Why don't history-dependent monetary policies work?*

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March 14, 2024
Abstract

History-dependent monetary policies (HDMP) can potentially address the challenges that standard monetary policy frameworks face, especially at the ELB. Using controlled laboratory experiments, we show that history-dependence does not work as intended. We examine participants' expectations and identify a weakened expectations channel as the underlying cause. We uncover three challenges people have in understanding HDMP. First, expectations are predominantly backward-looking, and they do not internalize the stabilization properties of monetary policy: many people fail to forecast in the intended direction and, those who do, do not fully appreciate the necessary *make-up* strategy for the HDMP to be successful. Second, within the set of HDMP, frameworks with level targets (e.g., price level targeting) introduce more cognitive complexity compared with average inflation rate targeting because they require participants to pay attention to more variables. Third, in level targeting frameworks, credibility proves difficult to establish and regain when lost. However, effective central bank communication through medium-term macroeconomic projections can reduce the complexities associated with HDMPs and significantly improve the performance of price level targeting frameworks.

1 Introduction

Monetary policy has undergone significant evolution since the Global Financial Crisis and the pandemic. Frameworks emphasizing history-dependent mandates, such as price level targeting (PLT), nominal GDP level targeting, and average inflation targeting (AIT), have risen to prominence [Williams, 2017, Bernanke, 2017]. These approaches potentially offer greater economic stabilization than traditional rate-targeting regimes. Their effectiveness hinges on the credibility of the regime and the strength of the expectations channel. The expectations channel works through forward-looking expectations that internalize future make-up strategies of history-dependent regimes. However, the benefits of history-dependent regimes may diminish or even reverse if expectations are not fully rational or are backward-looking [Kryvtsov and Petersen, 2013]. Although there is a growing interest in history-dependent monetary policies, practical experience with them remains sparse.[1] Moreover, evidence on public comprehension of these frameworks is limited and inconsistent. Surveys indicate that U.S. households struggle to grasp the implications of AIT for future inflation [Coibion et al., Forthcoming], while German households seem more responsive [Hoffmann et al., 2022].

To enhance our understanding of how history-dependent regimes would perform in practice, and to circumvent the issue of scarce empirical data, we conduct a series of controlled macroeconomic laboratory experiments. Given the pivotal role of expectations channel in the efficacy of history-dependent regimes, our goal is to understand the mechanisms behind expectation formation. Across treatments, we vary the degree of history-dependence in monetary policy, ranging from no history-dependence in inflation targeting (IT) and dual mandates (DM), to average inflation targeting mandates with short (4-quarter) and long-horizons (10-quarter) (AIT-4 and AIT-10), and finally the greatest history-dependence in price level (PLT) and nominal-GDP level (NGDP) targeting. Participants were tasked with making repeated independent forecasts first under stable conditions, followed by a significant demand shock that leads the economy to its effective lower bound (ELB), and finally a period of economic recovery. Participants' expectations fed into economic outcomes, and thus the advantage of our approach is that our findings do not need to rely on assumptions about any specific expectation formation model.

Our results reveal that the ability of monetary policy to stabilize the economy deteriorates with the degree of history-dependence, contrary to what is expected by theory. Economies

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[1]Sweden briefly adopted PLT in the 1930s [Berg and Jonung, 1999], while the U.S.A. implemented a flexible average inflation targeting framework in August 2020. Nominal GDP level targeting has yet to be employed anywhere.

with greater history-dependence in monetary policy exhibit significantly higher volatility in inflation and output. The difference between the regimes is especially evident during brief but significant contractions in economic activity that drive the economies to its ELB. While no or minimal history dependent frameworks restore stability relatively quickly, level-targeting regimes spiral into deflationary trends at the ELB. This was contrary to the anticipated stabilization benefits of such regimes during ELB periods. Furthermore, the extent of deterioration of the performance of history-dependent regimes is significantly worse than suggested by widely used models with bounded rationality.

We identify how the failure in the expectations channel underlies the poor performance of history dependent monetary policy frameworks. In our experimental economies, expectations come directly from the participants, and we use their rich individual-level expectations data to provide evidence on the sources of this failure. We uncover three key challenges people have in understanding history-dependence in monetary policy.

First, the nature of expectations formation undermines the expectations channel. Rather than relying on fundamentals and anticipated monetary policy, people in our experiments tend to rely on recent historical experiences to form their expectations. This results in a weaker expectations channel of monetary policy, which is key to the performance of history-dependent frameworks. People's expectations do not internalize the stabilization properties of monetary policy: the majority of people fail to forecast in the intended policy-consistent direction and, those who do, do not fully appreciate the necessary *make-up* strategy for the policy frameworks to be successful, in line with models of cognitive discounting and limited common knowledge [Gabaix, 2020, Angeletos and Lian, 2018].

We observe that only a small fraction of participants developed expectations that align with a basic grasp of monetary policy and its economic implications. During stable periods, the prevalence of such *policy consistent* forecasting in the intended direction was fairly similar across different monetary frameworks. Interestingly, the response to a significant negative demand shock showed an increase in the policy-consistence of participants' forecasts across all regimes, suggesting heightened attention to economic conditions and policy implications, in line with theories of rational inattention [Sims, 2010, Mackowiak and Wiederholt, 2009, Khaw et al., 2017]. Yet, in the post-shock phase, there was a notable decline in policy-consistency, more so in level-targeting regimes like PLT and NGDP than in rate-targeting regimes.

Second, the framing of the price level targeting mandate in terms of price levels increases the cognitive complexity of forming inflation expectations. Our lab experiments, designed to compare average inflation targeting (AIT) with a long averaging horizon (10 quarters) to price level targeting (PLT), enable us to examine the effects of framing monetary policy goals. AIT with a longer horizon approximates the history dependence of PLT. Weaker understanding of PLT is indicated by lower forecast accuracy, higher forecast dispersion, and less policy consistent forecasting than in AIT. This suggests that level-targeting poses greater cognitive challenges for participants than rate-targeting. The poorer understanding of the PLT framework results in a weaker expectations channel and greater economic instability.

Third, we observe low and very persistent central bank credibility, irrespective of the degree of history-dependence in monetary policy. Less than one-third of participants form expectations in a manner consistent with them viewing monetary policy as credible, and this share declines following the large negative demand shock in the middle of the experiment. Furthermore, participants' credibility in policy becomes more entrenched post-shock, and more strongly entrenched in history-dependent frameworks, indicating that participants are less likely to change their trust. This suggests that establishing credibility early on is crucial as it is very difficult to regain it.

By the time the economy enters the ELB, participants have established their views of how credible these monetary policy frameworks are (and not enough people view them as credible). This observed lack of credibility in monetary policy is particularly damning for the history-dependent frameworks. Although in our experiment PLT and NGDP frameworks are committed to making up all past misses, achieving these goals becomes unattainable as these policies come up against participants' lack of credibility and bounded rationality. The complexity of the level targeting regimes drives participants to use simple backward-looking forecasting models rather than the central bank's recent performance. Given that level-targeting frameworks rely so strongly on central bank credibility and the expectations channel to be successful, the breakdown of these two factors has the largest consequences.

Having observed such a poor performance of PLT in the laboratory, we conduct a follow-up treatment to explore whether adding central bank communication of macroeconomic projections of inflation and output can improve the performance of this level targeting framework. Communication in central banking can effectively guide macroeconomic expectations [Coibion et al., 2022, Cornand and M'baye, 2018]. We introduce communication about future inflation rate and output to help reduce the complexity of the PLT regime [Mokhtarzadeh

and Petersen, 2020]. Our results are very encouraging. Five of six sessions produce highly stable outcomes. PLT with communication can be even more effective at stabilizing the economy than the rate-targeting frameworks like IT and DM. This improvement comes from a high and persistent credibility in the projections, leading to less extrapolative and more policy-consistent expectations. Our results suggest an important role for central bank communication in the implementation of complex mandates such as PLT. Communication about inflation rates helps manage inflation expectations and address the challenge of framing PLT mandate in terms of the price level.

Our research contributes to the literature on monetary policy design and to an understanding of the effects of history-dependence in monetary policy, a concept widely acclaimed for its potential to stimulate economic activity when policy rates are at their effective lower bound [Svensson, 2002, Egg, Wolman, 2005]. While traditional models under rational expectations have underscored the potency of history-dependence through the expectations channel [Woodford, 2003, Vestin, 2006], recent work incorporating bounded rationality [Honkapohja and Mitra, 2014, 2020, Amano et al., 2020, Wagner et al., 2023] suggest limitations to these frameworks. Our findings align with the bounded rationality literature, though our results indicate even worse performance of history-dependent frameworks.

Our work contributes to the literature by providing novel evidence about the reasons *why* history-dependent monetary policy frameworks do not perform as intended. Other studies have also shown that some history-dependent regimes might not work well, especially at the ELB [Arifovic and Petersen, 2017, Arifovic et al., 2023a]. For example, Arifovic and Petersen [2017] shows that PLT implemented using a history-dependent inflation target performs worse compared with IT. Arifovic et al. [2023b] find that PLT works worse than IT, unless it is accompanied by communication of necessary make-up inflation strategy. Our work is related to an experimental research examining various monetary policy regimes [Pfajfar and Žakelj, 2014, 2016, Hommes and Makarewicz, 2021a, Hommes et al., 2019b, Mauersberger, 2021, Kryvtsov and Petersen, 2013, 2021, Kronick and Petersen, 2022].

We provide empirical support for models of expectation formation used in the behavioral macroeconomics literature. Bounded rationality manifests in our experimental subjects through extrapolative expectations and limited responses to economic fundamentals. This reflects both an under-reaction to policy changes and shocks, and an over-reaction to past trends, resonating with diagnostic expectations theory [Bordalo et al., 2020]. The heterogeneity in expectation formation mechanisms supports the use of heterogeneous agent models in

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macroeconomic analysis [Brock and Hommes, 1997]. The majority of our participants are not forward-looking and instead extrapolate their experiences when forming their expectations [Malmendier and Nagel, 2016]. However, we do observe spikes in attention and rationality consistent with models of rational inattention [Sims, 2010, Mackowiak and Wiederholt, 2009, Khaw et al., 2017]. We also find evidence supporting bounded rationality models based on cognitive limitations and limited common knowledge [Gabaix, 2020, Angeletos and Lian, 2018], where some participants correctly anticipate policy directions but underestimate the required adjustments. This suggests cognitive discounting and the influence of limited common knowledge, where expectations are moderated by the anticipation of others' bounded rational responses.

Finally, our study underscores the importance of effective central bank communication in implementing history-dependent policies such as price level targeting. Communication plays an essential role in central banking [Blinder et al., 2022, Haldane and McMahon, 2018, Levin, 2014, Ehrmann et al., 2022]. We show that history-dependent frameworks such as PLT may be better implemented if supplemented with well-designed central bank communication. Our results indicate that framing also matters when communicating about inflation in PLT framework. Communicating projection for inflation can increase the stability of the economy when implementing PLT in our experiments, whereas presenting information about *time-varying implied* inflation targets necessary to achieve the price level target can sometimes be ineffective [Arifovic and Petersen, 2017] or effective Arifovic et al. [2023b].

Overall, our findings not only challenge the assumed superiority of history-dependent regimes in certain economic conditions but also highlight the criticality of public understanding and the cognitive aspects of such policy frameworks. These insights provide a nuanced perspective on the practical application and potential pitfalls of history-dependent monetary policies.

2 Experimental Design

We design our laboratory experiment to collect individual-level expectations under different frameworks to inform the design of monetary policy. The data from the experiment is used to address the following questions. Do different monetary policy regimes perform in the lab as predicted by theory? Importantly, does history-dependence deliver the stability as promised by rational-expectations models? Does the framing of policy objectives and the degree of history-dependence matter for the management of expectations? Are participants able to

understand and incorporate monetary policy into their macroeconomic forecasts? That is, do participants update their forecasts in the correct direction and by sufficient magnitude?

2.1 Data-generating process

Our experimental environment is designed around a simple New Keynesian model that is commonly used for monetary policy analysis. We construct an economy that follows a data-generating process based on the canonical model [Woodford, 2003], an environment among many model candidates considered by the Bank of Canada in its 2021 monetary policy framework renewal [MPF, 2021, Dorich et al., 2021]. Similar monetary policy environments have been studied in Adam [2007], Pfajfar and Žakelj [2014], and Assenza et al. [2021].

The economy in which participants interact is described by the following system of equations:

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

$$x_t = \mathbb{E}_t x_{t+1} - \frac{1}{\sigma}(i_t - \mathbb{E}_t \pi_{t+1} - r_t^n) \tag{2}$$

$$r_t^n = (1-\rho)(-ln(\beta)) + \rho r_{t-1}^n + \sigma_{rn}\epsilon_t \tag{3}$$

Equation 1 describes the evolution of inflation in period t, π_t, in response to aggregate one-period-ahead inflation expectations, $\mathbb{E}_t \pi_{t+1}$, and the output gap, deviations of output from its steady state level, x_t. The output gap, given by Equation 2, is a function of aggregate expectations of one-period-ahead inflation and output gap expectations, $\mathbb{E}_t x_{t+1}$, as well as the deviations of the nominal interest rate, i_t, from the natural rate of interest, r_t^n. The natural rate of interest, described by Equation 3, is the rate of interest that keeps the economy at full employment while keeping inflation constant. The natural rate of interest is assumed to follow an AR(1) process and is subject to a sequence of demand shocks, ϵ_t. Parameters in our model are calibrated to quarterly data, as in Dorich et al. [2021], and are consistent with Canadian data. These values are used in Kryvtsov and Petersen [2021]. $\beta = 0.994$, $\sigma = 1$, $\rho = 0.8$, $\sigma_{rn} = 0.005$, $\kappa = 0.125$, $\pi^* = 0$, $x^* = 0$, $r_t^{n*} = 0$, $\bar{r} = i^* = 60$.

We have taken measures to simplify the experimental macroeconomy for participants through our 1) choice of DGP; 2) choice of shocks; and 3) linearization of the economy around a zero-inflation steady state. Firstly, we use the simple three-equation NK model as our experimental DGP. Importantly, some of the assumptions required for the log-linear approximation given in Equations 1-3 may not always hold in the experiment. Expectational errors may not be small and unbiased, and as emphasized by Preston [2005], the micro-founded New

Keynesian framework would produce meaningfully different dynamics for heterogeneous expectations. We refer interested readers to Online Appendix A for more details behind our experimental design.

To close the model, we include a policy rule that governs the evolution of the nominal interest rate, i_t. The policy rule is our key source of experimental variation. We consider six distinct ad hoc policy rules. The first three mandates we consider involve the central bank targeting various metrics of inflation and the output gap.

Under IT and DM regimes, the central bank sets the nominal interest according to the following general policy rule:

$$i_t = \bar{r} + \phi_\pi(\pi_t - \pi^*) + \phi_x(x_t - x^*) \tag{4}$$

where it seeks to minimize deviations of inflation and output gap from their targeted rates of zero. Parameters ϕ_π and ϕ_x govern the reactions of the central bank to deviations of inflation and output gap from their targeted rates. The difference between IT and DM is that the weight on the output gap, ϕ_x is assumed to be considerably larger and equal to ϕ_π under a dual mandate. In the IT regime, $\phi_\pi = 5.5$ and $\phi_x = 3.0$, while in DM, $\phi_\pi = \phi_x = 4.5$.

Under the AIT regime, the central bank sets the nominal interest rate to minimize deviations of inflation from its inflation target based on the recent average inflation rate. The central bank also places some weight on the output gap when making its policy decisions. The policy coefficients are the same as in IT: $\phi_\pi = 5.5$, $\phi_x = 3.0$. We consider two horizons for average inflation —a short horizon of 4 quarters and a long horizon of 10 quarters. Our reason for studying two horizons in AIT is twofold. First, we would like to explore how AIT with different horizons perform. Such results can be useful in guiding the choice of the horizon for policymakers. Second, theory predicts that AIT approaches PLT when the horizon in computing average inflation goes to infinity. Therefore, AIT with a longer horizon may be a more feasible way to achieve results comparable to those in PLT without many of the practical challenges in implementing PLT [Amano et al., 2020]. The two AIT policy rules we implement are given by Equations 5 and 6:

$$i_t = \bar{r} + \phi_\pi\left(\frac{\sum_{j=0}^{3} \pi_{t-j}}{4} - \pi^*\right) + \phi_x(x_t - x^*) \tag{5}$$

$$i_t = \bar{r} + \phi_\pi\left(\frac{\sum_{j=0}^{9} \pi_{t-j}}{10} - \pi^*\right) + \phi_x(x_t - x^*) \tag{6}$$

Next, under the price-level targeting mandate, the central bank responds to deviations of the price level, P_t from its targeted level, P^*, as well as the output gap:

$$r_t = \bar{r} + \phi_P(P_t - P^*) + \phi_x(x_t - x^*) \tag{7}$$

where $P_t = P_{t-1} + \pi_t$. $\phi_P = 0.8$, $\phi_x = 1.3$.

Finally, a nominal GDP level targeting mandate involves the central bank instead adjusting nominal interest rates in response to deviations of the nominal GDP level, $NGDP_t$ from its targeted level, $NGDP^*$:

$$i_t = \bar{r} + \phi_{NGDP}(NGDP_t - NGDP^*) \tag{8}$$

where $NGDP_t = x_t + P_t$. $\phi_{NGDP} = 1.1$

Parameters in the policy rules are derived from optimizing the following loss function as implemented by Dorich et al. [2021]:

$$L = \sum_{t=1}^{50} \left(\pi_t^2 + x_t^2 + 0.5(i_t - i_{t-1})^2 \right) \tag{9}$$

This ad hoc loss function gives a realistic description of the goals pursued by a central bank. Central banks are concerned not only about inflation and output gap stabilization but also interest rate variation. The coefficients in the policy rules in different monetary policy regimes were chosen to minimize this loss function while putting the frameworks on comparable footing, and are in line with the theoretical horse race conducted in Dorich et al. [2021].

2.2 Experimental implementation

Our experimental design followed closely the structure of previous New Keynesian learning-to-forecast experiments [Arifovic and Petersen, 2017, Hommes et al., 2019a]. In each period, each subject j submitted forecasts about inflation and the output gap for the subsequent period – $E_{j,t}\pi_{t+1}$ and $E_{j,t}x_{t+1}$. Actual outcomes for π_t, x_t, and i_t were determined based on the current period's realized ϵ_t and the median submitted forecasts for $t+1$ inflation and output gap according to Equations 1-3 and one of the policy rules given in Equations 4-8. Our decision to use the median rather than mean expectations as a measure of aggregate expectations was made to reduce the effect of a relatively small number of participants and

outliers in driving aggregate dynamics. This is a particularly valuable design decision as it reduces aggregate instability in the presence of an ELB and potentially boundedly rational participants.

The participants of the experiment provide one-period ahead expectations for inflation and output. There are many reasons to focus on short-term expectations. First, the largest predicted gains from history-dependent mandates come from stabilizing short-term expectations [Walsh, 1998]. In all of our mandates, long-term expectations are assumed to be anchored at 0%. Short-term expectations instead provide insight into the strength of the expectations channel. Second, our objective was to reduce the complexity of the forecasting task (participants have to repeatedly forecast two variables), and to allow for as many periods of forecasting as possible with more time per-period to process information across different types of scenarios.

Participants were provided with detailed information about the economy's data-generating process in the instructions, including very clear descriptions of how the central bank would set monetary policy and its impact on the economy. This information was presented both descriptively and quantitatively in the form of explicit equations. We also explained how participants' forecasts would translate into points and payoffs at the end of the experiment. The experimental instructions are in Online Appendix B. Participants did not have information about each others' expectations, as is the standard practice in the design of learning-to-forecast experiments and consistent with empirical evidence on the formation of expectations in the literature (Coibion et al. [2022]).[2] This design decision avoids strategic coordination on each other's forecasts and on the steady state.

Treatments We implemented a total of six treatments: each treatment corresponds to one of monetary policy regimes presented in equations 4-8. Thus, our treatments are IT, DM, AIT-4, AIT-10, PLT, and NGDP.

2.3   Procedures

Our experiment consists of six independent sessions for each of the six monetary policy treatments. For each session, we invited a group of seven inexperienced participants to play the

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[2]Survey respondents revise their views about inflation in response to the provision of publicly available information about forecasts of the Federal Reserve indicating that they are not aware of such information.

roles of professional forecasters tasked with making forecasts in 50 sequential periods.[3]

The exogenous shocks in the experimental economy were pre-drawn. This is described in the instructions to the participants. The shock sequence was chosen to implement two distinct phases in the experiment. Each session began with an initial stable phase during periods 1-19 and provided us with an opportunity to evaluate the relative performance of different policy mandates away from the effective lower bound. This phase was followed by a significant large negative demand shock in period 20 that brought the economy to the effective lower bound. The large negative demand shock dissipated rather quickly, returning to the steady-state level of zero by period 23. The remainder of the post-shock phase lasted 27 periods and enabled us to study how economies respond to and recover under the different monetary policy mandates following episodes at the ELB. Thus, we can test the stabilization properties of the monetary policy regimes during stable and unstable periods, including periods at ELB.

Participants' earnings during the experiment are determined based on the accuracy of their inflation and output gap forecasts. The points earned by subject j in period t were based on the absolute distance between their forecasts made in period $t-1$ and realized inflation and output in period t as in [Kryvtsov and Petersen, 2021]:

$$Points_{j,t} = 0.3 \left(2^{-.5|\mathbb{E}_{j,t-1}\{\pi_t\} - \pi_t|} + 2^{-.5|\mathbb{E}_{j,t-1}\{x_t\} - x_t|} \right) \tag{10}$$

Participants' total payoffs over all the forecasting periods were converted to Canadian dollars at an exchange rate of 50 cents per point.

Participants were presented with information about their experimental economy on the computer screen as it evolved during the experiment. Figure B1 in Online Appendix B shows the screenshot of the computer screen seen by the subjects during the experiment. The participants continuously observed four charts presenting shocks and interest rates, inflation, inflation target and the subject's private inflation forecast, output and the subject's private output forecast, nominal GDP level and price level, and the targets of the central bank (inflation in IT, DM, AIT-4, and AIT-10, as well as the price-level target in PLT and nom-

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[3]The size of the group can play an important role in driving aggregate dynamics, especially in settings with a high degree of strategic complementarities. Hommes et al. [2021] show that in asset pricing experiments with positive feedback (as in our environment at the ELB), increasing the group size from six participants to 90 to 100 participants does not significantly change pricing. In fact, increasing from six to 31-32 participants can speed up extrapolative pricing and deviations from equilibrium predictions [Bao et al., 2020]. Our decision to keep the group size relatively small likely reduced the coordination on extrapolative expectation models. Coordination on sunspots announcements is also less likely in experimental bank run settings with a large number of participants [Arifovic et al., 2023a].

inal output target in NGDP). The targets were displayed continuously as a horizontal line at zero (for inflation and output gap) and 1000 for the price-level and nominal output targets.

On the left-hand side of the screen, there were two input windows where subjects submitted their one-period-ahead forecasts of inflation and output in basis points. Subjects were given 75 seconds to submit their forecasts during the initial 10 periods and 50 seconds during the remaining periods of the experiment. If participants failed to input their forecast on time, the experiment would move on to the next round and they would simply earn zero points for their missed forecasts. The median forecast would instead be selected from the submitted forecasts. Subjects could submit any number they wished, positive, negative, or zero, with no upper or lower bounds on their forecasts.

Experiments were conducted online over Zoom with 252 undergraduate students from Simon Fraser University and Texas A&M University from May to July 2020 and from May to June 2021. Online sessions were necessary given health restrictions due to the pandemic and the closure of physical labs.Participants were recruited using SONA and ORSEE [Greiner, 2015] recruiting systems. The sessions for each treatment were equally split between the two institutions. Each session lasted approximately two hours, during which instructional time and Q&A was about 40 minutes, and four rounds of practice with the experimental interface lasted about 10 minutes.[4] Participants were able to ask experimenter questions throughout the session. Subjects were paid a show-up fee of $7 in addition to pay linked to their performance, with an average total pay of $25. Payments were made via e-Transfer in Canada and Venmo in the United States.

3   Experimental Hypotheses

Owing to the nature of the various policy mandates, the policy regimes are predicted to generate noticeably distinct aggregate dynamics. Figure 1 presents the rational expectation equilibrium solutions for inflation, output gap, and the nominal interest rate for considered monetary policy mandates associated with our pre-selected shock sequence. Note that while inflation deviates significantly more from the steady state under IT and DM than under NGDP and PLT.

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[4]A link to a web-hosted PDF of the instructions was sent to each participant through Zoom at the beginning of the session, allowing them to reference it at any point during the experiment. The PDF could not be downloaded and the URL to the instructions was changed after every session.

We formulate theoretical predictions about the stabilization performance of the different monetary policy regimes based on the loss function in Equation 9. Our model is simulated with each monetary policy regime under rational expectations using the sequence of demand shocks implemented in the experiment. Then we compute the average total loss in each regime as a square root of total loss (Equation 9) divided by 50 periods. The results are presented in Table 1. We break down the total loss into the losses associated with deviations of inflation, output, and interest rates from the steady state in Table C1 in Online Appendix C.

Given our simulated sequence of shocks, the overall total loss (as well as the loss associated with inflation) is predicted to be lowest under NGDP, followed closely by PLT. Thereafter, AIT with a 10-period horizon performs better than AIT with a 4-period horizon. DM and IT are predicted to produce relatively larger losses than the other regimes. It should be noted that losses across all these six regimes are quite close under rational expectations. Using these simulations and calculated losses, we form our key testable hypothesis:

Hypothesis 1: The realized losses under the six mandates are ordered as follows $L_{NGDP} < L_{PLT} < L_{AIT-10} < L_{AIT-4} < L_{DM} < L_{IT}$.

Other experimental studies of monetary policy regimes illustrate that participants' expectations are mostly non-rational [Anufriev et al., 2013, Assenza et al., 2021, Hommes and Makarewicz, 2021b]. Given this evidence, we introduce a very simple form of adaptive expectations – naïve expectations – into our model to understand the implications for stabilization properties of different monetary policy regimes. Naïve expectations are set as $E_t\pi_{t+1} = \pi_{t-1}$ and $E_t x_{t+1} = x_{t-1}$. We find that the presence of naïve agents can be disruptive to economies with certain monetary policy regimes. Level-targeting regimes such as PLT and NGDP can break down for certain shares of naïve agents. The threshold share of naïve agents is 33% in the PLT regime and 45% in NGDP; economies become unstable in these regimes with shares of naïve agents above the threshold level. IT, DM, and AIT tolerate 100% of naïve agents, remaining stable. In other words, PLT and NGDP are the least robust to the presence of naïve expectations.

We have simulated our model with different shares of naïve expectations using a sequence of demand shocks implemented in the experiment. We have evaluated the loss function (equation 9) for the model with rational expectations (REE) and for the models with adaptive expectations which are presented on Figure 2 and in Table 1 (more details are discussed in Appendix C).

For a small share of naïve agents (33%), NGDP level targeting performs better than other regimes (Figure 2). However, as the share increases to 45% , IT and DM turn out to be more effective and more robust to the presence of non-rational expectations in their ability to stabilize the economy and perform better than history-dependent regimes NGDP, AIT-10 and AIT-4. With 100% of adaptive expectations, IT and DM perform better than AIT-10 and and AIT-4.

The main reason for the weak performance of history-dependent regimes in the presence of naïve expectations is that naïve expectations are backward-looking and do not have a forward-looking aspect that internalizes the stabilization properties of history-dependent regimes. As a result, the presence of naïve expectations weakens the expectations channel on which history-dependent regimes rely for their superior performance in models with rational expectations. Evidence on the formation of expectations in the laboratory experiments suggest that participants tend to use relatively simple backward-looking heuristics [Hommes and Makarewicz, 2021b]. It is reasonable to expect that our participants may choose to form their expectations based on similar backward-looking mechanisms, and, as a result, history-dependent regimes may not perform as well as postulated in Hypothesis 1. Moreover, the simulations with adaptive agents Table 1 and Figure 2 suggests the likely direction of the relative performance of different monetary policy regimes in the experiments.

4 Aggregate findings

4.1 Dynamics and performance

Next, we present the time series of inflation, output, and interest rate in each of six sessions for each of our six treatments: DM and IT in Figure 3, AIT-4 and AIT-10 in Figure 4, NGDP in Figure 5 and PLT in Figure 6. For reference we include the series from the simulations with rational expectations in red.

The dynamics of inflation and output exhibit impressive consistency across the six sessions in IT and DM and are very similar to the rational predictions of the model. The consistency across sessions reflects a common understanding of the median forecasters in how aggregate shocks and monetary policy will influence the economy. Both DM and IT experience stable inflation and output in early periods 1–19, and then a brief episode at the ELB at the time of the large demand shock. These economies recover relatively quickly from this shock, al-

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though somewhat more slowly than in the simulation with RE. The experimental economies take 3-4 (4-5) periods in DM (IT) to lift off from the ELB compared with 2 periods under RE. By the end of the sessions, participants have learned to form very stable expectations.

The stability of IT and DM in our experiments may be due to the relatively high responsiveness of policy to both output and inflation. The coefficients in our DM are the strongest considered in the literature. For example, Cornand and M'baye [2018] and Hommes et al. [2019b] study flexible IT mandates (interest rate responding to both inflation and the output gap) with a relatively small coefficient on output gap ($\phi_x = 0.5$), while Kryvtsov and Petersen [2013] consider coefficients of as high as $\phi_x = 1$. Hommes et al. [2019b] show that in the presence of backward-looking expectations, a strong response to output is important for stabilizing output and inflation.

The dynamics of inflation and output indicate that AIT-4 is capable of stabilizing the economy similarly to IT and DM, whereas AIT-10 delivers less stability and reports less consistency across sessions than in IT, DM, and AIT-4 (Figure 4). The lift-off from the ELB takes four periods in both AIT treatments similarly to IT and DM. A stronger performance of AIT with a shorter horizon is consistent with Amano et al. [2020], who find that in a two-agent New Keynesian model with a fraction of backward-looking price setters a shorter horizon is optimal in AIT, and with the experimental results of Salle [2023].

Treatments with NGDP and PLT show more volatility and less consistency in dynamics before ELB shock than all other treatments (Figures 5 and 6). Following the ELB shock, all sessions in these regimes unravel into spiraling deflation and declining output. Only one session in each of NGDP and PLT experience some liftoff from the ELB, but eventually slide back into expectations-driven recession. Such unraveling deflationary dynamics were not observed in other policy regimes in our experiments. Evidence of deflationary spirals in the economies facing ELB have been reported in other experimental studies for IT and PLT [Arifovic and Petersen, 2017] and IT [Hommes et al., 2019a, Assenza et al., 2021].

We summarize the performance of the six monetary policy regimes in terms of their ability to stabilize inflation, output, and interest rate using the loss function (Equation 9). Table 2 and Figure 7 present losses by treatment and phase. We observe a distinct ranking between rate-targeting and level-targeting regimes. The ranking is somewhat different before the ELB shock and after it. During the stable periods 1-19, AIT-4 and AIT-10 perform better than DM and IT, which are followed by NGDP and PLT. After the ELB shock, the

performance of AIT-4 and AIT-10 deteriorates below that of DM and IT, which outperform NGDP and PLT. Overall, after the ELB shock, the rankings of the regimes decline as the degree of their history dependence increases. Wilcoxon rank order tests presented in Table 3 show that losses in DM are statistically significantly different from losses in AIT-10, AIT-4, NGDP, and PLT at 1% to 5% levels, and losses in AIT-4 and AIT-10 are statistically significantly different from losses in NGDP and PLT at 1% to 5% levels. The differences between losses in the rate targeting treatments, and differences between losses in the level targeting treatments are not statistically significant.

Based on this evidence from our experiments, we reject Hypothesis 1 about the relative stabilization performance of the six monetary policy frameworks outlined in Section 3. In our experiments, monetary regimes responding to concurrent inflation and output such as IT, DM, AIT-4, and AIT-10 outperform the most history-dependent regimes, PLT and NGDP. AIT-4 outperforms AIT-10, i.e. less history dependence results in better stabilization. The performance of the regimes declines with an increase in the extent of history dependence. Wagner et al. [2023] obtain similar results in a model with boundedly rational agents that exhibit cognitive discounting [Gabaix, 2020].

4.2   Estimation of conditional responses to demand shocks

Our experimental framework has the advantage that the exogenous process for demand shocks, r_t^n, is observed by the experimenter, enabling us to estimate the responses of endogenous variables as functions of the sequences of ϵ_t. Let $X_{k,t}$ denote individual i's forecast in period t. Using the local projections method [Jordà, 2005], we estimate for each treatment the following empirical specification for the change in $X_{i,t}$ over h periods:

$$X_{i,t+h} - X_{i,t-1} = c^h + \sum_{l=0}^{L} \beta_l^h + \epsilon_{t-l} + \sum_{n=0}^{N} \delta_n^h X_{i,t-n} + D_s + S_i + error_{kst}^h. \qquad (11)$$

Specification 11 conditions on the history of shocks ϵ_{t-l} and lags of endogenous aggregate variables $X_{i,t-n} \in \{x_{i,t-n}, \pi_{i,t-1}, i_{i,t-1}\}$ where $L = N = 2$. We estimate the pre-shock and post-shock periods separately with panel regressions that include session dummies, D_s, and subject fixed effects S_i. Standard errors for estimated coefficients are clustered at the session level. For the responses of aggregate variables, we estimate Specification 11 using the session-level change in aggregate variables over h periods. The estimated responses of forecasts to a $+1\%$ aggregate demand shock are presented in presented in Figure 8, while estimated responses of aggregate variables can be found in Figure D4 in the Online Appendix D.4.

Estimations are performed separately for pre-shock (blue line) and post-shock (green line) periods to highlight the effects of learning and brief episodes at the ELB.[5] Finally, the predictions of the FIRE model are included as red dashed lines to showcase the information frictions associated with different monetary policy regimes.

In the FIRE model, a positive and persistent demand shock increases output gap and inflation expectations on impact. In turn, aggregate variables rise, though stabilized both through the direct effects and expectations channel of monetary policy. History-dependence in monetary policy does not necessarily reduce the volatility of the macroeconomic variables on impact but does increase the speed at which the economy reverts back to the steady state, leading to overall lower deviations of the economy from steady state.

We begin with the rate-targeting treatments. Inflation and output gap expectations respond on impact to aggregate demand shocks in most treatments. In the rate targeting treatments, the initial responses of output gap expectations tend to be more muted than predicted under rational expectations and respond with a one-period lag. There is a distinct oscillatory pattern in expectations characteristic of a backward-looking component in beliefs, particularly trend-extrapolative expectations. These oscillatory dynamics in expectations are more pronounced when participants are inexperienced. We document individual-level forecasting heuristics in more detail in Section 5.

Under IT, inflation expectations increase significantly on impact of the shock, and are not significantly differently than predicted by the FIRE model. In all other rate-targeting treatments, inflation expectations increase on average in response to the shock, but not significantly when subjects are inexperienced. By the second phase of the experiment, inflation expectations are consistently responsive to shocks, indicative of learning and coordination of participants' forecasting heuristics. The DM regime produces the most stable expectations, both in the pre- and post-shock phases. We attribute this to both variables being well-managed, which in turns serves to further anchor both types of expectations. The behavioral advantages of a more aggressive policy response to output gaps has also been documented in Hommes et al. [2019b].

Level-targeting mandates produce far more heterogeneous responses in expectations. Compared with the other treatments, PLT output and inflation expectations are highly responsive

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[5]We plot only the pre-shock estimations for the level-targeting mandates as post-shock dynamics are explosive and very noisy.

to shocks when participants are inexperienced, and not significantly different from what is predicted by the FIRE model. In NGDP, we observe relatively muted responses. Unlike in the rate-targeting treatments, expectations overshoot the steady state and trend downward. This is a consequence of poorly managed expectations and monetary policy growing increasingly out of sync with the economy.

5   Why do history-dependent regimes not work better?

In this section, we show that the weak performance of history-dependent regimes in the experiments is due to a combination of participants having difficulty understanding these regimes ("don't get it") and the central bank having difficulty establishing their credibility ("don't buy it"). Limited comprehension of the regimes manifests itself in two ways: not enough participants forecast in the correct direction and, of those that do, forecasts fall short of what is rational and necessary to pull economies out of their deflationary spiral ("too little"). Even those who do try to forecast in the correction do so "too late."

5.1   Challenges in understanding monetary policy

5.1.1   Policy-consistent expectations

As the first assessment of the experimental participants' understanding of different monetary policy regimes, we analyze whether their forecasts are in the policy-consistent direction. Forecasts are *policy-consistent* if a participant adjust expectations in the direction intended by monetary policy. The shares of policy-consistent expectations of inflation and output are presented for each treatment in Table 4.[6]

During the pre-shock phase, about 50–60% of inexperienced subjects exhibit policy-consistent expectations for inflation or output, and about 30% of subjects demonstrate policy consistency in both forecasts. There is little difference in the prevalence of policy-consistency across treatments. On impact of a large aggregate demand shock in periods 20 and 21, the share of policy-consistent inflation forecasts increases sharply. That is, large shocks appear to temporarily reduce participants' inattention, as predicted by theory of rational inattention [Sims, 2010] and observed in the lab [Khaw et al., 2017]. The timing in this spike of attention during a significant and unfamiliar shift to the ELB is consistent with theoretical work by Mackowiak and Wiederholt [2009] who show that increased uncertainty increases

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[6]Time series are presented on Figure E2 in Online Appendix E.

rationally-inattentive agents' attention to shocks.

As the shock dissipates and fundamentals revert to the steady state, attention to the shock declines and the share of policy-consistent expectations falls significantly in most treatments. The decline is most pronounced under level-targeting frameworks, NGDP and PLT, for both inflation and output forecasts. Only 18% of NGDP participants and 26% of PLT participants hold policy-consistent forecasts in the post-shock phase, as these economies destabilize. We attribute the relatively larger decline in the policy consistency of expectations to the higher complexity associated with the make-up strategies of the level-targeting regimes. We discuss this in more detail in Section 5.2.

Even policy-consistent expectations fail to adjust sufficiently in response to the current economic fundamentals. Policy-consistent forecasts are closer to the rational solution than policy-inconsistent, but they fall short of what would have been expected if they had fully internalized the stabilization properties of monetary policy (Figures 9 and 10).

Importantly, the expectations channel of monetary policy is undermined by the lack of internalization of monetary policy in participants' expectations. These challenges in understanding are present across all regimes, but are more consequential in the frameworks with a higher degree of history-dependence. The rate-targeting regimes appear to be more robust to the weak understanding than level-targeting frameworks.

5.1.2   How people form expectations

We next evaluate the extent of common understanding among forecasters across different monetary policy regimes. We use the session-level interquartile range of inflation and output gap forecasts as a measure of dispersion across forecasters. Higher dispersion indicates more disagreement and less common understanding among forecasters. The dynamics of forecast dispersion are presented in Figure 11 and Table D2 in Appendix D1.

The dispersion in both inflation and output forecasts is consistently higher in level-targeting regimes than dispersion in the rate-targeting regimes, and dispersion is similar across IT, DM, AIT-4 and AIT-10. Disagreement in forecasts rises on the impact of the large aggregate demand shock in all regimes. And while it declines in all rate-targeting regimes after the shock, it grows larger in PLT and NGDP post-shock. The elevated disagreement in level-targeting regimes points to higher complexity of these particular frameworks relative to rate-targeting regimes.

The heterogeneity in expectations encourages us to examine in detail how people form their expectations. We analyze the distribution of forecasting models observed in all policy treatments. We consider several types of expectation models observed in surveys and used in the estimation of DSGE models [Milani, 2012]: ex-ante rational or model consistent expectations [Muth, 1961, Sargent and Wallace, 1975], cognitive discounting [Gabaix, 2020], constant gain learning [Branch and Evans, 2006], anchoring on targets [Coibion et al., 2018], and extrapolative trend-chasing [Frankel and Froot, 1990, Bordalo et al., 2020]. We assign a type to each participant that best fits their forecasting behaviour for each phase of the experiment. Interested readers can find more details of our approach and results in Online Appendix E.

Participants are rarely classified as ex-ante rational in either their inflation or output gap forecasts. Fewer than 5 percent of participants in any treatment can be classified as rational or *model consistent*, and in some cases, this share is close to zero (Figure E1 in Online Appendix E). Participants do not sufficiently appreciate how economic fundamentals and monetary policy will influence aggregate dynamics.

Backward-looking expectations – extrapolative and constant gain learning – are the dominant forecasting models, accounting for more than 90 percent of participants in each treatment. Trend-extrapolation is the most frequently-used model in all regimes ranging from about 50% in PLT to over 90% in DM, with similar shares during pre-shock and post-shock periods.

Given the prevalence of extrapolative expectations, we compare the empirical cumulative distribution functions of the trend-extrapolation parameter τ assigned to extrapolative forecasters in different treatments. Figure 12 plots these distributions for inflation and output forecasts for pre-shock and post-shock periods. Pre-shock, there is relatively little difference across treatments in the distribution of the strength of the response to past trends. The median subject has an assigned τ parameter between 0.1 to 0.4, depending on the treatment. By contrast, in the post-shock phase, we observe notable differences in how participants extrapolate trends across treatments. Subjects in rate-targeting treatments are significantly less responsive to past trends in inflation and output than those in level-targeting regimes. In the rate-targeting treatments, trend-chasing is characterized by a median value of a trend-chasing parameter of roughly zero, indicative of simple naïve forecasting. In PLT and NGDP, trend-chasing is very strong, with parameter τ close to or greater than 1. It is typically assumed that the formation of expectations is policy invariant. Our findings, together with Assenza et al. [2021], show that expectations of experimental participants tend to self-organize on

different forecasting models depending on the monetary policy regime.

As discussed earlier, the share of policy-consistent expectations declines in PLT and NGDP post-shock. Instead of forming their expectations based on the make-up strategies built in level-targeting frameworks, participants react more strongly to recent trends to catch up with economic dynamics. Strong trend-extrapolation further destabilizes the economy and leads to explosive deflationary dynamics in PLT and NGDP regimes following the ELB shock.

5.2   Framing and complexity of history-dependent frameworks

In this section, we disentangle the role of history-dependence versus the role of framing in the management of expectations. We first evaluate the extent of complexity in history-dependence by comparing expectations across the rate targeting treatments: a comparison of IT, AIT-4, AIT-10 and PLT allows us to understand the role of history dependence as the reaction horizon increases. We then examine PLT and AIT-10 to assess the role of framing in the management of expectations. The objective of monetary policy in PLT is formulated in terms of a price level target, while the objective of AIT-10 is specified in terms of the inflation rate. Theoretically, under RE, the performance of AIT approaches that of PLT as the horizon of AIT increases to infinity. Experimentally, AIT-10 has a sufficiently long reaction horizon to compare effectively with PLT to understand the question of framing.

Cognitive complexity is likely to be heightened in history-dependent monetary policy regimes. People need to understand the central bank's make-up strategies in order to form policy-consistent expectations. To do this, they need to pay attention to historical data. As the degree of history-dependence increases (from IT to AIT-4 and to AIT-10), the complexity of the forecasting task increases for participants as they need to review more of the past information, as our interface does not provide the historical average inflation rate. By contrast, in concurrent rate-targeting frameworks such as IT an ex-ante rational forecaster would only need to respond to expected fundamentals.

In the most history-dependent regime, PLT, participants need to translate the deviations of the price level from the price level target into the inflation rate necessary to achieve the price target. However, on the historical dimension, PLT may be viewed as less cognitively demanding than AIT-10 because the most recent price level deviation embodies all the past inflation deviations from target, i.e. participants do not need to review as much history.

We find that the rate targeting policies with different history dependence result in comparable aggregate stability and understanding of these regimes. The shares of policy-consistent forecasts and dispersion across the forecasts are similar across all rate targeting regimes (Figures 9, 10 and 11 discussed in earlier sections) . Moreover, the degree of trend-extrapolation is not notably different across these rate-targeting frameworks both before and after the shock (Figure 12.

These similarities indicate that history-dependence presents limited cognitive challenge. Rather, the big difference in all of these measures emerges when we compare PLT with the rate-targeting regimes. On all the metrics of understanding, PLT performs substantially worse, suggesting that framing the target in terms of the price level is much more difficult for people to process.

5.3 The evolution of central bank credibility

We next evaluate how a central bank's performance in achieving its targets influences its credibility and how credibility evolves over time. A proxy for a subject's credibility in the central bank is if the subject forecasts in the direction intended by the monetary policy, i.e. forms policy consistent expectations about inflation. We use the indicator variable $\mathbb{1}_{i,t}^{PolicyConsistent}$ that takes the value of one if participant i forms a policy-consistent expectation of $t+1$ in period t, as described in Section 5.1.1, and zero otherwise. The level of credibility thus tracks the share of policy-consistent expectations. We showed earlier in Table 4 that the share of such beliefs is relatively low and declines for most of the regimes in the post-shock period (see Section 5.1.1).

Recent central bank performance is measured as the absolute deviation of inflation from the central bank's target, $AbsDevFromTarget_{t-1}$. For IT and DM, we calculate the absolute deviation of inflation from the inflation target of zero. For AIT-4 and AIT-10, we compare the average inflation over the past four and ten periods with the target of zero. For PLT and NGDP, we compare the most recent price level and nominal GDP level with their respective targets of 1000. Finally, we control for persistence in credibility by including a one-period lag of the indicator variable in our specifications. We estimate the following panel logit regressions by treatment over our pre- and post-shock data:

$$\mathbb{1}_{i,t}^{PolicyConsistent} = \alpha + \beta_1 \mathbb{1}_{i,t-1}^{PolicyConsistent} + \beta_2 AbsDevFromTarget_{t-1} + \beta_4 \mu_i + \epsilon_{i,t} \qquad (12)$$

where μ_i is the subject fixed effect and $\epsilon_{i,t}$ are robust standard errors. Results are presented in Table 5.

Credibility is initially linked to the central bank's performance in the rate-targeting treatments. As deviations from target increase, participants in the rate-targeting frameworks are more likely to believe that the policy will restore inflation to its target. However, in level targeting regimes, deviations from target have neither a sizeable nor significant effect on credibility. This lack of response to economic conditions is further evidence of the additional complexity of the level-targeting frameworks.

We find that there is very strong persistence in central bank credibility. The persistence in credibility becomes stronger in the post-shock phase, and especially in the history-dependent regimes. The participants' credibility in policy become highly entrenched and participants are much less likely to adjust their credibility as the central bank's performance changes.

Our results demonstrate the challenge in restoring credibility after its been lost. In the post-shock phase, deviations from target are no longer linked to credibility in most treatments. With established forecasting models, participants respond more to recent trends in inflation than the level of deviations of inflation from target when forming their expectations. This higher persistence in credibility during the post-shock phase is discouraging because the level of the credibility is notably lower during this period (Table 4).

6 Improving learning of level-targeting mandates with central bank communication

Our experiments demonstrate how challenging it is for people to forecast under level-targeting mandates. Many people fail to understand that the central bank must bring the price level back to target, and even fewer people understand how much of a make-up strategy is necessary. One solution is to provide central bank guidance about the implied path of inflation. Recent research has demonstrated that relevant and precisely communicated point projections can effectively reduce the complexity of forecasting and guide expectations [Mokhtarzadeh and Petersen, 2020, Rholes and Petersen, 2021, Petersen and Rholes, 2022].

In a final treatment, PLT Comm, we extend our PLT treatment by introducing central bank communication of precise projected paths of inflation and the output gap to reduce the complexity of the task of forecasting inflation in price level targeting framework. We provide both qualitative and quantitative information. Participants were informed whether the price level was above (below) target, that the central bank would respond by increasing (decreasing) the interest rate, and the impact higher (lower) interest rates would be expected to have on inflation and output. Precise point projections were presented to participants on the charts on their screens as green point forecasts extending beyond the inflation and output gap time series for the next five periods. Subjects were told in the instructions that the projections were constructed using the data-generating process, and in particular, the exogenous shocks and recent price level. Six sessions of PLT Comm were conducted in July 2022 using the same protocols described in Section 2.

Aggregate dynamics from PLT Comm are presented in Figure 13. In both phases of the experiment, the communicated projections result in highly stable inflation and output gap dynamics, significantly outperforming all treatments in terms of minimizing aggregate losses (Table 2). Only one of the six sessions experiences a significant deflationary episode at the ELB that does not recover. The session-level differences in aggregate losses between PLT Comm and all other treatments are highly significant pre-shock when we consider all sessions, and post-shock when we exclude the outlier session 5 (Wilcoxon rank sum pairwise test in each phase, $p < 0.05$).

The increased economic stability is due to a notable change in the distribution of expectation models. Figures showing the distribution of expectation models are in Online Appendix F. The share of participants exhibiting trend-extrapolative models in their inflation forecasts declines from 55% in PLT (both phases) to 36% in the pre-shock phase and 43% in the post-shock phase in PLT with communication. We also observe an increase in ex-ante rational forecasting in the pre-shock phase from 2.2% in PLT to 7.1% in PLT with communication. Table 4 shows that the majority of PLT Comm participants in all phases of the experiment are able to forecast both variables in the correct direction. More than 60% of PLT Comm participants are able to form policy-consistent expectations during the pre-shock phase, while it is less than one-third in all other treatments.

We evaluate the effects of recent deviations of price level from target and the most recently observed inflation from the central bank's projected value, $|\pi_{t-1} - \pi_{t-2,t-1}^{Proj}|$ on the central

bank credibility. Results are presented in the last two columns of Table 5. Credibility in PLT Comm is considerably more persistent than in all other treatments, but fortunately initial credibility is relatively high. Similarly to our findings in the rate-targeting treatments, during the pre-shock phase, PLT Comm participants maintain their confidence in the central bank when either the price level deviates more from target or inflation deviates more from the projected value. And, as participants become more experienced, their credibility becomes more entrenched, as in all the other treatments. Even with communication, our findings emphasize the importance of establishing credibility early on and maintaining it carefully.

7 Conclusion

We have shown that history-dependent regimes do not work as well as previously suggested. We identify reasons *why* these frameworks fail to perform. These reasons are related to the complexity of these regimes and its impact on the formation of expectation resulting in weakened expectations channel and credibility. Our findings provide us with valuable insights into the design of monetary policy.

First, we provide evidence that shorter history-dependence works better. A small amount of history-dependence can work well to guide inflation expectations, however, too much history-dependence can be detrimental. This is because people rely heavily on recent trends to form their forecasts and insufficiently on the path of future monetary policy and fundamentals, and fail to understand the necessary make-up strategies critical in history-dependent frameworks. Monetary policy that exhibits longer history dependence will become increasingly out of sync with the way people form expectations, and in turn, fail to manage them well.

Second, framing of the target of monetary policy plays an important role in the success of history-dependent frameworks. Framing the target in terms of the inflation rate rather than the price level significantly reduces the cognitive complexity of forecasting inflation and results in less extrapolative expectations. With better managed expectations, monetary policy can be more effective at stabilizing the economy.

Lastly, communication should be an important component of the design of any history-dependent framework. We show that communication about *relevant* macroeconomic projections of inflation rate and the output gap can effectively guide forecasts through the complexities of a price level targeting framework. It is important to choose the appropriate information to communicate. Information about evolving targets, for instance, makes salient

the inability of a central bank to achieve its target and can result in a loss of credibility [Arifovic and Petersen, 2017]. Likewise, communicating about the path of monetary policy can create more confusion as forecasters may have difficulty in translating interest rate outlooks to inflation and output gap forecasts [Mokhtarzadeh and Petersen, 2020, Kryvtsov and Petersen, 2021].

Our framework provides ample room for future research. Our experiment focused specifically on aggregate demand shocks. The "divine coincidence" may have made it easier for people to understand the ability of monetary policy to stabilize both inflation and output simultaneously. However, in the aftermath of the pandemic, there is now a renewed interest in understanding monetary policy in the presence of persistent cost-push pressures. The framework can also be used to examine in greater detail and disentangle the roles of cognitive complexity and limited common knowledge in expectation formation, especially in the presence of heightened strategic complementarities.

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Figure 1: Simulations with rational expectations
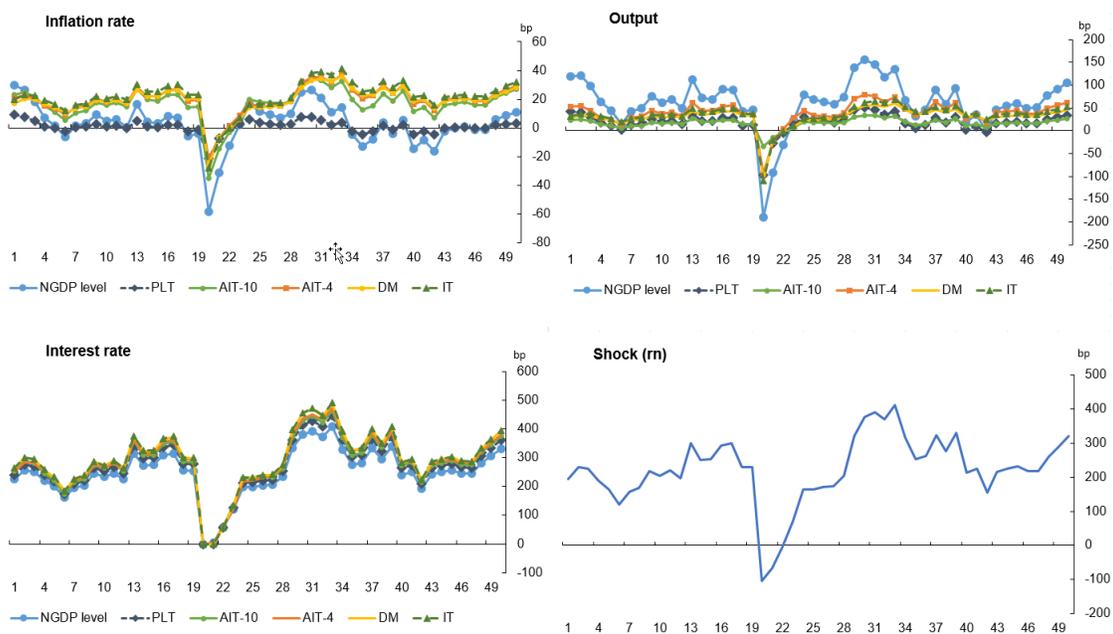
Figure 2: Summary of losses from simulations
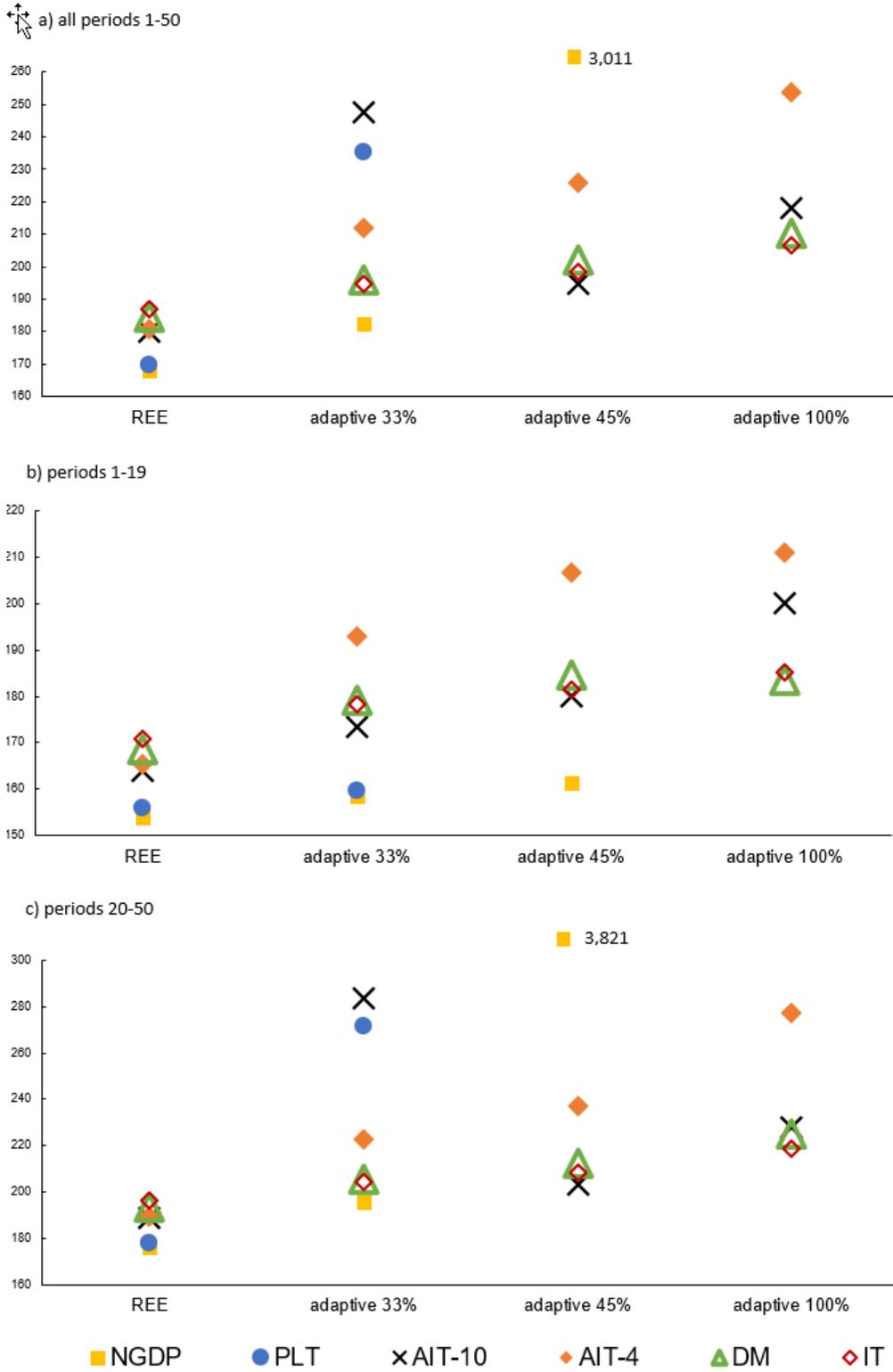
This figure shows results from simulations of New Keynesian model with rational expectations and simulations with naïve agents. We vary the shares of naïve agents from 0% (REE) to 33% (threshold in PLT), 45% (threshold in NGDP) and 100%.

Figure 3: Aggregate dynamics of inflation, output and interest rate in dual mandate (DM) and inflation targeting (IT) treatments

(a) Dual Mandate (DM)

(b) Inflation targeting (IT)

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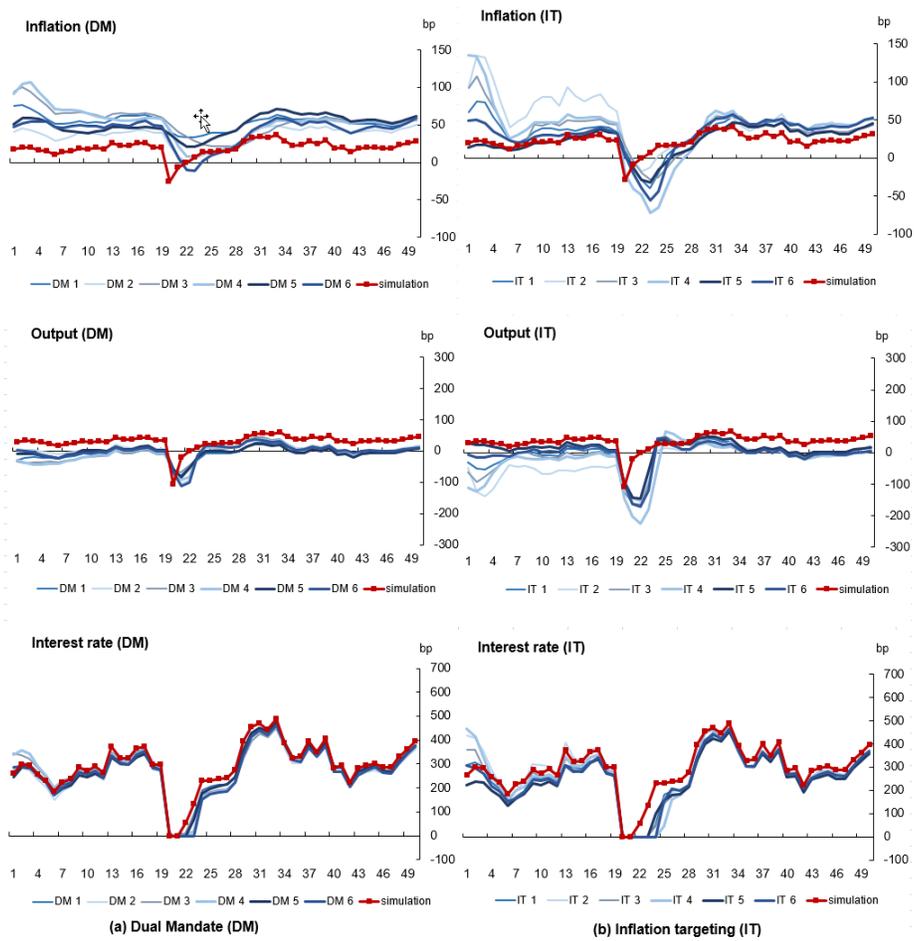
Figure 4: Aggregate dynamics of inflation, output, and interest rate in average inflation targeting (AIT) treatment
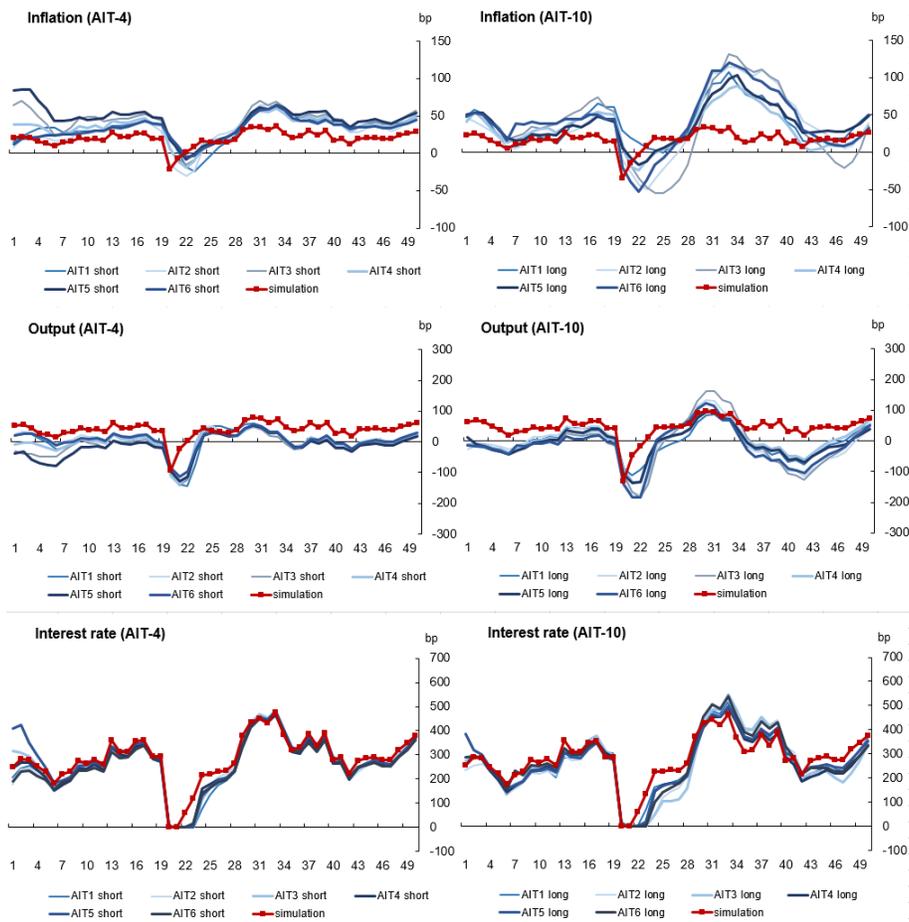
Figure 5: Aggregate dynamics of inflation, output, and interest rate in NGDP level targeting (NGDP) treatment
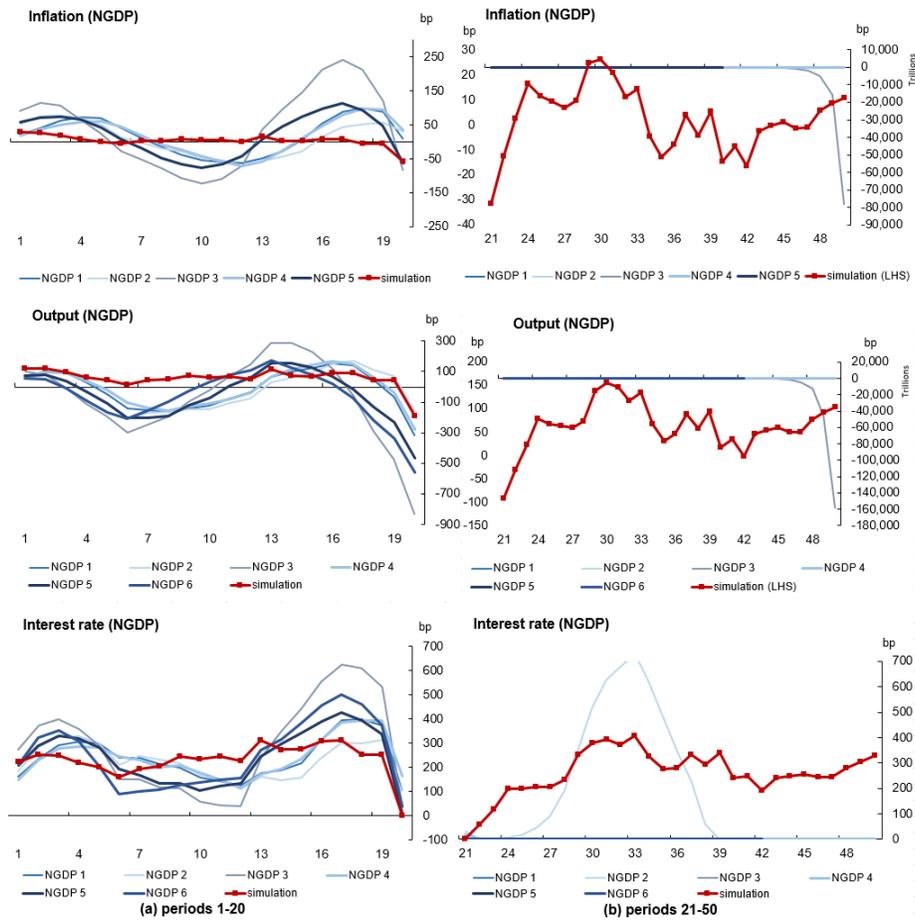
Figure 6: Aggregate dynamics of inflation, output, and interest rate in price-level targeting (PLT) treatment

(a) periods 1-25

(b) periods 26-50
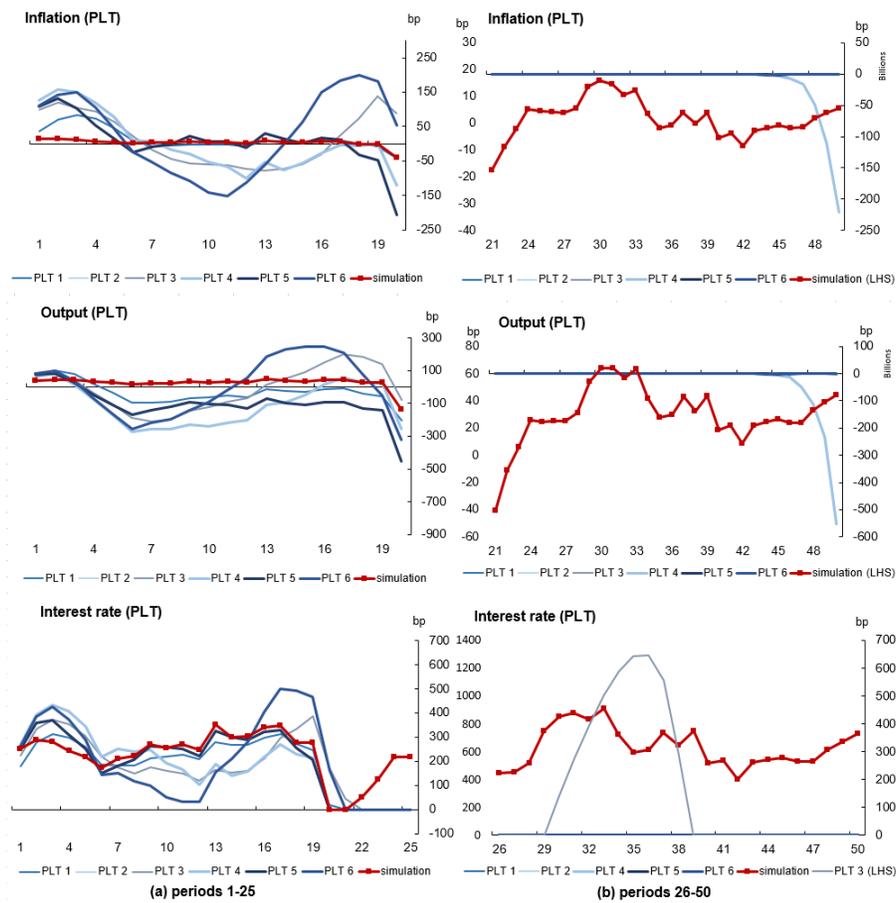
Figure 7: Distribution of session losses, by phase

(a) Pre-shock
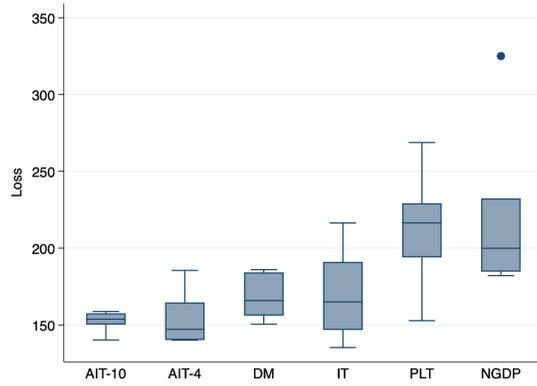
(b) Post-shock
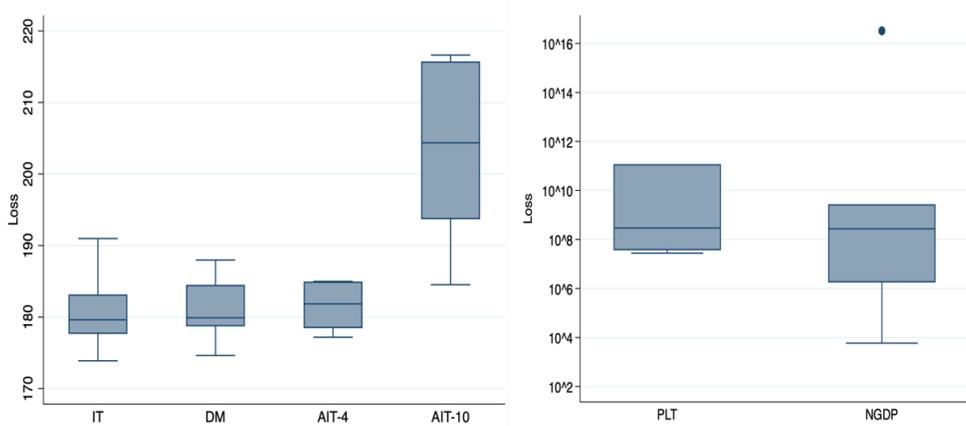
Dots in the figures represent values outside upper adjacent value (upper quartile $\pm\ 3/2$ times the interquartile range). The y-axis in Panel (b) for PLT and NGDP is a logarithmic scale.

Figure 8: Response of forecasts to a +1% demand impulse.
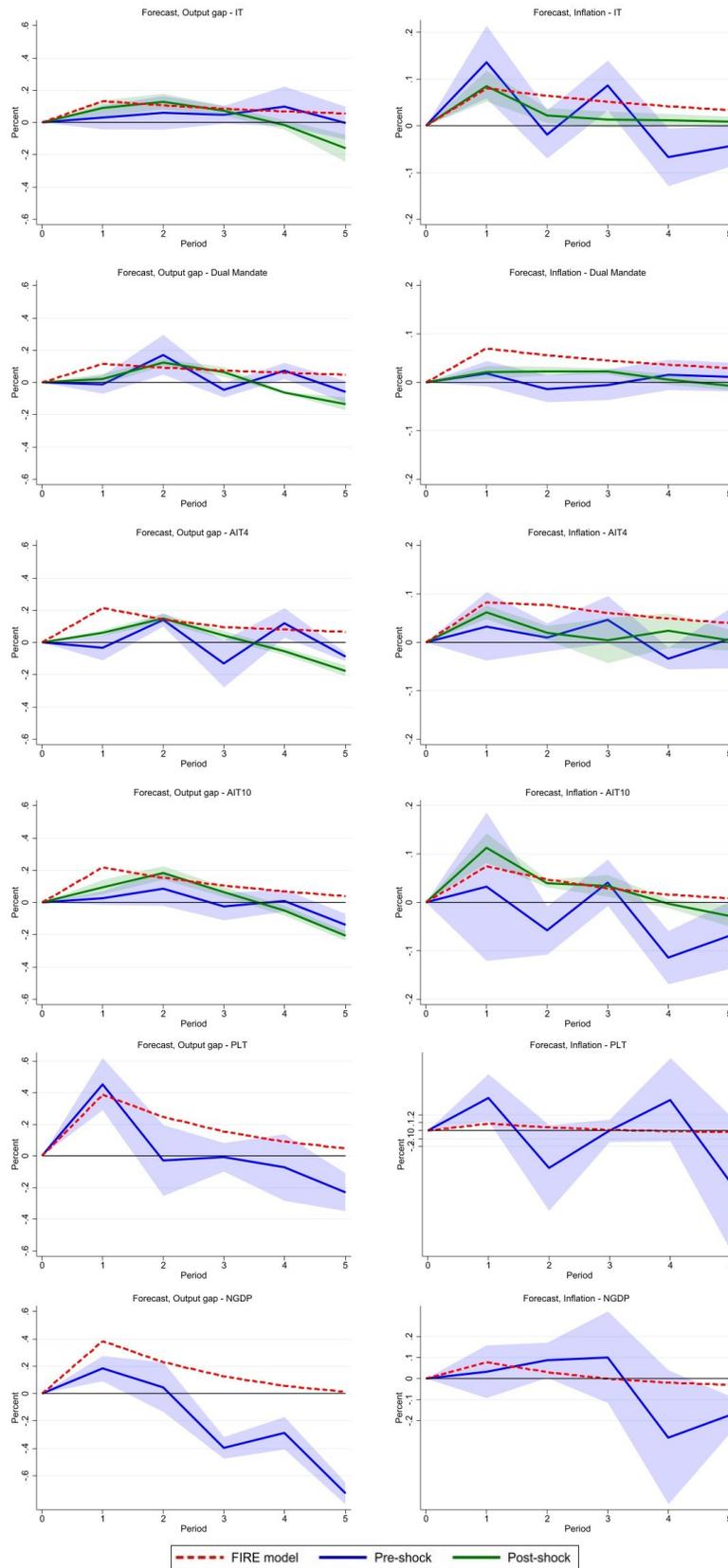
Notes: IRFs in the data are estimated by local projections using specification 11. Shaded areas denote the 90% confidence interval. IRFs in the FIRE model are the simulated responses to a one-standard deviation shock to aggregate demand.

Figure 9: Policy consistent and policy inconsistent inflation forecasts
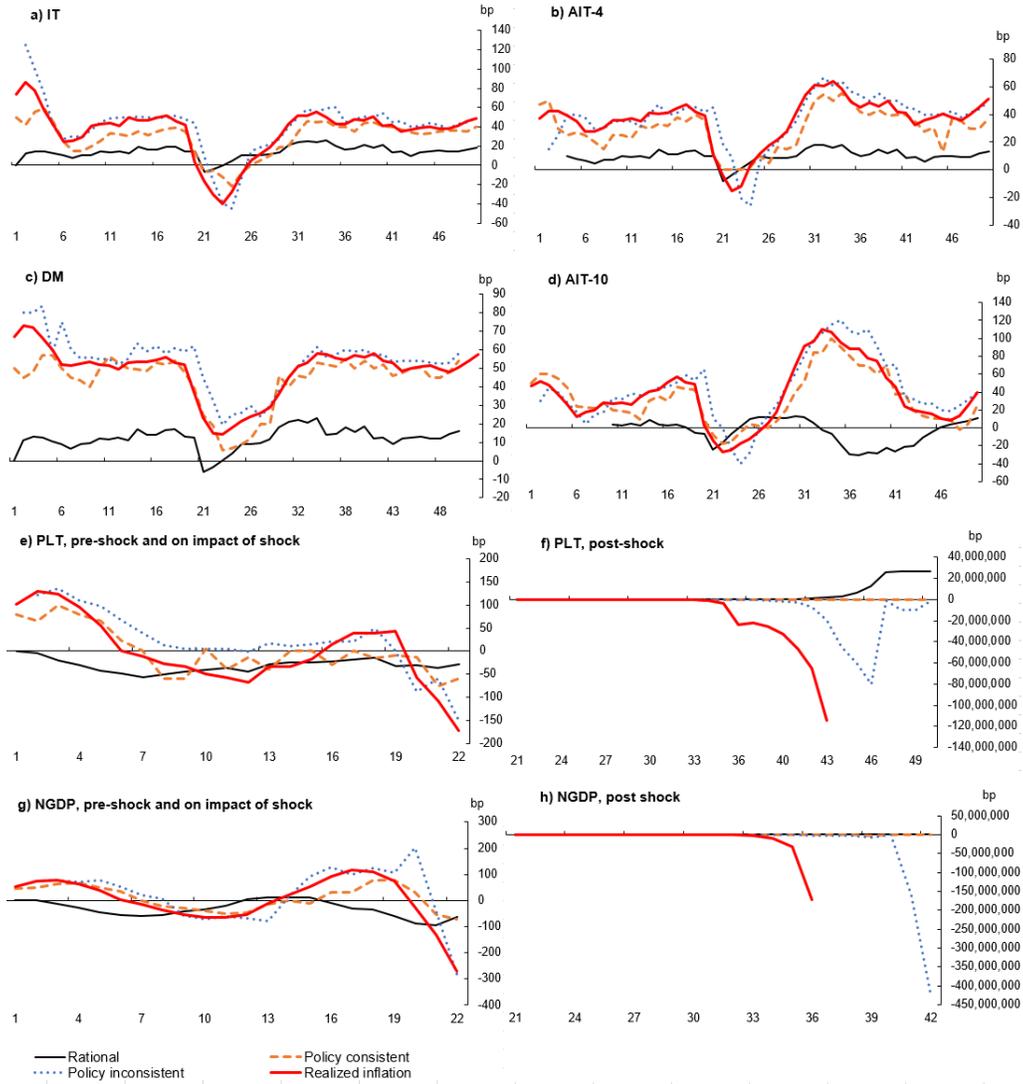
This figure presents the median policy consistent and policy inconsistent forecasts, averaged across all sessions of each treatment.

Figure 10: Policy consistent and policy inconsistent output forecasts
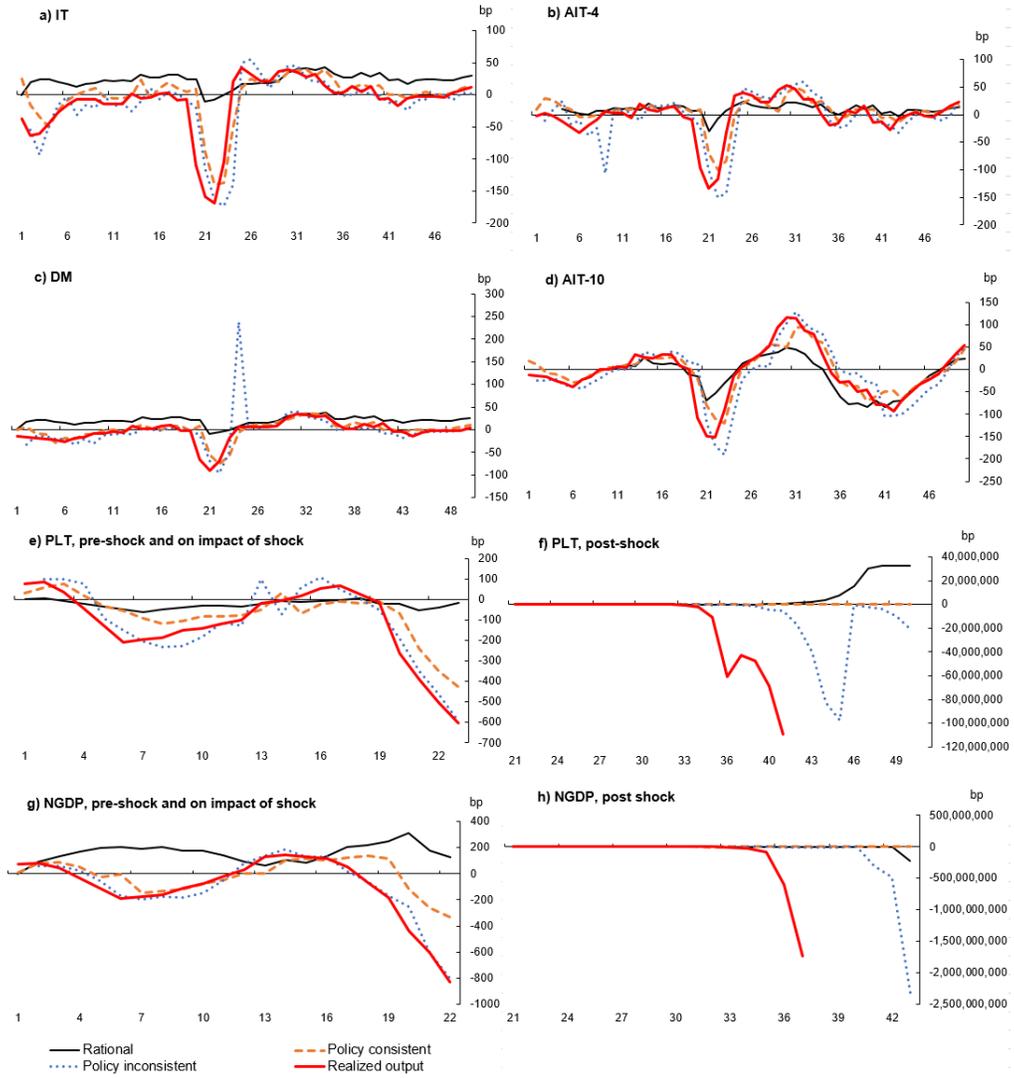
This figure presents the median policy consistent and policy inconsistent forecasts, averaged across all sessions of each treatment.

Figure 11: Dispersion of inflation and output forecasts

a) dispersion of inflation forecasts

b) dispersion of output forecasts

c) dispersion of inflation forecasts, PLT and NGDP, post-shock

d) dispersion of output forecasts, PLT and NGDP, post-shock
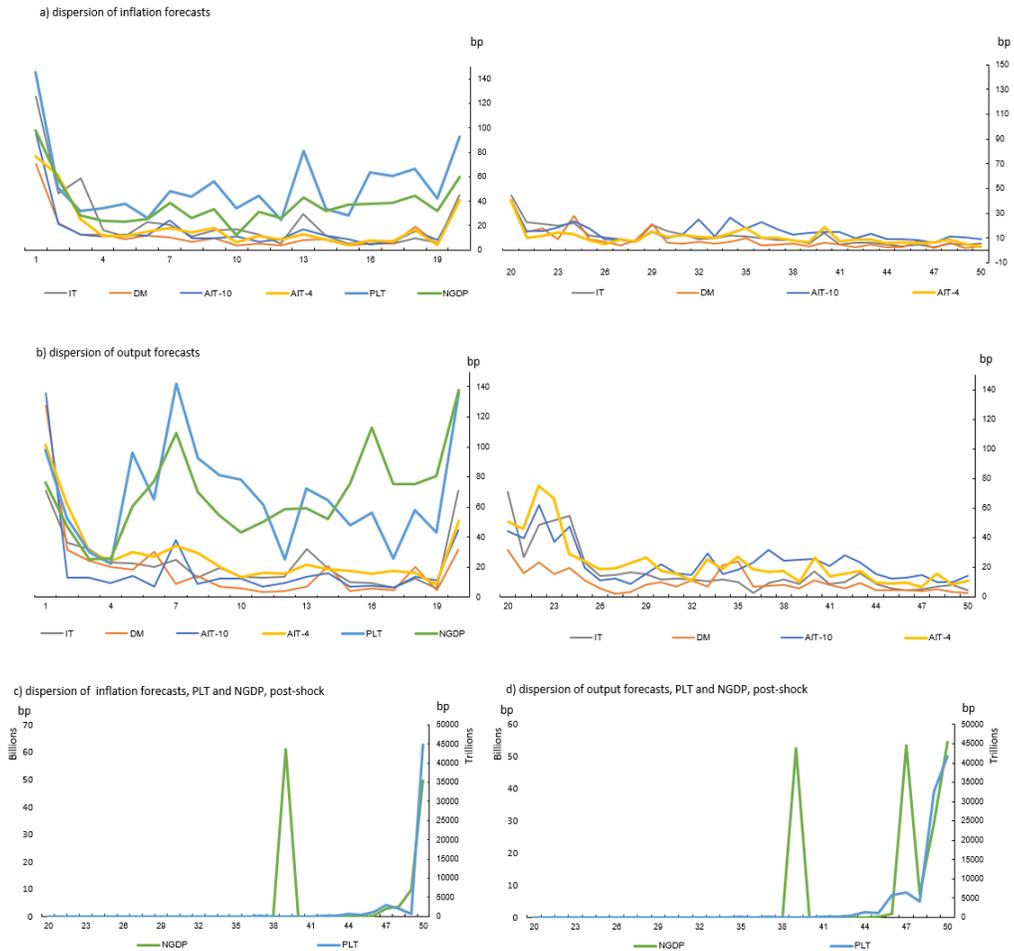
Notes: This figure presents the dispersion of inflation and output forecasts as measured by interquartile range, averaged for each period across all sessions of each treatment.

Figure 12: Distribution of trend-chasing parameter τ in inflation and output forecasts by phase
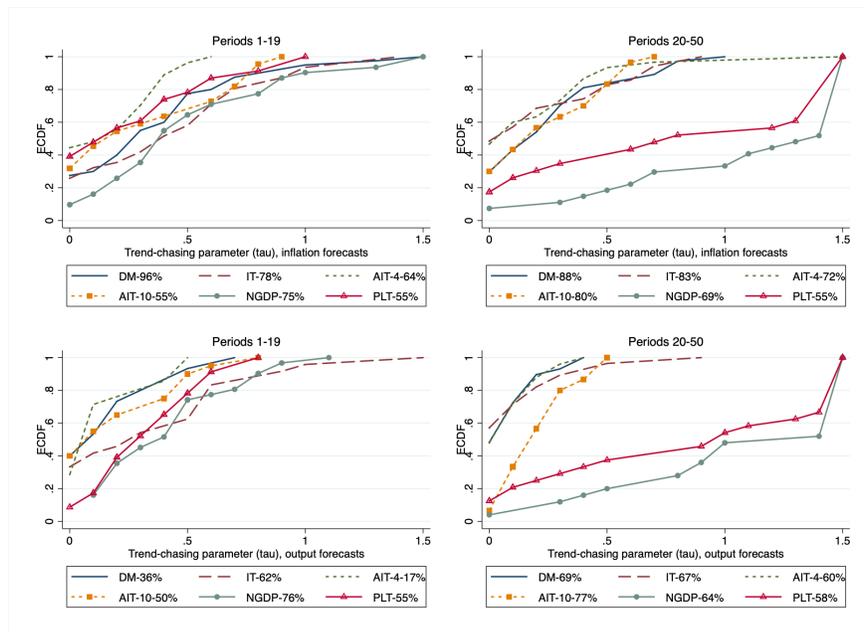
This figure presents CDFs of parameter τ for participants whose forecasts were classified as trend-chasing. Percentages in the legend indicate the proportion of forecasts classified as trend-chasing for the corresponding monetary policy regime during the phase depicted in the chart.

Figure 13: Aggregate dynamics of inflation, output, and interest rate in PLT Comm treatment
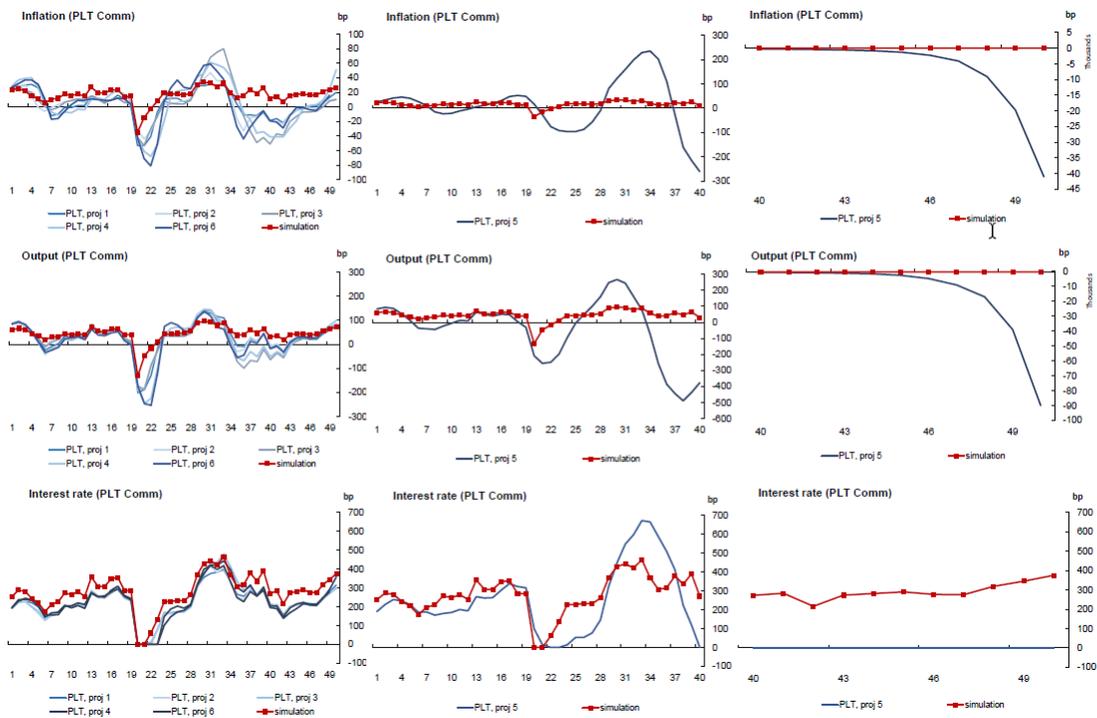
Table 1: Losses from simulations with rational and adaptive expectations

rational	(1)	adaptive	(2)
periods 1-50			
NGDP	168.2	AIT-10	194.7
PLT	169.8	IT	198.4
AIT-10	179.7	DM	202.2
AIT-4	180.8	AIT-4	226.0
DM	184.4	PLT	235.3
IT	186.9	NGDP	3010.6
periods 1-19			
NGDP	153.8	PLT	159.6
PLT	155.9	NGDP	161.4
AIT-10	164.0	AIT-10	180.1
AIT-4	165.3	IT	181.4
DM	168.5	DM	184.5
IT	170.8	AIT-4	206.8
periods 20-50			
NGDP	176.4	AIT-10	203.1
PLT	177.7	IT	208.2
AIT-10	188.7	DM	212.3
AIT-4	189.7	AIT-4	237.0
DM	193.5	NGDP	271.4
IT	196.2	PLT	3821.4

Notes: column (1) reports losses from the simulations with rational expectations. Column(2) reports losses from the simulations with a combination of rational expectations and naïve expectations. Shares of naïve expectations: 33% in PLT and 45% in all other regimes. Losses are expressed in basis points.

Table 2: Losses in laboratory experiments

Regime	Periods 1-50	Periods 1-19	Periods 20-50
AIT-4	172	154	182
DM	176	168	181
IT	177	170	181
AIT-10	186	152	203
PLT	31×10^9	213	39×10^9
NGDP	4×10^{15}	221	5×10^{15}
PLT Comm	2723 (155*)	131	3435 (169*)

This table presents losses averaged across all sessions of each treatment.
* Values in brackets exclude single outlier session.

Table 3: Wilcoxon rank order test, statistical significance

Periods 1-19					
	NGDP	PLT	DM	IT	AIT-4
PLT	0.435				
DM	0.008	0.019			
IT	0.039	0.027	0.436		
AIT-4	0.005	0.005	0.055	0.168	
AIT-10	0.002	0.008	0.027	0.212	0.261
Periods 20-50					
	NGDP	PLT	DM	IT	AIT-4
PLT	0.211				
DM	0.002	0.002			
IT	0.002	0.002	0.316		
AIT-4	0.002	0.002	0.374	0.316	
AIT-10	0.002	0.002	0.003	0.003	0.005
All periods					
	NGDP	PLT	DM	IT	AIT-4
PLT	0.211				
DM	0.002	0.002			
IT	0.002	0.002	0.436		
AIT-4	0.002	0.002	0.168	0.168	
AIT-10	0.002	0.002	0.100	0.100	0.013

Results from Wilcoxon rank order test based on the average losses from each of 6 sessions for all treatments. These results are for the hypothesis that losses in the treatments listed in the rows are equal to the losses in the treatments listed in the columns.

Table 4: Complexity and history-dependence

Panel A: Share of forecasts exhibiting policy consistent expectations

	Preshock (Periods 1-19)			Shock (Periods 20-21)			Postshock (Periods 22-50)		
	Inflation	Output	Both	Inflation	Output	Both	Inflation	Output	Both
NGDP	0.59	0.49	0.26	0.85	0.22	0.12	0.29	0.29	0.18
PLT	0.49	0.64	0.29	0.71	0.58	0.49	0.36	0.38	0.26
DM	0.47	0.49	0.25	0.63	0.56	0.27	0.36	0.57	0.16
IT	0.54	0.54	0.33	0.70	0.49	0.26	0.46	0.54	0.21
AIT-4	0.48	0.62	0.32	0.58	0.52	0.20	0.43	0.56	0.25
AIT-10	0.48	0.57	0.33	0.63	0.80	0.51	0.51	0.65	0.36
PLT Comm	0.71	0.74	0.62	0.92	0.85	0.82	0.66	0.62	0.50

Panel B: Forecast accuracy

	Preshock (Periods 1-19)		Shock (Periods 20-21)		Postshock (Periods 22-50)	
	Inflation	Output	Inflation	Output	Inflation	Output
IT	16.99	25.45	33.78	106.63	9.88	24.43
	(26.11)	(37.21)	(14.24)	(55.49)	(24.43)	(44.47)
DM	17.80	25.07	28.40	58.12	7.16	18.36
	(106.16)	(99.14)	(30.75)	(47.61)	(21.17)	(48.24)
AIT-4	21.10	33.47	28.53	81.87	16.30	27.53
	(55.13)	(77.97)	(14.96)	(53.12)	(77.97)	(38.39)
AIT-10	25.09	26.90	33.42	98.39	20.99	37.96
	(218.47)	(40.61)	(18.22)	(51.35)	(24.46)	(30.05)
NGDP	47.95	105.79	191.30	354.45	3.80E+23	3.80E+23
	(53.34)	(85.79)	(132.53)	(239.12)	(1.15E+25)	(1.15E+25)
PLT	54.99	86.92	108.60	266.84	8.53E+13	6.94E+12
	(119.57)	(96.09)	(58.39)	(122.08)	(2.83E+14)	(2.30E+14)
PLT Comm	17.64	39.31	50.34	130.12	19.10	40.66
	(45.68)	(68.39)	(132.62)	(142.61)	(34.70)	(48.40)

Panel A presents the share of forecasts in the direction of the rational expectations equilibrium solution. A forecast is *policy consistent* if it is higher (lower) than the previously realized outcome when the predicted REE is above (below) the previous outcome. *Both* indicates the share of the participants simultaneously submitting inflation and output forecasts are policy consistent. Panel B presents means (standard deviations) of absolute inflation and output gap forecast errors across phases. One outlier session in PLT Comm is excluded.

Table 5: Evolution of central bank credibility

Dep. Var. Pre-shock: Periods 1-19 $\mathbb{1}^{PolicyConsistent}_{i,t}$	IT	DM	AIT-4	AIT-10	PLT	NGDP	PLT Comm	
$\mathbb{1}^{PolicyConsistent}_{i,t-1}$	0.622***	0.364**	0.044	-0.512**	0.491***	0.492***	0.757***	0.816***
	(0.16)	(0.16)	(0.22)	(0.26)	(0.16)	(0.16)	(0.19)	(0.20)
$|\pi_{t-1} - \pi^*|$	0.024***	0.027***						
	(0.00)	(0.01)						
$|\frac{1}{4}\sum_{t-4}^{t-1}\pi_j - \pi^*|$			0.088***					
			(0.02)					
$|\frac{1}{10}\sum_{t-4}^{t-1}\pi_j - \pi^*|$				0.051***				
				(0.01)				
$|P_{t-1} - P^*|$					0.000		0.003*	
					(0.00)		(0.00)	
$|NGDP_{t-1} - NGDP^*|$						-0.001		
						(0.00)		
$|\pi_{t-1} - \pi^{Proj}_{t-2,t-1}|$								0.038***
								(0.01)
N	747	699	529	339	711	715	702	663
χ^2	51.13	15.62	34.78	29.53	9.567	13.99	16.94	37.82
p	0.000	0.000	0.000	0.000	0.008	0.000	0.000	0.000

Dep. Var. Post-shock: Periods 20–50 $\mathbb{1}^{PolicyConsistent}_{i,t}$	IT	DM	AIT-4	AIT-10	PLT	NGDP	PLT Comm	
$\mathbb{1}^{PolicyConsistent}_{i,t-1}$	0.604***	0.788***	0.463***	0.828***	1.545***	2.176***	1.172***	1.185***
	(0.12)	(0.12)	(0.13)	(0.13)	(0.13)	(0.16)	(0.14)	(0.14)
$|\pi_{t-1} - \pi^*|$	0.007	0.021***						
	(0.00)	(0.00)						
$|\frac{1}{4}\sum_{t-4}^{t-1}\pi_j - \pi^*|$			0.006					
			(0.00)					
$|\frac{1}{10}\sum_{t-4}^{t-1}\pi_j - \pi^*|$				0.001				
				(0.00)				
$|P_{t-1} - P^*|$					0.000		-0.000*	
					(0.00)		(0.00)	
$|NGDP_{t-1} - NGDP^*|$						0.000		
						(0.00)		
$|\pi_{t-1} - \pi^{Proj}_{t-2,t-1}|$								-0.000*
								(0.00)
N	1286	1287	1167	1185	1224	1044	1291	1287
χ^2	25.42	67.82	15.65	46.18	140.9	208.6	77.03	79.00
p	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

This table presents results from a series of fixed-effects logit panel regressions. The dependent variable is an indicator variable that takes the value of 1 if participant i in period t inflation exhibits policy consistent expectations. α denotes the estimated constant. NGDP post-shock results are estimated and reported with a random-effects specification due to convergence issues. Standard errors are in the brackets.