Essays on Macroeconomic Policies: Experiments and Simulations

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Abstract

The first paper of this thesis (Chapter 2) explores how expectations of inflation and output are influenced by central bank forward guidance within a learning–to–forecast laboratory macroeconomic environment. Subjects are incentivized to forecast the output gap and inflation. An automated central bank forms projections about the economy assuming subjects form expectations following the REE solution. The central bank communicates output and/or inflation projections, interest rate projections, or no information. Communicating about future output or inflation generally reduces the degree to which subjects rely on lagged information and increases their reliance on the REE solution. Interest rate projections, by contrast, do not significantly alter subjects' forecast accuracy or disagreement. Central bank credibility significantly decreases when the central bank makes larger forecast errors when providing forward guidance about either output and inflation, but not when they provide a dual projection. Our findings suggest that expectations are best coordinated and stabilized by communicating output and inflation forecasts simultaneously.

The second paper of this thesis (Chapter 3) evaluates the central bank communication of its future inflation and output expectations to reduce economic variations in the event of a demand or cost–push shock. Four communication strategies are tested: no communication, communicating output, communicating inflation, and communicating output and inflation. Two Taylor rules are considered: (a) central bank interest rate responds to inflation and output (flexible inflation targeting [IT]), and (b) central bank responds only to inflation (strict IT). We find that with a demand shock, communicating future inflation reduces output variations and increases inflation and interest rate variations; however, communicating output stabilizes inflation and interest rates and destabilizes output (the interest rate rule did not matter qualitatively). With a cost–push shock, communicating future output decreases inflation and interest rate variability, irrespective of Taylor rule qualitatively. In order to stabilize output, a central bank should be uncommunicative under flexible IT but

should communicate future inflation under strict IT.

The third paper of this thesis (Chapter 4) studies the effect of the degree of information observability on bank runs in a sequential laboratory environment. We conduct an experiment with ten depositors in a queue who are randomly ranked to submit their decisions. The depositors decide between withdrawing their deposit or waiting and leaving their deposit in a common experimental bank. Two treatments are considered: a sequential high–information treatment, and a sequential low–information treatment. In both treatments, depositors who are in the front of the queue tend to withdraw more than those at the back of the queue. Moreover, depositors are responsive to the information about the preceding withdrawals within a period. We find that in the sequential high–information treatment the possibility of observing preceding withdrawals increases the likelihood of bank runs compared to a sequential–low information treatment.

To Baba

"Distance between a drop here and a drop there in the ocean makes no difference to each drop's relation to the ocean."

— Meher Baba

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Chapters 2 of this Thesis is based on joint work with Luba Petersen. Chapter 4 is based on joint work with Jasmina Arifovic.

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All omissions and mistakes are my own.

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Chapter 1

Introduction

In central bank monetary policy, conventional wisdom used to be that monetary authorities should be uncommunicative and mysterious. Over the last two decades, the understanding of the importance of central bank transparency and communication has increased considerably, and it has become increasingly clear that managing expectations is an important part of a central bank's monetary policy toolkit. In the early 1990s, the Reserve Bank of New Zealand (RBNZ) began to adopt explicit inflation targeting and became more transparent about their inflation objective and mandate, followed by Norges Bank (the central bank of Norway) and Sveriges Riksbank (the central bank of Sweden) in 2001 and 2007, respectively. Central banks' communication of inflation targets led to increased transparency and credibility, and also allowed the markets to achieve low and stable inflation. 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. Norway (in 2005), Sweden (in 2007), Canada (in 2009), and the United States (in 2012) began to provide projections of key policy variables to manage market expectations. The RBNZ and Norges Bank have gone even further by publishing the central bank's projections of future inflation rates and output gap. As interest rates have crept towards the zero lower bound since the start of the Great Recession, the Federal Reserve, European Central Bank, and Bank of England have experimented with a variety of forms of forward guidance about the direction of their future policy rates. The literature has shown that increasing transparency and communication is key to developing central bank accountability. Transparency is thought to help the public's understanding of future policy decisions and to better coordinate expectations (Woodford, 2005). However, transparency is not without its own risks and challenges.

Mishkin (2004) cautioned 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 in fact it would be suboptimal to do so. Poorly designed communication strategies might be harmful, and under certain circumstances can lead to unwanted and unfavorable economic results. As a result, the key questions are what the central bank should communicate and whether it is successful in achieving its monetary objectives. The empirical macroeconomics literature often imposes important identifying assumptions to study the effect of the monetary policies on private agents' expectations. In Chapter 2 and Chapter 3 of this thesis, we study the effectiveness of communication strategies.

Chapter 2 conducts a laboratory testbed in a learning–to–forecast experiments (LTFEs). The expectations of subjects are elicited and aggregated with other participants' expectations in the experiment. The aggregate expectations are fed into the economy's data–generating process. To determine the effectiveness of communication strategies, five strategies are considered: no communication, communicating five-period ahead projections of output gap, inflation, dual projections of output gap and inflation, and the five–period ahead projections of future interest rate. Our findings show that the central bank projections of future variables significantly stabilize the economy by pushing the naive forecasters towards forming fundamentally driven rational expectations.

Chapter 3 evaluates the impact of a communication policy using impulse responses in a New Keynesian Model in which private agents' expectations are not necessarily in common with the central bank's expectations. Four communication strategies are considered: no communication (which is the baseline), communicating output, communicating inflation, and communicating both output and inflation. Our findings show that under a demand shock, the central bank faces a trade–off when implementing communication policies in stabilizing inflation and output. Under a cost-push shock, we find that the central bank should communicate output to stabilize inflation.

When a large number of depositors run to the bank to withdraw their deposits, the bank is forced to liquidate long–term investments in the fear that more depositors will withdraw their deposits. This situation often leads to a bank run and a bank's failure. The recent great economic depression led to extensive bank runs and panics among depositors. The news converges by media, showing the line–ups of depositors on the England Bank, Northern Rock, and other financial institutions such as Washington Mutual and the IndyMac Bank in the United States, helped to the spread of bank runs. Chapter 4 of this thesis conducts an experimental study based on the Diamond-Dybvig (1983) model to explore the likelihood of bank runs due to panics and self–fulfilling prophecy. The depositors are assumed to be in a queue in front of an experimental bank to submit their decisions. Two treatments are considered: (a) depositors are informed of the preceding withdrawals, the history of withdrawals in the last period, and their rank in the queue, and (b) depositors are only informed of the history of withdrawals in the last period and their rank in the queue. The results show that when depositors receive more information about the decisions of the preceding withdrawals, the probability of bank runs increases. Also the percentage of withdrawals of the depositors in front of the queue is greater that the percentage of withdrawals of the depositors at the back of the queue.

We use the methodology of laboratory experiments in Chapter two and four of this thesis which a privileged instrument to study the effect of information observability in bank runs and monetary policy effectiveness, due to the possibility of easily and effectively manipulating and controlling the environment.

Chapter 2

Central Bank Communication and Expectations

Joint work with Luba Petersen

2.1 Introduction

Forward guidance is a communication tool that central banks use to directly influence private agents' expectations and decisions by providing information about future policy and the state of the economy. Forward guidance can take many forms. 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. Whether central banks should provide forward guidance and whether it has been successful are questions of much debate. Much of the difficulty in satisfying this debate comes from the empirical challenge of identifying the effects of different forms of forward guidance on aggregate expectations.

This paper presents the first causal evidence of the effects of different forms of central bank projections on expectations and central bank credibility. We construct a laboratory testbed where subjects' incentivized expectations are elicited, aggregated with other participants', and fed into the economy's data-generating process. Importantly, each period the economy faces serially correlated shocks to aggregate demand. Subjects' expectations are elicited under one of five treatments. In our baseline treatment, participants only observe current fundamentals when forming their forecasts and historical outcomes. We compare our findings in the baseline to treatments that involve communicating to subjects central bank projections of five–period ahead output gap, inflation, dual projections of the output gap and inflation, and nominal interest rates. The projections are based on a rational-expectations equilibrium solution response to the current fundamentals. Using a systematic variation of information between independent groups of subjects, we are able to identify the effect of these forms of forward guidance on expectations and aggregate dynamics.

We find that central bank forward guidance significantly stabilizes expectations and the aggregate experimental economy by 'nudging' naive forecasters towards fundamentally-driven rational expectations. Moreover, forward guidance of either future output gap or inflation results in greater coordination of expectations and reduced forecast errors associated with the communicated variable. By contrast, forward guidance of nominal interest rates leads to mixed results. For relatively low variability in aggregate demand shocks, nominal interest rate projections are relatively stable and result in significantly more stable, 'rational' forecasts. However, as the variability of shocks increases, the benefits of such forward guidance weaken and subjects maintain a backward-looking forecasting heuristic.

Loss of credibility is an important concern central banks face when deciding whether to communicate forecasts of future economic activity or nominal interest rates. We find that this concern is valid. As the central bank's forecast errors of the output gap or inflation grow larger, the likelihood that subjects utilize the projections decreases. However, when central banks communicate output and inflation forecasts simultaneously, subjects do not significantly penalize the central bank for its forecast errors. Even if the central bank makes considerable forecast errors, subjects in our dual information treatment continue to utilize the information because it is easier to follow the projections than having to consider an alternative heuristic. By contrast, when only a single projection about output or inflation is communicated, subjects must exert greater cognitive effort in forecasting the non-communicated variable (and even more effort when only forward guidance of nominal interest rates is communicated).

The paper is organized as follows. The next section discusses related literature on central bank communication and expectations from theoretical, policy, and experimental viewpoints. 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 aggregate variables evolve under different forms of central bank communication, and Section 5 concludes.

2.2 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 agent's 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.[1] For decades, central banks were uncommunicative and mysterious about their operations to safeguard the central bank from political pressure, avoid credibility loss, and to achieve an element of surprise when they did change policy. However, in the early 1990's the Reserve Bank of New Zealand (RBNZ) began to adopt explicit inflation targeting and became more transparent about their inflation objective and mandate. Norway followed suit in 2001 and Sweden in 2007. Central banks' communication of inflation targets led to increased transparency and credibility and also allowed the markets to achieve low and stable inflation. Most recently, many central banks have moved toward explicitly communicating 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 forward guidance have been used to signal the likely future path of policy rates and the outlook of monetary policy in general.

Transparency is thought to be the key to developing accountability.[2] Transparency can range from communicating targets to providing full conditional forward guidance. Increased and *effective* transparency can help the public better understand and anticipate future policy decisions and reduce the overall uncertainty about the future state of the

[1]See Kang et al. (2013) for a more detailed discussion.

[2]This point has been emphasized by numerous authors, including Reis (2013), Ehrmann and Fratzscher (2007), and King (2000)

economy. Moreover, transparency is also thought to better coordinate expectations (Woodford (2005); Svensson (2006 and 2011); Eusepi and Preston (2010); Goodhart and Lim (2001); Mishkin (2004); Kool and Thornton (2012)). Credibility can be further strengthened if central banks can commit to a particular policy reaction. Of course, commitment is difficult because central banks do not (and should not) sign contracts binding themselves to a particular policy path. But by publishing its own forecasts of future interest rates, inflation and the output gap, a central bank may be better able to convince the public that it is committed to following a particular policy response (Woodford, 2005; Svensson, 2006a and 2008; Rudebusch and Williams, 2008; and Holmsen et al., 2008).

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 (2005), 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, policy, or communication of expectations and must often make important identifying assumptions about the structure of the economy and the information sets of agents. As a consequence of these empirical challenges, laboratory experiments have increasing been conducted to study how monetary policy can influence the expectation formation process.[3] The advantage to laboratory experimentation is that the researcher is able to carefully control for the many factors that might influence individuals' expectations in order to achieve more precise identification. The experimenter can control features of the data-generating process including important policy rules and communication strategies while systematically varying some feature of the economy.

[3]See Duffy (2012) for a highly comprehensive survey of macroeconomic experiments, Cornand and Heinemann (2015) 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.

Learning-to-forecast experiments (LTFEs) have been extensively used 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. We discuss below LTFEs focused on the role of central bank communication in influencing expectations.[4]

There are three key LTFEs that study the effects of central bank communication on expectation formation. Kryvtsov and Petersen (2015) study the robustness of the strength of the expectations channel to variations in the aggressiveness of monetary policy to inflation, persistence of shocks, and central bank forward guidance of future policy rates. Different from other LTFEs, the authors provide subjects with the full data generating process to provide subjects with the best opportunity to formulate rational forecasts. Among other things, 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 few subjects initially employ the projections in their forecasts, the announcement creates more confusion and expectations become increasingly destabilized.

Arifovic and Petersen (2015) extend the aforementioned LTFEs environment to study expectation formation at the zero lower bound. In a series of treatments, they consider the effects of history–dependent inflation targets that are communicated quantitatively or qualitatively on the coordination of expectations and economic stability. They find that qualitative communication of inflation targets tends to be more effective at stabilizing expectations because it minimizes the credibility loss when the central bank fails to meet its targets.

Cornand and M'Baye (2016) consider a more conventional LTFE where subjects only

[4]The learning-to-forecast methodology originates with Marimon and Sunder (1993) who study price forecasting in an OLG experimental economy. LTFEs have also been applied to study price expectations in partial equilibrium environments (Bao et al., 2013; Hommes et al. (2005)) and inflation expectations in Barro-Gordon frameworks (Arifovic and Sargent, 2003). 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, 2015, 2016)), Assenza et al. (2015), 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 (2015), Cornand and M'Baye (2016)).

have a qualitative understanding of the economy's data generating process. They consider the effectiveness of announcing the central bank's constant inflation target when a central bank follows strict and flexible inflation targeting. They find that the gains from communicating the target depend on the nature of the central bank's policy rule. Under strict inflation targeting, subjects learn more quickly the central bank's target 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.

2.3 Experimental Design and Implementation

Our experiment was designed to study how expectations are formed in the presence of central bank forward guidance and projections. The experiments were conducted at the CRABE Lab at Simon Fraser University where the subject pool consisted of undergraduate students from a variety of disciplines. The experiment closely follows the design of Kryvtsov and Petersen (2015). Each session involved groups of seven inexperienced subjects playing the role of professional forecasters who were tasked with submitting incentivized forecasts about the future state of the economy. The submitted forecasts were aggregated and used by computerized households and firms to form optimal decisions. The experimental economy's data-generating process was 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.[5] We focus on this general class of models because of its ubiquitous use in central banks over the last decade and for the important role expectations that play in driving aggregate dynamics.

The aggregate economy implemented in our experiment is described by the following system of equations:

$$x_t = E_t x^*_{t+1} - \sigma^{-1}(i_t - E_t \pi^*_{t+1} - r^n_t), \tag{2.1}$$

$$\pi_t = \beta E_t \pi^*_{t+1} + \kappa x_t, \tag{2.2}$$

$$i_t = \phi_\pi \pi_t + \phi_x x_t, \tag{2.3}$$

[5]See Woodford (2003) for detailed assumptions and derivations in a model with rational expectations.

$$r_t^n = \rho_r r_{t-1}^n + \epsilon_{rt}. \tag{2.4}$$

Equation (2.1) 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 (2.1) describes how the current output gap, x_t depends positively on expectations of next period's output gap, $E_t x_{t+1}^*$. Output also depends on deviations of the real interest rate, $i_t - E_t \pi_{t+1}^*$ from the natural rate of interest, r_t^n, and the role this deviation plays depends on σ, the coefficient of risk aversion.[6]

Equation (2.2) is the New Keynesian Phillips curve which describes the evolution of inflation, π_t in response to changes in expected future inflation, $E_t \pi_{t+1}^*$ and current real activity, x_t. Importantly, the central bank faces a tradeoff when stabilizing inflation and output. The coefficient κ is a function of parameters associated with the frequency and size of firms' price changes, and governs how sensitive prices are to aggregate demand, while the coefficient β is the subjective discount rate.

Equation (2.3) is the central bank's response function and describes the evolution of nominal interest rates. Under this specification the central bank contemporaneously respond 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.[7] Importantly, subjects only know with certainty the previous period's interest rate when forming their forecasts. Note that the implemented environment studies deviations around a constant steady state, ignoring the presence of the zero lower bound. That is, negative nominal interest rates were possible in our experiment.[8]

Finally, Equation (2.4) 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. where ϵ_{rt} is $i.i.d$ with mean zero and $N(0, \sigma_r)$.[9]

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

[7] We differ from Kryvtsov and Petersen (2015) in that they implement a policy rule that responds to deviations of expected inflation and output, formed in the previous period, from the central bank's target.

[8] 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.

[9] 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,

The experimental economy's data-generating process was calibrated to match moments of the Canadian data following Kryvtsov and Petersen (2015). We set $\sigma = 1$, $\beta = 0.989$, $\kappa = 0.13$, $\phi_\pi = 1.5$, $\phi_x = 0.5$, $\rho = 0.57$, and $\sigma = 1.13$. The environment had a unique steady state where $\pi^* = x^* = i^* = 0$.

Each session began with a 30-minute instruction phase where we explained the data generating process both qualitatively and quantitatively. The instructions were followed by a 10-minute practice phase where we walked subjects through the software they would interact with in four practice periods. This also provided subjects an opportunity to ask questions about the data-generating process and the task they would be participating in.

Over two 30-period horizons, subjects were tasked with submitting forecasts about the following period's output and inflation.[10] When forming forecasts, subjects had access to the following common information (and all subjects understood that this was common information). They observed all historical information up to and including the previous period's realized inflation, output, nominal interest rate and shocks, as well as their own personal forecasts.[11] They also observed the current period's shock, which allowed them to calculate the expected future shocks for the following periods. Subjects were provided 65 seconds for the first 10 rounds and 50 seconds thereafter to submit forecasts. Forecasts were submitted in basis point measurements and could be positive or negative. After all subjects submitted their forecasts or time elapsed, the median submitted forecasts for output and inflation were employed as the aggregate forecasts and implemented in the calculation of the current period's output, inflation, and nominal interest rate.

To motivate subjects to take seriously their forecasting decisions, we incentivized them based on forecast accuracy. Subject i's scores in each period t was a function of her inflation and output forecast errors:

$$Score_{i,t} = 0.3(e^{-0.01|E^*_{i,t-1}\pi_t - \pi_t|} + e^{-0.01|E^*_{i,t-1}x_t - x_t|}) \ , \tag{2.5}$$

where $E^*_{i,t-1}\pi_t - \pi_t$ and $E^*_{i,t-1}x_t - x_t$ were subject i's forecast errors associated with forecasts

Chapter 4) for details. We follow Kryvtsov and Petersen (2015), Arifovic and Petersen (2015), and Pfajfar and Zakelj (2013, 2016) in the implementation of a *AR(1)* shock process.

[10]Two distinct repetitions were employed to control for learning.

[11]In the U.S. and Argentinian survey experiment, Cavallo et al. (2015) find that a significant fraction of the disagreement about future inflation may be a consequence of disagreement about past inflation. Our experiment mitigates the degree of disagreement in future expectations by providing subjects accurate and precise commonly observed historical information.

submitted in period $t-1$ for period t variables. The scoring rule was intuitively easy to explain to subjects: for every 100 basis point error made for each of inflation and output, a subject's score would reduce by 50%. Another convenient feature of this payoff function was that it continued to incentivize subjects even as forecast errors grew large. At the end of the experiment, a subject's scores from all periods were converted into dollars and paid out to them in cash.

To ensure consistency across treatments, we preselected the shock sequences and employed them across all treatments. Two conditions were considered to generate a vector of the shock; two-third of the time the shock takes a value between -138 and $+138$ and 95 percent of the time it takes a value between -276 and $+276$.

Treatments and Hypotheses

To investigate the impact of central bank projections on economic stability and forecasting heuristics, we systematically varied the type of projections subjects received in a between-subject experimental design. Central bank projections were presented in the form of five–period ahead projections of the nominal interest rate, output gap, inflation, or a combination of output gap and inflation, based on Equation (2.6) where the central bank assumes that agents form expectations according to the unique REE solution:

$$\begin{aligned} i_t &= 0.447157 \cdot r^n_{t-1} + 0.784487 \cdot \epsilon_t, \\ x_t &= 0.472198 \cdot r^n_{t-1} + 0.82847 \cdot \epsilon_t, \\ \pi_t &= 0.140706 \cdot r^n_{t-1} + 0.246852 \cdot \epsilon_t. \end{aligned} \tag{2.6}$$

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

$$\begin{aligned} E^{cb}_t x_{t+s} &= \rho^{s-1} \cdot x_t, \\ E^{cb}_t \pi_{t+s} &= \rho^{s-1} \cdot \pi_t, \\ E^{cb}_t i_{t+s} &= \rho^{s-1} \cdot i_t \end{aligned} \tag{2.7}$$

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

We conducted five treatments that differed in terms of the forecasts communicated by the central bank.

- Treatment I: *No Communication (NoComm)*– There were no supplementary communications by the central bank.
- Treatment II: *Output Projection (OutputProj)*– The central bank provided a five–period ahead projection of expected future output in each period.
- Treatment III: *Inflation Projection (InflationProj)*– The central bank provided a five–period ahead projection of expected future inflation in each period.
- Treatment IV: *Output and Inflation Projection (DualProj)*– The central bank provided a five–period ahead projection of expected future output and inflation in each period.
- Treatment V: *Interest rate Projection (IRProj)*– The central bank provided a five–period ahead projection of expected future interest rates in each period.

Subjects were informed that the central bank projections were simply forecasts formed by the central bank based on current and expected future shocks. We emphasized that the projections were not a promise but simply the central bank's best forecast of the future five periods. Subjects were also reminded that they were receiving identical information from the central bank.

The experimental design allows us to test a number of hypotheses regarding how subjects form expectations, both with and without forward guidance. Standard New Keynesian models make the simplifying assumption that agents form identically rational expectations about future output and inflation. If subjects form expectations consistent with the REE solution, they need only rely on parameters of the model and the current shock - both of which are common knowledge to them - to formulate their forecasts.

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

Extensive survey and experimental evidence suggests that individuals do not form expectations rationally but instead weight historical information significantly in their forecasts. Thus, we will test the alternative hypothesis that subjects place significant weight on historical information when formulating their forecasts.

Commonly observed forward guidance provides an important focal point for subjects to coordinate their forecasts on.[12] If a subject believes that the majority of participants will

[12]Forecasting heuristics can be manipulated through focal information. Kryvtsov and Petersen (2015) provide nine-period ahead forecasts of future nominal interest rates where the automated central bank assumes

utilize the central bank's (rational) prediction in their forecast, their best response is to also utilize the forecast. In that case, we predict that the forward guidance will reduce subjects' usage of non-fundamental information in their forecasts in favor of the fundamentally-driven central bank projection. This in turn should reduce the heterogeneity in subjects' output (inflation) forecasts will decrease when output (inflation) projections are communicated.

Hypothesis II: Forward guidance reduces subjects' reliance on historical information and increases their reliance on fundamentals when forming expectations.

Hypothesis III: Central bank projections of output (inflation) reduce the heterogeneity in output (inflation) forecasts.

The success of forward guidance depends on the central bank's credibility in achieving its projections. In our experiments, the automated central bank forms forecasts following an ad–hoc Taylor rule and assumes the median subject forms expectations according to the REE solution. The central bank's forecasts will frequently be incorrect due to the fact that future shocks may not be zero and subjects may use alternative heuristics to formulate their forecasts. As the projections become increasingly incorrect, we expect that the central bank will lose credibility and subjects reduce their willingness to utilize the central bank forecast 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.

In Table 2.1 we present the standard deviations of output and inflation across a various forecasting heuristics given a 1 standard deviation shock to r_t^n. Naive and trend–chasing heuristics increase the variability of output and inflation compared to under rational expectations. If central bank projections alter subjects' expectations away from backward–looking heuristics toward forecasting based on current fundamentals, then we expect to observe

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.

greater stability in output and inflation. The table also shows how the sum of absolute forecast errors changes with forecasting heuristics. A representative subject who increases the weight placed on the central bank's rational forecast will experience lower overall forecast errors.

Hypothesis V: Central bank projections of output (inflation) reduce output (inflation) forecast errors.

Hypothesis VI: Central bank projections of output (inflation) reduce the standard deviation of output (inflation).

Table 2.1: Theoretical Moments, by Forecasting Heuristic and Treatment

Forecasting Heuristic	Treatment	Model	σ_x	σ_π	FE_x	FE_π
Rational		$E_t^{REE}x_{t+1} = x_{t+1}$ $E_t^{REE}\pi_{t+1} = \pi_{t+1}$	1.14	0.34	0.94	0.28
Naive	NoComm	$E_t^N x_{t+1} = x_{t-1}$ $E_t^N \pi_{t+1} = \pi_{t-1}$	1.36	1.04	3.50	1.34
	OutputProj	$E_t x_{t+1} = 0.5E^{REE}x_{t+1} + 0.5E^N x_{t+1}$ $E_t^N \pi_{t+1} = \pi_{t-1}$	1.30	0.85	2.32	1.11
	InflationProj	$E_t^N x_{t+1} = x_{t-1}$ $E_t\pi_{t+1} = 0.5E^{REE}\pi_{t+1} + 0.5E^N \pi_{t+1}$	0.98	1.19	2.62	1.29
	DualProj	$E_t x_{t+1} = 0.5E^{REE}x_{t+1} + 0.5E^N x_{t+1}$ $E_t\pi_{t+1} = 0.5E^{REE}\pi_{t+1} + 0.5E^N \pi_{t+1}$	1.02	0.95	1.83	1.10
Trend-Chasing	NoComm	$E_t^T x_{t+1} = 0.5(x_{t-1} - x_{t-2}) + x_{t-1}$ $E_t^T \pi_{t+1} = 0.5(\pi_{t-1} - \pi_{t-2}) + \pi_{t-1}$	1.63	1.45	4.46	1.91
	OutputProj	$E_t x_{t+1} = 0.5E^{REE}x_{t+1} + 0.5E^T x_{t+1}$ $E_t^T \pi_{t+1} = 0.5(\pi_{t-1} - \pi_{t-2}) + \pi_{t-1}$	1.12	0.93	2.09	1.13
	InflationProj	$E_t^T x_{t+1} = 0.5(x_{t-1} - x_{t-2}) + x_{t-1}$ $E_t\pi_{t+1} = 0.5E^{REE}\pi_{t+1} + 0.5E^T \pi_{t+1}$	0.97	1.34	2.63	1.86
	DualProj	$E_t x_{t+1} = 0.5E^{REE}x_{t+1} + 0.5E^T x_{t+1}$ $E_t\pi_{t+1} = 0.5E^{REE}\pi_{t+1} + 0.5E^T \pi_{t+1}$	0.98	1.09	1.86	1.49

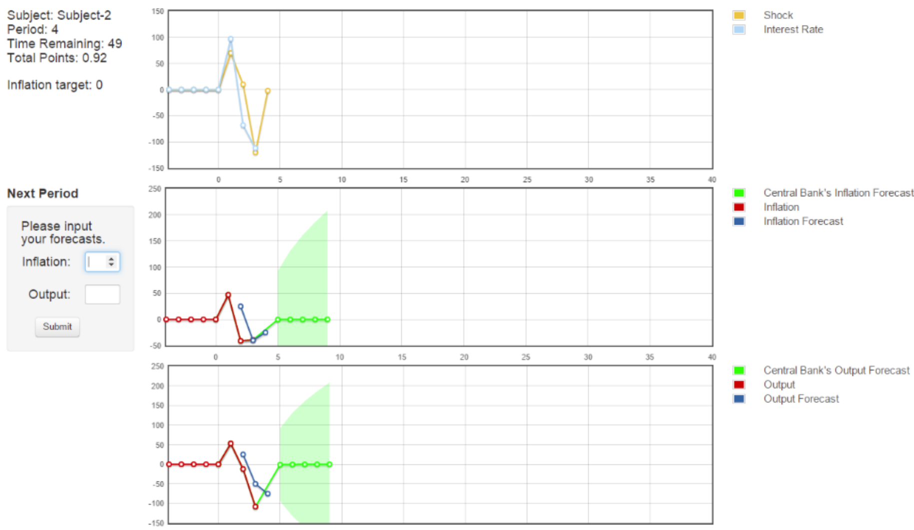
[1] FE_x and FE_π denote the sum of absolute forecast errors formed over a 40-period horizon in response to a surprise 1 standard deviation shock to the natural rate of interest.

Experimental Implementation

A total of 210 undergraduate students took part in the experiments at the CRABE lab located at Simon Fraser University from June to September 2015. For each of our five treatments we collected data from 6 groups of 7 subjects each. Thus, we have a total of 30 independent observations. 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. The experiments lasted for approximately 90 minutes including 30 minutes of instruction and four unpaid practice rounds to familiarize themselves with the software and task. No communication between subjects was allowed once they entered the laboratory. The average payment, including a CDN$7 show–up fee was CDN$25 and ranged from CDN$17 to $27. 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, the current period, time remaining, and the 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 graph was added to the history plots to represent the central bank's projection.

Figure 2.1 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.

Figure 2.1: Screenshot from DualProj Treatment



2.4 Experimental Results

Individual-level Analysis

How do agents form expectations about output and inflation? A common simplifying assumption is to assume agents form identical and rational expectations about the future. To test whether subjects indeed forecast rationally, we construct a series of specifications that consider the effects of projections on the weight subjects place on the REE solution relative to past outcomes and trends. Formally, our estimating equations are:

$$E_{i,t}z_{t+1} = \alpha + \beta z_{t-1} + \gamma z_{t+1}^{REE} + \epsilon_t \ , \tag{2.8}$$

$$E_{i,t}z_{t+1} = \alpha + \beta(z_{t-1} - z_{t-2}) + \gamma z_{t+1}^{REE} + \epsilon_t \ , \tag{2.9}$$

where z denotes either output gap or inflation, and $E_{i,t}z_{t+1}$ is subject i's expectation of the following period's z. Under the null hypotheses of rational expectations, forecasts should depend only on the REE solution and not lagged variables or the constant, ie. $\hat{\gamma} = 1$, $\hat{\beta} = 0$ and $\hat{\alpha} = 0$.

If subjects do not form rational expectations, then we are interested to know whether central bank projections reduce subjects' reliance on particular heuristics and encourage them to place more weight on the REE solution. To test for treatment effects, we interact our lagged, trend, and REE z with dummy variables indicating treatments:

$$E_{i,t}z_{t+1} = \alpha + \beta_1 z_{t-1} + \beta_2 z_{t-1} \times OutputProj + .. + \beta_5 z_{t-1} \times IRProj$$
$$+ \gamma_1 z_{t+1}^{REE} + \gamma_2 z_{t+1}^{REE} \times OutputProj + ... + \gamma_5 z_{t+1}^{REE} \times IRProj + \epsilon_t$$

and

$$E_{i,t}z_{t+1} = \alpha + \beta_1(z_{t-1} - z_{t-2}) + \beta_2(z_{t-1} - z_{t-2}) \times OutputProj + .. + \beta_5(z_{t-1} - z_{t-2}) \times IRProj$$
$$+ \gamma_1 z_{t+1}^{REE} + \gamma_2 z_{t+1}^{REE} \times OutputProj + ... + \gamma_5 z_{t+1}^{REE} \times IRProj + \epsilon_t$$

If central bank projections are effective at encouraging subjects to form more rational expectations, then we would expect to find that $\hat{\beta}_k < 0$ and $\hat{\gamma}_k > 0$ for $k > 2$. The results of these specifications are first presented by treatment in Table 2.2, and as a pooled set of regressions to identify treatment effects in Table 2.3. Specifications by repetition related to output forecasts are presented in columns (1)-(4) and inflation forecasts in columns (5)-(8).

First, we reject Hypothesis I that subjects form rational expectations. In Table 2.2 we see that in all treatments, subjects place significant weight on either lagged output and inflation, and in most cases places significant weight on past trends. For experienced subjects in the NoComm treatment, a 1% increase in lagged output and inflation leads to 0.89% and 0.74% increases in expected output and inflation. NoComm subjects do not consistently weight the REE prediction in their output forecasts, but do significantly respond to current fundamentals when forming their inflation forecasts. Central bank projections of output and inflation reduce the weight experienced subjects place on lagged output and inflation in their forecasts, and increase their reliance on the REE prediction. Experienced subjects' output forecasts are significantly more "rational" when they observed inflation and dual projections. Likewise, output, inflation and dual projections increase the weight placed on the REE solution for inflation forecasts. Interest rate projections have an overall positive effect on subjects' usage of central bank communication in their forecasts, the effect is heterogeneous and not statistically significant.

Table 2.2: Effects of central bank projections on weight placed on REE solution in output and inflation forecasts - By Treatment[I]

	Output Forecasts				Inflation Forecasts			
NoComm	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var	$E_{i,t}x_{t+1}$				$E_{i,t}\pi_{t+1}$			
x_{t-1}	1.330*	0.886**						
	(0.69)	(0.38)						
x_{t+1}^{REE}	-0.114	0.314	0.851***	0.922***				
	(0.48)	(0.32)	(0.16)	(0.08)				
$x_{t-1}-x_{t-2}$			-0.028	0.188***				
			(0.27)	(0.05)				
π_{t-1}					0.735***	0.740***		
					(0.04)	(0.04)		
π_{t+1}^{REE}					0.445***	0.575***	0.522***	0.783***
					(0.06)	(0.12)	(0.10)	(0.18)
$\pi_{t-1}-\pi_{t-2}$							0.342***	0.245***
							(0.08)	(0.09)
α	57.935	55.294	20.143	51.060	4.440***	5.356***	-3.271	17.258***
	(53.63)	(53.49)	(36.79)	(52.21)	(1.23)	(1.31)	(2.33)	(3.73)
Repetition	1	2	1	2	1	2	1	2
N	1215	1216	1173	1174	1215	1216	1173	1174
χ^2	309.6	355.9	225.2	176.8	667.2	503.5	119.8	110.1

OutputProj	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var	$E_{i,t}x_{t+1}$				$E_{i,t}\pi_{t+1}$			
x_{t-1}	0.338***	0.221***						
	(0.07)	(0.04)						
x_{t+1}^{REE}	0.268	0.696***	0.299	0.819***				
	(0.30)	(0.07)	(0.43)	(0.07)				
$x_{t-1}-x_{t-2}$			0.404	0.080***				
			(0.31)	(0.02)				
π_{t-1}					0.315	0.448***		
					(0.40)	(0.05)		
π_{t+1}^{REE}					0.365	1.044***	0.072	1.273***
					(0.41)	(0.16)	(0.91)	(0.15)
$\pi_{t-1}-\pi_{t-2}$							0.864	0.130***
							(0.67)	(0.04)
α	53.343	5.117***	43.602	3.582*	57.856	12.825***	61.590	22.837***
	(47.06)	(1.70)	(44.69)	(1.91)	(44.48)	(2.31)	(42.18)	(3.21)
Repetition	1	2	1	2	1	2	1	2
N	1198	1215	1150	1173	1198	1215	1150	1173
χ^2	141.2	224.9	159.3	170.8	0.840	360.8	33.32	132.6

InflationProj	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var	$E_{i,t}x_{t+1}$				$E_{i,t}\pi_{t+1}$			
x_{t-1}	0.396***	0.250***						
	(0.05)	(0.05)						
x_{t+1}^{REE}	0.444***	0.864***	0.663***	1.022***				
	(0.06)	(0.08)	(0.06)	(0.07)				
$x_{t-1}-x_{t-2}$			0.139***	0.045**				
			(0.03)	(0.02)				
π_{t-1}					0.292***	0.071		
					(0.05)	(0.05)		
π_{t+1}^{REE}					0.748***	1.012***	0.860***	1.056***
					(0.07)	(0.10)	(0.08)	(0.09)
$\pi_{t-1}-\pi_{t-2}$							0.148***	0.003
							(0.04)	(0.03)
α	6.723**	4.295***	-3.974	3.222*	6.104***	2.793***	5.276***	3.036***
	(3.01)	(1.62)	(3.84)	(1.67)	(1.33)	(0.84)	(1.48)	(0.90)
Repetition	1	2	1	2	1	2	1	2
N	1216	1208	1174	1159	1216	1208	1174	1159
χ^2	134.1	253.7	125.1	195.8	166.1	160.4	162.6	147.5

(I) These tables present results from a series of random effects panel regressions. α denotes the estimated constant in the random effects regressions. Robust standard errors are employed. *$p < 0.10$, **$p < 0.05$, and ***$p < 0.01$.

Table 2.2: Effects of central bank projections on weight placed on REE solution in output and inflation forecasts - By Treatment - Continued[I]

	Output Forecasts				Inflation Forecasts			
DualProj	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var	$E_{i,t}x_{t+1}$				$E_{i,t}\pi_{t+1}$			
x_{t-1}	0.222***	0.129***						
	(0.04)	(0.05)						
x_{t+1}^{REE}	0.580***	0.861***	0.697***	0.939***				
	(0.07)	(0.06)	(0.07)	(0.06)				
$x_{t-1} - x_{t-2}$			0.082***	0.040				
			(0.03)	(0.03)				
π_{t-1}					0.155	0.050		
					(0.14)	(0.05)		
π_{t+1}^{REE}					0.864***	1.105***	0.948***	1.123***
					(0.14)	(0.11)	(0.12)	(0.10)
$\pi_{t-1} - \pi_{t-2}$							-0.030	0.056*
							(0.10)	(0.03)
α	14.287*	11.680	8.266	11.980	15.148*	9.649*	13.767	9.857*
	(8.09)	(7.84)	(8.22)	(8.04)	(9.17)	(5.25)	(9.75)	(5.32)
Repetition	1	2	1	2	1	2	1	2
N	1209	1216	1168	1174	1209	1216	1168	1174
χ^2	159.5	330.0	140.8	355.5	84.43	222.6	81.49	122.6

IRProj	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var	$E_{i,t}x_{t+1}$				$E_{i,t}\pi_{t+1}$			
x_{t-1}	0.565***	0.425***						
	(0.05)	(0.05)						
x_{t+1}^{REE}	0.509***	0.621***	0.842***	0.866***				
	(0.09)	(0.09)	(0.11)	(0.09)				
$x_{t-1} - x_{t-2}$			0.169***	0.109***				
			(0.03)	(0.02)				
π_{t-1}					0.754***	0.701***		
					(0.08)	(0.07)		
π_{t+1}^{REE}					0.837***	0.650***	1.086***	0.750***
					(0.28)	(0.15)	(0.31)	(0.16)
$\pi_{t-1} - \pi_{t-2}$							0.290***	0.221***
							(0.08)	(0.06)
α	4.366	2.745	-11.970**	3.049*	4.507	0.242	-3.666	2.029
	(5.21)	(1.80)	(5.42)	(1.82)	(4.99)	(1.48)	(5.47)	(3.32)
Repetition	1	2	1	2	1	2	1	2
N	1215	1215	1173	1173	1215	1215	1173	1173
χ^2	155.0	224.0	130.2	165.2	121.8	188.7	17.70	44.06

(I) These tables present results from a series of random effects panel regressions. α denotes the estimated constant in the random effects regressions. Robust standard errors are employed. *$p < 0.10$, **$p < 0.05$, and ***$p < 0.01$.

Table 2.3: Effects of central bank projections on weight placed on REE solution in output and inflation forecasts[I]

	Output Forecasts				Inflation Forecasts			
	Lagged vs. REE		Trend-chasing vs. REE		Lagged vs. REE		Trend-chasing vs. REE	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var	$E_{i,t}x_{t+1}$		$E_{i,t}x_{t+1}-x_{t-1}$		$E_{i,t}\pi_{t+1}$		$E_{i,t}\pi_{t+1}-\pi_{t-1}$	
x_{t-1}	1.320**	0.885**						
	(0.67)	(0.37)						
$x_{t-1} \times OutputProj$	-0.989	-0.665*						
	(0.67)	(0.37)						
$x_{t-1} \times InflationProj$	-0.918	-0.638*						
	(0.66)	(0.37)						
$x_{t-1} \times DualProj$	-1.094*	-0.757**						
	(0.66)	(0.37)						
$x_{t-1} \times IRProj$	-0.748	-0.460						
	(0.66)	(0.37)						
x_{t+1}^{REE}	-0.127	0.315	0.323**	0.333***				
	(0.49)	(0.32)	(0.14)	(0.07)				
$x_{t+1}^{REE} \times OutputProj$	0.391	0.379	-0.549	-0.041				
	(0.58)	(0.32)	(0.46)	(0.09)				
$x_{t+1}^{REE} \times InflationProj$	0.580	0.551*	-0.137	0.215**				
	(0.50)	(0.33)	(0.14)	(0.10)				
$x_{t+1}^{REE} \times DualProj$	0.713	0.545*	-0.119	0.093				
	(0.50)	(0.32)	(0.15)	(0.09)				
$x_{t+1}^{REE} \times IRProj$	0.646	0.308	0.028	0.015				
	(0.50)	(0.33)	(0.16)	(0.10)				
$x_{t-1} - x_{t-2}$			-0.415	-0.254***				
			(0.26)	(0.05)				
$x_{t-1} - x_{t-2} \times OutputProj$			0.404	-0.121**				
			(0.40)	(0.05)				
$x_{t-1} - x_{t-2} \times InflationProj$			0.148	-0.171***				
			(0.26)	(0.05)				
$x_{t-1} - x_{t-2} \times DualProj$			0.076	-0.167***				
			(0.26)	(0.06)				
$x_{t-1} - x_{t-2} \times IRProj$			0.190	-0.076				
			(0.26)	(0.05)				
π_{t-1}					0.711***	0.711***		
					(0.04)	(0.04)		
$\pi_{t-1} \times OutputProj$					-0.261***	-0.261***		
					(0.07)	(0.07)		
$\pi_{t-1} \times InflationProj$					-0.643***	-0.643***		
					(0.07)	(0.07)		
$\pi_{t-1} \times DualProj$					-0.652***	-0.652***		
					(0.06)	(0.06)		
$\pi_{t-1} \times IRProj$					-0.050	-0.050		
					(0.08)	(0.08)		
π_{t+1}^{REE}					0.582***	0.582***	0.479***	0.547***
					(0.12)	(0.12)	(0.07)	(0.12)
$\pi_{t+1}^{REE} \times OutputProj$					0.456**	0.456**	-0.704	0.253
					(0.19)	(0.19)	(0.99)	(0.18)
$\pi_{t+1}^{REE} \times InflationProj$					0.430***	0.430***	-0.032	0.086
					(0.15)	(0.15)	(0.10)	(0.16)
$\pi_{t+1}^{REE} \times DualProj$					0.522***	0.522***	0.061	0.021
					(0.16)	(0.16)	(0.12)	(0.17)
$\pi_{t+1}^{REE} \times IRProj$					0.070	0.070	0.425	0.141
					(0.19)	(0.19)	(0.30)	(0.19)
$\pi_{t-1} - \pi_{t-2}$							-0.164**	-0.250***
							(0.07)	(0.08)
$\pi_{t-1} - \pi_{t-2} \times OutputProj$							0.590	-0.083
							(0.67)	(0.09)
$\pi_{t-1} - \pi_{t-2} \times InflationProj$							-0.091	-0.229***
							(0.08)	(0.08)
$\pi_{t-1} - \pi_{t-2} \times DualProj$							-0.241**	-0.139*
							(0.12)	(0.08)
$\pi_{t-1} - \pi_{t-2} \times IRProj$							-0.061	-0.085
							(0.11)	(0.09)
α	27.347*	15.837	39.781***	16.199	6.260***	6.260***	18.437**	1.289
	(14.38)	(10.82)	(11.72)	(10.54)	(1.26)	(1.26)	(8.33)	(1.16)
Repetition	1	2	1	2	1	2	1	2
N	6053	6070	5838	5853	6070	6070	5838	5853
χ^2	927.7	1394.6	278.3	966.9	1351.0	1351.0	195.1	509.4

(I) This table presents results from a series of random effects panel regressions. α denotes the estimated constant in the random effects regressions. Robust standard errors are employed. $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

Subjects exhibit trend-chasing heuristics when forming their expectations of output and inflation. Central bank projections of output, inflation, and dual projections significantly reduce the degree to which subjects form trend–chasing expectations. Inflation forecasts are also made significantly more contrarian with announced projections of inflation and dual projections. Importantly, while interest rate projections also reduce trend-chasing forecasting heuristics, their effect is not consistent across subjects. We now summarize our first two observations of individual forecasting behavior:

Observation I: Expectations formed in the NoComm treatment rely significantly on historical information such as lagged outcomes and past trends.

Observation II: With central bank projections of future output (inflation), subjects place more weight on the rational forecast of output (inflation) and less weight on last period's outcomes or past trends. This response is highly significant for experienced output forecasts and both inexperienced and experienced inflation forecasts. Nominal interest rate projections do not lead to significantly different forecasting heuristics.

Central bank projections provide a common focal piece of information for subjects' to potentially coordinate their forecasts on. We quantify the degree of coordination by calculating the degree of disagreement or standard deviation in forecasts each period across subjects in a single group. For each group and repetition, we calculate the mean disagreement. Summary statistics, measured at the treatment-level, of mean disagreement are reported in Table 2.4.[13] 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 mean disagreements across treatments fails to reject that the 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 ($p = 0.037$) and the InflationProj treatment ($p = 0.025$). Moreover, communicating only output projections leads to significantly greater disagreement about future inflation than communicating only inflation projections ($p = 0.078$).

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

However, with experience, subjects in Repetition 2 coordinate significantly better when presented with certain central bank forecasts. Subjects that observe output gap projections disagree significantly less than their NoComm counterparts when forming output forecasts. The average standard deviation of output forecasts falls from 102.54 in the NoComm treatment to 42.87 in the OutputProj treatment. Rank–sum tests reject the null hypothesis that the measure of disagreement is identical across the two treatments ($p = 0.025$). Similarly, the average inflation disagreement falls significantly from 39.40 in the NoComm treatment to 19.85 in the InflationProj treatment ($p = 0.037$). While inflation projections appear to reduce output gap disagreements considerably (output disagreement falls to 37.50, $p = 0.055$), output projections worsen inflation disagreements on average (inflation disagreement increases to 43.85, $p = 0.262$). Communicating output gap projections rather than inflation projections leads experienced subjects to disagree significantly more about inflation ($p = 0.025$). Moreover, inflation disagreements worsen when the central bank presents its inflation projection with an output gap projection. The inflation disagreement in the DualProj treatment is 46.47 and is significantly greater than in the InflationProj treatment ($p = 0.078$). Finally, as with inexperienced subjects, interest rate projections tend to be more effective at coordinating experienced output forecasts than inflation forecasts. In the IRProj treatment, output disagreements decrease considerably to 41.30 ($p = 0.109$) and inflation disagreements decrease insignificantly to 29.65 ($p = 0.873$). Finally, the central bank is significantly more effective at coordinating inflation forecasts when it communicates only an inflation projection than if it were to communicate an interest rate projection ($p = 0.055$).

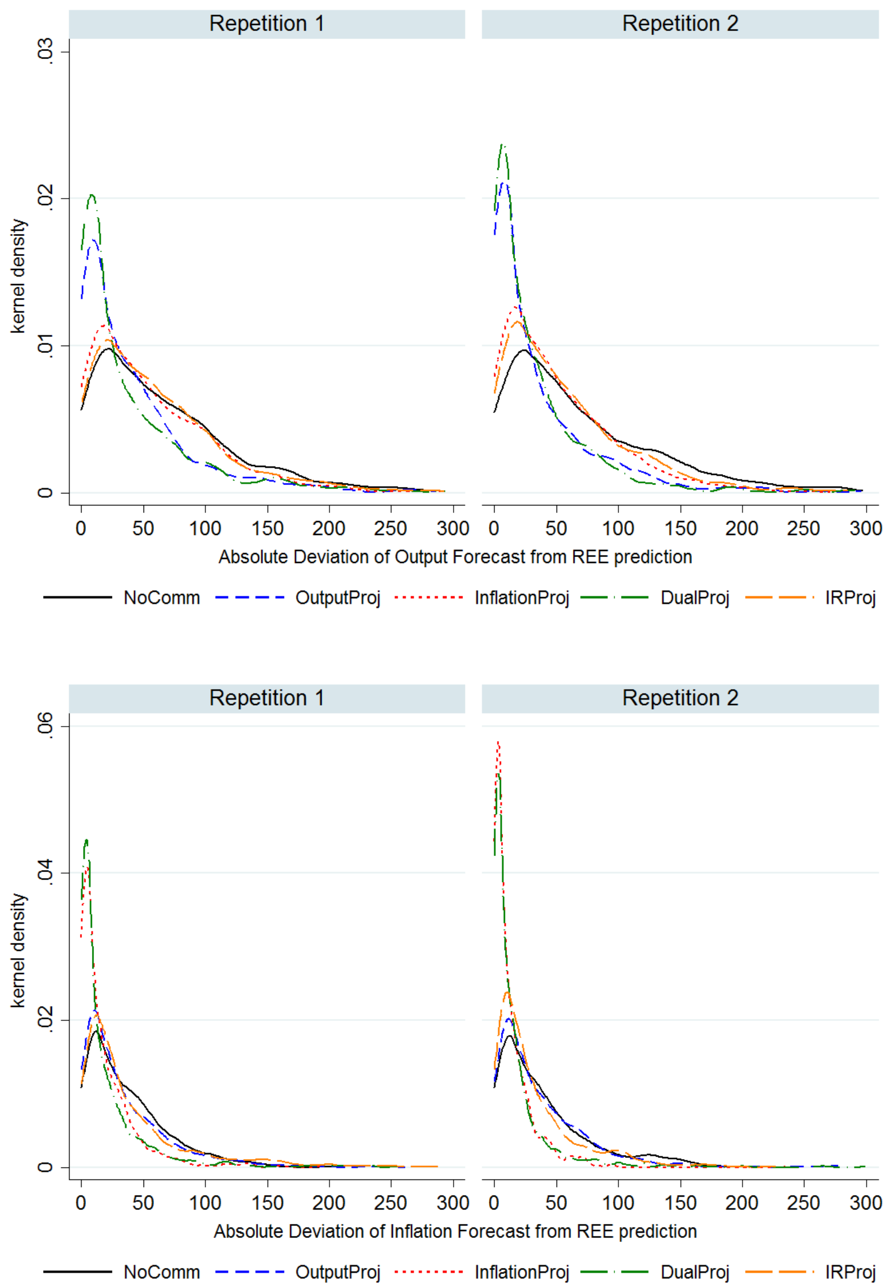
Table 2.4: Forecast Disagreement By Treatment and Repetition

Treatment		Repetition–1		Repetition–2	
		Output	Inflation	Output	Inflation
NoComm					
	Mean	65.31	39.06	102.54	39.40
	std.	39.59	17.51	132.65	32.04
OutputProj					
	Mean	61.38	59.18	42.871	43.85
	std.	40.06	37.94	27.30	34.18
InflationProj					
	Mean	29.17	34.76	37.50	19.85
	std.	13.65	12.34	17.80	4.91
DualProj					
	Mean	40.81	45.87	53.12	46.47
	std.	15.23	14.84	31.70	23.73
IRProj					
	Mean	35.49	40.45	41.30	29.65
	std.	21.91	16.06	11.67	13.53
Rank–sum test:		p–value	p–value	p–value	p–value
NoComm–OutputProj		0.423	0.200	0.025	0.262
NoComm–InflationProj		0.873	0.631	0.055	0.037
NoComm–DualProj		0.749	0.873	0.200	0.423
NoComm–IRProj		0.873	0.037	0.109	0.873
OutputProj–InflationProj		0.873	0.078	0.423	0.025
OutputProj–DualProj		0.749	0.522	1.000	0.200
OutputProj–IRProj		0.423	0.749	0.200	0.423
InflationProj–DualProj		1.000	0.631	0.423	0.078
InflationProj–IRProj		0.873	0.025	0.522	0.055
DualProj–IRProj		0.631	0.337	0.423	0.749

The entries are the average and the standard deviation of the mean 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 mean disagreements are equal to zero for all treatments and repetitions ($p = 0.028$ in all cases).

The extent to which subjects' forecasts deviate from the REE solution is depicted in Figure 2.2. The figure presents kernel densities of the absolute deviation of output and inflation forecasts from the REE solution's predicted forecasts. Compared to the NoComm baseline, a much larger mass of output (inflation) forecasts are exactly or very close to the REE forecast when subjects observe output (inflation) and dual projections. Moreover, the degree to which subjects coordinate their forecasts on these central bank projections increases with experience. While experienced output (inflation) forecasts are considerably better coordinated on the REE prediction with inflation (output) and interest rate projections than with no forward guidance, the differences are less stark. These findings provide support for Hypothesis IV.

Figure 2.2: Kernel densities of absolute deviation of output and inflation forecasts from the REE prediction



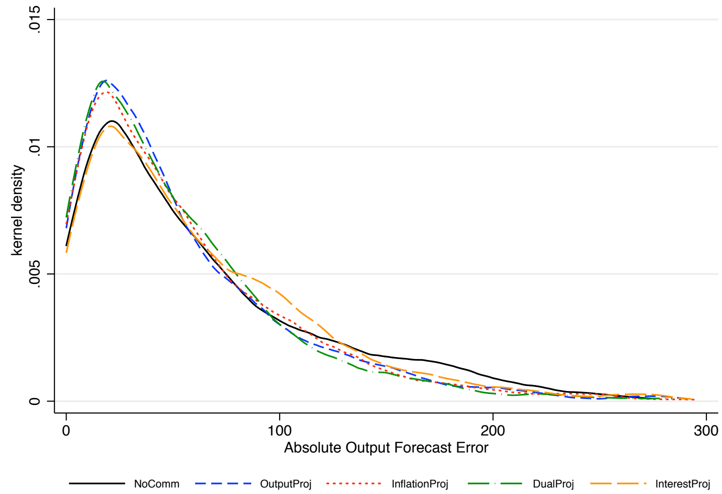
Observation III: By the second repetition, central bank projections of output (inflation) result in significantly less disagreement in output (inflation) forecasts. Communication of output projections on their own or combined with inflation projections increases disagreement about future inflation. Interest rate projections are relatively more effective at coordinating expectations about output than inflation.

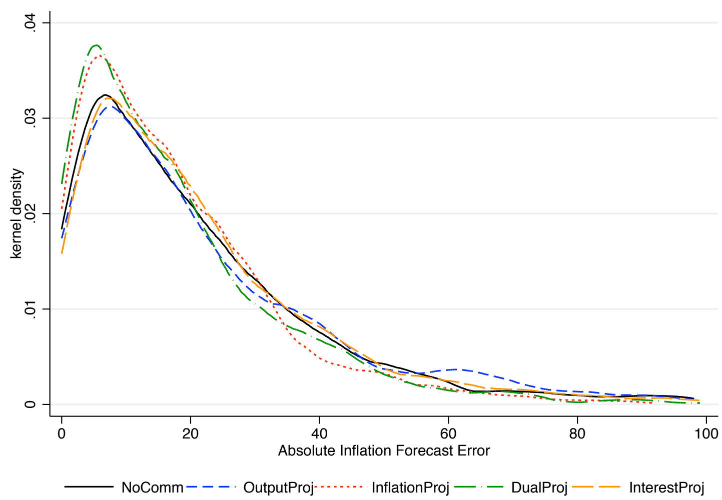
Central bank projections are meant, among other things, to help forecasters better anticipate the future. Thus, one measure of the success of a central bank's projection is its ability to reduce forecast errors. We compute subjects' absolute forecast errors as the absolute difference between their forecasts and the realized outcome. Summary statistics on absolute forecast errors are presented in Table A.1 in the appendix and distributional plots of all Repetition 2 absolute forecast errors by treatment are presented in Figure 2.3.

Experienced output forecast errors decrease by roughly 50% with central bank projections. Repetition 2 mean absolute output forecast errors in the NoComm treatment are approximately 122 bps (s.d. 485). Introducing output and/or inflation projections reduces the mean forecast errors to under 61 bps, while interest rate projections result in a mean output forecast error of 62 bps. However, the reduction in mean output forecast errors is only statistically significant at the 10% level in the OutputProj treatment ($p = 0.078$). Mean inflation forecast errors are minimally and insignificantly altered by central bank projections of output, both output and inflation, or nominal interest rates. Only when the CB communicates an inflation projection do inflation forecast errors fall significantly ($p = 0.025$).[14] The kernel densities of absolute forecast errors provide a more complete understanding of the distributional differences across treatments. Output forecast errors in the OutputProj, DualProj, and InflationProj treatments are skewed downward compared to those observed in the NoComm and IRProj treatments. Similarly, inflation forecast errors in the InflationProj and DualProj treatments have a larger mass near zero than the other three treatments. Together, these results suggest that forecast errors are considerably reduced when subjects are presented with a highly relevant projection.

[14]In most cases, central bank projections do not have a significant effect on mean absolute forecast errors for inexperienced subjects. The one exception is that inexperienced mean absolute inflation forecast errors increase in the presence of interest rate projections ($p = 0.109$).

Figure 2.3: Kernel densities of absolute output and inflation forecast errors - Repetition 2





Observation IV: Highly relevant central bank projections skew experienced forecast errors toward zero. Projections of future nominal interest rates do not significantly reduce forecast errors.

Finally, we consider how central bank forecast errors influence subjects' willingness to utilize the public communications as their own forecasts. We focus on subjects' likelihood of utilizing central bank projections in the OutputProj, InflationProj, and DualProj treatments where it is more obvious whether they are using the supplementary information.[15] Our dependent 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 10 basis points from the central bank's projection and 0 otherwise.[16] We employ a series of random effects probit models to understand how the probability subjects utilize the central banks projection 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, $|FE^{cb}\pi_{t-1}| = |E^{cb}_{t-2}\pi_{t-1} - \pi_{t-1}|$.[17] 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. Specification (1) and (2) focuses on output and inflation forecasts formed in the OutputProj and InflationProj treatments, respectively. Specifications (3) and (4) consider how output and inflation forecasts formed in the DualProj treatment responds to central bank and personal forecast errors of output and inflation, individually. Finally, specifications (5) and (6) consider the effects of both output and inflation forecast errors on both output and inflation forecasts. The results are presented in Table 2.5 by repetition.

[15] In the IRProj treatment, a subject may be using the projected interest rate to formulate their forecast, but may make calculation errors.

[16] According to this definition of utilization, subjects utilized output projections 33% of the time in the OutputProj treatment and 36% of the time in the DualProj treatment. Inflation projections were utilized 25% of the time in the InflationProj treatment and 54% of the time in the DualProj treatment. Subjects utilized both projections in the DualProj treatment 29% of the time. Our results remain qualitatively similar if we instead consider a stronger definition of utilization where subjects' forecasts must be less than 2 basis points from the central bank's projection.

[17] The central bank's mean output forecast errors in the OutputProj and DualProj treatments ranged from 78-79.3 basis points with standard deviations ranging from 62 to 64 points. The central bank's mean inflation forecast errors in the InflationProj and DualProj treatments ranged from 23.46 to 24.04 basis points with standard deviations ranging between 19.41 and 19.90 points. In short, there was very little difference in the magnitude and distribution of central bank forecast errors. Kernel density and cumulative distribution functions of the absolute forecast errors can be found in the Appendix. We include IRPRoj forecast errors of the nominal interest rate for reference.

Subjects' usage of the central bank forecast decreases as the central bank's forecast errors about output grow large. Specification (1) shows that in the OutputProj treatment, a 10-basis point error reduces the probability a subject uses the output projection by 5-6%. While past utilization of the central bank's output projections does increase the likelihood of continued utilization, the effect is not statistically significant. Likewise, past forecast errors do not have a large or significant effect on subjects' willingness to utilize output projections. In the DualProj treatment, subjects' use of output projections decreases as the central bank forms larger output forecast errors, but the effect is not significant.

Table 2.5: Credibility of Central Bank Projections of Output and Inflation - By Repetition [I]

Panel A: Repetition 1

Treatment	OutputProj	InflationProj	DualProj			
Dep.Var: Prob(Utilized CB Forecast=1)	$E_{i,t}x_{t+1}$	$E_{i,t}\pi_{t+1}$	$E_{i,t}x_{t+1}$	$E_{i,t}\pi_{t+1}$	$E_{i,t}x_{t+1}$	$E_{i,t}\pi_{t+1}$
	(1)	(2)	(3)	(4)	(5)	(6)
$\|FE^{cb}x_{t-1}\|$	-0.006***		-0.002		-0.002	0.000
	(0.00)		(0.00)		(0.00)	(0.00)
$(\|FE^{cb}x_{t-1}\|)^2$	0.000*		0.000		0.000	0.000
	(0.00)		(0.00)		(0.00)	(0.00)
$UtilizedCBxForecast_{t-2}$	0.037		0.262**		0.169	0.393**
	(0.14)		(0.13)		(0.15)	(0.16)
$\|FEx_{i,t-1}\|$	-0.001		-0.002***		-0.002*	0.000
	(0.00)		(0.00)		(0.00)	(0.00)
$\|FEx_{i,t-1}\| \times UtilizedCBxForecast_{t-2}$	0.000		0.000		0.000	-0.001
	(0.00)		(0.00)		(0.00)	(0.00)
$\|FE^{cb}\pi_{t-1}\|$		-0.006		-0.009	-0.000	-0.011
		(0.01)		(0.01)	(0.01)	(0.01)
$(\|FE^{cb}\pi_{t-1}\|)^2$		0.000		0.000	-0.000	-0.000
		(0.00)		(0.00)	(0.00)	(0.00)
$UtilizedCB\pi Forecast_{t-2}$		0.522***		0.462***	0.192	0.360***
		(0.12)		(0.13)	(0.13)	(0.13)
$\|FE\pi_{i,t-1}\|$		-0.001		-0.002	-0.002	-0.003
		(0.00)		(0.00)	(0.00)	(0.00)
$\|FE\pi_{i,t-1}\| \times UtilizedCB\pi Forecast_{t-2}$		-0.004		-0.004	0.002	-0.003
		(0.00)		(0.00)	(0.00)	(0.00)
lnsig2u						
α	-0.743**	-1.229***	-0.810***	-0.584**	-0.856***	-0.727**
	(0.29)	(0.29)	(0.29)	(0.29)	(0.30)	(0.30)
N	1150	1174	1167	1167	1167	1167
χ^2	38.88	38.85	34.37	45.35	45.80	55.07

Panel B: Repetition 2

Treatment	OutputProj	InflationProj	DualProj			
Dep.Var: Prob(Utilized CB Forecast=1)	$E_{i,t}x_{t+1}$	$E_{i,t}\pi_{t+1}$	$E_{i,t}x_{t+1}$	$E_{i,t}\pi_{t+1}$	$E_{i,t}x_{t+1}$	$E_{i,t}\pi_{t+1}$
	(1)	(2)	(3)	(4)	(5)	(6)
$\|FE^{cb}x_{t-1}\|$	-0.005**		-0.003		-0.006	-0.002
	(0.00)		(0.00)		(0.00)	(0.00)
$(\|FE^{cb}x_{t-1}\|)^2$	0.000*		0.000		0.000	0.000
	(0.00)		(0.00)		(0.00)	(0.00)
$UtilizedCBxForecast_{t-2}$	0.121		0.299**		0.181	0.501***
	(0.14)		(0.14)		(0.16)	(0.17)
$\|FEx_{i,t-1}\|$	-0.000		-0.001		-0.000	-0.000
	(0.00)		(0.00)		(0.00)	(0.00)
$\|FEx_{i,t-1}\| \times UtilizedCBxForecast_{t-2}$	0.000		-0.001		-0.001	-0.002
	(0.00)		(0.00)		(0.00)	(0.00)
$\|FE^{cb}\pi_{t-1}\|$		0.013**		-0.002	0.010	0.000
		(0.01)		(0.01)	(0.01)	(0.01)
$(\|FE^{cb}\pi_{t-1}\|)^2$		-0.000**		0.000	0.000	-0.000
		(0.00)		(0.00)	(0.00)	(0.00)
$UtilizedCB\pi Forecast_{t-2}$		0.333***		0.423***	0.230	0.307**
		(0.13)		(0.13)	(0.15)	(0.14)
$\|FE\pi_{i,t-1}\|$		0.001		-0.001	-0.005**	-0.001
		(0.00)		(0.00)	(0.00)	(0.00)
$\|FE\pi_{i,t-1}\| \times UtilizedCB\pi Forecast_{t-2}$		-0.006		-0.003	-0.002	-0.002
		(0.00)		(0.00)	(0.00)	(0.00)
lnsig2u						
α	-0.262	-0.370	-0.118	-0.214	-0.170	-0.369
	(0.28)	(0.29)	(0.28)	(0.30)	(0.29)	(0.31)
N	1173	1166	1175	1175	1175	1175
χ^2	12.78	15.86	17.78	16.24	29.04	29.91

(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 takes the value of 1 if a subject's output and inflation forecast in period t about period $t+1$, respectively, were less than 10 basis points away from the central bank's projected forecast. $|FE^{cb}x_{t-1}|$ and $|FE^{cb}\pi_{t-1}|$ denote the absolute forecast errors the central bank made in period $t-2$ about period $t-1$ output and inflation, respectively. $|FEx_{i,t-1}|$ and $|FE\pi_{i,t-1}|$ denote subject i's forecast errors formed in period $t-2$ about period $t-1$ output and inflation, respectively.

Observation V: Central banks lose credibility in the OutputProj and InflationProj treatments as their forecast errors become large. In the DualProj treatment, subjects do not significantly reduce their reliance on the central bank's projections when forecast errors grow large.

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 1-standard deviation shock to aggregate demand. The results for Repetition 2 are presented in Figure 2.4 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, however, we observe a consistently sluggish decline in output and by the fourth period following the initial shock, 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 tends to exhibit a relatively muted response. Thereafter, inflation rises for roughly 2 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 (2015).

Introducing central bank projections has varying effects on the transition paths of output and inflation. The estimated impulse response functions associated with the OutputProj treatment are presented as short dashed lines, with the InflationProj treatment as dotted lines, with the DualProj as long dash–dot–long dash lines, and finally with the IRProj as long dash lines. Generally, output tends to exhibit less overall volatility and a quicker return to the steady state in the presence of central bank projections. We do however note that, as the shock dissipates and the shocks are more volatile (as in Sequences 2 and 4), IRProj are associated with a greater contractionary overshooting effect of output, suggestive of a larger backward–looking nature of forecasts.

Figure 2.4: 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.

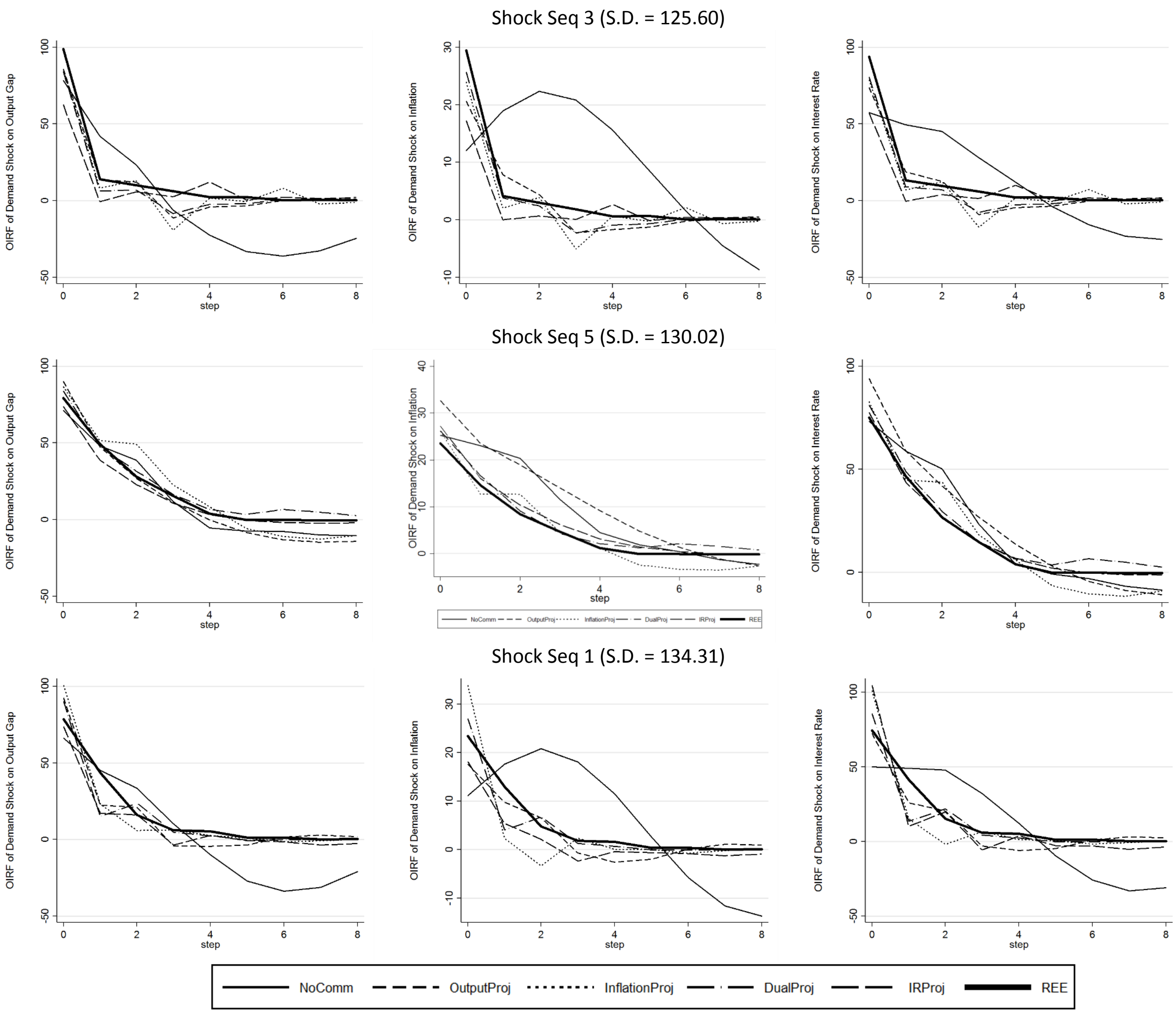
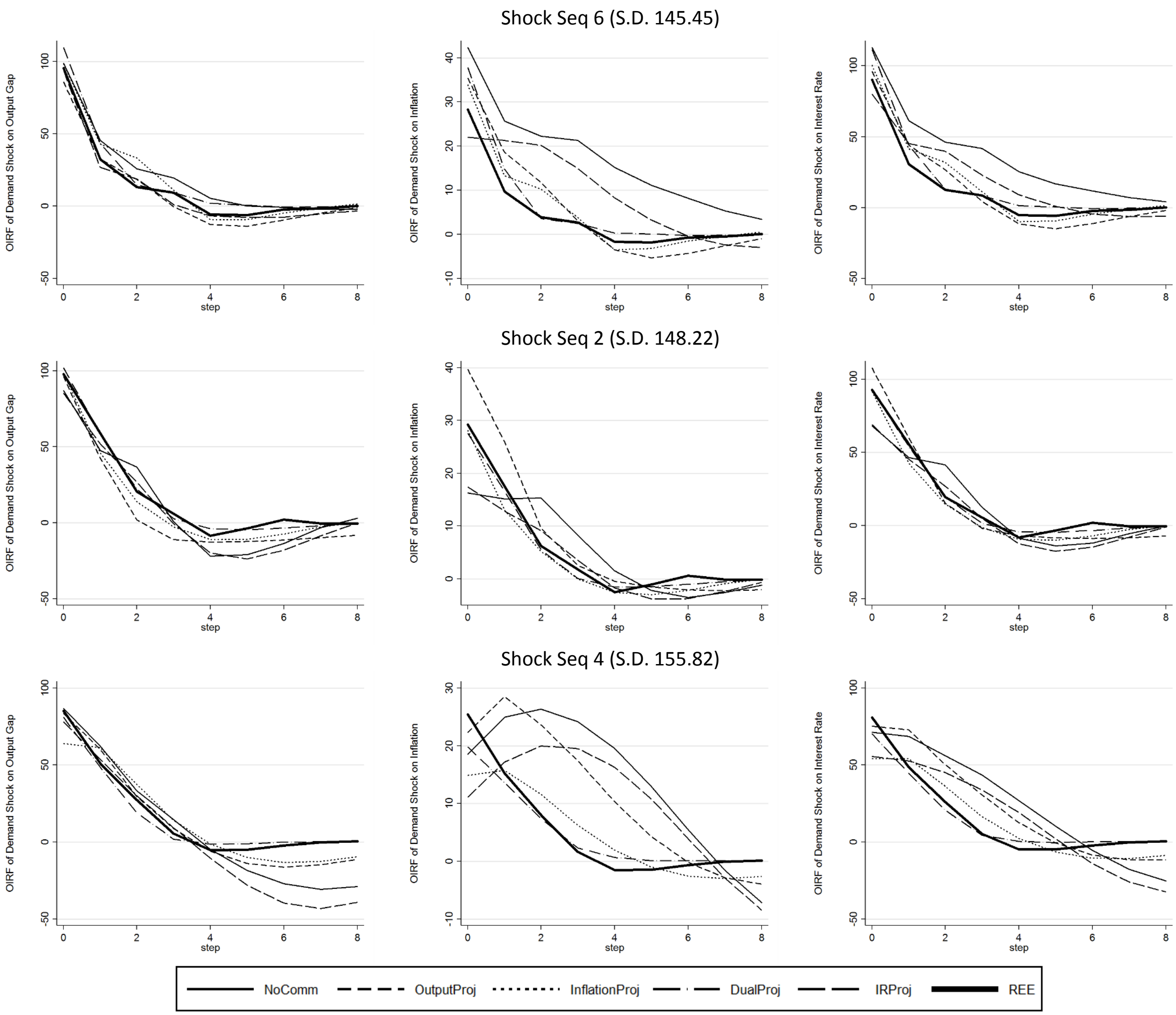


Figure 2.4: Estimated Impulse Responses of Endogenous Variables to 113 basis points shock

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



The effects of central bank communication are more stark when we consider the estimated responses of inflation. Inflation projections, communicated alone or in combination with output projections, leads to a response of inflation that is considerably more in line 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. When output is the only variable projected, we observe a variety of responses, ranging from a relatively muted, but stepwise-similar transition path to the REE prediction in Sequences 1 and 3, to a significantly more volatile initial response to shocks in Sequence 2. However, with the exception of Sequence 4, inflation tends to follow the same transition pattern as the REE solution, indicative of a reduction in adaptive forecasting. Similarly, 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 lower. 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 how subjects forecast. 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 2.6.[18] The results are also presented visually in Figure 2.5 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 1 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 and this difference is significant at the 5% level. Output and inflation variability are considerably lower in the presence of most forms of central bank communication than in the NoComm treatment, and with experience with the central bank projections, both output

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

and inflation are not significantly different from the REE prediction at the 10% level.

Table 2.6: 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
OutputProj					
	Mean	0.96*	1.10	0.95	1.27
	std.	0.04	0.19	0.05	0.36
InflationProj					
	Mean	0.95*	0.97	1.06	1.06
	std.	0.08	0.18	0.07	0.08
DualProj					
	Mean	0.96	1.06	0.97	1.04
	std.	0.04	0.20	0.04	0.12
IRProj					
	Mean	0.98	1.49	0.99	1.14
	std.	0.09	0.47	0.15	0.48
Rank–sum test:		p–value	p–value	p–value	p–value
NoComm–OutputProj		0.109	0.337	0.010	0.337
NoComm–InflationProj		0.109	0.149	1.000	0.055
NoComm–DualProj		0.109	0.262	0.010	0.055
NoComm–IRProj		0.522	0.749	0.262	0.200
OutputProj–InflationProj		0.631	0.262	0.016	0.337
OutputProj–DualProj		0.873	1.000	0.522	0.337
OutputProj–IRProj		1.000	0.749	0.873	1.000
InflationProj–DualProj		0.749	0.522	0.037	0.631
InflationProj–IRProj		1.000	0.522	0.262	0.749
DualProj–IRProj		1.000	0.522	0.522	0.749

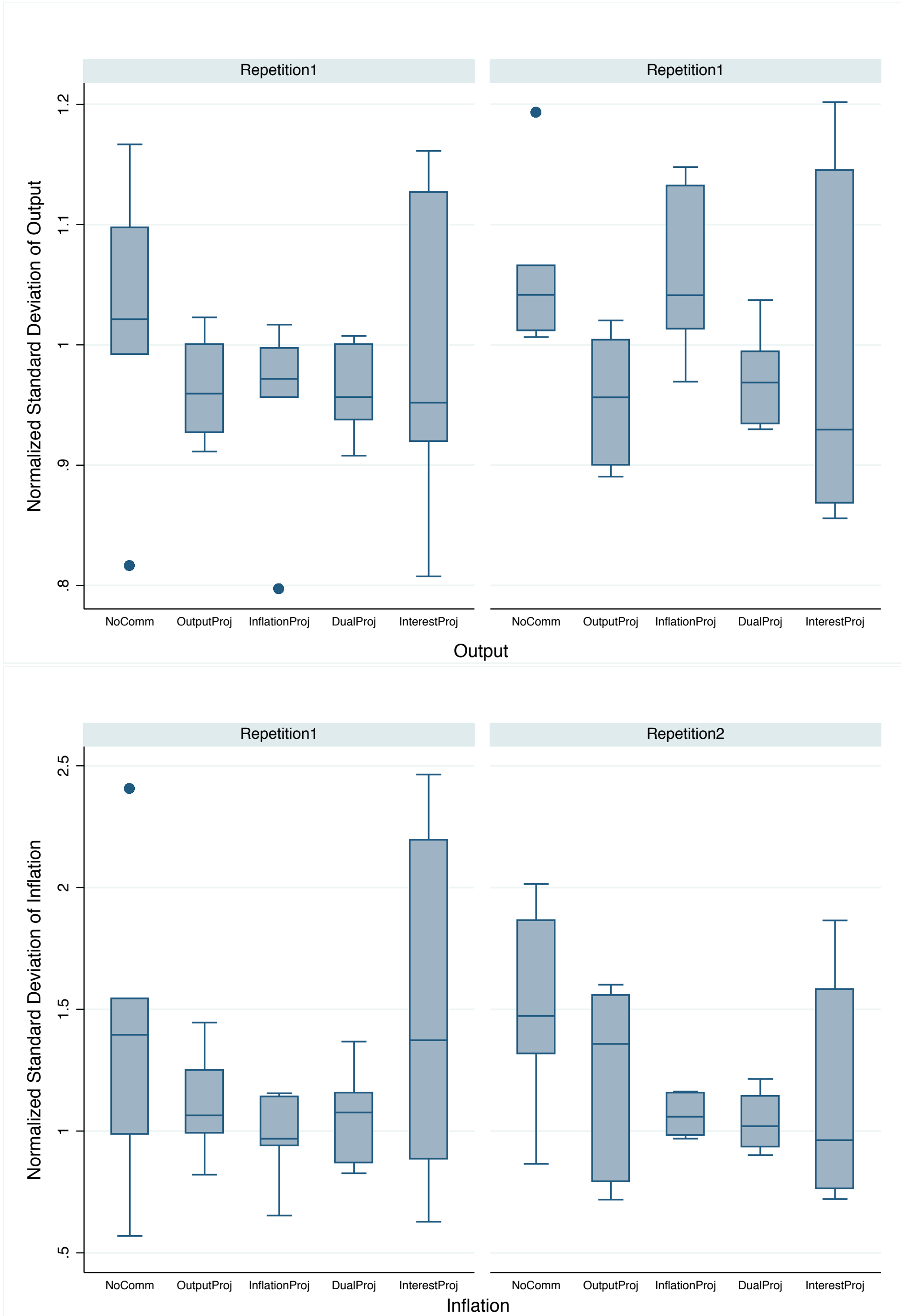
We report summary statistics on the standard deviation of output and inflation, measured at the session-repetition level, divided by the rational expectations equilibrium solution's respective standard deviations. $N = 6$ observations are computed per treatment-repetition. The top panel presents means and standard deviations of the variable of interest. Asterisks denote whether the mean result is significantly different from 1 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.

The ability of central bank projections to enhance economic stability is mixed. While the projections lead to considerably lower variability in output and inflation, the differences are not statistically significant when subjects are inexperienced in Repetition 1. However, by the second repetition, output variability is 11 percentage points lower in the OutputProj treatment and 9 percentage points lower in the DualProj treatment. This difference is statistically significant at the 1% level. Inflation variability is also significantly reduced by roughly 45 percentage points in the second repetition of the InflationProj and DualProj treatments (Wilcoxon rank sum tests reject the null hypothesis that the variability is identical across treatments: $p = 0.055$ in both cases). While central bank projections of future nominal interest rates lower mean aggregate variability, we observe some sessions where stability is significantly worse than under NoComm. Central bank forecast accuracy matters less when it comes to inflation projections. Subjects in the InflationProj do not begin penalizing the central bank for forecast errors unless the errors exceed roughly 75 basis points. Past utilization also plays an important role in whether subjects continue to make use of the central bank's inflation projection. However, in the DualProj treatment, central bank inflation forecast errors do not matter quantitatively or significantly.

These results provide a further reason for central banks to communicate output and inflation projections simultaneously. With a dual projection, even when the central bank's forecast errors increase, subjects do not significantly penalize the central bank. That is, subjects are more forgiving of central bank forecast errors. Given that actual utilization and central bank forecast errors are not considerably different across treatments, we attribute the subjects' willingness to accept central bank forecast errors in the DualProj treatment to the ease of using the information. Subjects are tasked with submitting two forecasts and the central bank provides a complete set of forecasts. By contrast, in the OutputProj and InflationProj treatments, the information set is relatively incomplete and subjects must use a secondary heuristic to forecast the non-communicated variable. It may be easier in these single-projection treatments to abandon usage of the central bank communication and simply follow an alternative heuristic.

Observation VI: With experience, output and inflation variability in the baseline NoComm treatment are significantly greater than predicted by the REE solution. Introducing central bank projections lowers macroeconomic variability to the REE predicted levels. Communicating output (inflation) projections reduces the normalized standard deviation of output (inflation), while communicating nominal interest rate projections has no significant effect on variability.

Figure 2.5: Standard Deviation of Output and Inflation Normalized by REE



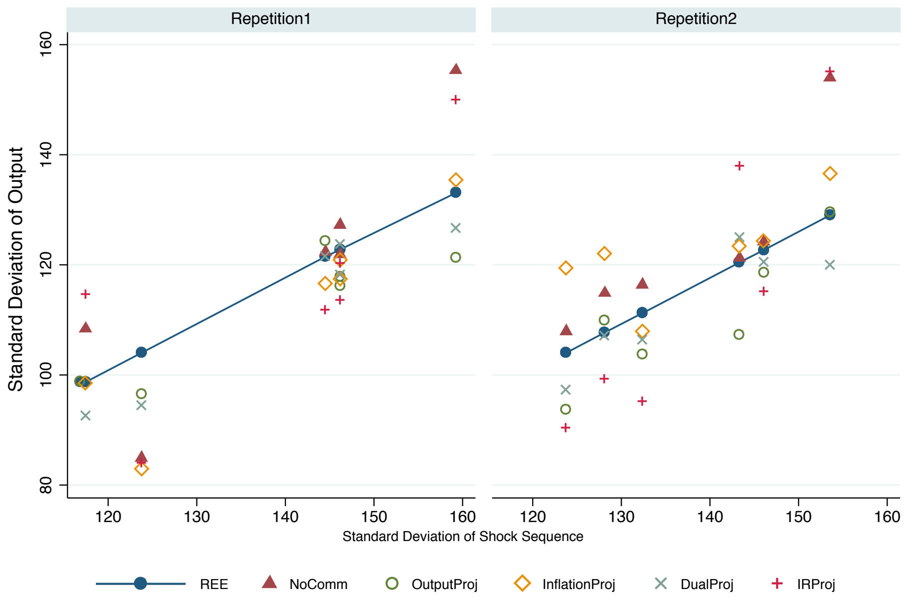
The figure represents the standard deviation of output and inflation at the treatment–repetition level.

To see how the effectiveness of central bank communication changes as aggregate demand becomes more volatile, we plot in Figure 2.6 the standard deviations of output and inflation by the standard deviation of shock sequences. The results are separated by repetition. First, note that in the NoComm treatment the variability in output and inflation grows nonlinearly with variability in shock sequences. As shock sequences become highly volatile, output and inflation variability increase more than one-for-one. This is in contrast to the REE prediction that predicts a strict linear relationship between variability in shocks and aggregate variables.

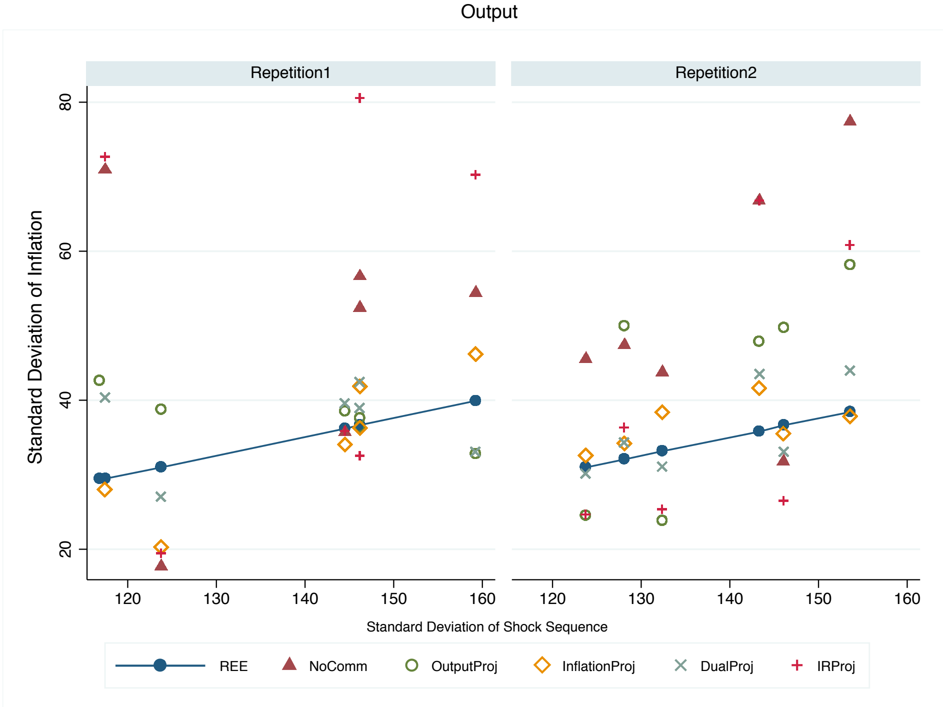
With experience, projections tend to reduce output and inflation volatility, especially as shock sequences become highly variable. Compared to their NoComm counterparts, variability of output is lower in all 6 OutputProj sessions, 2 of 6 InflationProj, 5 of 6 DualProj sessions, and 4 of 6 IRProj sessions. Likewise, the variability of inflation is lower than the NoComm counterpart in 4 of 6 OutputProj sessions, and 5 of 6 InflationProj, DualProj, and IRProj sessions.

We measure the 'stability gains from communication' as the standard deviations of output (inflation) under NoComm minus the standard deviations of output (inflation) under a particular form of communication. Output projections and dual projections make output increasingly more stable as shocks become more volatile (that is, the output stability gains from output and dual projections are increasing significantly in the standard deviation of shocks). Likewise, inflation, dual, and nominal interest rate projections make inflation increasingly more stable as shocks become more volatile.

Figure 2.6: Standard Deviation of Output and Inflation relative to REE



Output



2.5 Final remarks

Forward guidance has become an increasingly important instrument that central banks use to influence aggregate expectations. Identifying the effects of forward guidance 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. 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 forward guidance to influence expectations comes from the additional cognitive challenge of how to employ such projections into one's own forecast. Subjects must consider about how nominal interest rates directly influence the output gap and, indirectly, inflation, and this is considerably more difficult.

Chapter 3

Communication Strategies in the New Keynesian Model: An Exercise

3.1 Introduction

Communication is one of the main channels through which a central bank can influence market beliefs and expectations about its future economic actions. If the central bank fails to anchor expectations, it might result in economic instability. Therefore, an important issue that arises for central banks is considering what type of communication will reduce economic fluctuations (Hansen & McMahon, 2016).

The conventional wisdom in central banking monetary policy is that monetary authorities should communicate as little as possible. However, over recent decades, central banks' monetary policy in managing expectation has become clearer in that they have realized that communication and transparency are important instruments (Woodford, 2005). Two key questions arise in the literature: What should the central bank communication strategy be, and does communication contribute to the success of monetary policy? Two main strands of studies in the literature attempt to answer these questions. The first strand of studies focuses on the influence of central bank communication on the financial markets. They study the influence of communication in steering expectations through asset market pricing, and find that in the majority of advanced countries, asset market prices reacts to communication (Blinder et al., 2008; Connolly & Kohler, 2004; Gurkaynak et al., 2005; Kohn & Sack, 2004;

Reeves & Sawicki, 2007). The second strand of studies relates to the differences in communication strategies across central banks or across time. These communication strategies vary–a bank may provide its policy targets qualitatively, provide its targets explicitly, or provide its projections of future interest rate, output, and inflation. The Reserve Bank of New Zealand, the Norges Bank of Norway, and the Riksbank of Sweden are among the leaders of central bank communication. The central bank of Canada and the United States have increased their focus on communication strategies after the 2008 financial crisis (Blinder et al., 2008).

With the development of inflation–targeting policies, central bank forecasts have become an integral tool of central bank communication. Theoretically, an influential central bank's monetary policy implementation should be more effective due to its impact on private expectations, at least in terms of the interpretation of policy actions, reduction in transmission lags, and reputation. The theoretical research looks at whether central bank transparency is desirable.[1] While Bernanke and Woodford (1997) and Muto (2011) show that central bank communication influences private agents' forecasts, Amato and Shin (2006) and Morris and Shin (2002) emphasize that central bank influence may cause private agents to stop forming their specific sets of information and rely only on information from the central bank. Also, Garaats (2002) argues that in the models based on diverse private information, the central bank pronouncements may lead to more economic instability. This debate illustrates that controversy exists regarding the welfare effect of central bank communication.[2]

The mainstream of monetary theory used for policy analysis is based on the simplification assumption that agents are homogenous and have complete knowledge of the structure of the model. However, adaptive learning literature relaxes this assumption and assumes that agents share the same knowledge, which is not complete and might vary among them. Orphanides and Williams (2003) study the effect of imperfect knowledge in designing monetary policies. Their findings show that the polices that are efficient under rational expectations and perfect knowledge may perform poorly under imperfect knowledge, and also polices should be more reactive to inflation variations under imperfect knowledge to anchor inflation expectations and economic stability. Evans and Honkapohja (2003a) examine the effects of inconsistency between private agents and central bank's beliefs about the true structure of the economy. They show that expectations based policy rules would lead to

[1] Eusepi & Preston, 2008; Faust & Svensson, 2001, 2002, 2006; Geraats, 2002, 2005; Woodford, 2005

[2] Hubert Paul(2015)

E–stability and determinacy even if the beliefs were not consistent. However, Fucak (2006) finds that in the presence inconsistent beliefs, monetary policy should be less reactive to reduce economic instability in order to achieve E-stability. In this paper, we address the inconsistency of beliefs between private agents and the central bank. For simplicity, we assume that agents are backward–looking in forming their expectations and we extend the paper by including the adaptive learning in the future.

Recent empirical studies evaluated the effect of increased central bank communication and transparency on private agents' expectations (Capistran & Ramos-Francia, 2010; Cecchetti & Hakkio, 2009; Guurkaynak, Levin, & Swanson, 2010; Jansen & De Haan, 2007; Levin, Natalucci, & Piger, 2004). Kelly (2008) finds that in the United Kingdom, the link between inflation and inflation expectations vanishes after the realization of inflation targeting and forecast communication, and that private expectations are better anchored in this situation. Boero, Smith, and Wallis (2008) find that private forecasters tend to follow the GDP growth forecasts of the Bank of England.

Over the last two decades, experimental approaches have become increasingly popular in assessing the relative efficacy of central bank communication strategies on managing expectations and economic performance.[3] A recent study by Mokhtarzadeh and Petersen (2016) explore how expectations of inflation and output are influenced by central bank forward guidance within a learning–to–forecast environment. They find that communicating future output or inflation generally reduces the degree to which agents rely on lagged information and increases their reliance on the rational expectations equilibria (REE) solution. Mokhtarzadeh and Petersen suggest that expectations are more stabilized when the central bank communicates inflation and output simultaneously. Arifovic and Petersen (2015) study the expectation formation at the zero lower bound. They focus on the quantitative and qualitative effects of communicating the history–dependent inflation targeting. Their findings suggest that qualitative communication of inflation targets tends to be more effective at stabilizing expectations. Kryvtsov and Petersen (2015) document that a central bank, which indicates its expectation for future interest rates lead to mixed forecasting behaviour. Many inexperienced participants incorporate the forward guidance into their forecast, and greater stability is observed as a result. If only a few agents have initially employed the projections in their forecasts, the central bank's forward guidance would have created more

[3] Adam, 2007; Arifovic & Petersen, 2015; Arifovic & Sargent, 2003; Assenza et al., 2015; Cornand & M'Baye, 2016; Hommes et al., 2015a; Hommes et al., 2015b; Kryvtsov & Petersen, 2015; Pfajfar & Zakelj, 2014, 2015, 2016; Hommes, Massaro, & Weber, 2015; Moktharzadeh & Petersen, 2016.

confusion and economic instability. Cornand and M'Baye (2016) consider the effectiveness of announcing the central bank's constant inflation target under strict and flexible inflation targeting. Their theoretical results show that with strict and flexible inflation targeting, the economic variability is lower compared to no communication under rational expectations. In their experimental results, they find that communicating inflation targets helps to reduce economic volatility if the central bank employs flexible inflation targeting, but makes no difference if the central bank uses strict inflation targeting. Hommes, Massaro, and Weber (2015) deviate from the rational expectations assumption to study the inflation volatility and consider that expectations are formed according to a heuristics switching model. They find that inflation volatility can be lowered if the central bank reacts to the output gap in addition to inflation in their theoretical and experimental results.

In this paper, we assess the effectiveness of varying central bank communication strategies in response to economic shocks. Our analysis is therefore structured into two main questions:

1. How does central bank communication of its own expectations of future inflation and output gap influence expectations of private agents and economic fluctuations?

2. What type of communication leads to less economics variability in the presence of demand shock or cost–push shock?

In this paper, we assume that central banks' expectations and private agents' expectations are not the same. The central bank forms its expectations of future economic variables using rational expectations, while private agents are using simple adaptive expectations.[4] The central bank uses four communication strategies: (a)no communication (NoComm), (b)communicating only output (OutputComm), (c)communicating only inflation (InflationComm), and (d)communicating both inflation and output (DualComm). Two Taylor rules are considered. The central bank uses either flexible inflation targeting (IT) in which the bank adjusts the interest rate according to current inflation and output, or strict IT in which the bank adjusts the interest rate according to current inflation only. Our findings show that the central bank confronts a trade–off when communicating either the future inflation or future output under demand shocks, irrespective of the Taylor rule qualitatively. Communicating future inflation stabilizes output but leads to more variations in inflation and interest

[4] Branch & McGough, 2009; Cukierman & Meltzer, 1986; Faust & Svensson, 2001, 2002

rates compared to no communication policy. However, communicating future output stabilizes inflation and interest rates and generates more output variations. With a cost-push shock, the central bank should communicate future output to stabilize inflation and interest rates under both the flexible IT and strict IT. However, to reduce output variations, the central bank should be uncommunicative with flexible IT, and should communicate future inflation with strict IT.

The rest of the paper is organized as follows. In Section 3.2, we present the theoretical model and provide the REE and simple adaptive expectations (AE) transition paths. In Section 3.3, we discuss the results of the simulations and impulse responses, and our conclusions follow in Section 3.4.

3.2 Theoretical Model

We follow the basic New Keynesian business cycle model. There are three agents in the economy: households, firms, and the central bank. Households make decision about consumption, labour, and money holdings to maximize their welfare over their lifetime. Firms produce in a monopolistic, competitive, production sector to maximize their profit by choosing the level of output, prices, and labour demand. The firms use Calvo's (1983) pricing mechanism to set their prices. The interest rate is determined by the central bank according to current inflation and output.

We use the simplified three equations of New Keynesian Model, which is described by *IS curve* (driven from households' Euler equation), *Philips curve* (driven from firm's oligopolistic pricing rule), and the central bank's policy rule:

$$x_t = E_t x_{t+1} - \sigma^{-1}(i_t - E_t \pi_{t+1}) + u_t \tag{3.1}$$

$$\pi_t = \beta E_t \pi_{t+1} + \kappa x_t + v_t \tag{3.2}$$

$$i_t = \phi_x x_t + \phi_\pi \pi_t \tag{3.3}$$

where x_t is the output gap (which is the deviation of actual output from the output in a frictionless economy), π_t is the inflation rate, and i_t is the interest rate set by the central bank. The variables u_t and v_t are demand shocks and cost–push shocks, respectively, assumed to follow *AR(1)* processes according to the following:

$$u_t = \rho u_{t-1} + \epsilon_t \tag{3.4}$$

$$v_t = \rho v_{t-1} + \epsilon_t \tag{3.5}$$

where ϵ_t is a random component (*i.i.d.* with mean zero and standard deviation of σ^2_ϵ), σ is the risk aversion parameter, β is the household's time preference, and κ is the inflation elasticity with respect to the output gap parameter. The coefficients ϕ_x and ϕ_π are the central bank's responses to the deviations of actual inflation from the target inflation, and to the deviations of current output from the potential level of output, respectively. For simplicity the central bank's targets of inflation and output gap are set at zero. The central bank is more responsive to the deviation of inflation from their target than to the deviation of output gap in that $\phi_\pi > \phi_x$. Finally, we assume that the central bank observes the shocks in each period and determines the interest rate according to the current information.

We follow Eusepi and Preston (2012) in assuming that the central bank forms rational expectations of the future variables, while the agents use last period information to form their expectations. Hence, the model takes the form:

$$x_t = \hat{E}_t x_{t+1} - \sigma(i_t - \hat{E}\pi_{t+1}) + u_t \tag{3.6}$$

$$\pi_t = \beta \hat{E}_t \pi_{t+1} + \kappa x_t + v_t \tag{3.7}$$

$$i_t = \phi_x x_t + \phi_\pi \pi_t \tag{3.8}$$

where $\hat{E}_t x_{t+1}$ and $\hat{E}_t \pi_{t+1}$ represent private agents' expectations of future output and inflation. We assume the central bank determines interest rates in respond to both current inflation and output, called flexible inflation targeting (flexible IT), or in response to only inflation variability, called strict inflation targeting (strict IT).

1. flexible IT: $i_t = \phi_x x_t + \phi_\pi \pi_t$

2. strict IT: $i_t = \phi_\pi \pi_t$

In general, we consider rational expectations and simple adaptive expectations as the following: We assume rational expectations operator takes the form $E_t x_{t+1} = x_{t+1}$ and adaptive expectations is $E_t x_{t+1} = \theta x_{t-1}$.[5] If $\theta = 1$, the operator is called "naive" expectations; if

[5] Branch & McGough (2009)

$\theta < 1$, the operator is adaptive in that the agents are simple backward–looking (Simple AE); and lastly when $\theta > 1$ is called "extrapolative" or trend–chasing expectations. For the purpose of this paper, we assume that the central bank forms its expectations according to rational expectations and makes accurate forecasts given the information in the current period, while private agents form simple backward–looking adaptive expectations.[6] The central bank objective is to reduce the economic variations by communicating its expectations of future variables.

Assume that the central bank knows agents are forming their expectations according to simple AE, and knows that the agents use announced information of inflation and output by the central bank in their predictions without verification. Additionally, the central bank is fully aware of the shocks in the current period and the economy's data–generating process. The interest rate id determined by Equation (3.3) and sets the rate based on the current information of the variables and the shocks. As a result, the central bank's expectations of output and inflation are as follows:

$$E_t^{cb} x_{t+1} = x_{t+1} \tag{3.9}$$

$$E_t^{cb} \pi_{t+1} = \pi_{t+1} \tag{3.10}$$

where E_t^{cb} and E_t^{cb} are the central bank's expectations of future output and inflation, respectively. The communication policy is defined by communicating the expected future of thr output, inflation, or both output and inflation with private agents using Equation (3.9) and Equation (3.10).[7] Further, suppose that private agents fully implement central bank communication in their expectations. For simplicity, assume that they take a weighted average of central bank communication and their expectation.

$$\hat{E}_t x_{t+1} = (1-\alpha_x)\theta x_{t-1} + \alpha_x E_t^{cb} x_{t+1} \tag{3.11}$$

$$\hat{E}_t \pi_{t+1} = (1-\alpha_\pi)\theta \pi_{t-1} + \alpha_\pi E_t^{cb} \pi_{t+1} \tag{3.12}$$

$$\alpha_x, \alpha_\pi \varepsilon \{0, 0.5\}$$

[6]Branch & McGough (2005, 2009), Branch (2002), and Brock & Hommes (1997, 1998) have considered adaptive expectations.

[7]Central bank expectation formation is not according to the fundamental REE rather the central bank is correctly forecasting the economy given private agents' expectations. In our future work, we incorporate communication using REE solutions.

3.2.1 Model Determinacy

Given that the economy is confronted either with a demand shock or a cost–push shock under each Taylor rule, there could be four possible economic situations (see Table 3.1). According to each state, the central bank can choose to be uncommunicative, communicate future output, communicate future inflation, or communicate both future output and inflation. In the following, we solve the model under REE, simple AE.

Table 3.1: The state of the economy

Demand Shock–flexible IT	Cost–push shock–flexible IT
Demand Shock–strict IT	Cost–push shock–strict IT

First, we solve the model assuming that the central bank and agents form accurate expectations of future output and inflation to find the unique REE solution in which communication is not needed. Next, we consider the heterogeneity between private agents and central bank expectations formation, which generate the possibility for the effectiveness of communication strategies. The full representation of the model is as follows:

$$x_t = E_t x_{t+1} - \sigma(i_t - E\pi_{t+1}) + u_t \tag{3.13}$$

$$\pi_t = \beta E_t \pi_{t+1} + \kappa x_t + v_t \tag{3.14}$$

together with the following policy rules:

$$\textbf{Flexible IT} \qquad i_t = \phi_x x_t + \phi_\pi \pi_t \tag{3.15}$$

$$\textbf{Strict IT} \qquad i_t = \phi_\pi \pi_t \tag{3.16}$$

REE Solution: Suppose the central bank and private agents use rational expectation in which $E(.)_{t+1} = (.)_{t+1}$ to form their expectations of future output and inflation. In this case, $\hat{E}(.)_{t+1} = E^{cb}_{t+1} = (.)_{t+1}$. We solve the model fully with demand shock and cost–push shock and present the transition paths separately in the appendix. Under both flexible and strict IT, the solution of the model is described by the following equations:[8]

[8]Note that under strict IT, $\phi_x = 0$.

Replace Equation (3.15) and Equation (3.14) into Equation (3.13):

$$x_t = E_t x_{t+1} - \sigma^{-1}\{\phi_\pi(\kappa x_t + \beta E_t \pi_{t+1} + v_t) + \phi_x x_t - E_t \pi_{t+1}\} + u_t. \tag{3.17}$$

Rearranging this equation gives the following:

$$x_t = \frac{1}{1+\sigma^{-1}(\phi_\pi\kappa + \phi_x)} E_t x_{t+1} - \frac{\sigma^{-1}(\phi_\pi\beta - 1)}{1+\sigma^{-1}(\phi_\pi\kappa + \phi_x)} E_t \pi_{t+1} + \frac{\sigma^{-1}}{1+\sigma^{-1}(\phi_\pi\kappa + \phi_x)}(u_t - \phi_\pi v_t). \tag{3.18}$$

Inserting Equation Equation (3.18) into Equation (3.14), we obtain:

$$\pi_t = \frac{\kappa}{1+\sigma^{-1}(\phi_\pi\kappa + \phi_x)} E_t x_{t+1} + (\frac{\beta + \beta\sigma^{-1}\phi_x + \kappa\sigma^{-1}}{1+\sigma^{-1}(\phi_\pi\kappa + \phi_x)}) E_t \pi_{t+1} + \frac{\kappa\sigma^{-1}}{1+\sigma^{-1}(\phi_\pi\kappa + \phi_x)}(u_t - \phi_\pi v_t). \tag{3.19}$$

Finally the interest rate is:

$$i_t = \frac{\phi_x + \phi_\pi\kappa}{1+\sigma^{-1}(\phi_\pi\kappa + \phi_x)} E_t x_{t+1} + \frac{\phi_x\sigma^{-1} + \phi_\pi(\beta + \kappa\sigma^{-1})}{1+\sigma^{-1}(\phi_\pi\kappa + \phi_x)} E_t \pi_{t+1} + \frac{\kappa\sigma^{-1}\phi_\pi + \sigma^{-1}\phi_x}{1+\sigma^{-1}(\phi_\pi\kappa + \phi_x)}(u_t - \phi_\pi v_t). \tag{3.20}$$

Simple AE Solution & No Communication: Under simple AE, $\hat{E(.)}_{t+1} = E(.)_{t+1} = \theta(.)_{t-1}$ in which $\theta < 1$. We solve the model assuming that the central bank does not communicate in order to find the baseline transition paths to investigate the effectiveness of communication strategies. Under both flexible and strict IT we obtained the following solutions:

$$x_t = \frac{1}{1+\sigma^{-1}(\phi_\pi\kappa + \phi_x)} \theta x_{t-1} - \frac{\sigma^{-1}(\phi_\pi\beta - 1)}{1+\sigma^{-1}(\phi_\pi\kappa + \phi_x)} \theta \pi_{t-1} + \frac{\sigma^{-1}}{1+\sigma^{-1}(\phi_\pi\kappa + \phi_x)}(u_t - \phi_\pi v_t) \tag{3.21}$$

$$\pi_t = \frac{\kappa}{1+\sigma^{-1}(\phi_\pi\kappa + \phi_x)} \theta x_{t-1} + \frac{\beta + \beta\sigma^{-1}\phi_x + \kappa\sigma^{-1}}{1+\sigma^{-1}(\phi_\pi\kappa + \phi_x)} \theta \pi_{t-1} + \frac{\kappa\sigma^{-1}}{1+\sigma^{-1}(\phi_\pi\kappa + \phi_x)}(u_t - \phi_\pi v_t) \tag{3.22}$$

$$i_t = \frac{\phi_x + \phi_\pi\kappa}{1+\sigma^{-1}(\phi_\pi\kappa + \phi_x)} \theta x_{t-1} + \frac{\phi_x\sigma^{-1} + \phi_\pi(\beta + \kappa\sigma^{-1})}{1+\sigma^{-1}(\phi_\pi\kappa + \phi_x)} \theta \pi_{t-1} + \frac{\kappa\sigma^{-1}\phi_\pi + \sigma^{-1}\phi_x}{1+\sigma^{-1}(\phi_\pi\kappa + \phi_x)}(u_t - \phi_\pi v_t) \tag{3.23}$$

Simple AE Solution & Communication: Under simple AE and central bank communication, $\hat{E(.)}_{t+1} = (1-\alpha_{(.)})\theta(.)_{t-1} + \alpha_{(.)}(.)_{t+1}$ in which $\alpha_x, \alpha_\pi \varepsilon \{0, 0.5\}$. We allow the central bank to communicate future output, future inflation, or both future output and inflation to simple AE agents. Here, we solve the model under communicating future output and inflation with both flexible and strict IT:

$$x_t = \frac{1}{1+\sigma^{-1}(\phi_\pi\kappa+\phi_x)}((1-\alpha_x)\theta x_{t-1}+\alpha_x E_t^{cb}x_{t+1}) - \frac{\sigma^{-1}(\phi_\pi\beta-1)}{1+\sigma^{-1}(\phi_\pi\kappa+\phi_x)}((1-\alpha_\pi)\theta\pi_{t-1}+\alpha_\pi E_t^{cb}\pi_{t+1})$$
$$+ \frac{\sigma^{-1}}{1+\sigma^{-1}(\phi_\pi\kappa+\phi_x)}(u_t-\phi_\pi v_t) \tag{3.24}$$
$$\pi_t = \frac{\kappa}{1+\sigma^{-1}(\phi_\pi\kappa+\phi_x)}((1-\alpha_x)\theta x_{t-1}+\alpha_x E_t^{cb}x_{t+1}) + \frac{\beta+\beta\sigma^{-1}\phi_x+\kappa\sigma^{-1}}{1+\sigma^{-1}(\phi_\pi\kappa+\phi_x)}((1-\alpha_\pi)\theta\pi_{t-1}+\alpha_\pi E_t^{cb}\pi_{t+1})$$
$$+ \frac{\kappa\sigma^{-1}}{1+\sigma^{-1}(\phi_\pi\kappa+\phi_x)}(u_t-\phi_\pi v_t) \tag{3.25}$$
$$i_t = \frac{\phi_x+\phi_\pi\kappa}{1+\sigma^{-1}(\phi_\pi\kappa+\phi_x)}((1-\alpha_x)\theta x_{t-1}+\alpha_x E_t^{cb}x_{t+1}) + \frac{\phi_x\sigma^{-1}+\phi_\pi(\beta+\kappa\sigma^{-1})}{1+\sigma^{-1}(\phi_\pi\kappa+\phi_x)}((1-\alpha_\pi)\theta\pi_{t-1}+\alpha_\pi E_t^{cb}\pi_{t+1})$$
$$+ \frac{\kappa\sigma^{-1}\phi_\pi+\sigma^{-1}\phi_x}{1+\sigma^{-1}(\phi_\pi\kappa+\phi_x)}(u_t-\phi_\pi v_t) \tag{3.26}$$

Our objective is to examine the effect of variant communication polices qualitatively and quantitatively. Consequently, we compute the impulse response functions (IRFs) using *Dynare* under REE and simple AE. We use the calibrated parameters from Kryvtsov and Petersen (2015): $\sigma = 1$, $\beta = 0.989$, $\kappa = 0.13$, $\phi_\pi = 1.5$, $\phi_x = 0.5$, $\rho = 0.57$, and $\sigma_\epsilon = 1.3$ and we assume θ is fixed at 0.9. Following the four states of the economy, the impulse responses are computed and transitions paths are provided in the appendix.

When private agents use rational expectations in the presence of a demand shock or a cost–push shock, no communication is needed. The economy adjusts fully in response to the shocks and converges to the steady-state equilibrium. However, when agents use last period observation to form their expectations of current output and inflation, they are not being responsive to current shocks. As a result, we expect to observe more variations in the economy under a demand or cost–push shock (with hump-shaped impulse responses) compared to REE.

In the next section, we will show the findings under variant communication rules, and compare the impulse responses under each communication policy to the baseline.

3.3 Results and Discussion

In this section we provide the results of the simulations. To discuss the success of central bank communication policy in economic stability, we look at the standard deviations of output, inflation, and interest rate under various communication policies reported by *Dynare* with a demand shock and once with a cost–push shock. We assume the shocks follow an *AR(1)* process according to Equation (3.4). In this environment, the central bank correctly forecasts the future inflation and output gap, knowing that agents fully implement the central bank's communication in their expectation formations.[9] Indeed, simple AE agents take last period observations to form their expectations of output and inflation. The findings are represented in Table 3.2 under flexible IT and in Table 3.3 under strict IT. Also, we plot the impulse responses of output, inflation, and interest rate under demand and cost–push shocks in Figure 3.1 and Figure 3.2.

A positive demand shock leads to an excess demand, which causes the output to increase above the equilibrium level. In response, price levels rise, which pushes inflation upwards depending on the output gap elasticity (κ). In response, the central bank increases the interest rate, which leads to an increase in real interest rates, hence there is a downward push on the output gap and consequently lower inflation. Under a demand shock, both output and inflation can be stabilized simultaneously.

A cost-push shock (such as unexpected oil price fluctuations) increases inflation immediately. To keep inflation from rising, contractionary polices are called for that would worsen the decline in output (increasing the interest rate); to stabilize the output gap, an expansionary policy is called for that would aggravate inflation (reducing the interest rate). Therefore, there is a trade–off between inflation and output gap stabilization in the presence of cost–push shock (Walsh, 2010).

Our results show that in a homogeneous environment with consistency between the central bank and private agents' expectations, first, the economy is more variable in response to the shocks under simple AE than REE (Table 3.2 and Table 3.3). Second, there is no need for communication policy. The importance of communication arises when private agents' expectations is not consistent with central bank's expectations. We present the simulation results of the central bank's communication strategies when central bank communicates using rational expectations ($E(.)_{t+1} = (.)_{t+1}$) with private agents who form simple AE

[9] $E_t x_{t+1} = x_{t+1}$ and $E_t \pi_{t+1} = \pi_{t+1}$.

$(E(.)_{t+1} = \theta(.)_{t-1})$.

3.3.1 Demand Shock

Flexible IT– With flexible IT and a positive demand shock, the interest increases to stabilize inflation and output gap. Under REE, a demand shock increases the output variations to 1.3107, inflation variations to 0.3906, and interest rate variations to 1.2412 in the current period but the economy adjusts fully in the subsequent periods and the communication policy is not needed (see Figure 3.1). However, when agents use simple AE, they are non-responsive the shocks. As a result, the output, inflation, and interest rate go up compared to the last period. Output variation rises to 1.3875 (an increase of about 5.9%), the inflation variation increases to 0.7267 (an increases of about 86%), and interest rate variation increases to 1.5773 (an increases of about 27%). The hump–shaped IRFs are observed in Figure 3.1. Hereafter, we compare the impact of various communication strategies knowing that private agents form their expectations of future output and inflation using last period output and inflation (simple AE).

In this setup, the central bank that communicates future output aggravates the output variability, 1.4039, and reduces inflation and interest rate variability to 0.6403 and 1.4489, respectively, compared to the variations under NoComm (1.3875, 0.7267, and 1.5773, receptively). The intuition behind this outcome is that when the central bank communicates its expected future output gap, agents fully incorporate the communication in their expected future output and become more responsive to the shocks. Thus, the output expectation is the weighted average of the last period output and the expected future output communicated by the central bank, according to Equation (3.11). Expected future output rises, and accordingly current period output increases.[10] According to Equation (3.2), inflation is determined by the expected future inflation via almost a one–to–one relationship, and the output gap through κ which is 0.13. With OutputComm, agents' expectation of inflation is based on simple AE. Therefore, the private agents' response increases current output, which increases the inflation rate slightly. We find that inflation variability is 0.6405 compared to the inflation variability under NoCom (0.7267). OutputComm indirectly reduces the interest rate variability under flexible IT. We plot the impulse responses in Figure 3.1.

[10]The output in the New Keynesian model is equivalent to the demand. Indeed, it is assumed that agents smooth their demands across periods. Therefore, if they expect higher output and demand in the future, they will increase their demand in the current period. (Walsh 2010)

Under demand shock with OutputComm, on impact the output is above the output with NoCommand is more variable, but eventually the output will be less than NoComm. Inflation follows a hump shaped under OutputComm and NoComm, but on impact, inflation is less than NoComm and eventually converges to NoComm. On impact, the interest rate is slightly greater than NoComm because of the higher output variability.

Under InflationComm, output is less responsive to the shocks, while inflation and interest rates are more responsive. When the central bank communicates its inflation expectation, private agents use that information to form their expectation of inflation (Equation (3.11)) and become more reactive to the shocks. This would increase inflation and consequently decrease the real interest rate. As a result, output increases. The interest rate will continue to increase to the extent such that it may offset the effect of expected inflation on real interest rates, thus reducing the output variability. We find that the output variation is 1.1653 compared to NoComm at 1.3875. As shown in Figure 3.1, the output is hump shaped but below the NoComm on impact and it decreases smoothly over time. Inflation increases at a nearly one-to-one relationship with expected inflation; even the downward pressure of output variability does not help to reduce inflation variations (0.9415). Last, the interest rate varies more as a result of high inflation variability. In Figure 3.1, InflationComm shows a spike in inflation and interest rates compared to the humped–shape of the same variables in the NoComm policy. We find similar results with DualComm in which the agents are more responsive to the current shock when the central bank communicates both future inflation and output. With flexible IT, the interest rate rule responds to inflation and output gap, but is more responsive to inflation than to output($\phi_\pi > \phi_x$). Hence, the interest rate rises sharply in response to shocks, which reduces the variation of output to 1.2237 compared to NoComm (1.3875). Additionally, inflation and interest rates are more varied (0.8036 and 1.7558, respectively) in relation to NoComm (0.7267 and 1.5773, respectively). Also, we observe that DualComm gives rise to less inflation and interest rate variability, and more variability in output relative to InflationComm, suggesting that more communication reduces the variation of inflation and exacerbates the output gap. On impact, output is slightly above the output in NoComm, but it decreases faster over time because agents are being responsive to the shock by DualComm in forming their expectations of inflation and output. Inflation and interest rates represent more variations compare to the NoComm policy (see Figure 3.1).

Table 3.2: Descriptive Statistics: Standard Deviations(Flexible Inflation Targeting)

Communication	Demand Shock			Cost–Push Shock		
	Output	Inflation	Interest rate	Output	Inflation	Interest rate
REE	1.3107	0.3906	1.2412	2.7941	2.7941	2.7941
NoComm	1.3875	0.7267	1.5773	3.6856	3.6856	3.6856
OutputComm	1.4039	0.6405	1.4489	3.8118	3.5726	3.5283
InflationComm	1.1653	0.9415	1.9512	3.8593	4.0872	4.3350
DualComm	1.2237	0.8036	1.7558	4.1265	4.1265	4.1265

The entries are the standard deviations of output, inflation, and interest rate as reported by *Dynare* in various communication policies. Under a communication policy, we assume the central bank forms rational expectations and private agents form simple adaptive expectations.

Strict IT– Under REE, a positive demand shock increases the variability of output, inflation, and the interest rate (2.2375, 0.6667, 1.0001, respectively). With REE, the economy adjust itself and converges to the steady–state in the following periods. However, with simple AE agents and no central bank communication, the variation of output increases to 2.6395 (of about 18%), the variation of inflation increases to 1.3879 (of about 108%), and the interest rate increases to 2.0819 (of about 198%). Two main reason for the massive variations are offered. First, the agents use last period observations to form their expectations which leads to more economic instability. Second, the interest rate rule reacts strongly to the inflation variations (an increase of about 198%). The impulse responses in Figure 3.2 provide the graphic presentations of the results.

Similar to flexible IT, communicating future output leads the agents to be more responsive to a demand shock. Inflation and interest rate variabilities are reduced by the slight influence of the output on inflation, and on the interest rate.[11] In Table 3.3, we show that output variability increased from 2.6395 to 2.6760 (an increase of about 1.3%), which is less than the change in inflation variability from 1.3879 to 1.0844 (a decrease of about 21.8%). This suggests that in the presence of a demand shock, OutputComm is effective in reducing inflation variations (at the cost of increasing output variations) compared to the NoComm policy. In Figure 3.2, on impact, the output under OutputComm is above NoComm and

[11]Under demand shock, the increase in output slightly increases inflation and hence the interest rate. Higher interest rates reduces the output.

shows more variation; however, inflation and the interest rate are, on impact, lower than the NoComm inflation and interest rate, and remain lower than NoComm over time.

Indeed, InflationComm leads to a great reduction in output variability (1.8182) because the central bank is prominently responsive to inflation compared to NoComm under strict IT. Inflation rises directly through the increase in private agents' response to the shocks, and indirectly through the increase in output. The central bank sharply increases the interest rate, which reduces the output, yet the reductions in output slightly impact inflation. Consequently, inflation variability increases from 1.3879 with NoComm to 1.6104 with InflationComm. We show that Figure 3.2 confirms our observations. On impact output under InflationComm is below NoComm and decreases slowly over time, but inflation and interest rates represent large deviations from NoComm. In line with our result under flexible IT, DualComm decreases output variability (2.0525), but it also reduces inflation and interest rate variabilities (1.3305, 1.9957, respectively). This suggests that under strict IT, the economy is more stabilized when the central bank communicates both future inflation and future output. One possible explanation for this outcome is that with the strict rule, the real interest rate goes up sharply in reaction to inflation variability, which reduces the output gap so that its impact dominates the increase in expected inflation (see Figure 3.2).

Qualitatively, we find similar results under the flexible IT and strict IT. However, under InflationComm and DualComm, output variability decreases by 16% and 12%, respectively, with flexible IT; with strict IT, the reduction almost doubled to 31% and 22%, respectively. We find that the percentage decrease in inflation variability relative to NoComm is almost double compared to OutputComm across two polices; a 12% decrease compared to 22%. Additionally, the percentage increase in inflation variability is 30% under the flexible IT and 16% under the strict IT. A similar pattern is found for the interest rate. Finally, DualComm lead to different results across the policies. More communication stabilizes all the variables under the strict IT but stabilizes only the output variability under the flexible IT.

Table 3.3: Descriptive Statistics: Standard Deviations (Strict Inflation Targeting)

Communication	Demand Shock			Cost–Push Shock		
	Output	Inflation	Interest rate	Output	Inflation	Interest rate
REE	2.2375	0.6667	1.0001	4.7607	2.2054	3.3080
NoComm	2.6395	1.3879	2.0819	7.0365	2.6062	3.9093
OutputComm	2.6760	1.0844	1.6267	7.4295	1.7793	2.6689
InflationComm	1.8182	1.6104	2.4156	5.9351	2.7233	4.0849
DualComm	2.0525	1.3305	1.9957	6.8838	1.9772	2.9659

The entries are the standard deviations of output, inflation, and interest rate as reported by *Dynare* in various communication policies. Under a communication policy, we assume the central bank forms rational expectations and private agents form simple adaptive expectations.

Observation I: *With a demand shock, the economy is more variant with strict IT than with flexible IT. Among the communication polices, InflationComm and DualComm reduce the output variability, and OutputComm decreases inflation and interest rate variations under both Taylor rules, qualitatively. DualComm reduces the variabilities of output, inflation, and interest rate under strict IT, but only reduces the variability of output under flexible IT.*

3.3.2 Cost–Push Shock

Flexible IT– A trade–off situation between stabilizing output and stabilizing inflation can develop with a cost–push shock. The shock immediately increases inflation. In response, an increase in the interest rate lowers inflation but worsens the output gap. Likewise, a decrease in the interest rate escalates the output gap and aggravates inflation. Under the specific flexible IT, $\phi_\pi > \phi_x$, the central bank is more responsive to inflation variations. Therefore, the central bank increases the interest rate; thus, the real interest rate rises and output decreases. The result under REE represents all the variations of all the variables increases by 2.7941. The IRFs in Figure 3.2 show that in response to a cost–push shock, the output decreases below the steady–state, the inflation and interest rate greatly increase above the steady–state. However, the economy returns to the steady state over time. Under NoComm with simple AE, all the variables show a variation of 3.6856 (an increase of about 39.1%). The economy is more variable when agents are non responsive to the current cost–push shocks and the impulse responses are humped shape in Figure 3.2.

Under OutputComm, we find that in response to a cost–push shock, output is more variant, and inflation and interest rates are less variant. The central bank's OutputComm affects agents' expectations by lowering their expectations of output. Therefore, the output gap declines because of the increase in the real interest rate plus the decrease in expected output by the agents. The great reduction in the output gap pushes the inflation variability downward, and as a result, interest rate variability is lower in relation to the NoComm. The output variation is 3.8118 compared to the output variation of 3.6856 for NoComm. Moreover, the inflation and interest rate variabilities are 3.5726 and 3.5283, respectively, compared to the NoComm with 3.6856 and 3.6856. In the second column of Figure 3.2, we plot the impulse responses of output, inflation, and interest rates to a cost–push shock. Under OutputComm, on impact, the output is above the output under NoComm and is more of a humped shape. However, inflation and interest rates both represent humped shapes as well, and are below the NoComm inflation and interest rate. If the central bank provides its expectation of future inflation to private agents, the improvement of agents' expectation of future inflation strongly aggravates inflation, which overcomes the effect of the increase in interest rates. Hence, we observed more inflation variability and indirectly more interest rate variability. Our results give a variation of 4.0872 in inflation, 4.3350 in interest rate, and 3.8593 in output relative to NoComm (3.6856 in all of the variables). The results remain the same using DualComm. We see that the output and inflation variations are even greater than the other communication polices. A possible explanation for this result could be the following: In response to a cost–push shock and with DualComm, agents react more to the shocks, so they expect lower output and higher inflation in the current period. Therefore, they adjust their demand by consuming less today, which worsens the output. Meanwhile, the agents expect high inflation in the current period, which exacerbates inflation (using the Phillips curve). Communicating the the inflation is highly received, and it substantially increases the real interest rate and imposes more variations on output (4.1265). Our results suggest that with cost-push shock, as soon as the central bank communicates inflation, the agents become more responsive to the shock, which leads to more economic variations. In Figure 2, central bank communication of inflation or inflation and output generate more humped shapes in our variables, both on impact and over time.

Observation II: *With a cost–push shock and flexible IT, OutputComm is successful in reducing inflation and interest rate variability. The other communication polices generate more instability in the economy.*

Strict IT– In response to a cost-push shock, output and interest rates are more variable and inflation is less variable under strict IT compared to flexible IT. A cost-push shock increases inflation, but the central bank will only respond to the change in inflation and increases the interest rate, which imposes significant downward pressure on the output gap. Under REE, the output variability is 4.7607 while the inflation and interest rate variabilities are 2.2054, and 3.3080, respectively. The results represents the trade–off between output and inflation variations in the presence of a cost–push shock with strict IT. Under NoComm, the output varies massively to 7.0365 an increase of about 47% compared to REE. The inflation and interest rate variations are 2.6062, and 3.9093 representing an increase of about 18.2% compared to REE. We find hump shaped IRFs in Figure 3.2.

OutputComm leads agents to lower their expectations of output gap in response to the shocks, thus reducing their demand in the current period, which exacerbates output variability to 7.4295 compared to 7.0365 under NoComm. However, the central bank aiming to stabilize only inflation helps to reduce inflation variations (1.7793) and thus interest rate variations (2.6689) significantly compared to no communication (2.6062 and 3.9093, respectively). The impulse responses in Figure 3.2 show that under OutputComm, on impact the output is greater than that of NoComm and represents more variations over time. However, inflation and interest rates are lower than NoComm on impact and follow a smooth path over time.

With InflationComm, agents tend to be more responsive to the shock by forming inflation expectations, which reduces real interest rates and increases output. Therefore, output variability goes down to 5.9351 under InflationComm. The impulse responses of output on impact and over time are less than that of NoComm. The inflation variability increases to 2.7233, which is slightly above NoComm (2.6062), and the interest rate is also more variant as a result of the central bank communication policy (4.0849). In Figure 3.2, inflation and interest rates are on impact greater than in NoComm and represent large variations over time.

A DualComm policy, however, stabilizes inflation and the output gap at the same time. We conclude that the central bank communicating inflation and the output gap together makes private agents to be more responsive to the shock. Therefore, agents will reduce their demand in the current period to the extent that it helps to stabilize the inflation, with less variation in interest rates as a consequence. We observed that inflation variability goes down to 1.9772 and output variability to 6.8838 relative to 2.6062 and 7.0365, respectively, under the NoComm policy. Also, interest rate variability goes down to 2.9659 from a value of 3.9093 under NoComm. The impulse responses show that on impact, the variables are slightly above the NoComm but they suddenly decrease over time, which makes the policy effective under DualComm, suggesting that DualComm could reduce the variations of all the variables to some extent.

Observation III: *With a cost–push shock and strict IT, DualComm reduces the variation of all the variables. Qualitatively, OutputComm and InflationComm represent a trade–off between inflation stabilization and output stabilization.*

Comparing the two polices under a cost–push shock, we find that qualitatively strict IT lead to better results in economic stabilization relative to flexible IT. OutputComm reduces inflation and interest rate variabilities by 32% relative to NoComm under strict IT, while the same policy reduces inflation and interest rate variabilities by about 3% and 4%, respectively, under flexible IT. Also, while InflationComm creates more instability overall with flexible IT, it reduces the output variability by 16% with strict IT and increases the inflation and interest rate variabilities only slightly (4%). DualComm is successful in stabilizing the economy under strict IT (output variation is reduced by 2%, and inflation and interest rate variation reduces by 24%); however, the same communication strategy promotes economic instability under flexible IT (by about 12%).

Observation IV: *: Comparing flexible IT with strict IT, the central bank should employ OutputComm under flexible IT and DualComm under strict IT to reduce inflation and interest rate variability.*

3.4 Final remarks

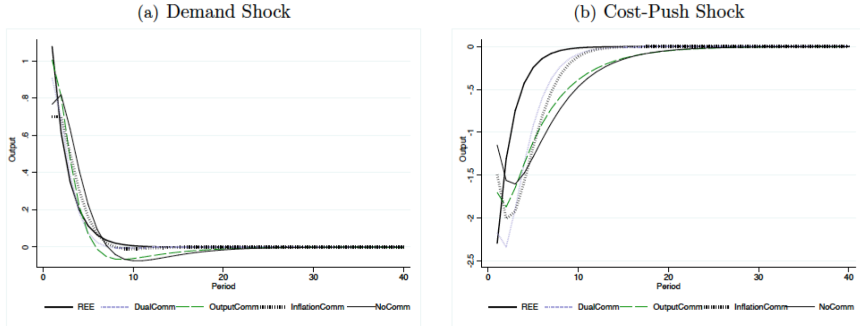
Using a simple New Keynesian model, this paper represents how central bank communication could improve the economic fluctuations under demand shock and cost–push shock with variant Taylor rules. Overall, our results suggest that the central bank faces a trade–off when communicating under a demand shock between output and inflation stabilization. To lower the output variability, the central bank should communicate future inflation, but to lower inflation and interest rate variability, it should communicate future output. We find that the central bank's choice of flexible or strict IT does not matter qualitatively.

Our findings show that under a cost–push shock, the choice of Taylor rule is not a factor when stabilizing inflation and interest rate variability. However, the central bank has to choose not to communicate when its objective is to reduce output variability under flexible IT, and to communicate only its future inflation forecast under strict IT. Finally, communicating both future inflation and output is successful in reducing the variations of output, inflation, and interest rates when the central bank uses strict IT in response to a demand shock or cost–push shock.

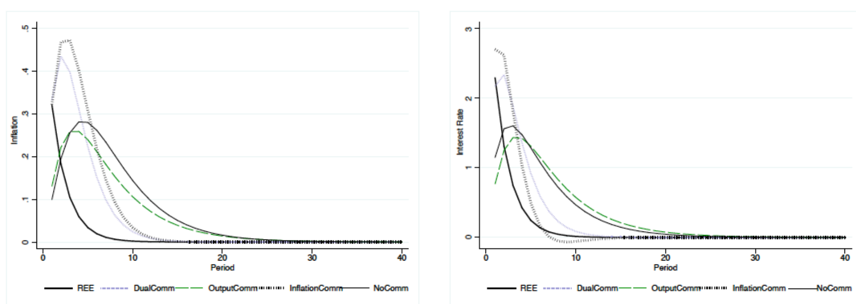
For future research, within the same environment, we plan to let the central bank communicate with private agents using REE to in order to investigate the differences in policy influences. We would also like to introduce a central bank loss function into the model to solve for the optimal communication strategy. Last, we would like to incorporate heterogeneous expectations of private agents and central bank credibility.

Figure 3.1: Impulse responses of inflation, output gap, and interest rate to a demand shock and a cost–push shock for flexible IT.

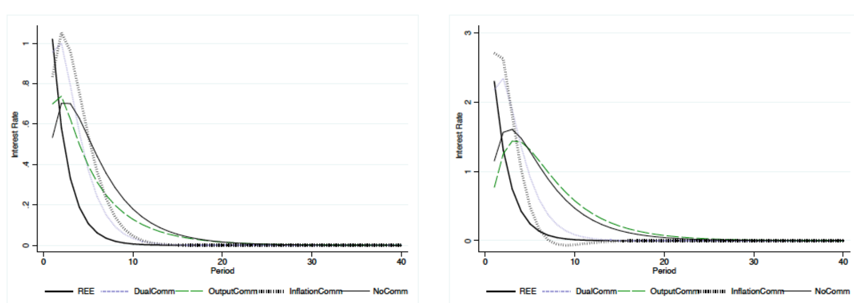
(a) Demand Shock (b) Cost-Push Shock



Output



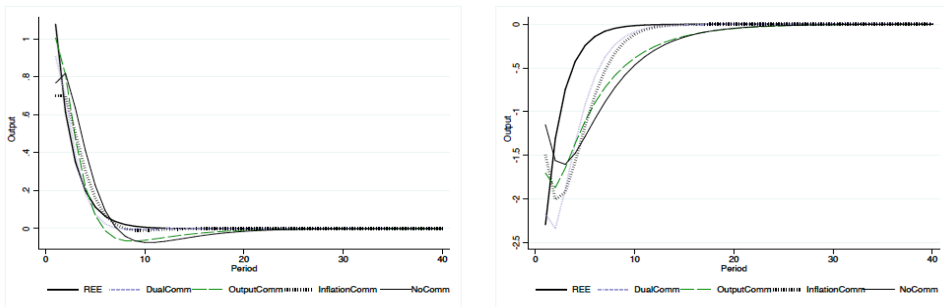
Inflation



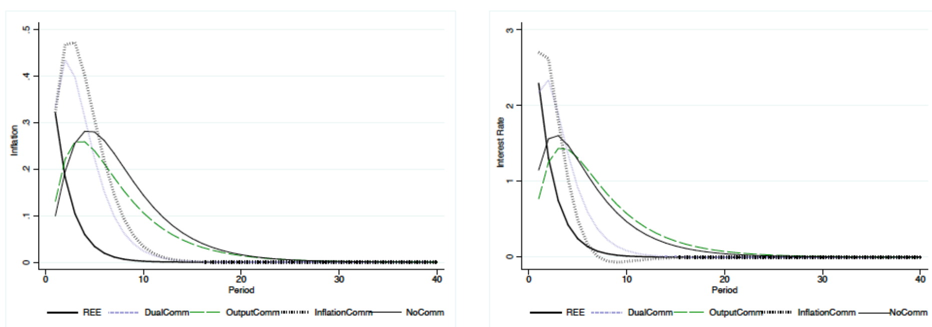
Interest Rate

Figure 3.2: Impulse responses of inflation, output gap, and interest rate to a demand shock and a cost–push shock for strict IT.

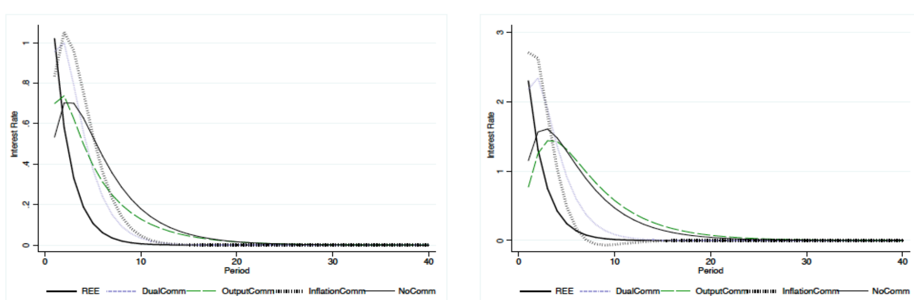
(a) Demand Shock (b) Cost-Push Shock



Output



Inflation



Interest Rate

Chapter 4

Information Observability and Bank Runs

Joint with Jasmina Arifovic

4.1 Introduction

In this paper, we investigate how the degree of information observability affects the frequency of bank runs in an experimental environment. A bank run occurs when the bank does not have enough liquid investments or reserves to serve the depositors' withdrawals demand when they all choose to withdraw their deposits in the fear that other will do the same which leads to a self–fulfilling bank run.

Bank runs are frequently occurred in the economic history. Before the mid 1930s, the United States experienced many bank runs. In 2001, the widespread of runs in Argentina caused a temporary freezing of the banking system. The recent financial depression led to substantial runs and panics among depositors. In additions, the media coverage of the run on the England bank, Northern Rock, and Washington Mutual and the IndyMac bank in the US, and the bank of East Asia in Hong Kong displayed line–ups of depositors in front of banks that helped to spread of runs.

The strand of theoretical literature on bank runs originating from self–fulfilling is based on the paper by Diamond and Dybvig (1983) (hereafter, DD). The authors present a model that highlights the insurance gains of banks as intermediaries. Banks provide liquidity insurance to depositors who are, *ex ante*, uncertain about their preferences over consumption.

Although the deposit contract provides insurance to depositors, an inefficient equilibrium exists where bank runs are driven by the expectations of pessimistic depositors. Therefore, all depositors rush to withdraw because they fear the bank will run out of funds. In the run equilibrium, the bank is forced to liquidate its profitable long-term investments to fulfill the demand of depositors. The empirical literature on bank runs suggest that depositors are responsive to the withdrawal decisions of the other depositors.[1]

In this paper we use experimental methods to test the degree of information observability on the likelihood of bank runs in the DD model. Ten depositors have endowments of 10 experimental dollars (hereafter, ED) deposited in an experimental bank. The depositors are randomly assigned a position in the queue to submit their decision, either to withdraw their deposit or to wait and leave their deposit in the bank. We follow Nosal and Wallace (2009) in using a sequential service constraint where the queue is not used in the sense of a line of people, each of whom is in touch with those nearby, but instead, the queue resembles the order in which people arrive at a drive-up window. We consider two types of depositors: 1) impatient depositors always choose to withdraw immediately at period 1; and 2) patient depositors always prefer higher returns and their withdrawal decision is conditioned on whether they receive a higher payoff in periods 1 or 2. The depositors' type is realized when it is actually their turn to submit their decision. In the experiment, impatient depositors are simulated by computers, which are called "robots" and are forced to withdraw all the time. The other type of depositors has the opportunity to withdraw or wait. Two treatments are used in the experiment: sequential high–information and sequential low–information. The degree of information varies in these two set–ups. In the sequential high–information treatment, depositors are informed of the number of preceding withdrawals, number of withdrawals in the last period, and their position in the queue. In the sequential low–information treatment, the depositors only know the number of withdrawals in the last period and their position in the queue. The experiment begins with two trial periods and is followed by 20 periods, and in each period the depositor's position is determined randomly. The sequential service constraint captures an important feature of the banking system where the bank pays depositors as they arrive at the window and cannot condition the current payment on future information about the number of withdrawal requests.[2] Therefore, the

[1]Wicked (2001), Bruner and Carr (2007), Iyer and Puri (2012). Starr and Yilmaz (2007) study the bank run in Turkey in 2001 and find that depends on the size of their deposit, depositors' decision is influenced by the behaviors of others.

[2]Ennis and Keister (2009).

bank should liquidate long-term investment gradually to honor the demand for withdrawals. If a depositor asks to withdraw, his or her payoff depends on the number of preceding withdrawals and if the depositor asks to leave his or her money in the bank, his or her payoff depends on the total number of withdrawals at the end of the period after all depositors submit their decisions. The bank knows the total number of impatient depositors but not the individual depositors' type. In our experiment, we assume three depositors are impatient *ex ante* and each time when there is an additional withdrawal request above three, the bank has to liquidate one unit of long term investments and pay for the liquidation cost. In the experiment, the liquidation cost is set as the deposits left after paying the last withdrawals divided by the number of depositors who have not withdrawn their deposit. This paper contributes to the literature by showing how the degree of information observability might lead to panics among depositors. Our findings show that, depositors who are earlier in the queue would rather withdraw their deposits in sequential high–information and low–information treatments. We also show that less information about the history of preceding withdrawals lead to fewer runs on the bank.

Schotter et al. (2009) study the effect of information observability on bank runs. They consider three treatments: sequential high-information, sequential low-information, and simultaneous treatment. In sequential low-information and simultaneous treatment, participants are informed of the history of decisions in the last period. The likelihood of runs increases in both treatments, however, in the sequential high–information treatment knowing the preceding action of depositors lead to fewer withdrawals from the bank. In a different study Kiss et al. (2012) find that in a sequential treatment more information decreases the likelihood of bank runs compared to a simultaneous treatment with no information. In contrast, we find opposite result and we show that in a sequential environment more information leads to more bank runs. The rest of the paper is organized as the followings. Section 4.2 describes the relevant literature. Section 4.3 provides the theoretical model, which is followed by the presentation of the experimental design and the experimental results in Section 4.4 and Section 4.5. Section 4.6 summarizes the main findings.

4.2 Literature Review

Two main reasons for the occurrence of the bank runs offered by the literature: the change in the fundamental macroeconomic variables and the self-fulfilling prophecy that results from a coordination failure among depositors. Along with this result, the literature considers the influence of the degree of information on depositors' decision in a sequential service environment.

With the first view, Green-Lin(2003) show that when depositors are given their position in the queue to contact the bank, no bank run occurs. However, Peck and Shell (2003) prove the existence of multiple equilibra with the possibility of bank runs when depositors are allowed to know their liquidity type and not their position in the queue. Nosal and Wallace(2009) discuss the possibility of preventing bank runs by withholding some information.

With regards to self–fulfilling prophecy, many studies are formed around the DD model in which bank's contracts are insensitive to the aggregate liquidity demand and that opens up the possibility of bank runs when the liquidity needs are uncertain. A large body of laboratory experimental studies are based on the DD model to investigate the possibility of bank runs.

Using a within–subject design, Madies (2006) examines the short and long–term suspension of deposit convertability policy. He finds that a bank run could turn into a panic when it spreads over a long number of rounds. Participants are given one minute to submit their decision. They are assumed to be all patient *ex ante* with their payoff depends on when they submit their choices. Although the sequential service constraint gives participants enough time to submit their decision, once a run begins, they could rush to submit their decision, which would aggravate the run on the bank. Contrary to Madies (2006), we randomly assign a rank to the participants in which their payoff depends on their choice and the choice of other depositors.

Schotter and Youlmazer (2009) use a dynamic four-period DD model to explain the dynamics and severity of bank runs with variant in information. The authors define a simultaneous treatment, low–information sequential treatment, and high–information sequential treatment. In the sequential high–information treatment, after each period, the number of depositors who withdrew and their payoffs are revealed. In the sequential low-information treatment; however, no information is revealed to depositors after each period. Their findings from the simultaneous treatment, where depositors are ignorant of the decision of others, are the same as those from the low-sequential information treatment. The authors find that the more information the agents expect to learn about an ongoing crisis, the more willing they are to restrain themselves from withdrawing their funds. Nevertheless, we allow for some partial information to the participants in the sequential low–information treatment and we show that more information leads to more withdrawals and panics among depositors instead.

Arifovic et al. (2010) indicate the effect of coordination requirements on bank runs. They fix the long term interest rate to keep the quality of investments constant and allow for variant short term interest rate. Accordingly they define the minimum number of depositors who are required to wait at each level of interest rate to prevent a bank run and that is called coordination parameter. Their findings show that if the coordination parameter is below some threshold, there exists less probability of runs and if it is above the threshold the coordination is more difficult and therefore high probability of runs. In this paper, similarly we study the bank runs as a result of coordination failure among depositors but we interested in exploring the impact of varying the information. Garrate and Keister (2009) show that with multiple withdrawal opportunities, participants are more likely to withdraw, compared to single withdrawal opportunities.

In a study that is very similar to ours, Kiss et al. (2012) demonstrate how the optimal choice of depositors depends on the history of information. They consider an environment with three depositors, in which one is impatient and simulated by a computer; the bank run is defined when one of the other two participants decides to withdraw. They conclude that if depositors receive information about all previous decisions, it is enough to eliminate a bank run. In their sequential treatment, each depositor is assumed to observe the entire history of previous decisions including payoffs to each depositor and their individual decisions. In the simultaneous treatment, depositors receive partial information about the number of withdrawals in the last period (not in the current period), which is similar to the low–information treatment in our study.

4.3 Theoretical Model

The model is a modification of the DD with sequential service constraint by Ross and Cooper (1998) and Ennis and Keister (2009) with the introduction of costly liquidation.[3]

Consider an economy where N agents live for three periods 0, 1, and 2. The agents

[3]The theoretical model is the simplified model by Ennis and Keister (2009)

are endowed with one unit of consumption goods and face with a liquidity shock that determines their preferences over goods at period 1 and period 2. Assume π is a binomial random variable with support 0, 1 that represents the preferences. If the realized value of π is zero, the depositor becomes impatient and only cares about consumption at period 1. If π is 1, the depositor is indifferent about consumption at period 1 and period 2. By the law of large numbers, π is also the fraction of depositors in the population who will be impatient, and assumed to be non–stochastic. Agents are informed about π. Let c_E and c_L denote consumption at period 1 and period 2, respectively. Assume $u(c)$ is the utility function over consumption, which is strictly increasing and strictly concave, and it satisfies the Inada condition, $u'(0) = \infty$ and $u(0) = 0$.

Two technologies are available. The illiquid investment provides a productive means of moving resources from period 0 to 2, with a return of $R > 1$ over two periods. Nevertheless, liquidation of long-term investments using this technique yields $1 - \tau$ in period 1 per unit of period 0 investment, where $\tau \epsilon [0, 1]$.[4][5] The other technology is the liquid technology that yields one unit in period 1 per unit of period 0 investment. It is less productive than the illiquid technology over two periods; however, the liquid technology provides a higher one-period return.

Investment	Period 0	Period 1	Period 2
Illiquid Investment	-1	$1-\tau$	R
Liquid Investment	-1	1	1

At the social optimal allocation, impatient depositors consume only at period 1 and patient depositors consume only at period 2. Let i denote the fraction of the total endowment placed into long–term investment. The planner would choose c_E, c_L, and i to solve:

$$\begin{aligned} \max_{c_E, c_L, i} \; & \pi u(c_E) + (1-\pi) u(c_L) \\ s.t \quad & \pi c_E = 1 - i \\ & (1-\pi) c_L = Ri \\ c_E \geq 0, c_L \geq 0 \qquad & and \qquad 1 \geq i \geq 0, \end{aligned} \tag{4.1}$$

[4] According to Cooper and Ross (1998), the magnitude of τ can be determined by market in a more general economic model. For the purpose of this paper; however, we assume τ depends on how much the bank should liquidate the illiquid investment depending on the withdrawal demands.

[5] DD assume τ=0.

The first best allocation is:

$$u'(c_E^*) = Ru'(c_L^*)$$

where (c_E^*, c_L^*) are the solutions to the problem, which is characterized by $R > c_L^* > c_E^* > 1$.

The bank pays according to the sequential service constraint in which depositors inform the bank of their decisions by lining up in a queue and the bank pays on a first–come first–served basis. As long as the proportion of withdrawals is smaller or equal to π, the bank pays them c_L^*. Otherwise, the bank should liquidate its long-term investment to fulfill the withdrawal demand at a liquidation cost of τ.

Generally, impatient depositors always choose to withdraw at period 1. A patient depositor who expects all other patient depositors to wait and withdraw in period 2, is better off to wait since $c_L^* > c_E^*$. If, however, the patient depositor expects all other depositors to withdraw in period 1, he or she knows the bank will not be able to satisfy all withdrawal requests, and the best response is to try to withdraw in the first period. Thus, an equilibrium exists when all depositors try to withdraw, which leads to a self–fulfilling bank run. In the following section, we explain the experimental design and the payoffs of the experiment.

4.4 Experimental Design

Two independent experiments are conducted on a computer in groups of 7 participants (total of 70 students). The software program was written in z-Tree (Fischbacher, 2007). In the experiment, participants are assigned to a computer keyboard through which they can input their decisions to withdraw or wait (see the Appendix for the experimental instructions). Communication among the participants is not allowed during the experiment. Most of the participants were 2nd or 3rd year undergraduate students at Simon Fraser University (SFU), Burnaby, Canada. Each experiment lasts for approximately one hour. Participants earn an average of CDN $15 including a show–up payment of CDN $7.

We use a between-subject design and ran a total of 5 sessions for each treatment. In each session, the instructions are read aloud to the participants, who are then asked to raise a hand if they have any questions, and their questions are answered privately.

In each session, 10 depositors exist including 3 impatient depositors and 7 patient depositors. The impatient depositors are automated machines that always prefer to withdraw in period 1. Therefore, all participants are of the patient type. Each session lasts for 20 periods. At the beginning of each period, each participant starts with 10 experimental dollars (ED) deposited in an experimental bank. Participants are asked to form their expectations about the total number of withdrawals at the end of the period.[6]A random number is assigned to each depositor, including robots, which determines their rank in the queue. They are informed of their rank when it is actually their turn to make a decision. When their turn comes up, they are asked to choose either "Withdraw" or "Wait". The participants know of the existence of robots and their decisions but the participants do not know where the robots are located in the queue.

Payoff tables are provided to list the possible payoffs that a participant will receive according to their decision and the decision of other participants. At the end of each session, the total payoff to each participant is calculated as the sum of the all payoffs throughout the session, which is converted into cash at an exchange rate of 18 ED for 1 Canadian dollar.

The bank knows the proportion of impatient depositors but not their types. The bank keeps 30 ED in reserves to fulfill the demand of impatient depositors and invests the rest in the long–term investment at the rate of return of $R = 1.3$.[7] Participants who are willing to withdraw can withdraw their initial endowment of $c_E^* = 10$ ED, as long as the bank has enough reserves to fulfill their demand. Beyond that, the bank must liquidate some of its long-term investments until it has no further resources. Also, those who choose to wait will obtain $c_L^* = 13$ ED according to the rate of return of 1.3 when the number of withdrawal demands is less than or equal to the proportion of impatient depositors. Otherwise, their payoff is strictly less than 13 ED. In Section 4.4.1 the payoffs are calculated.

In the sequential high–information treatment, participants, on their turn, are informed of their position in the queue, the number of withdrawals before the participant, and the total withdrawals in the last period. In the sequential low–information treatment, participants are only informed about their position in the queue and the total number of withdrawals in the last period. In both treatments, at the end of each period, participants are presented with the history of their choices, payoffs, expectation of withdrawals, and total number of withdrawals. The treatments are distinct in providing the number of preceding withdrawals.

To our knowledge, this is the first study in the literature of bank runs investigating

[6]We call this variable "guess" in the instruction which has to be greater or equal to three.

[7]According to Arifovic et al. (2012) we fix the rate of return to rule out the possibility that a bank run occurs by the weak performance of the bank's investment portfolio

the degree of information observability in the sequential environment within a group of depositors including patient and impatient depositors.

4.4.1 Payoff Table

To set up the payoff tables, we use the DD model in which impatient depositors always withdraw at period 1 and patient depositors prefer to wait in combination with liquidation costs, as introduced by Cooper and Ross (1998) and extended by Ennis and Keister (2009). According to DD, a bank is a coalition of depositors who form the bank to prevent uncertainty about their types. Therefore, any cost or benefit for the bank directly affects their return. We use this definition to endogenize the liquidity cost.

One important aspect of our experimental design is that the bank receives information about the withdrawal requests gradually when participants submit their decisions. Accordingly, we provide a payoff table considering the sequential decision.[8]A bank runs is when one of the patient participants (excluding robots) decide to withdraw

Whenever one more withdrawal request occurs above three, the bank liquidates one unit of long–term investment, which imposes a liquidation cost on all depositors except those who already withdrew. Suppose, for instance, three depositors had already withdrawn their deposits and there is a fourth withdrawal request. The bank is only able to fulfill the withdrawal requests for the first three requests. Therefore, it has to liquidate one unit of long-term investment to pay for the fourth withdrawal request. The liquidation cost is $\frac{10}{7} = 1.4$ ED. The numerator is the initial deposit in the bank and the denominator is the number of depositors remaining plus the depositor who placed the withdrawal request (the penalty is shared among the remaining depositors). The payoff to the depositor is $10 - 1.4 = 8.6$ ED and the other remaining depositors are left with 8.6 ED from their initial endowment in the bank. Subsequently, a fifth withdrawal request implies a liquidation cost of $\frac{8.6}{6} = 1.4$ ED and the depositor would receive $8.6 - 1.4 = 7.2$ ED while 7.2 ED is left for the remaining depositors in the bank. As a result, the payoff to those choosing to withdraw would depend on the total number of preceding withdrawals. Conversely, the payoff to those choosing to wait would depend on the total number of withdrawals over the course of a period. If the total number of withdrawals at the end of the period is four or five, then the

[8]Ennis and Keister (2009), document that“the banking system pays depositors as they arrive to the bank and cannot condition current payments to depositors on future information.” Brunnermeier (2001) explains that “Although withdrawals by deposit holders occur sequentially in reality, the literature typically models bank runs as a simultaneous–move game.”

payoff to the depositors choosing to wait would be $8.6 \times 1.3 = 11.2$ ED and $7.2 \times 1.3 = 9.4$ ED, respectively.

In Table 4.1, we show the payoffs for choosing to withdraw, which would depend on the number of preceding withdrawals.

Table 4.1: Payoff–If choosing to withdraw

The number of preceding withdrawals	Payoff
0	10
1	10
2	10
3	8.6
4	7.2
5	5.7
6	4.3
7	2.9
8	1.4
9	0

The entries are the payoff of choosing to withdraw which depends on the number of preceding withdrawals which is the endowment left in the bank subtracted from liquidation cost.

In Table 4.2 we show the payoffs for choosing to wait, which depends on the total number of withdrawals at the end of a period. If a depositor decides to wait, he or she can receive a maximum of 13 ED, if the number of withdrawals is smaller or less than three. If, however, the number of withdrawals is more than three, the payoff is strictly less than 13 ED.[9]

Table 4.2: Payoff– If choosing to wait

Total number of withdrawals at the end of the period	Payoff
3	13
4	11.2
5	9.4
6	7.4
7	5.6
8	3.8
9	1.8
10	0

The entries are the payoff of choosing to wait which depends on the number of withdrawals over the course of a period.

[9]We cannot solve for the equilibrium strategy of a typical depositor in an extensive form because the vectors of the ranks are randomly set. Also, our participants do not know where the simulated computers robots are located in the queue.

We define a bank run as a situation in which one of the participants excluding robots places a withdrawal request. Our focus is on the frequency of runs not the existence of bank runs.

4.5 Experimental Results

In this section, we present the results of the experiment. The summary statistics for the average number of withdrawals in each period over all sessions, by treatment, is provided in Table 4.3. Note that we exclude the withdrawals made by robots in our data analysis. The average withdrawals of sequential high-information is 2.67, which is substantially greater that the average withdrawals in sequential low-information at 0.85. This suggests that the likelihood of bank run increases when depositors obtain information of the preceding withdrawals. The variation of the average withdrawals is higher in the low-information treatment (0.535) compared to the high-information treatment (0.380).

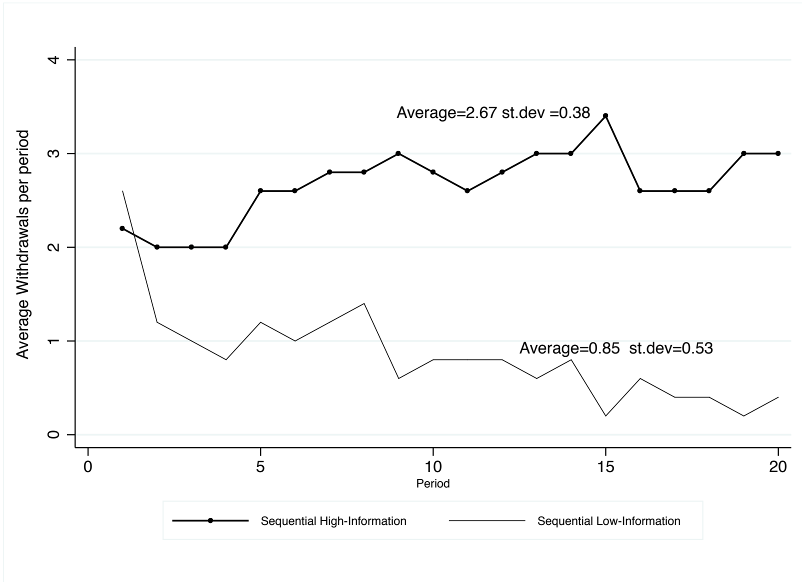
Table 4.3: Summary statistics for the average number of withdrawals– by treatment

Treatment	averageWD	st.dev
sequential high–information	2.67	0.380
sequential low–information	0.85	0.535

The entries are the average and the standard deviation of the number of withdrawals treatment level by period. N=20 observations per treatment.

In Figure 4.1 , we can see that the average number of withdrawals in the sequential high–information treatment is greater than the average number of withdrawals in the sequential low–information treatment and it remains higher over time. Furthermore, a gap exists between the average number of withdrawals across treatments, which increases over time. Intuitively, knowing the preceding withdrawals could increase the probability of withdrawals in each period and over time. Although, initially some withdrawals are observed in the sequential low–information treatment, however, participants learn over time that coordination can help them and the other depositors to achieve higher payoff. Therefore, the average number of withdrawals remains low and decreases over time. In the sequential high–information treatment, the average number of withdrawals increases as participant obtain information about the number of preceding withdrawals.

Figure 4.1: Average number of withdrawals per period by treatment



We also present the average and standard deviation of the number of withdrawals at the session–treatment level (Table 4.4). The average number of withdrawals in in the sequential high–information treatment is greater than sequential low–information treatment, except for session 1.4, which has an average of 0.7. In general, we find more variation in the sequential high-information treatment.

Table 4.4: Summary statistics for the average number of withdrawals–by session per treatment

sequential high–information				sequential low–information		
session	averageWD	st.dev		session	averageWD	st.dev
session 1.1	3.7	1.031		session 2.1	0.75	0.966
session 1.2	2.35	0.933		session 2.2	1.75	0.850
session 1.3	4.05	0.825		session 2.3	0.6	0.753
session 1.4	0.7	0.801		session 2.4	0.2	0.523
session 1.5	2.55	1.145		session 2.5	0.95	0.825
Rank–sum test	p–value		0.0472			

Averages and standard deviations for withdrawals at the session-treatment level. Session i.j represents session i in treatment j. N =20 number of observations.
The average number of withdrawals per session is used as a single observation and we obtain five observations per treatment for the rank-sum test.

These statistics indicate that on average more information observability increases the likelihood of runs on the bank. Further, we examine our results using a two-sided Wilcoxon–Mann–Whitney rank sum test. We use the average number of withdrawals at the session-treatment level with the null hypothesis being that the averages are coming from the same treatments. The resulting *p-value* is 0.0472, which rejects the null hypothesis at a 5% significance level.

Observation I: *The likelihood of bank runs increases in the sequentially high–information treatment compare to sequentially low– information treatment. Information of past withdrawals increases the average number of withdrawals at the session–treatment level.*

Arguably, the decision of the participants can be influenced by their rank in the queue. Therefore, we consider two groups of participants: located at a rank between 1 to 5 or 6 to 10. In each group we first calculate the percentage of withdrawals using the number of withdrawals at each rank, divided by the number of decisions made by the participants in each session (excluding from robots). Finally, we take the average percentage of withdrawals over ranks 1 to 5 and 6 to 10, accordingly, over the sessions.

The findings are represented in Table 4.5 including the result at the session–treatment level. In both treatments, the average percentage of withdrawals for those at the front of the queue is greater than the average for those at the back of the queue. Indeed, in the sequential high–information treatment, the average number of withdrawals for participants ranked 1 to 5 is 59%, compared to 23% for those in the sequential low–information treatment. The average percentage of withdrawals for those ranked 6 to 10 is 17.8% in the sequentially high–information treatment, compared to 1.8% for those in the sequentially low–information treatment. This indicates that, regardless of the position in the queue, participants, on average, choose to withdraw more when they receive more information.[10]At the session–level, the average percentage of withdrawals is greater among participants who are nearer the front of the queue, compared to those at the back of the queue in both treatments.

[10]We run a questionnaire at the end of each session and ask participants how they made their decisions. We find that in the sequential high–information treatment participants pay more attention to the number of preceding withdrawals and they focus on their own payoffs rather than on the payoffs to the group. In contrast, in the sequential low–information treatment participants consider the group payoff and coordinate on waiting to increase the payoffs to all participants. Box 1 in Section C.2 provides the participants' responses for two treatments that are in alignment with our observations.

Table 4.5: Average percentage of withdrawals by rank, at the session–treatment level

Treatment	Rank 1–5	Rank 6–10
sequential high–information	59	17.8
sequential low–information	23	1.8
session 1.1	19	1
session 1.2	84	26
session 1.3	60	7
session 1.4	78	37
session 1.5	54	18
session 2.1	18	3
session 2.2	46	6
session 2.3	19	0
session 2.4	5	0
session 2.5	27	0

Average percentage of withdrawals in each group is calculated at the session level and average over treatment. We use the number of withdrawals at each rank, divided by the number of decisions made by the participants excluding from robots.

The two sided Wilcoxon-Mann Whitney rank–sum at the session–treatment level give *p–values* of 0.0361 and 0.0264, respectively which reject the null hypothesis that the average percentage of withdrawals is the same among rank 1 to 5 and 6 to 10. This confirms that these observations come from different treatments.

Observation II: *The average percentage of withdrawals among depositors who are near the front of the queue is more than the average percentage of withdrawals at the back of the queue in both treatments. The average percentage of withdrawals of the depositors in the queue is higher in the sequential high–information treatment, compared to the low–information treatment at the session level.*

In the following section, we pool the data from each treatment and study the results at the participant–level.

4.5.1 Regression Results

We use *probit* regression for each treatment with pooled data. The dependent variable is the probability of withdrawals, and the explanatory variables are the position of a participant in the queue (called "*Rank*"), the total number of withdrawals in the last period (called "TWD_{t-1}"), and the preceding withdrawals ("WD_{-i}") in which i represents the rank of the participant.[11]

The regression results with pooled data in treatment with sequential high–information are presented in Table 4.6. With single–variable regression, the probability of withdrawals is negatively related with *Rank* and is significant at 1%. A depositor who is at the back of the queue less likely chooses to withdraw. More preceding withdrawals WD_{-i}lowers the the probability withdrawals at 1% significant level. With more TWD_{t-1} in the last period, the probability of withdrawals decreases in the current period. The last two results are in contradiction to the observations as session–treatment level.

With multi–variable regression, considering the effect of *Rank* and WD_{-i} in *Model IV*, the probability of withdrawals significantly decreases at higher ranks and increases with the number of preceding withdrawals at the 1% and 5% level of significance, respectively (-0.164 and 0.114, respectively). In *Model V*, *Rank* is negatively related to the probability of withdrawals but we find that more total number of withdrawals in the past period, TWD_{t-1}, increases the probability of withdrawals in the current period, at the 1% level of significance. Using WD_{-i} and TWD_{t-1} in *Model VI* we find that the preceding withdrawals decreases the probability of withdrawing, and total number of withdrawal increases the probability of withdrawing (at the 1% significance level). Lastly, in *Model VII*, we use all the variable in the *probit* regression. We find that *Rank* is negative and significant, WD_{-i} is positive and insignificant, and TWD_{t-1} is positive and significant. Our findings in Table 4.6 suggest that in a sequential high–information treatment participants will less likely to withdraw if they are ranked further in the queue. Also, total number of withdrawal positively influences the probability of withdrawals in the current period. However, the preceding withdrawals gives mixed results. We suspect that multicollinearity may be occurring between WD_{-i} and TWD_{t-1}.

[11]A rank closer to the front is called low rank and further to the back is called high rank.

Table 4.6: Pooled Regression–Sequential high–information

	Single–variable regression				Multi–variable regression		
Dep.Var	Probability of Withdrawals						
Explanatory Variables	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
Rank	-0.98***			-0.164***	-0.292		-0.322***
	(0.008)			(0.027)	(0.022)		(0.038)
WD_{-i}		-0.147***		0.114**		-0.375***	0.051
		(0.14)		(0.044)		(0.030)	(0.54)
TWD_{t-1}			-0.30***		0.224***	0.165***	0.222*
			(0.008)		(0.020)	(0.018)	(0.20)
N	700	700	700	700	700	700	700
chi2	148.17	111.17	121.80	159.43	181.16	157.91	177.21

The results from a series of probit regressions in sequential high–information treatment are presented.Robust standard errors are used. $*p < 0.10$, $**p < 0.05$, and $***p < 0.01$.
Rank is participants' position in the queue, WD_{-i} is the number of preceding withdrawals, and TWD_{t-1} is total number of withdrawals in the last period.

We provide the results of *probit* regression in sequential low–information treatment in Table 4.7. Single variable regression of the probability of withdrawals are presented in *Model I* and *Model II*. We find that the probability of withdrawals increases if participant are located near the front of the queue at the significant level of 1%. Also, TWD_{t-1} is negatively related to the probability of withdrawals and is significant at the 1%. The regression results are similar to single–variable regression in sequential high–information treatment. Considering both variable in *Model III*, *Rank* is negatively related to the probability of withdrawals (significant at the 1%) and TWD_{t-1} positively affects the probability of withdrawals and it is insignificant.

Table 4.7: Pooled Regression–Sequential low–information

	Single–variable regression		Multi–variable regression
Dep.Var	Probability of Withdrawals		
Explanatory Variables	(I)	(II)	(III)
Rank	-0.278***		-0.290***
	(0.017)		(0.030)
TWD_{t-1}		-0.286***	0.014
		(0.018)	(0.032)
N	700	700	700
chi2	276.050	244.371	261.271

The results from a series *probit* regressions in low–sequential treatment are presented.Robust standard errors are used.$*p < 0.10$, $**p < 0.05$, and $***p < 0.01$.
Rank is participants' position in the queue, and TWD_{t-1} is total number of withdrawals in the last period.

In general, our results show that rank has a negative effect in both treatments, which implies that those who are earlier in the queue would prefer to withdraw and those who are later in the queue would prefer to wait. More withdrawals in the last period leads to more withdrawals in the current period, in the sequential high-information treatment, but not in the sequential low–information treatment. The number of preceding withdrawals is the distinguishing variable in the sequential high–information treatment, and we expect that more preceding withdrawals would increase the probability of withdrawals. Our results, however, do not show a significant effect, which might be a result of multi-colinearity between WD_{-i} and TWD_{t-1}.

In Table 4.8, we provide the regression results of pooled data from the two treatments to find whether there is significant differences between the two treatment. We define a dummy variable that takes a value of 0 if it is the sequential high-information and 1 if it is the sequential low-information treatment.

Table 4.8: Probit Regression for the probability of bank runs

Probability of Withdrawals Explanatory vars.	Coef.
TWD_{t-1}	0.254***
	(0.033)
Rank	-0.283***
	(0.023)
$TWD_{t-1} \times Low$	-0.196***
	(0.040)
$Rank \times Low$	0.008
	(0.038)
cons	-0.232
	(0.176)
N	1400
χ^2	336.964

A dummy variable is defined for the sequential low–information treatment.*$p < 0.10$, **$p < 0.05$, and ***$p < 0.01$.

We find substantial differences between the two treatments. In sequential high–information treatment, TWD_{t-1} increases the probability of withdrawals and *Rank* decreases the probability of withdrawals. Nevertheless, in the sequential low–information treatment, TWD_{t-1} reduces the probability of withdrawals and *Rank* does not show significant impact of the probability of withdrawals. Our conclusion is that when participants are informed of the preceding withdrawals before submitting their decision, the probability of withdrawals increases, and as a result the likelihood of bank runs increases. The history of withdrawals significantly influences the withdrawals in the current period. Furthermore, in the sequential high-information treatment, depositors are highly responsive to the received information of the preceding withdrawals which is directly related to their position in the queue.

4.6 Final remarks

In this paper, we study the degree of information observability on the emergence of bank runs with a sequential setup in a laboratory environment. We consider two treatments: sequential high-information and sequential low-information. Participants know that the bank pays for the withdrawal requests on a first–come first–served basis and if the bank runs out of reserves, it has to liquidate the long–term investment which imposes a liquidation cost. We find that, on average, participants who are at the front of the queue tend to withdraw more than those at the back of the queue.

Participants in the high-information sequential treatment are clearly responsive to the number of preceding withdrawals and the likelihood of bank runs increases in this treatment. Nevertheless, in the low–information sequential treatment, participants tend to coordinate on waiting and it is less likely that they choose to withdraw.

For future research, we intend to investigate the effect of a freezing policy on the likelihood bank runs. In particular, we wish to focus on how the timing of freezing might slow down or aggravate the number of withdrawals.

Chapter 5

Conclusions

The results of the three papers presented in this thesis offer important policy implications to reduce economic instability.

Chapter 2 studies the elicitation of expectations by forward guidance in an LTFE environment. The central bank's forward guidance is through providing the future five–period projections of output gap, projections of inflation, dual projections of output gap and inflation, and projections of nominal interest rates. The findings show that forward guidance of either future output gap or inflation results in a greater coordination of expectations and a reduction in forecast errors associated with the communicated variable. However, forward guidance of nominal interest rates leads to mixed results. For relatively low variability in aggregate demand shocks, nominal interest rate projections are relatively stable and result in significantly more stable, "rational" forecasts. However, as the variability of shocks increases, the benefits of such forward guidance weaken, and agents maintain a backward-looking forecasting heuristic.

Chapter 3 evaluates how a central bank could anchor the expectations by communicating its expected future of output gap and/or inflation to private agents who are nonresponsive to current shocks. We discuss the effect of communication on reducing economic instability in response to a demand shock or a cost-push shock under flexible IT and strict IT. Communicating future inflation decreases output variations and increases inflation and interest rate variations, and communicating output decreases inflation and interest rate variability and increases output variations qualitatively, no matter what Taylor rule is used. With a cost–push shock, a central bank communicating expected future output reduces inflation and interest rate variability under flexible IT and strict IT. Under a cost-push shock, the central bank should be uncommunicative in order to reduce the output variations when using flexible IT, but it should communicate inflation when using strict IT. Finally, under strict IT, communicating both expected future output and inflation is successful in reducing the variations of output, inflation, and interest rates in response to a demand shock and a cost–push shock.

In Chapter 4, we conduct an experiment in order to study the effect of information observability on bank runs in a sequential environment. Depositors are randomly assigned a rank in a queue to submit their decision, and they are informed of their rank when it is actually their turn. Two treatments are considered: a sequential high-information treatment (in which participants are informed of the history of previous decisions, their spot in the queue upon their turn, and the number of preceding withdrawals), and a sequential low–information treatment (in which subjects are informed of the history of previous decisions and their spot in the queue upon their turn). The results show that in both treatments, depositors who are at the front of the queue tend to withdraw more on average compared to the back of the queue. In addition, depositors are clearly responsive to receiving information about other depositors' decisions in that, on average, more withdrawals have been observed in the sequential high–information treatment compared to the sequential low–information treatment.

The findings presented in Chapter 2 and Chapter 3 are evidence of the pervasive effect of central bank communication policy in economic stability. The results are in favour of increasing transparency through communication. Chapter 4 presents important insights of the responsiveness of depositors to the received information of other depositors' behaviour.

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Appendix A

Central Bank Communication and Expectations

A.1 Solving the model under rational expectations

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

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

Rearrange the equation:

$$x_t = E_t x_{t+1} - \sigma^{-1}(\phi_\pi \kappa + \phi_x) x_t - \sigma^{-1}(\phi_\pi \beta - 1) E_t \pi_{t+1} + \sigma^{-1} r_t^n \tag{A.2}$$

$$[1 + \sigma^{-1}(\phi_\pi \kappa + \phi_x)] x_t = E_t x_{t+1} - \sigma^{-1}(\phi_\pi \beta - 1) E_t \pi_{t+1} + \sigma^{-1} r_t^n \tag{A.3}$$

We get:

$$x_t = \frac{1}{1 + \sigma^{-1}(\phi_\pi \kappa + \phi_x)} E_t x_{t+1} - \frac{\sigma^{-1}(\phi_\pi \beta - 1)}{1 + \sigma^{-1}(\phi_\pi \kappa + \phi_x)} E_t \pi_{t+1} + \frac{\sigma^{-1}}{1 + \sigma^{-1}(\phi_\pi \kappa + \phi_x)} r_t^n \tag{A.4}$$

Replace equation(8) into (2):

$$\pi_t = \kappa x_t + \beta E_t \pi_{t+1}, \tag{A.5}$$

$$\pi_t = \kappa\{\frac{1}{1+\sigma^{-1}(\phi_\pi\kappa+\phi_x)}E_t x_{t+1} - \frac{\sigma^{-1}(\phi_\pi\beta-1)}{1+\sigma^{-1}(\phi_\pi\kappa+\phi_x)}E_t\pi_{t+1} + \frac{\sigma^{-1}}{1+\sigma^{-1}(\phi_\pi\kappa+\phi_x)}r_t^n\} + \beta E_t\pi_{t+1} \tag{A.6}$$

We get:

$$\pi_t = \frac{\kappa}{1+\sigma^{-1}(\phi_\pi\kappa+\phi_x)}E_t x_{t+1} + (\frac{\beta+\beta\sigma^{-1}\phi_x+\kappa\sigma^{-1}}{1+\sigma^{-1}(\phi_\pi\kappa+\phi_x)})E_t\pi_{t+1} + \frac{\kappa\sigma^{-1}}{1+\sigma^{-1}(\phi_\pi\kappa+\phi_x)}r_t^n \tag{A.7}$$

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

$$i_t = \frac{\phi_x+\phi_\pi\kappa}{1+\sigma^{-1}(\phi_\pi\kappa+\phi_x)}E_t x_{t+1} + \frac{\phi_x\sigma^{-1}+\phi_\pi(\beta+\kappa\sigma^{-1})}{1+\sigma^{-1}(\phi_\pi\kappa+\phi_x)}E_t\pi_{t+1} + \frac{\kappa\sigma^{-1}\phi_\pi+\sigma^{-1}\phi_x}{1+\sigma^{-1}(\phi_\pi\kappa+\phi_x)}r_t^n \tag{A.8}$$

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

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:

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

A.2 Additional Results

Table A.1: Absolute forecast errors of output and inflation, by treatment

Treatment		Repetition–1		Repetition–2	
		Output	Inflation	Output	Inflation
NoComm					
	Mean	134.88	21.90	121.57	22.20
	std.	553.17	22.67	485.41	32.75
OutputProj					
	Mean	106.20	66.56	53.42	25.05
	std.	550.84	512.79	51.16	29.64
InflationProj					
	Mean	66.74	19.99	55.98	18.30
	std.	62.49	21.45	51.16	19.33
DualProj					
	Mean	69.42	29.93	60.95	23.66
	std.	101.00	108.08	142.20	52.77
IRProj					
	Mean	70.52	32.57	62.22	23.53
	std.	70.71	58.34	53.96	32.32
Rank–sum test:		p–value	p–value	p–value	p–value
NoComm–OutputProj		1.000	0.631	0.078	0.337
NoComm–InflationProj		0.749	0.337	0.109	0.025
NoComm–DualProj		0.423	1.000	0.337	0.262
NoComm–IRProj		0.749	0.109	0.522	0.873
OutputProj–InflationProj		0.749	0.109	0.873	0.055
OutputProj–DualProj		0.631	0.423	1.000	0.337
OutputProj–IRProj		1.000	0.749	0.109	0.631
InflationProj–DualProj		0.873	0.522	0.749	0.337
InflationProj–IRProj		0.749	0.025	0.109	0.078
DualProj–IRProj		0.522	0.262	0.631	0.262

The entries are the average and the standard deviation of all absolute forecast errors. Rank sum tests are conducted on session-level mean absolute forecast errors. N=6 observations per treatment. Signed rank tests reject the null hypothesis that the session-level mean absolute forecast errors are equal to zero for all treatments and repetitions ($p = 0.028$ in all cases).

Table A.2: Absolute Forecast Error of Inflation Within Treatments

Treatment		Repetition–1		Repetition–2	
		Mean	std.	Mean	std.
NoComm					
	Session–1	21.37	19.68	18.65	15.95
	Session–2	16.21	17.06	19.66	19.76
	Session–3	27.20	31.35	27.59	66.65
	Session–4	23.22	25.13	26.82	23.68
	Session–5	20.18	16.25	19.11	18.63
OutputProj					
	Session–1	21.09	20.81	19.52	19.21
	Session–2	318.57	1320.06	36.94	42.92
	Session–3	20.67	18.73	16.74	17.56
	Session–4	21.30	32.69	27.82	24.50
	Session–5	22.44	27.71	23.12	35.33
InflationProj					
	Session–1	25.39	26.37	25.94	32.20
	Session–2	14.74	17.12	17.13	13.39
	Session–3	19.34	17.24	16.34	18.49
	Session–4	18.12	19.17	17.16	13.48
	Session–5	20.68	25.96	14.97	14.12
DualProj					
	Session–1	18.32	19.10	16.97	18.53
	Session–2	14.41	13.93	19.47	21.09
	Session–3	27.13	40.18	20.00	21.58
	Session–4	76.34	252.78	50.87	118.43
	Session–5	23.36	27.42	17.66	19.89

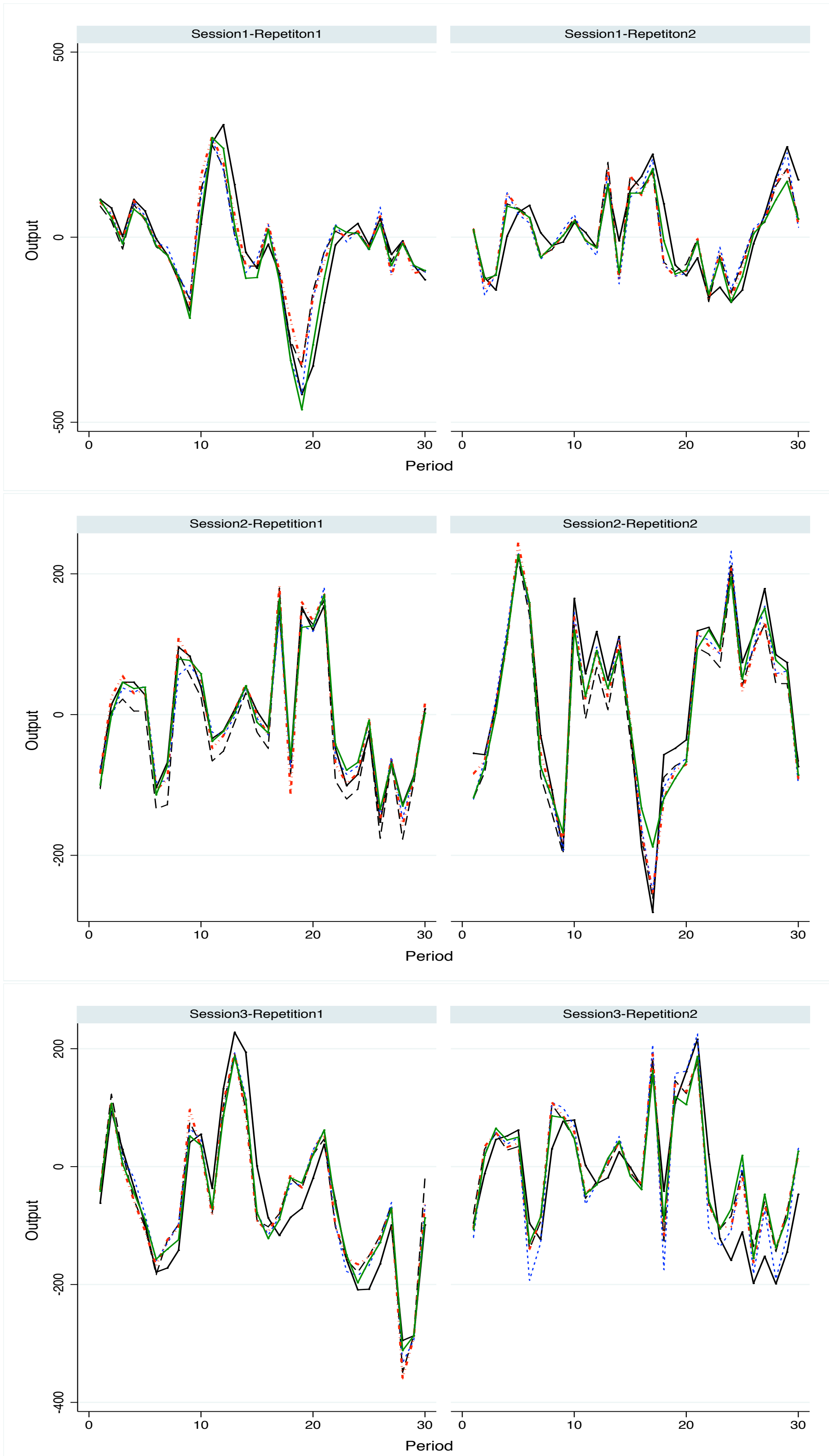
We take the mean and the standard deviation of the absolute forecast error of inflation at the session–repetition level.

Table A.3: Summary Statistics on the Standard Deviations of Output and Inflation, by Treatment and Repetition

Treatment		Repetition–1		Repetition–2	
		std.Output	std.Inflation	std.Output	std.Inflation
NoComm					
	Mean	119.61	46.20	123.43	49.13
	std.	23.44	18.38	16.34	15.36
OutputProj					
	Mean	111.73	37.80	111.08	41.25
	std.	11.89	3.26	12.48	14.47
InflationProj					
	Mean	110.13	32.92	122.02	35.69
	std.	18.20	8.75	9.35	2.20
DualProj					
	Mean	110.66	35.74	110.22	34.48
	std.	14.48	5.16	9.01	5.03
Shocks					
	Mean	138.22		136.80	
	std.	15.50		11.27	
Rank–sum test:		p–value	p–value	p–value	p–value
NoComm–OutputProj		0.4647	0.4647	0.3472	0.9168
NoComm–InflationProj		0.4647	0.2506	0.7540	0.1172
NoComm–DualProj		0.4647	0.3472	0.1745	0.0758
OutputProj–DualProj		0.9168	0.9168	0.9168	0.6015
InflationProj–DualProj		0.6015	0.1482	0.0758	0.3472
OutputProj–InflationProj		0.6015	0.2506	0.1745	0.6015

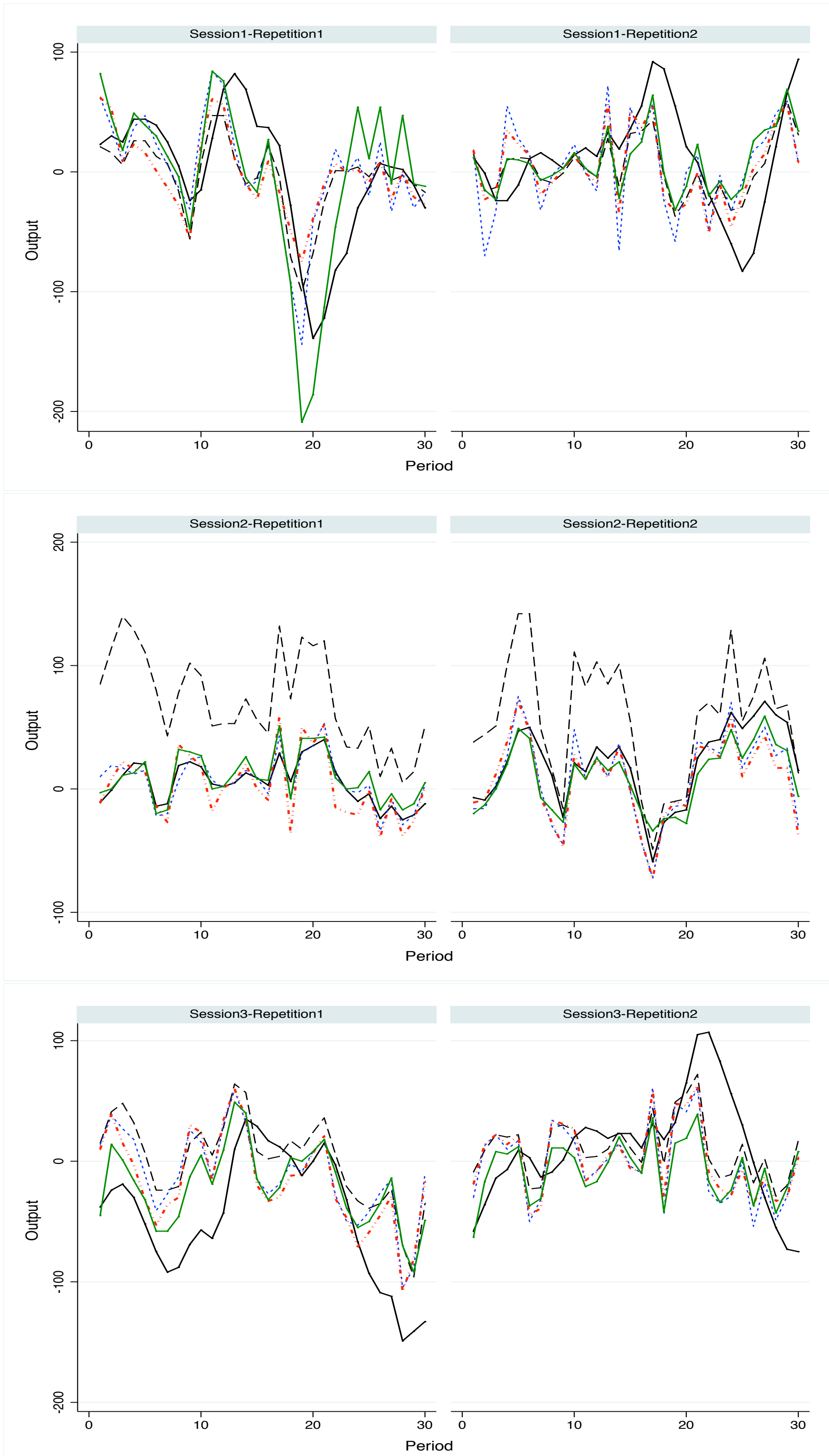
[1] The entries are the standard deviation of output and inflation in each session per treatment.
[2] Asterisks denote whether the samples standard deviations are different across treatments. The significant levels are at $*p < 0.10$, $**p < 0.05$, and $***p < 0.01$.
[3] We produced the same table by normalizing the entries using the standard deviation of the shocks. The results of the rank–sum test remain the same.

Figure A.1: Time series of the output gap by session and repetition




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

Figure A.2: Time series of the inflation by session and repetition



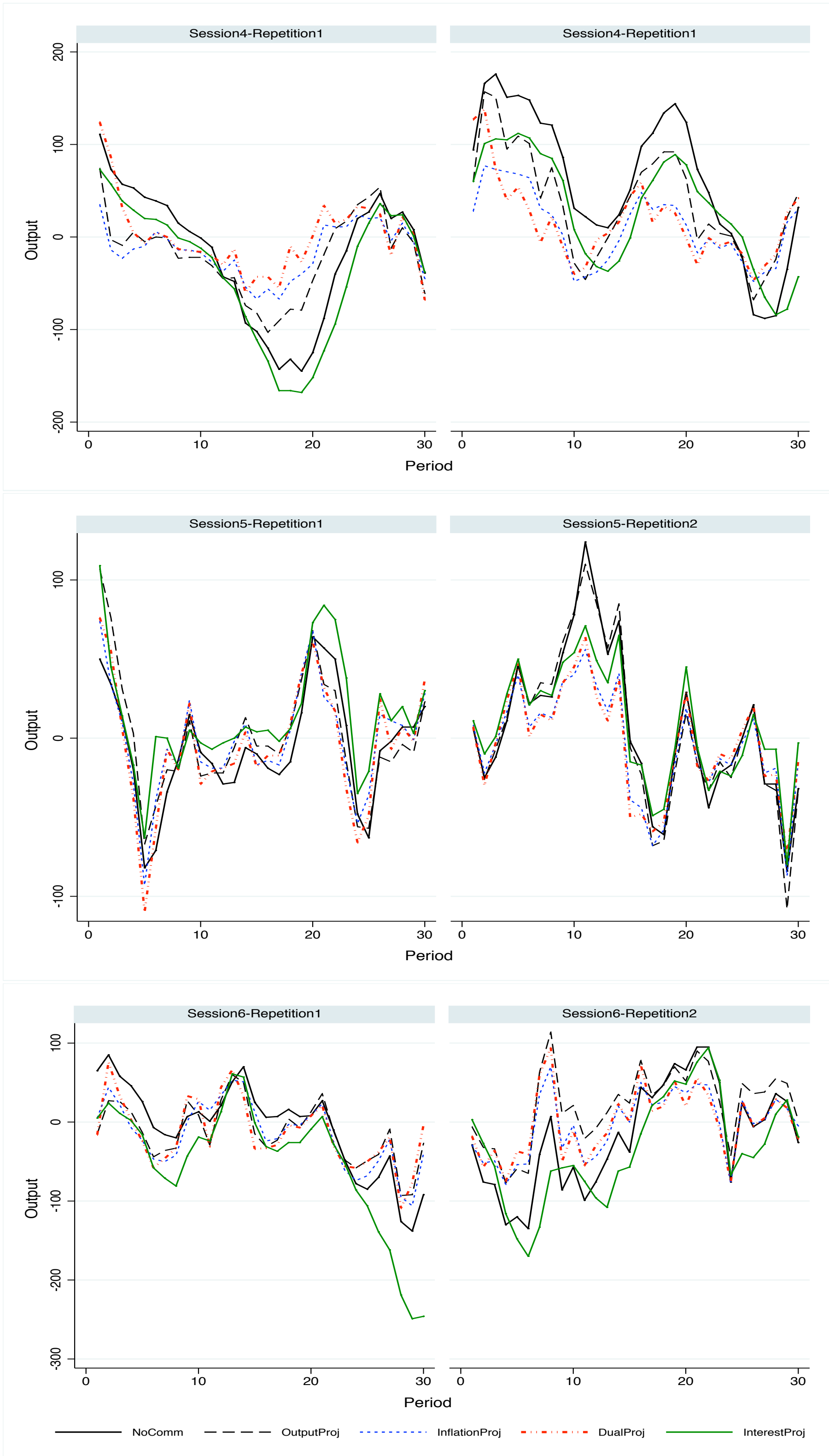
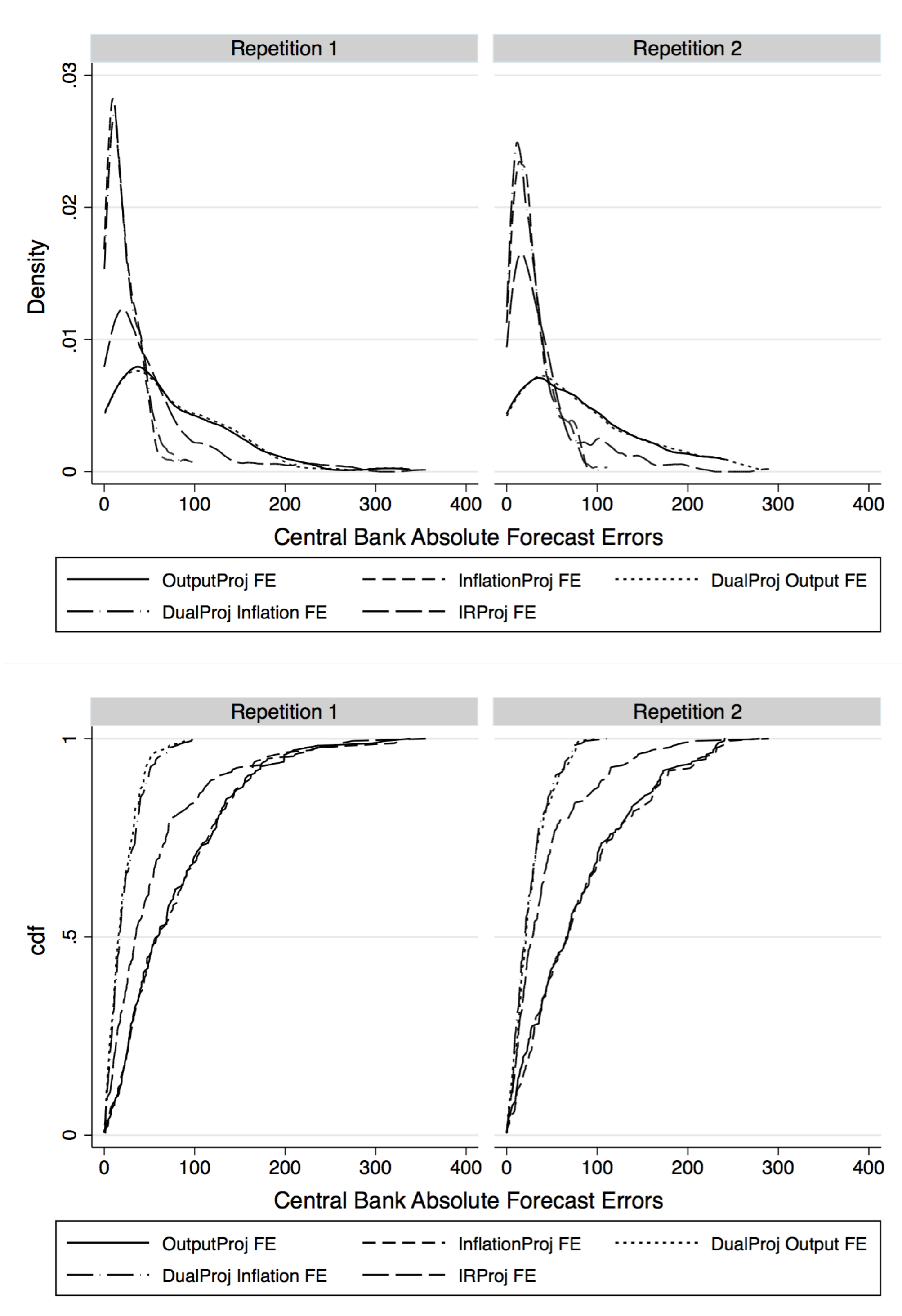

Session4-Repetition1
Session4-Repetition1
Output
Period
Session5-Repetition1
Session5-Repetition2
Output
Period
Session6-Repetition1
Session6-Repetition2
Output
Period
NoComm
OutputProj
InflationProj
DualProj
InterestProj

Figure A.3: Central bank absolute forecast errors by repetition



A.3 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 $ 7 dollars 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 $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:

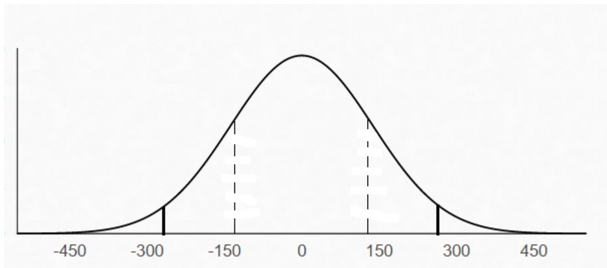
1% = 100 basis points 3.25% = 325 basis points -0.5% = -50 basis points -4.8%= -480 basis points

- 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.

Appendix B

Communication strategies in New Keynesian Model: An Exercise

B.1 Transition Path

The results of the REE with flexible IT are presented in Equation (B.1) and Equation (B.2)

$$\begin{aligned} \textbf{Demand Shock} \quad x_t &= 0.472198 \cdot u_{t-1} + 0.82847 \cdot \epsilon_t \\ \pi_t &= 0.140706 \cdot u_{t-1} + 0.246852 \cdot \epsilon_t \\ i_t &= 0.447157 \cdot u_{t-1} + 0.784487 \cdot \epsilon_t \end{aligned} \tag{B.1}$$

$$\begin{aligned} \textbf{Supply Shock} \quad x_t &= -1.006587 \cdot v_{t-1} - 1.765942 \cdot \epsilon_t \\ \pi_t &= 1.006587 \cdot v_{t-1} + 1.765942 \cdot \epsilon_t \\ i_t &= 1.006587 \cdot v_{t-1} + 1.765942 \cdot \epsilon_t \end{aligned} \tag{B.2}$$

The results of the REE with strict IT are presented inEquation (B.3) and Equation (B.4)

$$\begin{aligned} \textbf{Demand Shock} \quad x_t &= 0.806084 \cdot u_{t-1} + 1.414183 \cdot \epsilon_t \\ \pi_t &= 0.240198 \cdot u_{t-1} + 0.420198 \cdot \epsilon_t \\ i_t &= 0.360296 \cdot u_{t-1} + 0.632099 \cdot \epsilon_t \end{aligned} \tag{B.3}$$

$$\begin{aligned} \textbf{Supply Shock} \quad x_t &= -1.718336 \cdot v_{t-1} - 3.014625 \cdot \epsilon_t \\ \pi_t &= 0.794500 \cdot v_{t-1} + 1.393859 \cdot \epsilon_t \\ i_t &= 1.191749 \cdot v_{t-1} + 2.090788 \cdot \epsilon_t \end{aligned} \tag{B.4}$$

Under simple AE, the transition paths with demand shock is represented in Equation (B.5), and with a cost-push shock the transition paths is represented in Equation (B.6), assuming flexible IT:

Demand Shock
$$x_t = 0.530973 \cdot x_{t-1} - 0.256726 \cdot \pi_{t-1} + 0.336283 \cdot u_{t-1} + 0.589971 \cdot \epsilon_t \tag{B.5}$$
$$\pi_t = 0.069027 \cdot x_{t-1} + 0.856726 \cdot \pi_{t-1} + 0.043717 \cdot u_{t-1} + 0.076696 \cdot \epsilon_t$$
$$i_t = 0.369027 \cdot x_{t-1} + 1.156726 \cdot \pi_{t-1} + 0.233717 \cdot u_{t-1} + 0.410029 \cdot \epsilon_t$$

Supply Shock
$$x_t = 0.530973 \cdot x_{t-1} - 0.256726 \cdot \pi_{t-1} - 0.504425 \cdot u_{t-1} - 0.884956 \cdot \epsilon_t \tag{B.6}$$
$$\pi_t = 0.069027 \cdot x_{t-1} + 0.856726 \cdot \pi_{t-1} + 0.504425 \cdot u_{t-1} + 0.884956 \cdot \epsilon_t$$
$$i_t = 0.369027 \cdot x_{t-1} + 1.156726 \cdot \pi_{t-1} + 0.504425 \cdot u_{t-1} + 0.884956 \cdot \epsilon_t$$

The results of simple adaptive expectations with strict IT are presented in Equation (B.7) and Equation (B.8)

Demand Shock
$$x_t = 0.753138 \cdot x_{t-1} - 0.364141 \cdot \pi_{t-1} + 0.476987 \cdot u_{t-1} + 0.836820 \cdot \epsilon_t \tag{B.7}$$
$$\pi_t = 0.097908 \cdot x_{t-1} + 0.842762 \cdot \pi_{t-1} + 0.062008 \cdot u_{t-1} + 0.108787 \cdot \epsilon_t$$
$$i_t = 0.146862 \cdot x_{t-1} + 1.264142 \cdot \pi_{t-1} + 0.093013 \cdot u_{t-1} + 0.163180 \cdot \epsilon_t$$

Supply Shock
$$x_t = 0.753138 \cdot x_{t-1} - 0.364142 \cdot \pi_{t-1} - 0.715481 \cdot u_{t-1} - 1.255230 \cdot \epsilon_t, \tag{B.8}$$
$$\pi_t = 0.097908 \cdot x_{t-1} + 0.842762 \cdot \pi_{t-1} + 0.476987 \cdot u_{t-1} + 0.836820 \cdot \epsilon_t,$$
$$i_t = 0.146862 \cdot x_{t-1} + 1.264142 \cdot \pi_{t-1} + 0.715481 \cdot u_{t-1} + 1.255230 \cdot \epsilon_t,$$

B.2 Matlab Codes

```
%addpath /Applications/Dynare/4.4.3/matlab
%dynare CommPolicy
% Rational-Adaptive Expecation
% Demand Shock-Supply Shock
% Agents are all Homogenous
% Inflation, Output, Both or No Communication
%% Update:
% Taylor Rule
%Type of Communication
% Type of Shocks
%-----------------------------------------------------------------
%% Defining variables
%-----------------------------------------------------------------
var x pi i u;
var Ex Epi Ex Epi CBx CBpi ;
varexo e;
parameters beta sigma kappa theta rho sigmae phipi phix alpha_x
alpha_pi;
%-----------------------------------------------------------------
%% Calibration
%-----------------------------------------------------------------
beta = 0.989;
rho=0.57;
sigma = 1;
kappa = 0.13;

theta=0.9;
sigmae=2;

% Flexible IT
phipi=1.5;
phix = 0.5;
% Strict IT
phipi=1.5;
phix = 0;

%DualComm
alpha_x = 0.5;
alpha_pi = 0.5;

%NoCommunication
alpha_x = 0;
alpha_pi = 0;

%-----------------------------------------------------------------
% 3. Model
%-----------------------------------------------------------------
model(linear);

%% STANDARD HOMOGENEOUS EXPECTATION MODEL-DemandShock
x = Ex - (sigma^-1)*(i - Epi)+u;
pi = beta*Epi +(kappa*x);
i = phipi*pi + phix*x;
u = rho*u(-1)+e;
```

```
%% STANDARD HOMOGENEOUS EXPECTATION MODEL-SupplyShock
x = Ex - (sigma^-1)*(i - Epi);
pi = beta*Epi +(kappa*x)+u;
i = phipi*pi + phix*x;
u = rho*u(-1)+e;

%Describe expectations-RE
%Agents are Rational and Cb rational
Ex=(1-alpha_x)*x(+1)+alpha_x*CBx;
Epi=(1-alpha_pi)*pi(+1)+alpha_pi*CBpi;

%CB-RE
CBx =  x(+1);
CBpi = pi(+1);

%Describe expectations-Agents Simple AE-CB Rational/With Communication
%Agents are simple Adaptive Expectations
Ex=(1-alpha_x)*theta*x(-1)+alpha_x*CBx;
Epi=(1-alpha_pi)*theta*pi(-1)+alpha_pi*CBpi;

%CB-RE
CBx =  x(+1);
CBpi = pi(+1);

%Describe expectations-Agents Simple AE-CB Rational/NoCommunication
%Agents are simple Adaptive Expectations
Ex=theta*x(-1);
Epi=theta*pi(-1);

end;

%----------------------------------------------------------------
% 4. Computation
%----------------------------------------------------------------
shocks;
var e = sigmae^2;
end;
steady;
%----------------------------------------------------------------
% 5. Some Results
%----------------------------------------------------------------
stoch_simul;
save data
filename = 'data.xlsx';
A = [x_e, pi_e, i_e, CBx_e, CBpi_e];
xlswrite(filename,A)
```

Appendix C

Information Observability and Bank Runs

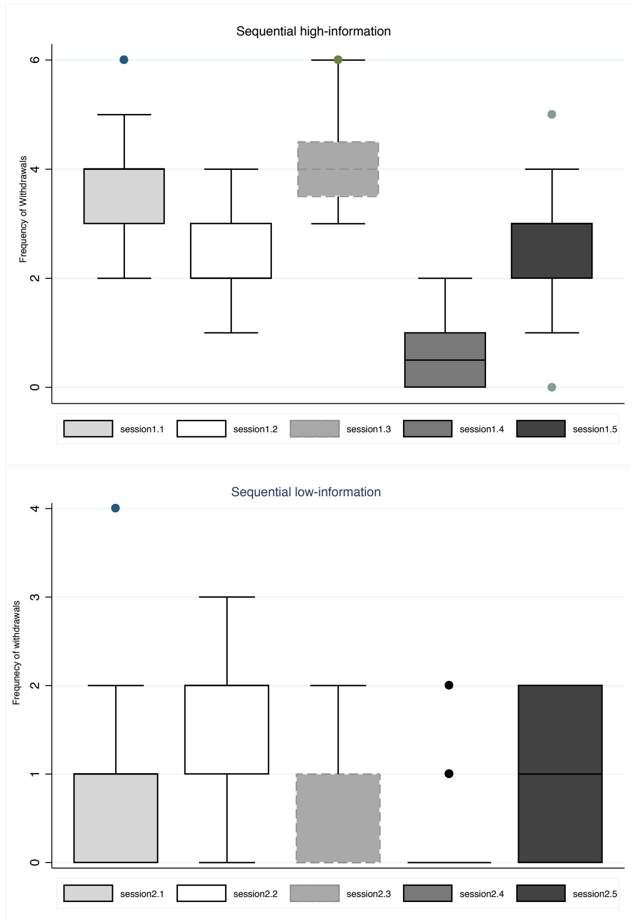
C.1 Tables and Figures

Table C.1: The Percentage of Withdrawals at session–treatment level by rank

Rank	1	2	3	4	5	6	7	8	9	10
Session 1.1	100.00	93.33	90.91	76.92	57.14	61.54	40.00	20.00	0.00	6.67
Session 1.2	63.64	88.89	83.33	28.57	33.33	12.50	16.67	0.00	0.00	6.67
Session 1.3	80.00	100.00	100.00	60.00	50.00	66.67	57.14	23.08	23.08	14.29
Session 1.4	36.36	23.53	5.88	12.50	18.18	7.14	0.00	0.00	0.00	0.00
Session 1.5	70.59	75.00	60.00	30.77	33.33	23.08	20.00	7.14	27.27	13.33
Session 2.1	35.71	20.00	23.08	13.33	0.00	6.67	0.00	0.00	7.14	0.00
Session 2.2	66.67	84.62	21.43	36.36	20.00	23.08	6.25	0.00	0.00	0.00
Session 2.3	45.45	26.67	14.29	6.67	0.00	0.00	0.00	0.00	0.00	0.00
Session 2.4	6.67	7.14	6.67	6.25	0.00	0.00	0.00	0.00	0.00	0.00
Session 2.5	31.25	28.57	30.77	21.43	23.08	0.00	0.00	0.00	0.00	0.00

The table presents the percentage of withdrawals in each session by treatment among human participants.

Figure C.1: Frequency of Withdrawals by session and treatment



C.2 Participants' Report

We present the results of the questionnaire in the two of sessions of the treatments.

Sequential High–Information:

1. Decision about the expectation of total withdrawals at the end of the period:
   - *I changed my guess according to the average of past withdrawals.*
2. Decision about the choice of "withdraw" or "wait":
   - *If I was placed near the beginning or before many withdrawals had occurred, I would withdraw. Otherwise, I would look at howmany withdrawals occurred so far and my spot in line to maximize my return.*
3. The expectation about the behavior of other participants :
   - *Coordination is obviously the best choice but everyone thinks only about himself or herself.*

Sequential Low–Information:

1. Decision about the expectation of total withdrawals at the end of the period:
   - *I looked at the number of withdrawals in the previous few periods to see how other people were making their choices. I initially made some withdrawals, but later I started to wait.*
2. Decision about their choice of "withdraw" or "wait":
   - *I have decided to wait all the time. I was convinced it was a good idea particularly in the end because as the experiment went on, more people waited and there was no reason that they change because they also gained more money.*
3. The expectation about the behavior of other participants :
   - *I expected them to keep on waiting, just like me, because the payoff was higher. There was no "reasonable" reason to change.*

C.3 Instruction

This experiment has been designed to study decision-making behavior in groups. During today's session you will earn income in an experimental currency called "experimental dollars" or for short ED. At the end of the session, the currency will be converted into dollars and 10 ED corresponds to 1 dollar. The participants may earn different amounts of money in this experiment because each participant's earnings are based partly on her decisions and partly on the decisions of the other group members. If you follow the instructions carefully and make good choices, you may earn a considerable amount of money. The experiment will last for one hour.

Please read the instructions very carefully. If you have any questions, raise your hand and the experimenter will come to your desk and provide answers.

Number of Periods

The experiment will last for 22 periods in total. Before we formally start the experiment, you will have the chance to practice your decision making for 2 periods. This is an opportunity for you to become familiar with the task you will perform during the experiment. Your decision in the practice periods will not be counted toward your total earnings in the experiment. The remaining 20 periods will be used to determine your final payoff, so please make sure you understand the experiment.

Description

At the beginning of each period, you and 9 other depositors will begin with 10 ED (experimental dollar) deposited in an experimental bank. You must decide whether to withdraw your 10 ED or to wait and leave it deposited in the bank.

Among the 10 depositors there are three depositors that are simulated by computers which we call "robots". It is important to know that robots will always choose to withdraw their deposit. To fulfill the withdrawal demand for the robots, the bank keeps 30 ED as reserves to pay to the robots.

The bank promises to pay you gross rate of return of 1.3 to each ED if all human participants choose to wait while robots choose to withdraw.You and 9 other depositors (which includes robots) will submit your decision in a particular order. You will be given a random number between 1 to 10 which determines when you can make your decision. The bank pays based on a first–come first–served basis. This means that if you are given a number between 1 to 3 and decide to withdraw, you will receive your full deposit (10 ED) back. Note that if more than three depositors desire to withdraw, the bank will not be able to pay back the full deposit(10 ED) to the extra withdrawal demands.

Task

At the beginning of each period all participants will be asked to make a guess about the total number of withdrawals at the end of the period. Note that your guess must be equal or greater than 3 as robots will always choose to withdraw. Your guess does not impact your payoff. After you make your guess, you will be given your number in the queue to decide whether to "Withdraw" or "Wait".

Notice: You are NOT PAID for what you do while waiting but you are PAID for your choice of "Wait", or " Withdraw".

Payoff

Your payoff depends on your own decision and the decisions of the other 9 depositors in the group. Your payoff from choosing to "Withdraw" depends on how many depositors chose to withdraw before you. Your payoff from choosing to "Wait" depends on how many depositors place withdrawing requests over the course of the period.

The bank promises to pay 10 ED to the first three withdrawers. And if all other participants decide to wait, the bank pays "$1.3 \times 10 = 13$" to them.

However if there are more than three withdrawers, the bank will not have enough reserves to fulfill their request. In this case, the bank imposes a penalty on you and all the remaining depositors in the queue.

Example 1: Assume you are number 4 in the queue and you know that there are three withdrawals before you. If you decide to withdraw, the bank imposes a penalty of "10/(you and all the remaining in the queue)"$= \frac{1}{7} = 1.4$ from 10 ED . Therefore, you would receive "$10 - 1.4 = 8.6$" when you choose to withdraw. And if all those participants after you chose to wait (total number of withdrawals is 4 at the end of the period), they would receive "$8.6 \times 1.3 = 11.18$". Note that in the example we assumed those three withdrawers are robots. Generally, robots might be distributed differently.

Example 2:

Assume you are number 5 in the queue and you know that there are four withdrawals before you (while robots are among those four withdrawers). If you decide to withdraw, the bank imposes a penalty of "8.6/(you and all the remaining in the queue)"$= \frac{8.6}{6} = 1.43$ from 8.6 ED .

Therefore, you would receive "$8.6 - 1.43 = 7.2$" when you choose to withdraw. And if all the other depositors in the queue after you chose to wait (total number of withdrawals is 5 at the end of the period), they would receive "$7.2 \times 1.3 = 9.4$".

Note: If you choose to withdraw, your payoff depends on the number of withdrawals before you. If you choose to wait your payoff depends on total number of withdrawals at the end of the period. On the last page, you can find the payoff table that lists the payoffs associated with the two choices–to withdraw or to wait. **Remember the following:**

1. Robots will always choose to withdraw. Robots are assigned with random numbers and may be in the queue.

2. Every period you will be informed of the number of withdrawals before you and your position in the queue. But you can not observe the decision of others. (In the second treatment, participants only know their position in the queue.)

3. Your total payoff is the sum of the payoff in three random periods.

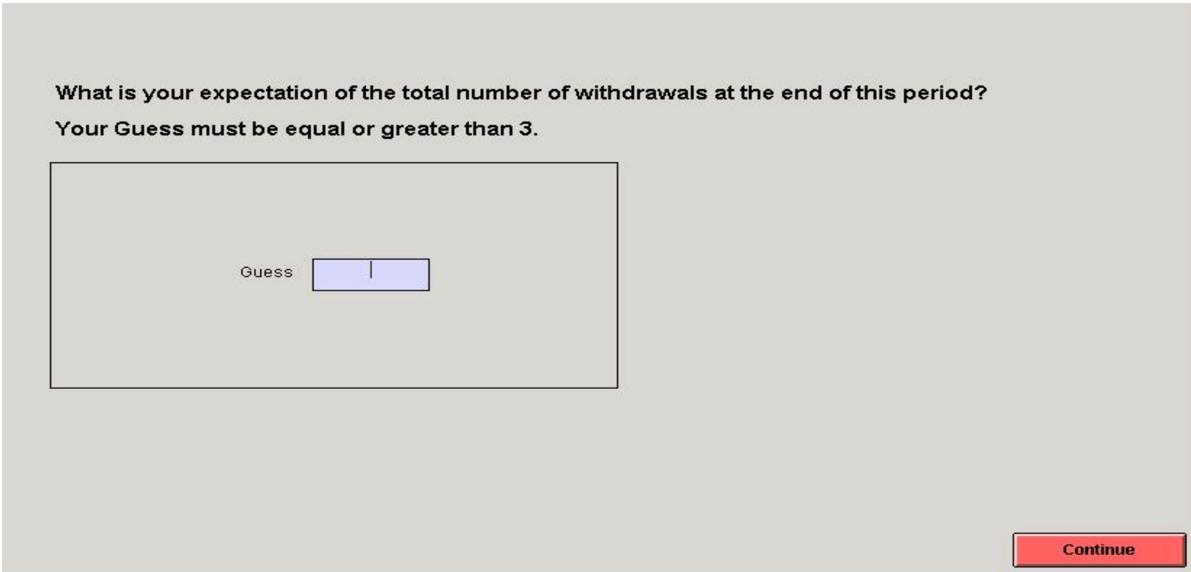
Table C.2: Payoff–If choosing to withdraw

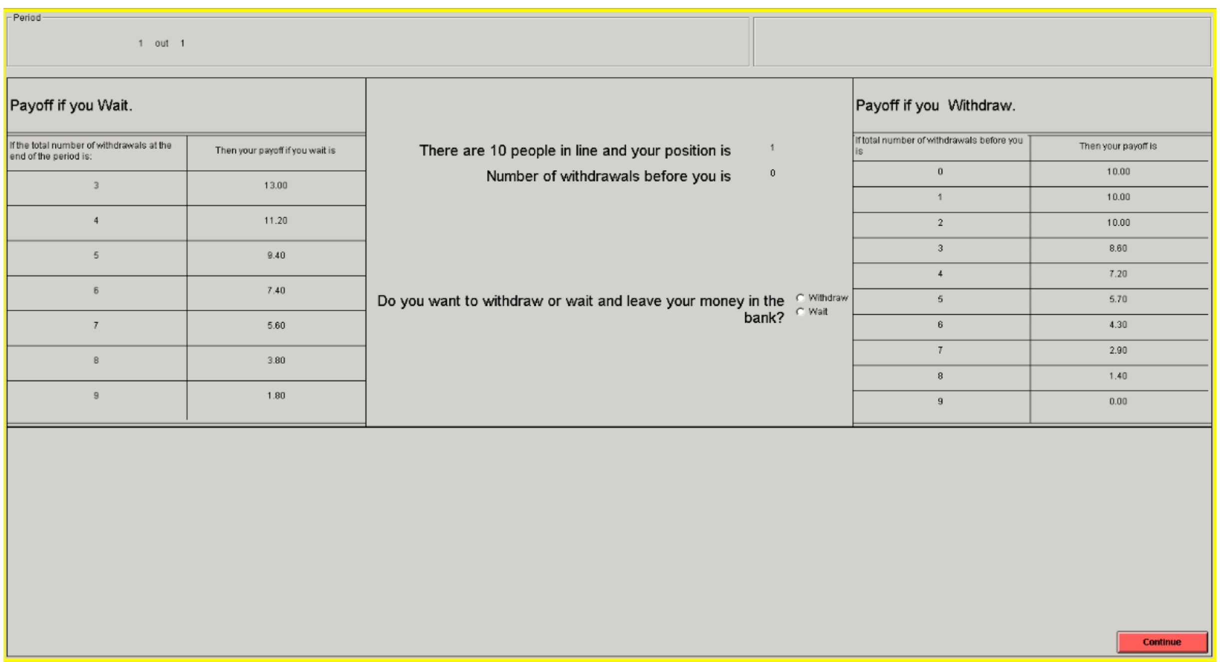
The number of preceding withdrawals	Payoff
0	10
1	10
2	10
3	8.6
4	7.2
5	5.7
6	4.3
7	2.9
8	1.4
9	0

Table C.3: Payoff– If choosing to wait

Total number of withdrawals at the end of the period	Payoff
3	13
4	11.2
5	9.4
6	7.4
7	5.6
8	3.8
9	1.8
10	0

We will now start with the two practice periods of the experiment. At the end of each practice period, you may ask questions to make sure that you have understood the procedure. If you have any doubt afterwards, please raise your hand and remain silent. You will be attended by the experimenters as soon as possible. Talking is not allowed during this experiment.


What is your expectation of the total number of withdrawals at the end of this period?
Your Guess must be equal or greater than 3.
Guess
Continue


Period
1 out 1
Payoff if you Wait.
If the total number of withdrawals at the end of the period is:
Then your payoff if you wait is
3 13.00
4 11.20
5 9.40
6 7.40
7 5.60
8 3.80
9 1.80
There are 10 people in line and your position is 1
Number of withdrawals before you is 0
Do you want to withdraw or wait and leave your money in the bank?
Withdraw
Wait
Payoff if you Withdraw.
If total number of withdrawals before you is
Then your payoff is
0 10.00
1 10.00
2 10.00
3 8.60
4 7.20
5 5.70
6 4.30
7 2.90
8 1.40
9 0.00
Continue

Period

1 out 1

Remaining time 5

Period	Your Guess	TotalNumberofWithdrawals	Your Choice	Payoff
1	-100	1	Wait	15.00

OK