Macroeconomic expectations, central bank communication, and background uncertainty: a COVID-19 laboratory experiment*

Luba Petersen **Ryan Rholes**

Simon Fraser University University of Oxford

July 2021

Abstract

This paper explores the effects of COVID-19 on public signal credibility and laboratory expectation formation. We exploit the recent pandemic as a source of exogenous background uncertainty in a New Keynesian learning-to-forecast experiment (LtFE) where participants receive projections of varying precision about future inflation. We compare our results to those obtained from an identical LtFE completed immediately before the pandemic. Without additional communication, forecaster behaviour is very similar in both LtFEs, suggesting limited cognitive overload during the pandemic. During COVID, precise point projections are perceived as less credible and are relatively less effective at anchoring participants' expectations. Point projections combined with density forecasts are comparably effective at managing expectations in both LtFEs. Overall, heightened background uncertainty due to the pandemic has not qualitatively changed how people forecast in LtFEs, which suggests LtFEs are robust to non-idiosyncratic exogenous shocks.

JEL classifications: C9, D84, E52, E58
Keywords: expectations, monetary policy, inflation communication, credibility, laboratory experiment, experimental macroeconomics, uncertainty, strategic, coordination, COVID-19

---

*We thank the Social Science and Humanities Research Council of Canada and the National Science Foundation for generous financial support. We have benefited from useful discussions and feedback from Joy Buchannan, John Duffy, Aidin Hajikhameneh, Frank Heinemann, Rosemarie Nagel, Daniela Puzzello, Justin Reitz, and Hitoshi Shigeoka, and participants at the 2021 CEF Meetings and EMEFA Workshop. We thank Ekeme Afia, Michael Mirdamadi, and Fatemeh Mokhtarzadeh for outstanding research assistance. Author name order is randomized.
Petersen: Department of Economics, Simon Fraser University, 8888 University Drive, Burnaby, BC, V5A 1S6, Canada, lubap@sfu.ca. Rholes: Department of Economics, University of Oxford, Manor Road Building, Oxford, OX1 3UQ, rar145@tamu.edu.

1 Introduction

The COVID-19 pandemic has been a major social, health, and economic shock that changed how we work, study and interact, and - depending on the country - either shaken or restored confidence in public institutions. The pandemic led to an unprecedented job, income and wealth loss. These detrimental effects were caused at least partially by pandemic-induced pessimism and uncertainty (Baker et al. 2020; Fetzer et al., 2020; Coibion, et al. 2020).

This once-in-a-lifetime aggregate uncertainty shock allows us to ask: how robust are learning-to-forecast experiments (LtFE) to background uncertainty? Specifically, we ask, do such external uncertainty shocks influence the perceived credibility of internally-credible public signals received within a laboratory economy? Answers to these questions are important from the perspective of designing and drawing inference from LtFEs. Macroeconomists have used LtFEs to study expectation formation and equilibria selection (Adam, 2007, Bao et al., 2012), how various monetary policy rules and targets affect expectation formation (Pfajfar and Žakelj, 2014, 2016, 2018; Assenza et al. 2013; Hommes, Massaro, Weber, 2019; Hommes, Massaro, Salle, 2019; Cornand and M'Baye, 2018a), and the design of central bank communication (Kryvtsov and Petersen, 2013, 2021; Arifovic and Petersen, 2018; Cornand and M'Baye, 2018b; Mokhtarzadeh and Petersen, 2021, Ahrens, Lustenhower, Tettamanzi, 2018). Because macroeconomists increasingly use these experimental frameworks as an apparatus for testing policy and communication, it is imperative to understand the role that background uncertainty plays in shaping laboratory expectation formation.[1]

Evidence that the lab insulates expectations formation from even the most severe external shocks would suggest that LtFEs reliably provide insights based solely on experimental conditions. That is, elicited expectations are internally consistent. From a more general perspective, this is important given that experimental studies rely crucially on the implicit assumption that the laboratory provides experimental control that is robust to external shocks and that subjects' decisions depend only on carefully controlled laboratory conditions.

[1]The Bank of Canada actively uses New Keynesian Learning-to-Forecast experiments to inform policy design. See Amano, Engle-Warnick, and Shukayev (2011) and Kostyshyna, Petersen, and Yang (2021) for applications to the Bank's 2011 and 2021 mandate renewal, and Amano, Kryvtsov, and Petersen (2013) for a survey on the application of such experiments to the design of monetary policy. LtFEs have also been used to study expectation formation in other market settings such as financial assets and housing markets (Bao, Hommes, and Makarewicz 2017; Bao and Hommes, 2019; Kopányi et al. 2019; Kopányi-Peuker and Weber, 2020).

To gain insight into these questions, we study inflation expectation formation and forecaster confidence in New Keynesian (NK) LtFEs. We conducted the experiments before the pandemic (October and November 2019) and shortly after the CDC declared a pandemic (April to June 2020) using American and Canadian participants. During the pandemic data collection, participants in both countries were subject to lock-downs and faced high levels of aggregate background uncertainty. Crucially, we implement almost identical experimental protocols before and during the pandemic so that any observed differences in forecast behavior were the consequence of external COVID-19 factors.

We designed our Fall 2019 sessions to study the effects of higher-order moments in central bank communication on expectation formation. We systematically varied the communication of central bank inflation projections in a between-subjects design. Subjects received a five-period inflation path forecast presented either precisely or as a symmetric distribution capturing forecast uncertainty. We observed that the precise point projections successfully managed expectations and increased forecaster confidence. Communicating uncertainty around point projections reduced the relative efficacy of the projections. Interested readers can find these results in Rholes and Petersen (2021).

The pandemic made salient the importance of public signals to coordinate behavior in many domains. We exploited the external increase in attention to public communication during the pandemic by re-implementing our communication treatments in our Spring 2020 sessions. Comparing results from Fall 2019 and Spring 2020 sessions allows us to identify the extent to which heightened background uncertainty influences participants' forecasting behavior and confidence and their perception of public signal credibility.

We find no evidence that forecast performance decreased meaningfully during the pandemic. If there was any externally-generated cognitive overload associated with the pandemic and the associated lock-downs, it did not influence our participants' ability to forecast. Likewise, we do not observe any evidence of background uncertainty decreasing participants' confidence in their forecasting abilities. Rather, we see a small decrease in conveyed uncertainty during COVID-19, especially in the extreme ends of the distribution.

COVID-19 did influence participants' responsiveness to public signals. In particular, the pandemic reduced participants' willingness to use overly precise signals in our Point projection treatment. Various metrics of participants' credibility and willingness to employ the central bank point forecast reduced by between four and 29 percentage points. By contrast, public signals presented with uncertainty were comparably adopted by forecasters, with no loss of credibility during the pandemic. While those participants presented with the Point&Density projection did not significantly change their forecasting heuristics or credibility in the projection, they conveyed significantly greater confidence in their own forecasting abilities.

Our results demonstrate the robustness of laboratory-elicited expectations to increases in background uncertainty. The robustness of expectations data generated in New Keynesian LtFEs has also been observed by Cornand and Hubert (2019), who show that experimental participants' forecasts reasonably match inflation forecasting patterns observed in surveys of households, firms, and professional forecasters. They also observe a high degree of consistency in terms of forecasting heuristics across independently conducted experiments.

This paper also contributes to the literature studying whether and how the pandemic shifted people's preferences in various domains. Harrison, Hofmeyr, Kincaid and Munroe (2020) compare the same participants' a-temporal risk preferences elicited pre-COVID (May and October 2019) and post-COVID (May to October 2020). Within a Rank-Dependent Utility framework, they find that pre-pandemic participants were overall risk neutral if not borderline risk-loving. By contrast, during the pandemic, these same participants exhibited overall risk aversion. The authors also elicit time preferences identical experimental designs collected from independent samples of participants in 2013 and 2020 drawn from the same sample. The distribution of estimates of exponential discounting (β) is impressively stable over time. The effects of COVID-19 on hyperbolic discounting are mixed, with more variability in hyperbolic discounting estimates (δ) during the pandemic. Cognitive abilities have also been impacted by the social changes associated with the pandemic. De Pue et al. (2021) note that 8-10% of older adults self-reported declines in cognitive function such as memory, concentration, multi-tasking, recall, and forgetfulness. To the best of our knowledge, this is the first paper to explicitly compare expectation formation in learning-to-forecast experiments (LtFEs) across two time periods, and in particular, before and during COVID. Our findings suggest that large external events can shape how people respond to information in LtFEs.

This paper is organized as follows. Section 2 outlines our experimental design and procedures. Section 3 presents our experimental findings and Section 4 concludes.

2 Experimental Design

The experimental framework is based on Rholes and Petersen (2021). Participants in the experiment were incentivized to act as forecasters tasked with predicting the future path of inflation in an endogenously evolving economy. Each experimental session consisted of seven subjects who formed individual inflation expectations privately using common information.

Each experimental session comprised two independent sequences of 30 sequential decisions. In each period $t \in [1, 30]$, participants submitted forecasts about $t+1$ and $t+2$ inflation. Subjects also provided measures, each period, of their own forecast errors, which provided a measure of their subjective uncertainty.

2.1 Data-generating process

Our economy's data generating process arises from a log-linearized, representative-agent New Keynesian (NK) framework where we eliminate the need for expectations about the output gap. The dynamic system is driven by one- and two-period-ahead inflation expectations and aggregate disturbances. This reformation of the reduced form NK model reduces the cognitive complexity of this game by allowing subjects to forecast the evolution of a single variable.

We begin with the typical three-equation, reduced-form NK model

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

$$i_t = \phi_\pi \pi_t + \phi_x x_t \tag{2}$$

$$x_t = \mathbb{E}_t\{x_{t+1}\} - \sigma^{-1}[i_t - \mathbb{E}_t\{\pi_{t+1}\} - r_t^n]. \tag{3}$$

Parameter values, selected from Kryvtsov and Petersen (2013), are presented in Panel A of Table 1. Following a series of algebraic manipulations we derive a simpler data-generating process as a function of one- and two-period ahead inflation expectations:

$$\pi_t = 1.54\mathbb{E}_t\{\pi_{t+1}\} - 0.58\mathbb{E}_t\{\pi_{t+2}\} + 0.08r_t^n \tag{4}$$

$$i_t = 4.44\mathbb{E}_t\{\pi_{t+1}\} - 3.12\mathbb{E}_t\{\pi_{t+2}\} + 0.41r_t^n. \tag{5}$$

The Online Appendix contains a detailed derivation and discussion of this dynamic system.

2.2 Payoffs

We incentivized expectations using Equation (6), which exhibits exponential decay in the absolute forecasting error. Notice from Equation (6) that subjects received payment for $t+1$ expectations formed in $t \in [1, 29]$ and $t+2$ expectations formed in $t \in [1, 28]$.

$$F_{i,t} = 2^{-.5|\mathbb{E}_{i,t-1}\{\pi_t\} - \pi_t|} + 2^{-.5|\mathbb{E}_{i,t-2}\{\pi_t\} - \pi_t|} \tag{6}$$

Subjects also provided measures of the uncertainty surrounding their inflation forecasts, which we denote here as $u_{i,t+1}, u_{i,t+2}$. Thus, we collected subject-level density forecasts in each period for both forecast horizons. We assume each subject's uncertainty measure is symmetric around her point forecast, and restrict subjects to non-negative values for this uncertainty measure. We use the scoring rule given in Equation (7), similar to Pfajfar and Žakelj (2016), to incentivize subjects to accurately convey their forecast uncertainty. Subjects earn nothing for uncertainty measures if realized inflation values fall outside their confidence bounds. However, subjects' payoffs are decreasing in this uncertainty measure. Thus, conditional on actually capturing realized inflation in their confidence bounds, subjects were incentivized to create the smallest bounds possible. Further, we randomly paid either $F_{i,t}$ or $U_{t+1} + U_{t+2}$ in each period to prevent hedging.

$$U_{i,t+k} = \frac{15}{10 + u_{i,t+k}} \tag{7}$$

2.3 Treatments

This study explores how forecasters' expectations respond to varying degrees of precision in central bank projections both before and during the pandemic. Our primary goal is to determine whether the external uncertainty shocks induced by the pandemic altered expectations formation and forecaster confidence in public signals in the lab. Table 1 summarizes our 3x2 between-subject experimental design.

Participants interacted in an online platform that featured a single screen that updated as new information became available. Figure 1 presents an example screenshot from the experiment. In all treatments, the screen displayed in the top left corner a subject's identification number, the current decision period, time remaining to make a decision, and the total number of points earned through the end of the previous period. The interface also featured three horizontal history plots. The topmost plot displayed past interest rates, and both past and current shocks. The second panel displayed the subject's one-period-ahead inflation forecast (blue dots), the subject's uncertainty surrounding this one-period-ahead forecast (blue shading), and all realized values of inflation (red dots). The third history panel displayed the subject's two-period-ahead inflation forecast (orange dots), the subject's uncertainty surrounding this two-period-ahead forecast (orange shading), and all realized values of inflation (red dots).

The first leg of our experimental design involved studying the effects of central bank projections on expectation formation. Information treatment variation appeared in the second and third history plots. In NoComm, participants received no supplementary information about the central bank's outlook for inflation. In Point, the second and third history plots displayed the central bank's evolving, five-period inflation path point forecast as green connected dots. In Point&Density, the second and third history plots contained the central bank's evolving point forecasts with its corresponding level of uncertainty (green shading) as shown in Figure 1. The central bank's point projections assumed ex-ante rationality and in the Point&Density treatment, provided a symmetric one standard-deviation band centered around its point forecast.

The second leg of our experimental design involved studying expectation pre-COVID and during the COVID-19 pandemic. We use earlier collected data discussed in Rholes and Petersen (2021) for the pre-COVID sample and collected new data from April 16 to June 25, 2020, for the COVID sample.

2.4 Procedures

We begin by describing the procedures that were common to both the pre- and post-COVID sessions. We recruited participants through online subject databases at Simon Fraser University (SONA) and Texas A&M University (ORSEE) (Greiner, 2015). We used the first 7 registrants that arrived at each session while later arrivals received a standard $10 show-up fee and were invited to participate in a later session. Average payoffs were $21 pre-pandemic and $22 during the pandemic. We paid subjects immediately following each experimental session.

We conducted six sessions of each of the three information treatments and two timing treatments for a total of 36 experimental sessions. Each session involved seven participants forecasting for two sequences of 30 rounds each. Each sequence employed a different variation of the shock sequence so that subjects did not repeat an identical game in the second block of decisions. We pre-drew shock sequences (one per session in a given treatment) so that we could hold these constant across treatments. We drew all sequences from a mean-zero normal distribution with the same standard deviation.

We disseminated and read-aloud instructions at the beginning of each experimental session. The instructions can be found in the Online Appendix. Our instructions included detailed information about subjects' inflation forecasting task, forecast uncertainty task, how we would incentivize forecasts and uncertainty, and how the experimental economy evolved in response to expectations and aggregate shocks. Participants knew they could use the computer's calculator or spreadsheets if desired. We encouraged subjects to ask clarifying questions at any time and allowed them to refer to the instructions at any point during the experiment. Following the instructions, subjects played four unpaid practice periods during which they could ask questions and then played through the two incentivized sequences.

Subjects had 65 seconds in the first 9 periods, and 50 seconds for the remaining 21 periods, of each 30-period sequence. Subjects submitted inflation forecasts and corresponding uncertainty measures in basis points using only integer values. Inflation forecasts could be any real value while uncertainty measures had to be non-negative. We elicited forecasts in terms of basis points, which allowed subjects to forecast with a precision of $\frac{1}{100}$th of 1%. The experiment progressed immediately to the next decision period after all participants submitted decisions or once time expired.

Panel B of Table 1 presents the key experimental procedures in each wave of the experiment. The procedures in the pre-pandemic and pandemic sessions differed in two meaningful ways. First, sessions during the pandemic were conducted remotely as opposed to in-person in the lab because of imposed health restrictions. This may have led to some loss of control as we were unable to monitor whether a subject was communicating through some other means (e.g. cell phone, email) with other people. We did, however, insist that participants keep their cameras and microphones on at all times to mimic the laboratory environment as best as possible. In none of the sessions did we suspect participants of communicating with others.

Second, participants in the pre-pandemic sessions had paper instructions while those in the pandemic sessions received the instructions through an online link where the file could not be downloaded. Paper instructions together with digital instructions have been found to improve comprehension and performance in pre-experiment quizzes as well as reduces non money-maximizing behavior (Freeman et al., 2018). However, our experimental findings suggest no meaningful reduction in performance in our post-COVID sessions. If anything, participants' forecast errors were slightly lower in our online sessions.

The form of payments also differed across the timing treatments. Participants were paid in cash pre-pandemic and through electronic transfers (e-Transfer in Canada, Venmo or PayPal in the U.S.) during the pandemic. Show-up fees remained the same during the pandemic even though there was potentially less time, transportation and effort cost for participants to come to the laboratory.

2.5 Hypotheses

It is difficult to say how the COVID-19 shock should have manifested itself in our COVID-era sessions. During this time, people in Canada and the United States faced relatively greater health and economic uncertainty, as well as increased social isolation. Approval of federal and provincial leaders improved during COVID-19 in Canada (Grenier, 2020), while there was no significant change in the United States among individuals who faced lock-down (Coibion, Gorodnichenko, Weber, 2020). More time was spent online, suggesting that participants may have become more comfortable engaging in online tasks.

Still, the experimental economy we implement is independent of the real world. None of the features of our experiment changed. The only thing that might impact the accuracy and credibility of the central bank projections is participants' own usage of the projections. As our experiment was exploratory in nature, we are hesitant to form any hypotheses about the effects of the COVID-19 shock on participants' behavior.

3 Results

Summary statistics of participants' forecasting performance are presented in Table 2. Participants' mean absolute forecast errors, deviations from the REE forecast, mean disagreement (measured as the interquartile range each period for each session) and mean uncertainty for one- and two-period ahead inflation. A series of random effects panel regressions are used to compare treatment means within and across time periods.

Credibility

We begin by considering how credibility in central bank projections changed during COVID. A participant is denoted as perceiving the central bank's projection as credible if she uses its projected point forecast to formulate her expectation for the given horizon. To allow for rounding errors, we consider a range of five basis points of the communicated point projection. For the Point&Density treatment, we consider the projection to be perceived as credible if a participant's forecast falls in the communicated density.

Credibility in Point projections decreased from 41% pre-COVID to 38% during the COVID sessions. Credibility in the Point&Density projections was relatively lower but remained unchanged over time at 35%. Likewise, over 99 percent of forecasts in the Point&Density treatment are within the forecasted range, with no change during COVID. Differences in credibility between one- and two-period ahead forecasts is less than one percentage point.

Forecast Errors

Figure 2 presents kernel density functions of participants' one and two-period ahead absolute forecast errors across the two waves of our experiment. Forecast accuracy varies little across information treatments and experimental waves. Forecasts range between 31 and 36 bps for one-period ahead forecasts and 35 and 43 bps for two-period ahead forecasts. Point projections reduce forecast accuracy relative to NoComm and Point&Density, with the effect of the treatment being statistically significant Pre-COVID but not during COVID. During COVID, we observe relatively larger forecast errors in the Point projection treatment with a greater variance in forecast accuracy.

Deviations from REE

As shown in Rholes and Petersen (2021), rationally constructed projections are highly effective at nudging expectations toward the REE solution. Compared to NoComm, deviations from the REE decreased by roughly 60% in Point and 50% in Point&Density pre-COVID, with Point providing significantly greater coordination on the REE than Point&Density.

During COVID, we see a small but significant improvement in rational forecasting for one-period ahead forecasts in NoComm. Point projections are significantly less effective at managing expectations during COVID, with deviations increasing by about 6 bps for both forecasts. COVID did not have a notable impact on how participants utilized the Point&Density projection, and during this time period, we do not observe significant differences in rationality.

Disagreement

Disagreement decreased significantly when participants were presented with precise Point projections. Pre-COVID, the interquartile range (IQR) decreased by about 23% for one-period ahead forecasts and 35% for two-period ahead forecasts. Point&Density projections during this period were significantly less effective at coordinating expectations, with only a 15% reduction in disagreement relative to NoComm for two-period ahead inflation forecasts.

COVID did not have any sizeable or significant effect on the dispersion in NoComm participants' forecasts. It did, however, increase the disagreement among those forecasters presented with Point projections, with mean IQR increasing by 4 to 6 bps relative to Pre-COVID. The ability of Point&Density projections to reduce disagreement was largely unaffected by COVID. The relative benefit of Point over Point&Density in reducing dispersion in forecasts was eliminated post-COVID.

Uncertainty

In all treatments, we observe an increase in confidence in participants' forecasting abilities during the pandemic. During the second wave of our experiment, uncertainty, measured as participants' expected errors for one- and two-period ahead forecasts, decreased by 6-8 bps in NoComm, 1-4 bps in Point, and 7-11 bps in Point&Density. This increase in confidence was highly significant in NoComm and Point&Density.

Pre-COVID participants' confidence in their forecast accuracy increased significantly when participants were provided precise Point projections. Their one- and two-period ahead perceived forecast errors decreased by 35%. Post-COVID, the relative boost in confidence compared to NoComm decreased as participants, overall, became more confident in their forecasting ability.

Heuristics

Following Rholes and Petersen (2021), we classify all participants into one of five general classes of forecasting heuristics. The distribution of inexperienced and experienced one-period ahead forecasting heuristics are presented in Figure 4 and Figure 5, respectively.

In the NoComm treatment, we observe a considerable increase in the proportion of participants forming model-consistent expectations during COVID. Ex-ante rational forecasting increases by 12 (18) percentage points for inexperienced (experienced) participants, as subjects shift away from constant-gain learning (12 and 21 percentage point declines in Repetitions 1 and 2, respectively). We noted earlier that forecast accuracy did not change quantitatively or significantly between the two experimental waves. This is likely because an insufficient number of participants shifted toward rational forecasting. Fewer than 40 percent of participants formed ex-ante rational expectations and were likely not to be the median forecaster driving aggregate dynamics.

The vast majority of participants presented with the Point projection pre-COVID were classified as ex-ante rational (86% and 79% in Repetitions 1 and 2, respectively). During COVID, the proportion of ex-ante rational forecasters declined by 29 percentage points to 57% in Repetition 1 and by 13 percentage points to 66% in Repetition 2. Constant gain learning and trend-chasing forecasting heuristics become more prevalent during COVID when participants are provided point projections.

We observe the opposite pattern in the Point&Density treatment. The Point&Density projection was relatively less effective at coordinating inexperienced participants' expectations on the rational expectations equilibrium pre-COVID, with only 57% of participants in Repetition 1 forming model-consistent expectations. During COVID, this share increases to 69%, suggesting inexperienced participants perceived the Point&Density projection as relatively more credible during COVID. With experience, the differences in ex-ante rational forecasting are minor (76% pre-COVID and 78% post-COVID).

4 Conclusion

This paper capitalizes on the global shock created by the COVID-19 pandemic and the timing of a previous experiment to explore the robustness of laboratory-elicited expectations to background uncertainty shocks. We do this within a workhorse New Keynesian learning-to-forecast experimental (LtFE) framework where we test the relative ability of three central bank communication strategies to manage inflation expectations immediately before and after the onset of the global pandemic. Given the ubiquity and severity of the COVID-19 pandemic, this exploratory experiment provides an extreme test of the robustness of LtFEs.

Our findings suggest that forecasting behavior in LtFEs is largely robust to external phenomena. We see no decrease in forecast performance following the onset of the pandemic and no transmission of the general background uncertainty shock to individual-level forecast uncertainty. Furthermore, outcomes for our baseline NoComm treatment are essentially identical across pandemic conditions. Where behavior does seem to change is in the confidence in information and own forecasting abilities. Our results provide suggestive evidence that the COVID-19 pandemic influenced how people respond to public signals. In particular, the pandemic reduced participants' willingness to use overly precise signals in our Point treatment.

Importantly, this seemingly pandemic-induced change in how participants incorporated public signals into their own beliefs did not lead to meaningful qualitative changes in our overall communication-related results reported in Rholes and Petersen (2021). The key exception is that precise communication in the Point-COVID treatment did not significantly nudge participants toward the REE relative to Point&Density-COVID treatment, as it did pre-COVID. We interpret this as a reduction in confidence associated with overly precise information during the pandemic.

Overall, we conclude that precise central bank projections effectively manage laboratory-elicited expectations regardless of the presence of heightened background uncertainty. This gives us further confidence in the robustness of expectations elicited in New Keynesian learning-to-forecast experiments.

References

[1] Ahrens, S., Lustenhouwer, J., & Tettamanzi, M. (2018). The Stabilizing Role of Forward Guidance: A Macro Experiment. BERG Working Paper 137.

[2] Assenza, T., Heemeijer, P., Hommes, C. H., & Massaro, D. (2013). Individual expectations and aggregate macro behavior.

[3] Baker, Scott R., et al. COVID-induced economic uncertainty. No. w26983. National Bureau of Economic Research, 2020.

[4] Bao, T., & Hommes, C. (2019). When speculators meet suppliers: Positive versus negative feedback in experimental housing markets. Journal of Economic Dynamics and Control, 107, 103730.

[5] Bao, T., Hommes, C., & Makarewicz, T. (2017). Bubble Formation and (In) Efficient Markets in Learning-to-forecast and optimise Experiments. The Economic Journal, 127(605), F581-F609.

[6] Bao, T., Hommes, C., Sonnemans, J., & Tuinstra, J. (2012). Individual expectations, limited rationality and aggregate outcomes. Journal of Economic Dynamics and Control, 36(8), 1101-1120.

[7] Coibion, O., Gorodnichenko, Y., & Weber, M. (2020). The cost of the COVID-19 crisis: Lockdowns, macroeconomic expectations, and consumer spending (No. w27141). National Bureau of Economic Research.

[8] Cornand, C., & Hubert, P. (2019). On the external validity of experimental inflation forecasts: A comparison with five categories of field expectations. Journal of Economic Dynamics and Control, 103746.

[9] Cornand, C., & M'baye, C. K. (2018a). Does inflation targeting matter? An experimental investigation. Macroeconomic Dynamics, 22(2), 362-401.

[10] Cornand C. & M'baye C. K. (2018b), "Band or Point Inflation Targeting? An Experimental Approach", Journal of Economic Interaction and Coordination, 13(2) : 283-309.

[11] De Pue, S., Gillebert, C., Dierckx, E., Vanderhasselt, M-A, De Raedt, R., Van den Bussche, E. (2021). The impact of the COVID-19 pandemic on wellbeing and cognitive functioning of older adults. Sci Rep 11, 4636 (2021). https://doi.org/10.1038/s41598-021-84127-7

[12] Thiemo Fetzer, Lukas Hensel, Johannes Hermle &Christopher Roth; Coronavirus Perceptions and Economic Anxiety. The Review of Economics and Statistics 2020

[13] Freeman, D. J., Kimbrough, E. O., Petersen, G. M., & Tong, H. T. (2018). Instructions. Journal of the Economic Science Association, 4(2), 165-179.

[14] Gosselin, P., Lotz, A., & Wyplosz, C. (2008). The Expected Interest Rate Path: Alignment of Expectations vs. Creative Opacity. International Journal of Central Banking, 4(3), 145-185.

[15] Greenspan, A. (2004). Risk and uncertainty in monetary policy. American Economic Review, 94(2), 33-40.
Greiner, B (2015). Subject Pool Recruitment Procedures: Organizing Experiments with ORSEE. Journal of the Economic Science Association 1 (1), 114-125.

[16] Grenier, E. (2020, Dec. 12). Across Canada, polls suggest it's (mostly) better to be in power during a pandemic. CBC News. https://www.cbc.ca/news/politics/grenier-pandemic-polling-bumps-1.5837958

[17] Harrison, G. W., Hofmeyr, A., Kincaid, H., Monroe, B., Ross, D., Schneider, M., & Swarthout, J. T. (2020). Subjective Beliefs and Economic Preferences During the COVID-19 Pandemic. Working Paper.

[18] Hommes, C., Massaro, D., & Weber, M. (2019a). Monetary policy under behavioral expectations: Theory and experiment. European Economic Review, 118, 193-212.

[19] Hommes, C., Massaro, D., & Salle, I. (2019b). Monetary and fiscal policy design at the zero lower bound: Evidence from the lab. Economic Inquiry, 57(2), 1120-1140.

[20] Kopányi, D., Rabanal, J. P., Rud, O. A., & Tuinstra, J. (2019). Can competition between forecasters stabilize asset prices in learning to forecast experiments? Journal of Economic Dynamics and Control, 109, 103770.

[21] Kopányi-Peuker, A. & Weber, M. (2020). Experience does not eliminate bubbles: Experimental evidence. Review of Financial Studies, 1-36.

[22] Kryvtsov, O., & Petersen, L. (2013). Expectations and monetary policy: experimental evidence (No. 2013-44). Bank of Canada.

[23] Kryvtsov, O., & Petersen, L. (2021). Central bank communication that works: Lessons from lab experiments. Journal of Monetary Economics. Forthcoming.

[24] Mokhtarzadeh, F., & Petersen, L. (2021). Coordinating expectations through central bank projections. Experimental Economics. Forthcoming.

[25] Pfajfar, D., & Žakelj, B. (2014). Experimental evidence on inflation expectation formation. Journal of Economic Dynamics and Control, 44, 147-168.

[26] Pfajfar, D., & Žakelj, B. (2016). Uncertainty in forecasting inflation and monetary policy design: Evidence from the laboratory. International Journal of Forecasting, 32(3), 849-864.

[27] Pfajfar, D., & Žakelj, B. (2018). Inflation expectations and monetary policy design: Evidence from the laboratory. Macroeconomic Dynamics, 22(4), 1035-1075.

[28] Rholes, R., Petersen, L. (2021). Should central banks communicate uncertainty in their projections?. Journal of Economic Behavior Organization, 183, 320-341.

5 Tables and Figures

Table 1: Treatments and Experimental Design

Panel A: Treatments		
Timing Treatment	Information Treatment	Dates
Pre-COVID	NoComm	October 15-22, 2019
	Point	October 17-November 1, 2019
	Point&Density	October 17-24, 2019
COVID	NoComm	April 16-May 28, 2020
	Point	April 22-May 29, 2020
	Point&Density	April 27-June 25, 2020

Panel B: Experimental Design		
Procedures	Pre-COVID	COVID
Recruiting	SONA and ORSEE	SONA and ORSEE
Check-in	In-person with R.A.	Online with R.A. over Zoom
Consent form	Received once in lab	Mailed in advance
Instructions	Paper copy	Digital link, no downloads
Instructions read	Aloud in person	Aloud over Zoom
Payment	Cash	E-transfer (Interac and Venmo)
Show up fee	$7	$7
Average payment	$21	$22
Session length	1.5 hours	1.5 hours

Table 2: Forecast statistics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Abs. Forecast Error		Abs. Deviation from REE		Interquartile Range		Uncertainty	
	$E_{i,t}\pi_{t+1}$	$E_{i,t}\pi_{t+2}$	$E_{i,t}\pi_{t+1}$	$E_{i,t}\pi_{t+2}$	$E_{i,t}\pi_{t+1}$	$E_{i,t}\pi_{t+2}$	$E_{i,t}\pi_{t+1}$	$E_{i,t}\pi_{t+2}$
Pre-COVID								
NoComm	35.9	42.67	34.31	32.5	28.52	33.42	26.69	32.89
	(55.87)	(54.80)	(55.44)	(49.88)	(21.89)	(24.88)	(36.95)	(91.62)
Point	30.84*	34.86***	13.77***	13.02***	22.04***	21.66***	17.33***	21.1***
	(27.67)	(27.29)	(20.45)	(17.06)	(17.04)	(16.40)	(17.13)	(23.93)
Point&Density	33.75†	37.9†	18.22***, † † †	16.57***, ††	28.79†	28.25***, †	30.35 † † †	34.83 † † †
	(31.07)	(35.47)	(24.17)	(26.10)	(22.25)	(21.60)	(29.36)	(32.32)
COVID								
NoComm	33.28	40.29	27.58▲	29.63	29.81	32.72	19.65 ▲▲	23.61▲▲
	(32.96)	(41.25)	(29.91)	(36.18)	(22.09)	(21.03)	(16.35)	(23.08)
Point	32.58	37.55	19.46***,▲▲▲	19.56***, ▲▲▲	26.17**, ▲▲▲	27.37***, ▲▲▲	16.38	17.35**
	(34.25)	(40.28)	(31.21)	(36.96)	(23.00)	(24.53)	(27.38)	(24.36)
Point&Density	32.68	37.41	17.91***	18.24***	27.09*	26.83***	23.18††,▲▲	24.57 ††,▲▲▲
	(41.05)	(55.67)	(37.08)	(50.90)	(19.57)	(20.59)	(32.02)	(28.23)

This table presents one- and two-period ahead inflation forecast statistics. Data from Repetitions 1 and 2 are pooled together. Columns (1) and (2) present the mean absolute forecast errors, Columns (3) and (4) present the mean deviations from the REE solution, Columns (5) and (6) present the mean interquartile range of forecasts, and Columns (7) and (8) present the mean perceived forecast errors. Standard deviations are displayed in parentheses. Asterisks denote whether a treatment (Point or Point&Density) differs significantly from NoComm in a given time period. Daggers denote whether Point&Density differs significantly from Point. Solid black triangles denote whether a COVID estimate is significantly different from pre-COVID. ***,†††,▲▲▲, **,††,▲▲, *,†,▲ denote significance at the 1%, 5%, and 10% levels respectively.

Table 3: Forecasting Heuristics

Model	Heuristic Name	Model
M1	Ex–Ante Rational	$E_{i,t}x_{t+1} = f(r^n_{t-1}, \epsilon_t)$ $E_{i,t}\pi_{t+1} = f(r^n_{t-1}, \epsilon_t)$
M2	Cognitive Discounting	$E_{i,t}x_{t+1} = \alpha f(r^n_{t-1}, \epsilon_t)$ $E_{i,t}\pi_{t+1} = \alpha f(r^n_{t-1}, \epsilon_t)$
M3	Constant Gain	$E_{i,t}x_{t+1} = E_{i,t-1}x_t - \gamma(E_{i,t-2}x_{t-1} - x_{t-1})$ $E_{i,t}\pi_{t+1} = E_{i,t-1}\pi_t - \gamma(E_{i,t-2}\pi_{t-1} - \pi_{t-1})$
M4	Steady State/Target	$E_{i,t}x_{t+1} = 0$ $E_{i,t}\pi_{t+1} = 0$
M5	Trend Chasing	$E_{i,t}x_{t+1} = x_{t-1} + \tau(x_{t-1} - x_{t-2})$ $E_{i,t}\pi_{t+1} = \pi_{t-1} + \tau(\pi_{t-1} - \pi_{t-2})$

Models of expectations as functions of exogenous or historical data.
$\alpha \in [0.1, 0.9]$, γ and $\tau \in [0, 1.5]$ in increments of 0.1.

Figure 1: Screenshot of participants' screen during the experiment.

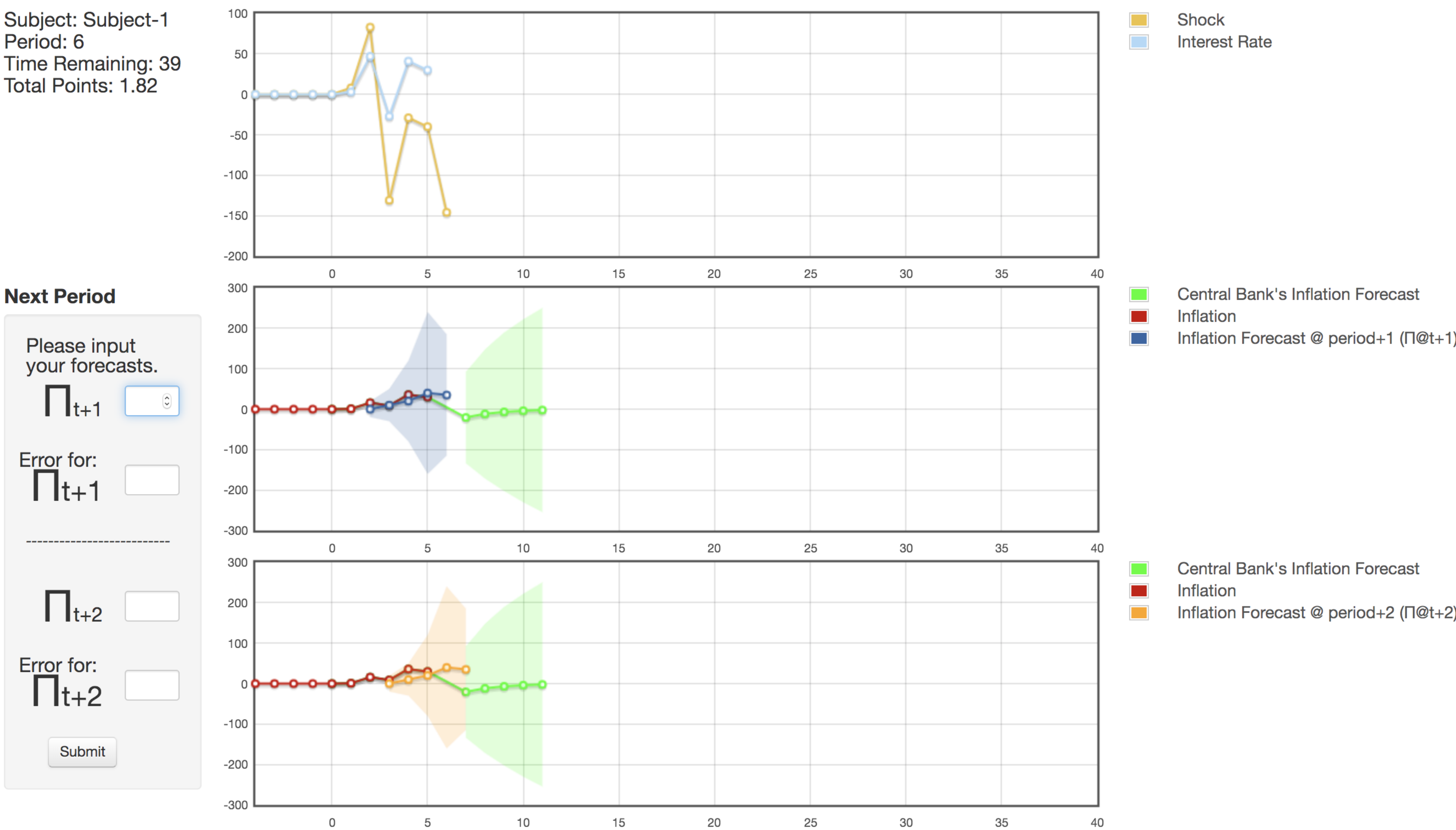


Figure 2: Absolute inflation forecast errors, basis points

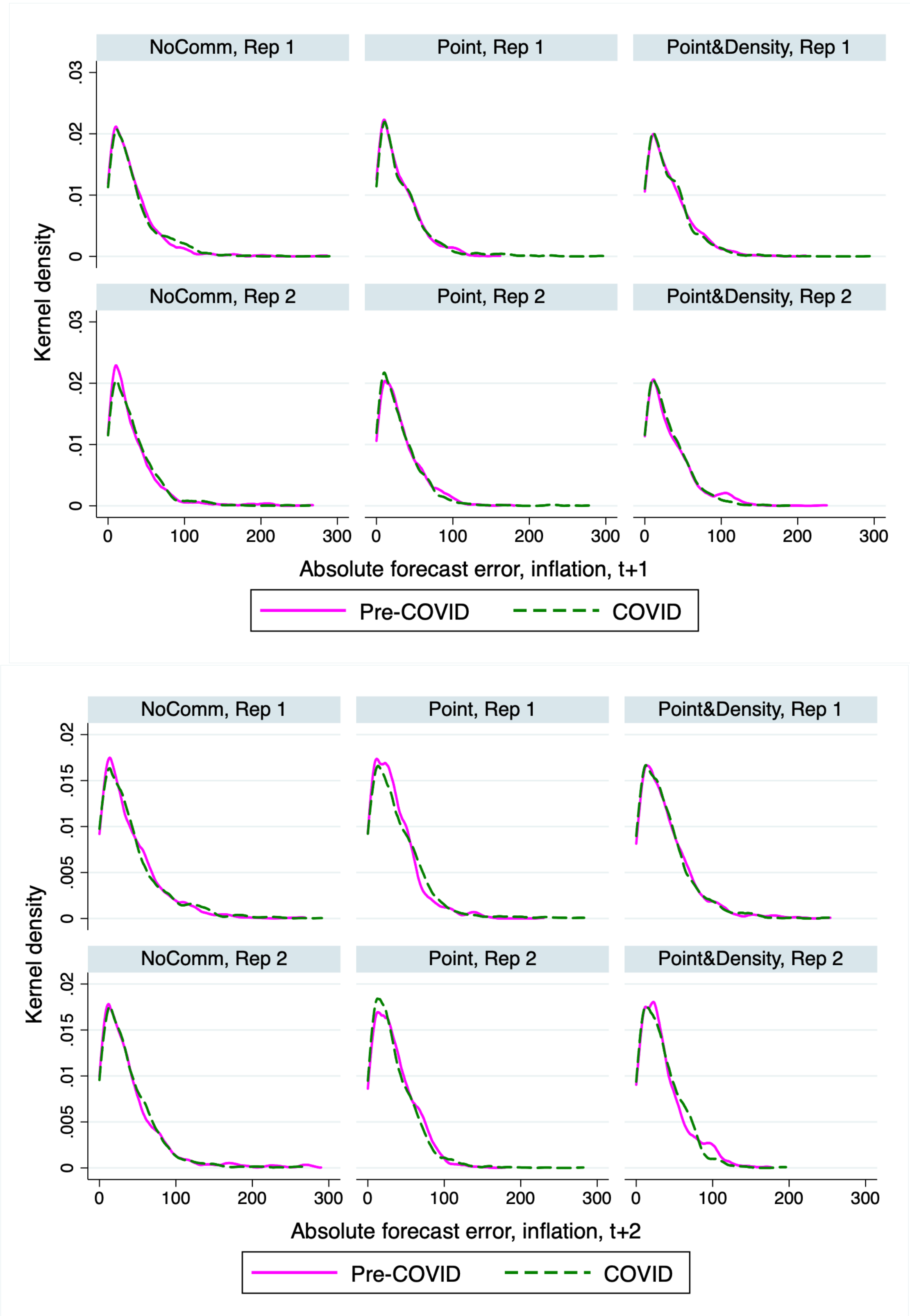


Figure 3: Forecast uncertainty, basis points

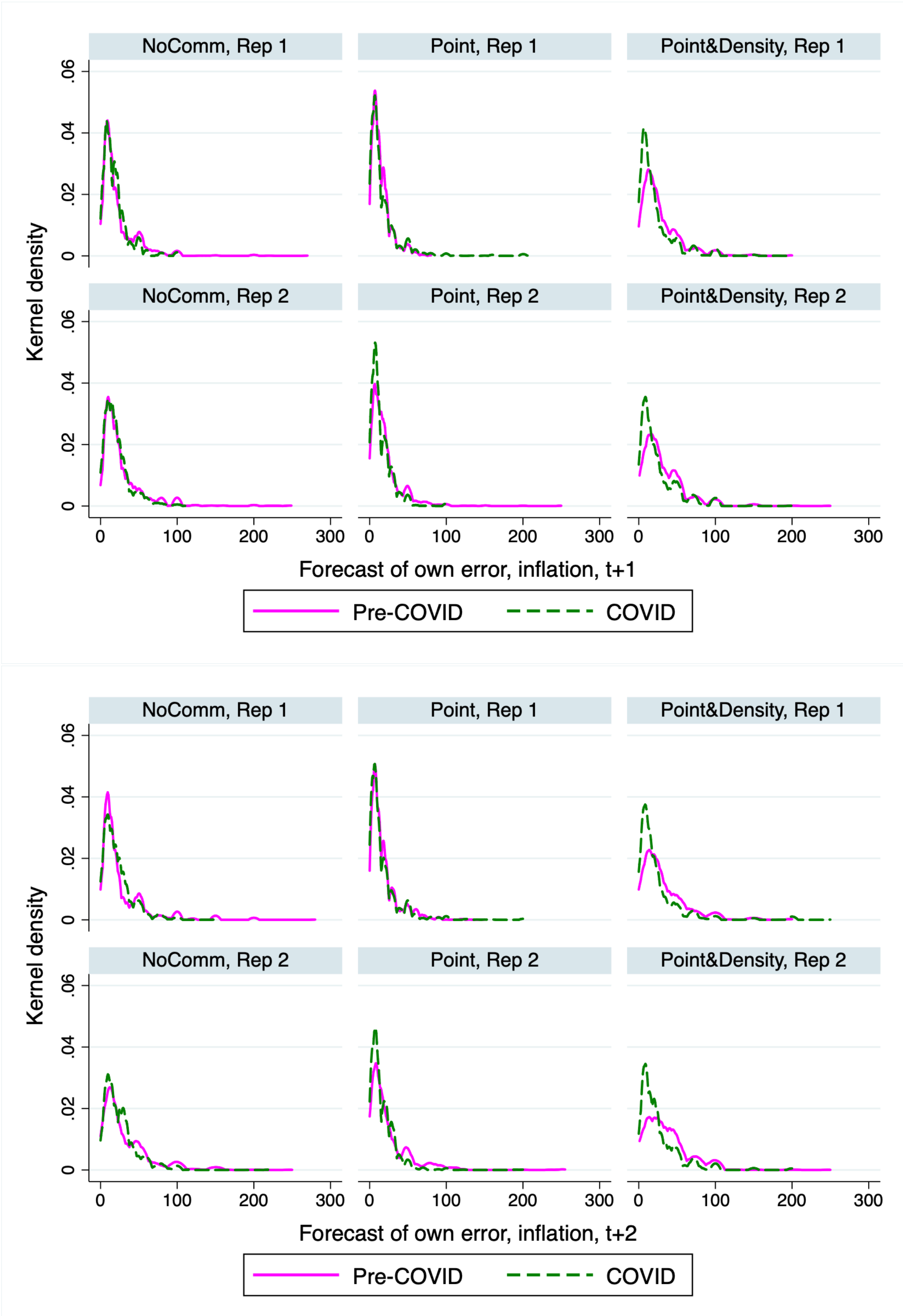


Figure 4: Inflation forecasting heuristics - Repetition 1

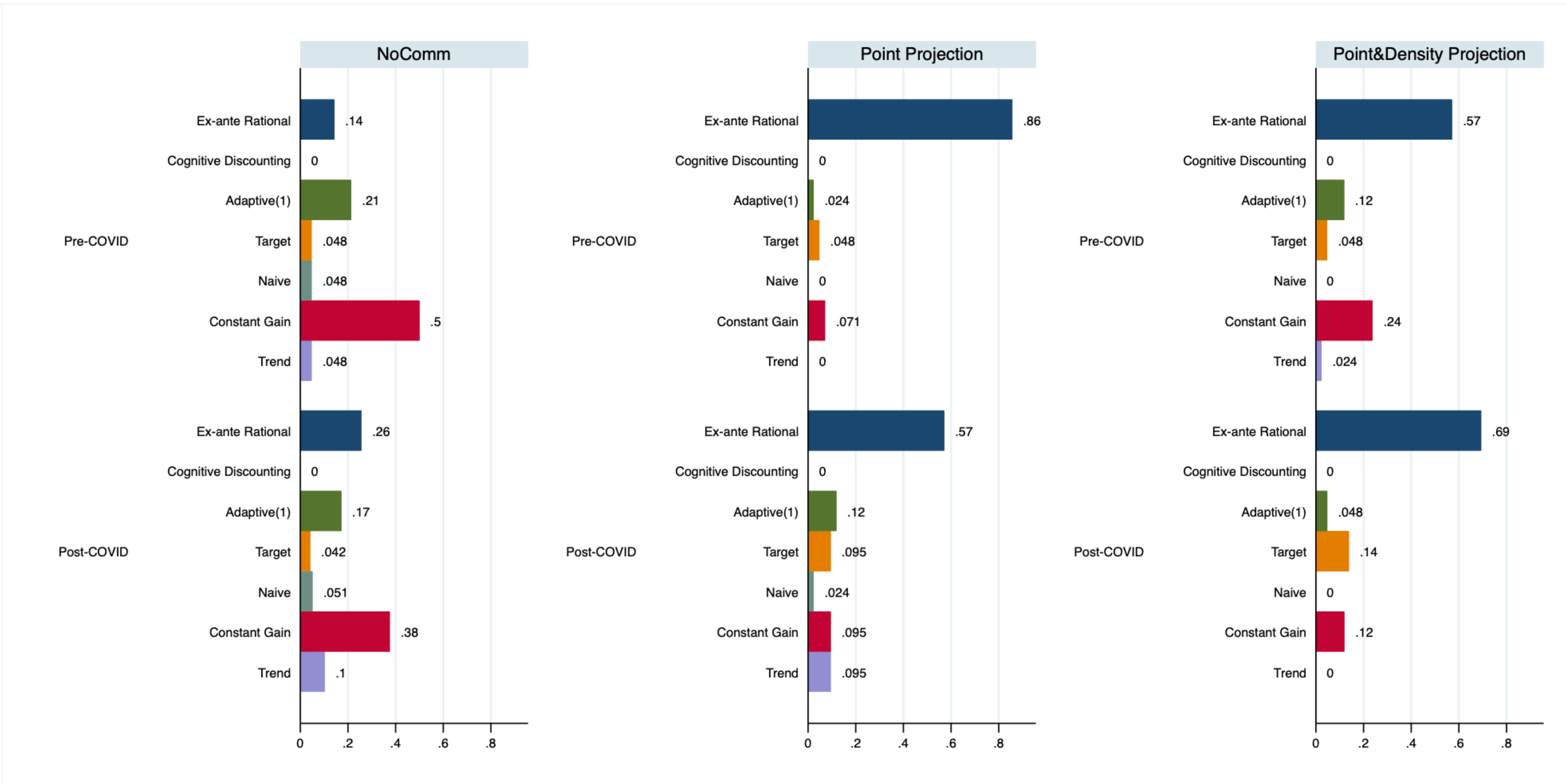
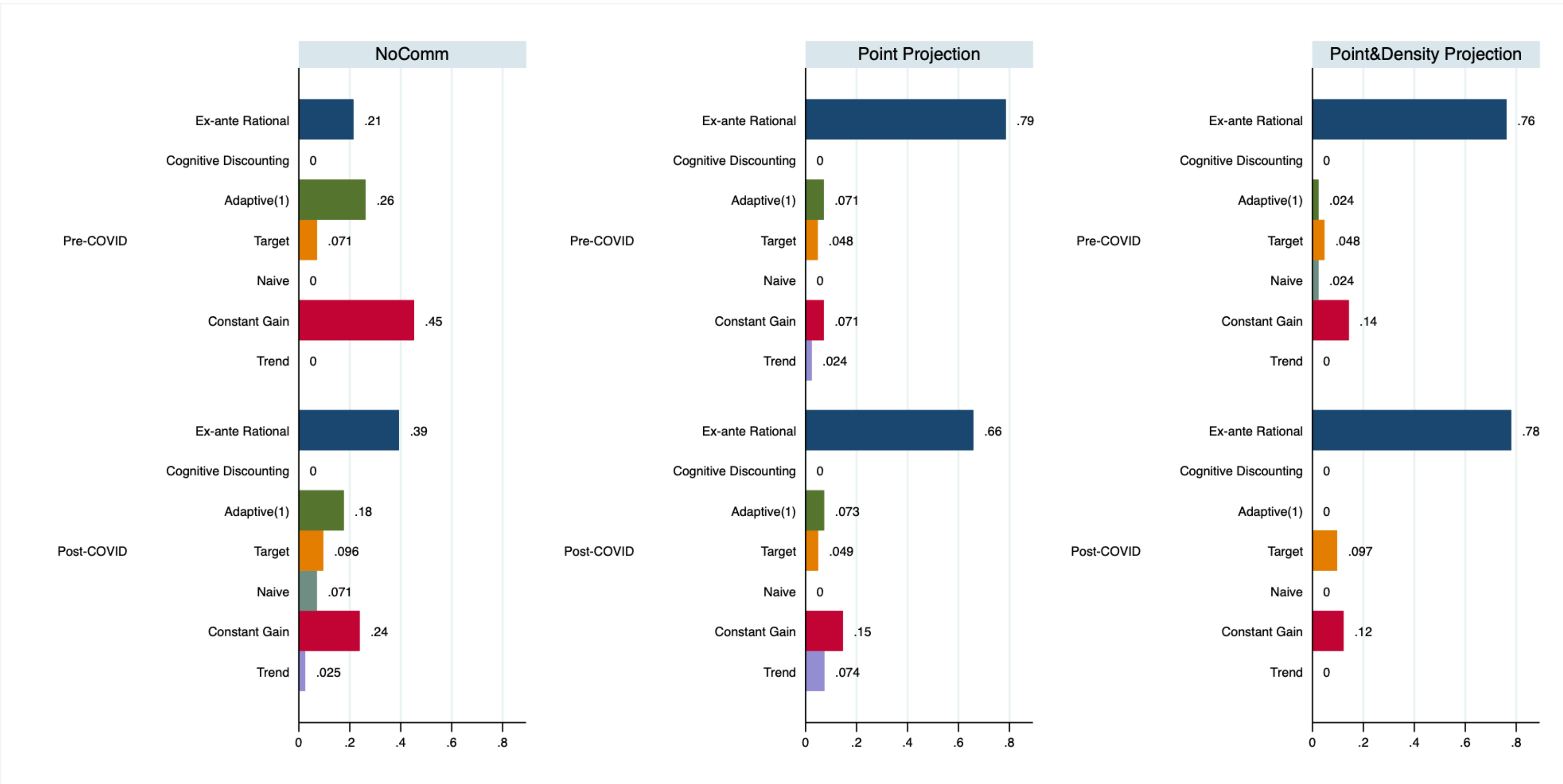


Figure 5: Inflation forecasting heuristics - Repetition 2



6 Appendix

6.1 Data Generating Process

This section provides more detail on how we modify the canonical three-equation, New Keynesian model. The purpose of this manipulation is to eliminate the need for subjects' output gap expectations. This reduces the complexity of the forecasting problem for our subjects and allows us to concentrate on variations in central bank communication surrounding inflation rather than the confluence of inflation and output.

We begin with the three-equation, reduced-form NK model

$$\pi_t = \beta \mathbb{E}_t\{\pi_{t+1}\} + \kappa x_t \tag{8}$$

$$i_t = \phi_\pi \pi_t + \phi_x x_t \tag{9}$$

$$x_t = \mathbb{E}_t\{x_{t+1}\} - \sigma^{-1}[i_t - \mathbb{E}_t\{\pi_{t+1}\} - r_t^n] \tag{10}$$

we rewrite Equation (10), iterate, apply the law of iterated expectations, and substitute:

$$x_t = (\kappa^{-1} + \sigma^{-1})\mathbb{E}_t\{\pi_{t+1}\} - \beta\kappa^{-1}\mathbb{E}_t\{\pi_{t+2}\} - \sigma^{-1} i_t + \sigma^{-1} r_t^n. \tag{11}$$

Further substitution yields the following representation of (3):

$$\pi_t = [\beta + \kappa\gamma_1\gamma_2]\,\mathbb{E}_t\{\pi_{t+1}\} - \gamma_1\beta\mathbb{E}_t\{\pi_{t+2}\} + \kappa\gamma_1\sigma^{-1} r_t^n \tag{12}$$

where we use

$$\gamma_1 = \left(\frac{\sigma + \phi_\pi\kappa + \phi_x}{\sigma}\right)^{-1} \tag{13}$$

$$\gamma_2 = (\kappa^{-1} + \sigma^{-1} - \sigma^{-1}\phi_\pi\beta). \tag{14}$$

This yields a dynamical system that can be solved using $\mathbb{E}_t\{\pi_{t+1}\}, \mathbb{E}_t\{\pi_{t+2}\}$, r_t^n. The demand shock r_t^n is an AR(1) process

$$r_t^n = \rho_r r_{t-1} + \epsilon_{r,t} \tag{15}$$

where $\epsilon_{r,t}$ is i.i.d. $\sim \mathcal{N}(0, \sigma_r)$ and ρ_r is a persistence parameter. We calibrate data-generating process to match moments of Canadian data following Kryvtsov and Petersen (2013); $\sigma = 1$, $\beta = 0.989$, $\kappa = 0.13$, $\phi_\pi = 1.5$, $\phi_x = 0.5$, $\rho_r = 0.57$, and $\sigma_r = 113$ bps.

With these parameters, we have

$$\pi_t = 1.54\mathbb{E}_t\{\pi_{t+1}\} - 0.58\mathbb{E}_t\{\pi_{t+2}\} + 0.08r_t^n \tag{16}$$

$$i_t = 4.44\mathbb{E}_t\{\pi_{t+1}\} - 3.12\mathbb{E}_t\{\pi_{t+2}\} + 0.41r_t^n. \tag{17}$$

where aggregate expectations from our subjects close the model. Note in Equation (16) and Equation (17) that one-period-ahead expectations are self-fulfilling but that two-period-ahead expectations are not. This counter-balancing of expectations makes sense from the perspective of consumption smoothing: if an agent expects inflation two days from now, then the agent will require more money to spend tomorrow than otherwise so that she can avoid paying higher prices two days from now. This puts downward pressure on spending today.

6.2 Instructions

In this subsection we reproduce instructions provided to our subjects. Importantly, we used identical instructions for pre- and post-COVID sessions. The only exception is that we told subjects in our post-COVID sessions they would received payment electronically rather than in cash.

EXPERIMENTAL STUDY OF ECONOMIC DECISION MAKING

Welcome! You are here to participate in an economic experiment. If you read these instructions carefully and make appropriate decisions, you may earn a considerable amount of money. We will pay you this money in cash immediately after this experiment.

Each of you will earn $10 for attending. This is your show-up fee. Throughout this experiment you will also earn points based on the decisions you make. Every point you earn is worth an additional $0.50. We reserve the right to improve the show up fee in your favour if average payoffs are lower than expected.

During the experiment you are not allowed to communicate with other participants. Please raise your hand if you have any questions. An experimenter will answer your questions privately. You will be excluded from the experiment and deprived of all payments aside from the show-up fee if you do not comply with these instructions.

This experiment is based on a simple simulation that approximates fluctuations in a real economy. Your task is to serve as private forecasters and provide real–time forecasts about future inflation in this simulated economy. These instructions will explain what inflation and the interest rate are, how they move around in this economy, and how they depend on your forecasts. We will allow you to practice making forecasts for several unpaid periods before we begin paid periods in this experiment. You will then participate in two sequences of 30 paid periods, for a total of 60 paid periods of play.

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. However, your earnings in this experiment depend on the accuracy of your individual forecasts.

You will also submit a measure of uncertainty about your forecast called your anticipated forecasting error. You will earn money if actual inflation is within the bounds of this error. Otherwise, you will earn nothing.

Please note that all values are 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.

Overview of the Economy

In each period, you will submit a forecast of inflation for the next two periods. For example, suppose it is now period 10. Then you will submit a forecast of inflation in period 11 and a forecast of inflation in period 12. By 'forecast of inflation' we mean your best guess of what inflation will be. The more accurate your guess, the more money you will earn.

Your forecasts should be given in basis points. Here are some examples of the relationship between basis points and percentages:

1% = 100 basis points

3.25% = 325 basis points

-0.5% = -50 basis points

-4.8% = -480 basis points

You can submit any forecast you wish, positive or negative or zero, but please only submit integers.

The economy consists of three main variables:

- **Inflation** – Inflation is the change in price that occurs between two periods.
- **Interest Rates** – The interest rate is the amount of money that people earn on savings. A higher interest rate entices consumers to save more and spend less on consumption. Thus, a higher interest rate puts downward pressure on inflation.
- **Shocks** – Shocks are changes to the amount consumers in the economy wish to purchase. Shocks change every period and are influenced by a random component and by past shocks. A positive shock today increases inflation today and vice versa.

Your goal in this experiment is to forecast future inflation as accurately as possible. Thus, we now provide detailed explanations of the factors that influence inflation and the relationships between the different variables in the economy.

Shocks:
Intuitively, you can think of shocks as weather shocks. Over the long run, the weather has no effect on how much consumers want to buy. However, from day to day, there may be

random changes to the weather that do influence what people do and buy. You can think of a positive shock as unexpectedly nice weather. When the weather is especially nice, consumers are spending more time out of their homes and increasing their expenditures (for example, buying ice cream, going out for a nice dinner, or going to the beach). A negative shock can be thought of as unexpectedly terrible weather. This bad weather makes it so that people do now want to leave their homes, causing expenditures to be relatively low. Gradually, the shocks, like weather, will revert back to their long-run levels. As the shocks dissipate, new random events occur that will make consumers want to increase or decrease their spending. Shocks will have a precise value and will be displayed on your screen.

Whenever a positive shock occurs and spending increases, this will put upward pressure on prices (i.e. upward pressure on inflation). Conversely, a negative shock will put downward pressure on prices (i.e. downward pressure on inflation).

We calculate the values of a shock in each period as follows:

$$Shock_p = 0.57(Shock_{p-1}) + RandomComponent_p$$

- 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

For example, shocks may evolve as follows:

$$\begin{aligned}
Shock_1 &= 30 \\
Shock_2 &= 30 \times 0.57 + New\ Draw \\
&= 17.1 + (newdraw) \\
Shock_2 &= 17.1 + (-150) \\
&= -132.9 \\
Shock_3 &= -132.9 \times .57 + New\ Draw \\
&= ...
\end{aligned}$$

Interest Rates: The central bank in this economy will adjust the nominal interest rate in each period to keep inflation as close to zero as possible. As inflation increases, the central bank will increase the nominal interest rate more than one-for-one with inflation. An increase in the nominal interest rate has a direct negative effect on consumer demand and production, and an indirect negative effect on inflation. Importantly, you will not observe the current interest rate when you are forming your inflation forecasts. After you submit your forecasts, the computer will solve for the current period's inflation using the median forecasts from all subjects in the room and the current-period shock shock (which you will see). It is important for you to realize that, even though the central bank is aiming for zero inflation, it will rarely accomplish this. This is because of the random shocks that occur in each period and the public's expectations. However, the central bank will keep the economy more stable than the economy would be in the absence of the central bank.

How the economy evolves:

Each period, you and the other forecasters in this room will submit your beliefs about inflation for the next period and the period after that. To be clear, if we are in period 10, you will submit an inflation forecast for period 11 and for period 12. The software will select the median of each of the two forecasts as the aggregate forecasts. The software uses the median, rather than the average forecast, so that a small number of subjects cannot have a significant effect on the economy.

These aggregate forecasts play an important role in determining inflation today. This is because inflation today is determined largely by aggregate forecasts about future inflation. If the majority of forecasters expect relatively high inflation tomorrow, then inflation today will be higher. The idea behind this is simple: If the professional forecasters communicate to the public that inflation is likely to rise tomorrow, consumers will spend more immediately to avoid paying the relatively higher prices tomorrow. This increase in demand today will cause prices to start rising today, and so inflation will increase today. Likewise, if the median forecaster predicts higher inflation for two days from now, households will need to have a bit more money tomorrow than they would otherwise to avoid paying the higher prices predicted for two days from now.

More precisely, inflation and interest rates evolve according to the following equations:

$$Inflation_t = 1.54(\text{Median forecast of Inflation}_{t+1}) - 0.58(\text{Median forecast of Inflation}_{t+2}) + 0.08(\text{Shock}_t)$$

$$\text{Interest Rate}_t = 4.44(\text{Median forecast of Inflation}_{t+1}) - 3.12(\text{Median forecast of Inflation}_{t+2}) + 0.41(\text{Shock}_t)$$

Important information about this economy:

- The Central Bank sets the target inflation at zero. In order to achieve this target it will adjust the nominal interest rate in each period. In some cases the nominal interest rate can become negative.
- Expectations about tomorrow (if in period 10, this is your forecast for period 11) are self-fulfilling in this economy. If you forecast higher inflation tomorrow then inflation will grow higher in the current period. Similarly, a median forecast of lower inflation tomorrow will cause inflation to fall in the current period.
- Expectations about two days from now (if in period 10, this is your forecast for period 12) relate negatively to inflation today. If you forecast higher inflation for two-days from now, then inflation today will fall. If instead you forecast lower inflation for two days from now, inflation today will increase.

Score

Your forecasting score in each period will depend on the accuracy of the forecasts you formed in the previous two periods. At the end of each period, the software will evaluate how accurate your forecasts from one- and two-periods ago were about the inflation rate in the current period. The difference between these numbers forms your absolute forecast error. The larger this absolute error, the lower is your forecasting score in that period. The letter p in the following example stands for 'period'.

- Absolute Forecast Error = $\|\text{Your Forecast} - \text{Actual Value}\|$

- Total $\text{Score}_p = 0.3(2^{-AbsoluteForecastError_{p-1}} + 2^{-AbsoluteForecastError_{p-2}})$

The maximum score you can earn for forecasting in each period is 0.60 points. Your score will decrease exponentially as your forecast error increases. Suppose your forecast errors for 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

Making decisions in this experiment
During this 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 you've earned through the previous period. You will also see three history plots on your screen.

The top history plot displays past interest rates and current and past shocks.

The second history plot shows your 1-period-ahead points forecasts of inflation (blue dots), error bands that you create with your anticipated forecasting error (blue shading centered around your point forecasts) and actual inflation (red dots). Note that the difference between your forecasts of one-period-ahead inflation (blue dots) and the actual levels of inflation (red dots) constitutes your one-period-ahead forecast error in past periods.

The third history plot shows your 2-period-ahead point forecasts of inflation (orange dots), error bands that you create with your anticipated forecasting error (orange shading centered around your point forecasts), and actual inflation (red dots). Note that the difference between your forecasts of two-period-ahead inflation (orange dots) and the actual levels of inflation (red dots) constitute your two-period-ahead forecast error in past periods.

Note: this section read one of three ways depending upon treatment:

For NoComm, skip directly to "You have 65 seconds...

For Point treatments:
Both the second and third plots also contain the Central Bank's forecast of inflation for the next five periods (green). It is important to remember that the projections are simply a forecast and not a promise. The Central Bank uses the model discussed earlier in these instructions, and the current and expected future shocks, to form its projections. In particular, it predicts that the economy will return to zero levels of inflation in the near future.

For Point&Density treatments:
Both the second and third plots also contain the Central Bank's forecast of inflation for the next five periods (green). This forecasts also includes green shading, which represents the Central Bank's level of uncertainty for its corresponding point projections. These bands will contain the correct realization of inflation about 66% of the time. It is important to remember that the projections are simply a forecast and not a promise. The Central Bank uses the model discussed earlier in these instructions, and the current and expected future shocks, to form its projections. In particular, it predicts that the economy will return to zero levels of inflation in the near future.

You have 65 seconds to make decisions in the first nine periods and only 50 seconds thereafter. You may submit both negative and positive forecasts and forecasts of 0. Please review your forecasts before pressing the SUBMIT button because you cannot revise your forecasts afterward.

The anticipated forecast error:
You must also submit a measure of how uncertain you are about your inflation forecasts. We call this your anticipated forecasting error.Note this value should always be positive and your error bounds are centered around your point forecast.

Suppose you forecast inflation tomorrow to be 10 basis points but feel more confident that actual inflation will fall between 5 and 15 basis points. You should indicate this by submitting an anticipated forecasting error of 5. This forms anticipated error bounds of 5 to 15 since $10-5=5$ and $10+5=15$. If actual inflation is any number from 5 to 15, we pay you. Otherwise, you earn nothing for this anticipated forecasting error.

If actual inflation falls within your anticipated forecast error bounds, then we pay your anticipated forecast error according to the following function:

$$AnticipatedErrorEarnings = \frac{15}{10+anticipated\ error}$$

Notice that your earnings for your anticipated forecast error decrease as your anticipated forecast error increases. However, it is important for you to understand that we pay you this amount ONLY if the realized value of inflation lies inside your anticipated forecasting error bands. If actual inflation is outside your anticipated forecasting error bands, then you earn 0 points for providing your anticipated forecasting error.

An example: Suppose it is period 3. Suppose in periods 1 and 2 you provided an inflation forecast of 10 basis points for period 3 inflation. Suppose your anticipated forecasting error in period 1 was 5 and in period 2 it was 10. Then your error bounds for period 1 are 5 to 15 and for period 2 are 0 to 20. Suppose actual inflation at the end of period 3 is 17. Then you earn 0 points for your anticipated forecast error provided in period 1. This is because 17 is not between 5 and 15. However, you would earn $\frac{15}{10+10}=.75$ points for your anticipated forecast error provided in period 2, since 17 is between 0 and 20.

Our software will randomly select (with equal probability) to pay you for **either** your point forecasts **or** for your anticipated forecast error in each period of play. **We will never pay for both in a single period**.