0.017	0.324***	0.020
	(0.06)	(0.03)	(0.08)	(0.05)	(0.08)	(0.04)
$\epsilon_{t-4} \times IRProj$	0.147	0.039	-0.038	-0.016	0.022	-0.019
	(0.09)	(0.04)	(0.11)	(0.07)	(0.12)	(0.06)
$\epsilon_{t-4} \times DualProj$	-0.018	-0.016	-0.075	-0.001	-0.129	0.025
	(0.09)	(0.04)	(0.11)	(0.07)	(0.12)	(0.06)
$\epsilon_{t-4} \times ADProj$	-0.087	-0.054	-0.156	-0.084	-0.191*	0.009
	(0.09)	(0.04)	(0.11)	(0.07)	(0.12)	(0.06)
α	-13.276***	-3.140	5.594	4.372	18.486***	11.339***
	(4.50)	(2.18)	(5.36)	(3.18)	(4.78)	(2.50)
SD r_t^n	145.45	145.45	148.22	148.22	155.82	155.82
N	698	698	699	699	698	698
χ^2	202.6	76.26	68.28	30.84	242.7	89.24

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

Sticky Information Models

Mankiw and Reis (2002) and Reis' (2003) models of inattention consider agents that obtain information infrequently due to costly information acquisition. When agents do receive information, they receive perfect information and are able to make optimal decisions. In the context of our experiment, this model would predict that agents would infrequently adjust their forecasts, but that their forecast errors would on average equal zero when they do adjust.

First, we note that the frequency of revision does vary considerably across subjects. Figure 11 presents the distribution of frequency of forecast updating across experienced subjects in each treatment.[c0] We see that there are considerably more subjects in the IRProj who fail to update their forecast frequently. For example, 15-20% of IRProj subjects update their output forecast less than 80% of the time. When subjects do update their forecast for the next period, they correctly forecast under 2% of the time. Forecast accuracy generally improves with almost all forms of projections and both low and high variability of shocks.[c0] While we find evidence of substantial infrequent updating of forecasts by some subjects, especially in the IRProj treatment, their relative success at updating is very low.

To better understand what influences a subject not to update their forecast between two periods, we conduct a series of probit regressions where we evaluate the effects of past revisions, past forecast errors, absolute magnitude of shocks, treatment–specific dummies, and interactions of those treatment-specific dummies with the absolute magnitude of shocks. Table **??** reports our results by repetition for low and high variable shock sequences. Consistently, past revisions and larger forecast errors tend to be a strong positive predictor of revising in the following periods. The magnitude of the current shock does not have a consistent effect on subjects' likelihood of revising their forecast. We do, however, observe that nominal interest rate projections increase the likelihood a subject will fail to update their forecast. This effect is large and statistically significant in most of our specifications.

Subjects that do update their forecast do not usually update correctly. Less than 10% of output forecasts are within 10-basis points of the correct forecast, while 16-23% of inflation forecasts are within 10-basis points of the correct forecast. While the sticky information model captures the fact that some of our subjects fail to update their forecasts as new information arises, it fails to describe our subjects' inability to respond optimally to that information when they do update their forecasts.

[c0]In the second repetition, the mean subject fails to update their output (inflation) forecast 3.6% (6.3%) of the time in NoComm treatment, 9% (12.3%) in the IRPRoj, 4% (6.7%) in the DualProj, and 4% (5.3%) in the ADProj treatments. The frequency of 'sticky information' is more than double in the IRProj than in the other treatments and occurs for both low and high variable shocks.

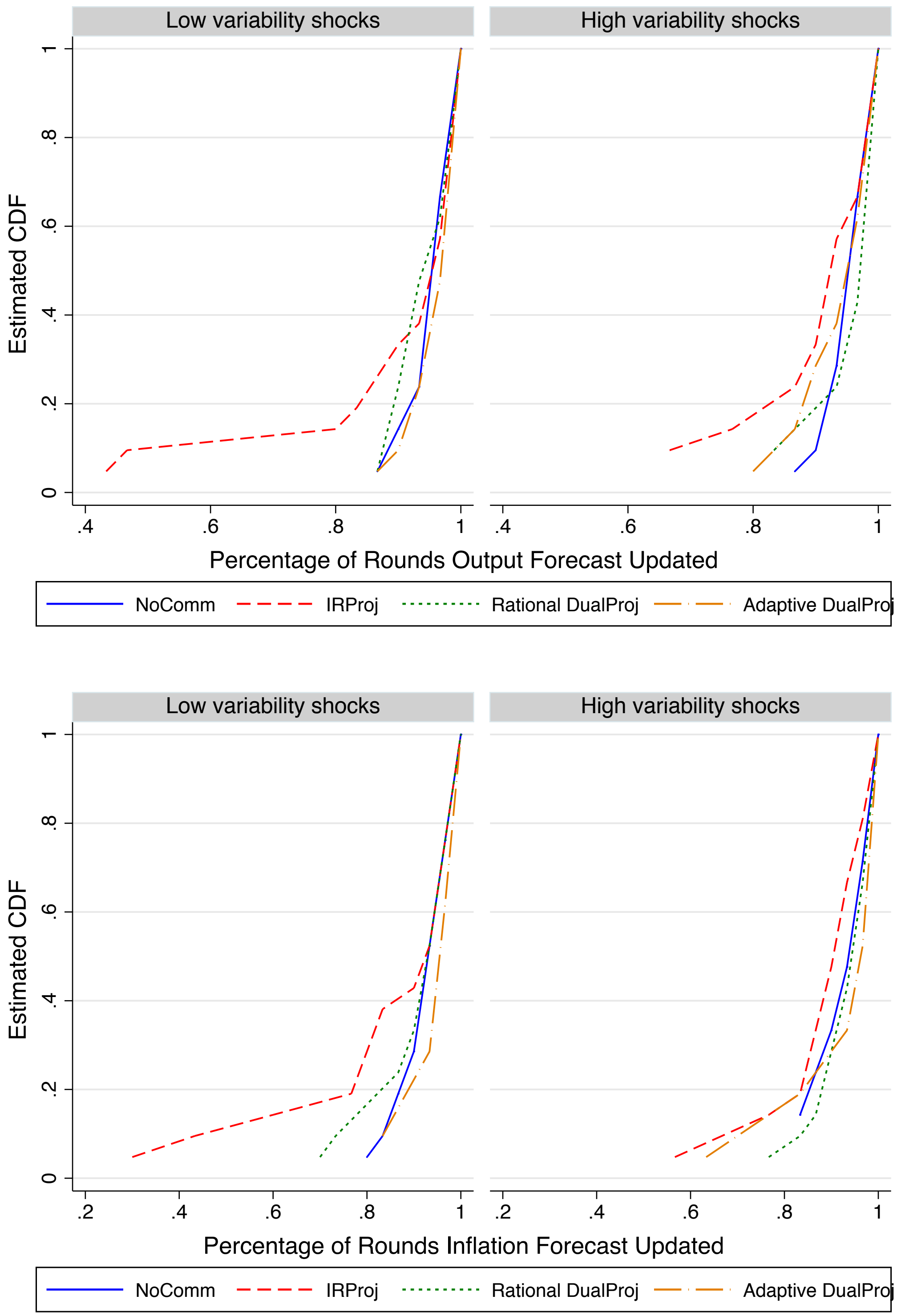
[c0]The exception is when subjects are forecasting inflation in the IRProj and ADProj treatments for low variability shocks. The proportion of accurate inflation forecasts drop from 1.02% in the NoComm treatment to 0.56% and 0.8% in the IRProj and ADProj treatments, respectively.

Table 10: Effects of central bank projections on the likelihood of forecast revision - Treatment effects[I]

	Repetition 1				Repetition 2			
	$Pr(\Delta E_t x_{t+1}) = 0$		$Pr(\Delta E_t \pi_{t+1}) = 0$		$Pr(\Delta E_t x_{t+1}) = 0$		$Pr(\Delta E_t \pi_{t+1}) = 0$	
SD of shocks	Low	High	Low	High	Low	High	Low	High
$\Delta E_{t-1} x_t = 0$	0.405***	0.520***			1.058***	0.569***		
	(0.15)	(0.12)			(0.13)	(0.14)		
$\lvert E_{t-2}x_{t-1} - x_{t-1}\rvert$	-0.002	-0.002***			-0.001	-0.002**		
	(0.00)	(0.00)			(0.00)	(0.00)		
$IRProj$	0.396**	0.405**	$0.307^{\dagger}$	0.062	0.426**	0.209	$0.242^{\dagger}$	$0.289^{\dagger}$
	(0.19)	(0.18)	(0.19)	(0.16)	(0.19)	(0.19)	(0.16)	(0.18)
$DualProj$	0.001	0.312*	0.085	-0.076	0.115	0.003	-0.187	-0.027
	(0.19)	(0.17)	(0.20)	(0.16)	(0.21)	(0.21)	(0.17)	(0.20)
$ADProj$	0.088	-0.146	-0.072	-0.226	0.029	$0.308^{\dagger}$	-0.514***	0.075
	(0.20)	(0.19)	(0.20)	(0.16)	(0.21)	(0.20)	(0.20)	(0.19)
$\lvert\epsilon_t\rvert$	0.001	-0.001	-0.001	-0.002*	0.000	-0.001	-0.002*	-0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$\lvert\epsilon_t\rvert \times IRProj$	-0.003	-0.002	-0.002	0.001	-0.001	0.002	0.001	-0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$\lvert\epsilon_t\rvert \times DualProj$	-0.001	0.001	-0.001	0.001	-0.000	-0.000	0.003*	-0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$\lvert\epsilon_t\rvert \times ADProj$	-0.001	0.001	0.001	0.002	-0.002	-0.002	0.004**	-0.002
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$\Delta E_{t-1}\pi_t = 0$			0.493***	0.314***			0.892***	0.624***
			(0.15)	(0.11)			(0.10)	(0.12)
$\lvert E_{t-2}\pi_{t-1} - \pi_{t-1}\rvert$			-0.005*	-0.012***			-0.013***	-0.007***
			(0.00)	(0.00)			(0.00)	(0.00)
α	-1.445***	-1.506***	-1.270***	-0.976***	-1.784***	-1.515***	-1.061***	-1.219***
	(0.14)	(0.15)	(0.15)	(0.13)	(0.16)	(0.16)	(0.13)	(0.14)
N	1619	3235	1619	3235	2433	2431	2433	2431
χ^2	21.45	68.79	33.78	58.87	92.13	46.87	140.7	67.27

(I) This table presents results from a series of mixed effects probit regressions. The dependent variables are binary variables that take the value of 1 if a subject keeps its previous forecast for the current round, and zero otherwise. IRProj, DualProj, and ADProj are treatment-specific dummies indicating the interest rate, rational dual projection, and adaptive dual projection treatments. $|E_{t-2}x_{t-1} - x_{t-1}|$ and $|E_{t-2}\pi_{t-1} - \pi_{t-1}|$ denote a subject's past forecast errors, and α denotes the estimated constant for the NoComm treatment. Robust standard errors are employed. $^{\dagger}p < 0.15$, $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

Figure 11: Distribution of forecast updating behavior



Appendix C– Instruction

EXPERIMENTAL STUDY OF ECONOMIC DECISION MAKING

Welcome! You are participating in an economic experiment at CRABE Lab. In this experiment you will participate in the experimental simulation of the economy. If you read these instructions carefully and make appropriate decisions, you may earn a considerable amount of money that will be immediately paid out to you in cash at the end of the experiment.

Each participant is paid CAN $7 for attending. Throughout this experiment you will also earn points based on the decisions you make. Every point you earn is worth $0.50. We reserve the right to improve this in your favour if average payoffs are lower than expected.

During the experiment you are not allowed to communicate with other participants. If you have any questions, the experimenter will be glad to answer them privately. If you do not comply with these instructions, you will be excluded from the experiment and deprived of all payments aside from the minimum payment of CAN $7 for attending.

The experiment is based on a simple simulation that approximates fluctuations in the real economy. Your task is to serve as private forecasters and provide real–time forecasts about future output and inflation in this simulated economy. The instruction will explain what output, inflation, and the interest rate are and how they move around in this economy, as well as how they depend on forecasts. You will also have a chance to try it out for 4 periods in a practice demonstration.

In this simulation, households and firms (whose decisions are automated by the computer) will form forecasts identically to yours. So to some degree, outcomes that you will see in the game will depend on the way in which all of you form your forecasts. Your earnings in this experiment will depend on the accuracy of your individual forecasts.

Below we will discuss what inflation and output are, and how to predict them. All values will be given in basis points, a measurement often used in descriptions of the economy. All values can be positive, negative, or zero at any point in time.

How the economy evolves

You will submit forecasts for the next period's inflation and output, measured in basis points:
1% = 100 basis points
3.25% = 325 basis points
-0.5% = -50 basis points
-4.8% = -480 basis points

The economy consists of four main variables:

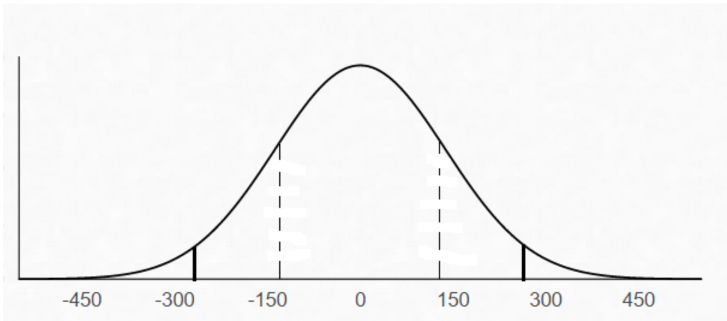
- Inflation, Output, Interest Rate, Shocks

At any time, t, the values of these variables will be calculated as follows:

$Shock_t = 0.57(Shock_{t-1}) + Random\ Component_t$

- The random component is 0 on average.

- Roughly two out of three times the shock will be between -138 and 138 basis points.
- 95% of the time the shock will be between -276 and 276 basis points.



E.g.

$$\begin{aligned} Shock_1 &= 30 \\ Shock_2 &= 30 \times 0.57 + New\ Draw \\ &= 17.1 + (30) \\ &= 47.1 \\ Shock_2 &= 17.1 + (-150) \\ &= -132.9 \end{aligned}$$

How the economy evolves:

$$Inflation_t = 0.989(Median\ forecast\ of\ Inflation_{t+1}) + 0.13(Output_t)$$

$$\begin{aligned} Output_t = {} & Median\ forecast\ of\ Output_{t+1} + Median\ forecast\ of\ Inflation_{t+1} - Interest\ Rate_t \\ & + Shock_t \end{aligned}$$

$$Interest\ Rate_t = 1.5(Inflation_t) + 0.5(Output_t)$$

- The Central Bank sets the target for output and inflation at zero. In order to achieve the target it will adjust the interest rate and in some cases this means the interest rate can become negative.
- Expectations are self-fulfilling in this economy. If the median subject forecasts higher inflation and output in the future, both inflation and output will grow higher in the current period. Similarly, median forecasts of negative inflation and output will cause the economy to recede in the current period.
- The Central Bank will make a five–period projection each period about the future levels of the inflation and output. It is important to remember that the projections are simply a forecast and not a promise. The Central Bank use the current and expected future shocks to form its projections. In particular, it predicts that the economy will return to zero levels of inflation and output in the near future.

Score

Your score will depend on the accuracy of your forecasts. The absolute difference between your forecasts and the actual values for output and inflation are your absolute forecast errors.

- Absolute Forecast Error= absolute(Your Forecast - Actual Value)
- Total Score = $0.30(2^{-0.01(ForecastErrorforOutput)}) + 0.30(2^{-0.01(ForecastErrorforInflation)})$

The maximum score you can earn each period is 0.60. Your score will decrease as your forecast error increases. Suppose your forecast errors for each of output and inflation is:

1. 0 : Your score will be 0.6
2. 50: Your score will be 0.42
3. 100: Your score will be 0.30
4. 200: Your score will be 0.15
5. 300: Your score will be 0.075
6. 500: Your score will be 0.02
7. 1000: Your score will be 0
8. 2000: Your score will be 0

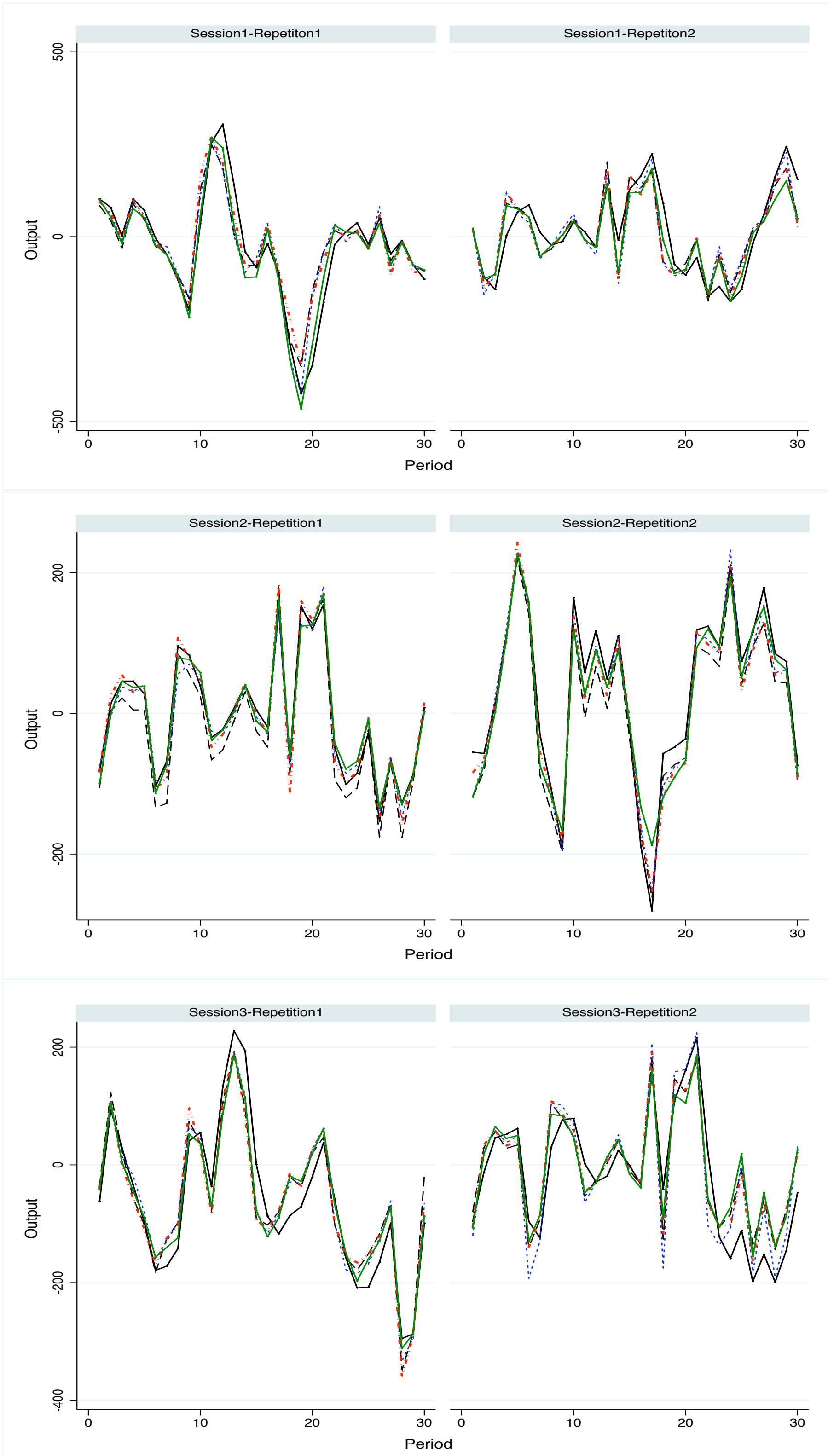
During the experiment, your main screen will display information that will help you make forecasts and earn more points.

At the top left of the screen, you will see your subject number, the current period, time remaining, and the total number of points earned. Below that you will see you will also see three history plots. The top history plot displays past interest rates and shocks. The second plot displays your past forecast of inflation and realized inflation levels, and the Central Bank projection. The final plot displays your past forecasts of output and realized output levels, and the Central Bank projection .

The difference between your forecasts and the actual realized levels constitutes your forecast errors. Your forecasts will always be shown in blue while the realized value will be shown in red. The central bank forecast will be shown in green. You can see the exact value for each point on a graph by placing your mouse at that point.

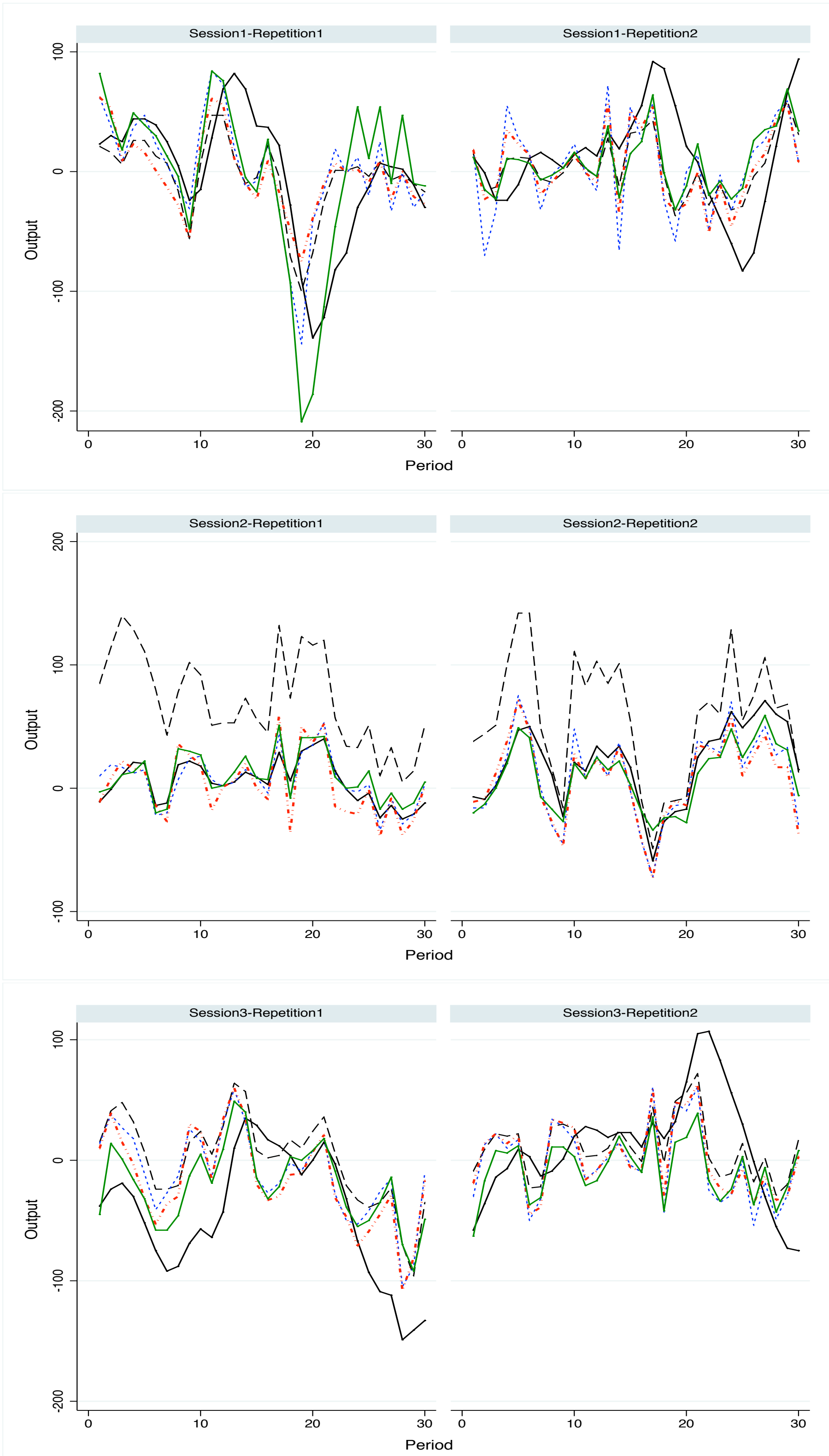
When the first period begins, you will have 65 seconds to submit new forecasts for the next period's inflation and output levels. You may submit both negative and positive forecasts. Please review your forecasts before pressing the SUBMIT button. Once the SUBMIT button has been clicked, you will not be able to revise your forecasts until the next period. You will earn zero points if you do not submit the two forecasts. After the first 9 periods, the amount of time available to make a decision will drop to 50 seconds per period. You will participate in two sequences of 30 periods, for a total of 60 periods of play. Your score, converted into Canadian dollars, plus the show up fee will be paid to you in cash at the end of the experiment.

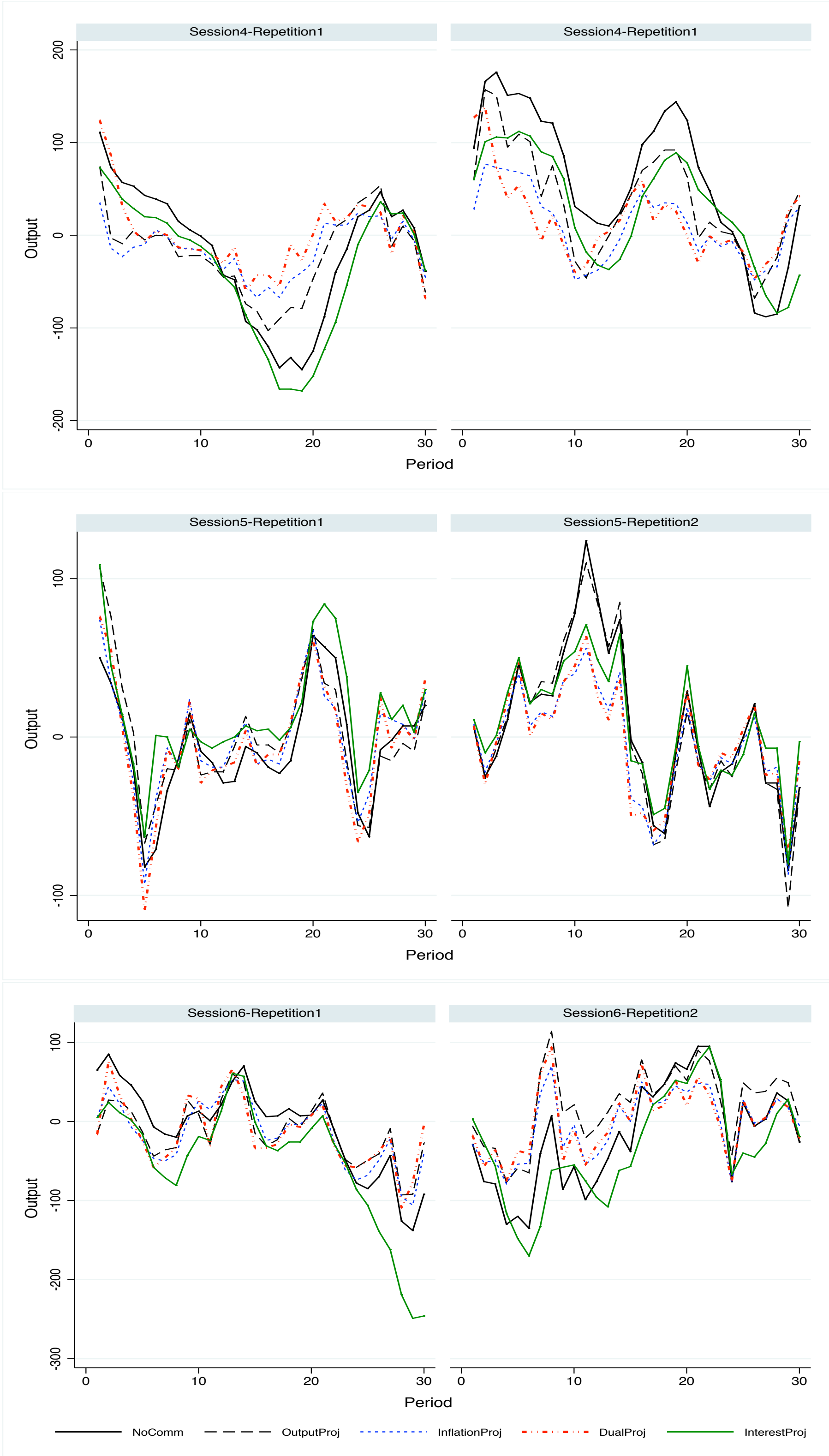
Figure 12: Time series of the output gap by session and repetition



Session4-Repetition1
Session4-Repetition2
Session5-Repetition1
Session5-Repetition2
Session6-Repetition1
Session6-Repetition2
Output
Period
400
200
0
-200
-400
10
20
30
NoComm
OutputProj
InflationProj
DualProj
InterestProj

Figure 13: Time series of the inflation by session and repetition





Session4-Repetition1
Session4-Repetition1
Session5-Repetition1
Session5-Repetition2
Session6-Repetition1
Session6-Repetition2
Output
Period
NoComm
OutputProj
InflationProj
DualProj
InterestProj