Macroeconomic Literacy and Expectations*

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Abstract

Do central bank communication and macroeconomic education campaigns improve how households form expectations? This paper provides experimental evidence that more information is not always better. We implement a macroeconomic experiment in which participants forecast inflation and output under varying levels of economic literacy and central bank target communication. Qualitative information and target communication worsen inflation forecast accuracy and disagreement by 17–70%, while improving output gap forecast performance. Precise quantitative information improves inflation forecasting relative to qualitative training, but still falls short of the no-information benchmark. To explain this asymmetry, we develop a behavioral learning model with heterogeneous beliefs and bounded cognitive capacity. A key mechanism is over-anchoring: agents interpret the communicated inflation target with a systematic downward bias — as though lower inflation is always preferred — rather than as a symmetric stabilization objective. This bias, absent for output targets, drives the deterioration in inflation expectations under communication. Our findings suggest that complex and vague central bank communication can hinder rather than anchor inflation expectations, with implications for the design of transparency and literacy campaigns.

JEL classifications: C9, D84, E52, E58

Keywords: expectations, macroeconomics, monetary policy, literacy, laboratory experiment

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1 Introduction

Do households need to understand the complex inner-workings of the macroeconomy for monetary policy to be effective? The long-standing view in policy circles had been no. So long as firms and financial markets participants understand the effects that monetary and fiscal policy have on the economy, policy is thought to trickle down to households through changes in market prices and employment opportunities. Since the 2008 Financial Crisis, however, central banks have grappled with understanding the relatively weak effect of conventional and unconventional monetary policy on public inflation expectations. One potential explanation for this poor transmission of monetary policy is that the general public has a widely heterogeneous understanding of how the economy and monetary policy evolve together (Carvalho and Nechio, 2014; Dräger et al., 2016).

This paper examines how macroeconomic literacy - that is, an understanding of the relationships between monetary policy, inflation, and production - influences the expectation formation process. This is an important avenue of study as many central banks including the Federal Reserve, Bank of England and the European Central Bank (ECB) continue to invest time and resources in designing and implementing their own education campaigns. Households' expectations about the economy affect their consumption, saving and investment decisions, which in turn affect macroeconomic outcomes. An economically literate populace would likely better understand the forces driving aggregate activity and form more rational expectations in response to policy.

To this end, we design and implement a laboratory experiment to study the expectation formation process under different macroeconomic information sets. We study expectation formation in a New Keynesian *Learning-to-Forecast Experiment* (LtFE), where the underlying economy in which participants interact evolves based on a linearized New Keynesian system of equations, exogenous and known shocks to aggregate demand, and subject-supplied macroeconomic expectations (Adam, 2007; Pfajfar and Žakelj, 2014). This simple model is widely used in policy analysis and is typically used in central bank public education documents.

The experiment was conducted on undergraduate students from a wide range of disciplines, where the vast majority of participants were not registered in an economics program. In a between-subject design, we vary the provision of information about the structure of the underlying experimental macroeconomy. The different levels of information are meant to resemble the different levels of macroeconomic literacy the public may have, ranging from absolutely no understanding of the relationship between macroeconomic variables to having the access to the central bank's forecasting model. In our baseline NoInfo treatment, participants are provided with no information about the relationship between macroeconomic variables. This environment can be thought of as a completely economically illiterate population who must learn the economy's data-generating process through experience. In our QualInfo treatment, subjects receive instructions explaining the qualitative relationship between all macroeconomic variables. This treatment mimics the qualitative education that central banks are increasingly providing to the public. In two additional treatments, we supplement the NoInfo and QualInfo treatments with information about the central bank's quantitative inflation and output gap targets. NoInfoTarget captures communication campaigns that focus solely on emphasizing the central bank's targets. The QualInfoTarget treatment seeks to improve macroeconomic literacy by providing additional qualitative details about how expectations, shocks, and monetary policy together influence the economy—much like the communication strategies of the Bank of Canada and the Bank of England. Finally, in our QuantInfo treatment, subjects receive instructions explaining in full detail the quantitative data-generating process, as one may read in a highly technical central bank's forecasting model.

In our baseline NoInfo treatment, we observe significant heterogeneity and forecast errors. Output gap expectations exhibit a notably larger upward bias (21 bps) than inflation expectations (8 bps). We attribute this difference to a home-grown preference for larger or more positive economic activity and a preference for low inflation (Afrouzi et al., 2024; Pfajfar and Winkler, 2025).

More information about the economy does not have a consistent effect on forecast performance and dispersion. Introducing information about the central bank's targets and providing qualitative information about the economy's data-generating process worsens inflation forecast accuracy. Forecast errors and disagreement increase by between 17 and 70% depending on the treatment and variable comparison. We attribute this poorer management of expectations to a combination of cognitive overload associated with the expanded information set and an *over-anchoring* of inflation expectations downwards due to information about the inflation target.

We observe the opposite with output gap forecasts, with targets and qualitative information significantly reducing forecast errors and dispersion. The significant upward bias in output expectations observed in the NoInfo and QualInfo treatments are effectively eliminated by information about the central bank's output gap targets. Qualitative information also helps to reduce forecast errors and dispersion by providing clarity of the variables that matter in determining output gaps. Subjects do, however, form more accurate and better-coordinated inflation forecasts when provided with precise quantitative information about the economy's structure. Relative to the QualInfoTarget treatment, mean inflation forecast errors in QuantInfo fall by 23% and disagreement by 32%. These improvements reflect greater clarity about the role of inflation expectations in driving inflation dynamics. However, compared to NoInfo, forecast errors are 66% higher, indicating that the additional information substantially increases the cognitive complexity of the forecasting task.

To interpret the experimental findings, we develop an empirically disciplined behavioral learning model that extends on the seminal framework by Arifovic et al. (2013), which embeds heterogeneous expectations in a New Keynesian environment and models their evolution through a parsimonious evolutionary learning process. Our model extends the evolutionary learning framework of Arifovic et al. (2013) in two directions: by disciplining initial beliefs with laboratory evidence and by incorporating bounded cognitive capacity and a target-induced bias. That is, our simulations are initialized by the observed *early-phase* forecast distributions of participants across treatments in the lab to capture the effects of the information treatments on initial forecasts of subjects. The model incorporates empirically grounded heterogeneous initial beliefs, finite information-processing capacity, endogenous target credibility, and a target-induced distortion in inflation expectations, and maps these ingredients into computerized counterparts of the five laboratory treatments. Within this framework, we replicate the controlled laboratory setting by holding the pool of agents fixed while varying the information treatment.

The simulations reproduce the main disparity observed in the data: while more macroeconomic training can improve output forecasts; for inflation forecasts, additional information worsen forecast accuracy and disagreement. In our model, this occurs because a fixed learning capacity must be allocated across more forecasting objectives (cognitive capacity is limited), and target communication further increases the dimensionality of the inflation-learning task through the additional target credibility updating. More importantly, our main behavioral specification—in which agents interpret the communicated inflation target through an asymmetric downward subjective bias (an over-anchoring effect), consistent with the negative skewness observed in the initial belief distributions of laboratory participants under target treatments—reproduces the experimental treatment effects. In particular, it links target communication to the deterioration in inflation forecast accuracy and the increase in disagreement among agents with limited macroeconomic training who are additionally informed about the targets. By contrast, benchmark specifications with no inflation target-induced bias or with a symmetric bias cannot account for the patterns observed in the lab. For output forecasts, the model suggests that communication about the output target does not induce a systematic behavioral bias (or over-anchor), but primarily serves to anchor and dampen expectations toward the target. Taken together, the results point to an asymmetric interpretation of communicated policy targets: agents appear to interpret the inflation target in a downward-biased manner, as though lower inflation were always preferred, rather than understanding the true central bank's objective as symmetric stabilization around the target. This mechanism does not appear to extend to output forecasts.

Our simulation results suggest that the effects of varying macroeconomic training arise from the interaction of the initial beliefs, bounded cognitive capacity, and importantly a downward interpretation of the inflation target. A key advantage of the model is its parsimony: it adds tractably a number of empirically grounded ingredients; namely, the initialized beliefs, finite information-processing capacity, endogenous target credibility paired with a target-induced bias, to an otherwise standard New Keynesian evolutionary learning environment (to be reviewed below). Precisely because it is lightweight, the framework can be disciplined with observed moments from laboratory or survey expectation data and then used for policy counterfactuals, such as comparing communication strategies, target regimes, or the robustness of policy rules when expectations are heterogeneous in the informational dimension (e.g., when agents have different lifetime experience, see, for instance Malmendier and Nagel, 2016). Our model complements the experimental evidence by extending it into a tractable framework for policy analysis, allowing policymakers to evaluate the implications of informational frictions and belief dynamics.

The paper is organized as follows. Section 2 discusses related empirical and experimental literature on expectation formation and financial literacy. Section 3 lays out our experimental design and hypotheses. Section 4 presents our experimental results and Section 5 our behavioral model and simulations. We conclude with a discussion and policy recommendations.

2 Related Literature

Standard macroeconomic models typically assume that agents understand the structure of the economy, including the relationships between monetary policy, inflation, and output. This assumption underlies the effectiveness of the expectations channel of monetary policy. However, a large empirical and experimental literature shows that, in practice, agents' beliefs are heterogeneous and often inconsistent with basic macroeconomic relationships (Mankiw et al., 2003; Croushore, 1997; Carvalho and Nechio, 2014; Dräger et al., 2016; Coibion and Gorodnichenko, 2015; Hommes, 2021). These findings suggest that limited macroeconomic literacy—rather than purely non-rational behavior—may be a key constraint on the formation of expectations.

This paper contributes to a growing literature on how individuals' understanding of the economy shapes their expectations. Survey evidence suggests that knowledge of core macroeconomic relationships is often limited. Dräger et al. (2016) find that both households and professional forecasters frequently form expectations inconsistent with the Phillips curve and Taylor rule, indicating that many agents do not internalize the relationships underlying standard policy models. More broadly, economic literacy is strongly correlated with education, income, and macroeconomic conditions (Jappelli, 2010), while less economically literate individuals tend to hold more biased and dispersed expectations (Bruine de Bruin et al., 2010). Experimental evidence similarly links literacy to expectation accuracy: Burke and Manz (2014) show that financial literacy is positively associated with inflation forecast accuracy in an incentivized setting. However, most existing studies treat literacy as a fixed individual characteristic. In a similar vein to Hommes et al. (2026) and McMahon et al. (2026), our approach treats macroeconomic literacy as an experimental object by directly varying participants' narratives of the economy through different types of structural information. This allows us to identify the causal effect of macroeconomic literacy on expectation formation.

Communicating inflation targets can influence household and firm expectations, but the effects depend critically on message design, salience, and public understanding and informedness (Walsh, 2009; Binder, 2017; Binder and Rodrigue, 2018; Cornand and M'baye, 2018a,b; Coibion et al., 2022; Ehrmann et al., 2022). Experimental evidence for U.S. households shows that simply informing respondents of the central bank's inflation target can shift expectations by roughly as much as providing full policy statements, indicating that clear, direct communication may outperform more technical announcements. However, these effects are often temporary and heterogeneous across individuals, reflecting limited attention and varying levels of economic literacy (Coibion et al., 2022). Using the European Commission (EC) household survey data (Eurobarometer) spanning from 1985 to 2008, Ehrmann et al. (2012) finds that while enhanced economic transparency and the announcement of quantified inflation targets are clearly noticed by the public, and can successfully lower the average level of inflation expectations across the population, transparency does not reduce disagreement. While the average survey respondent predicts lower inflation, the dispersion (or variance) of beliefs remains unchanged. In other words, the central bank's message acts as a signal that shifts the public's thinking in the same direction, but it fails to bridge the gap between diverse individual viewpoints.

A growing literature examines whether greater central bank transparency can become counterproductive when households and firms face limited attention or constraints in processing information. In these environments, the issue is not simply how much information is released, but whether economic agents can absorb and interpret it effectively. When communication becomes overly detailed, frequent, or technically complex, agents may ignore key messages, rely on heuristics, or misinterpret policy signals. Sims (2003, 2010) formalizes this idea through rational inattention, showing that information-processing capacity is scarce and must be allocated selectively. Applied to monetary policy, Reis (2013) argues that optimal transparency depends on the public's ability to use disclosed information, implying that more communication is not always welfare improving. Blinder (2007) notes that excessive communication can create "cacophony," where too many signals obscure rather than clarify policy intentions. Chahrour (2014) further shows that when agents struggle to process multiple public signals, additional disclosures may weaken coordination rather than strengthen it. Taken together, this literature suggests that the benefits of communicating inflation targets and policy objectives depend critically on simplicity, salience, and the public's capacity to understand the information provided.

Our work builds on these literatures by jointly varying macroeconomic literacy and central bank communication in a learning-to-forecast experiment. We show that providing more or richer information does not necessarily improve expectations. In particular, qualitative details of the economy and target communication can worsen forecast accuracy and coordination when agents lack a clear understanding of the underlying economic structure, while precise quantitative information is more effective at managing expectations than qualitative guidance. However, even quantitative communication can introduce additional complexity and comprehension challenges relative to providing no information at all.

Our behavioral learning model applies social learning, or more generally evolutionary learning, to expectation formation in monetary-policy environments, following the seminal contribution of Arifovic et al. (2013), particularly in New Keynesian settings. This framework has been used to study a range of issues, including the effectiveness of central bank communication under heterogeneous expectations (Hachem and Wu, 2017), equilibrium selection in liquidity traps (Arifovic et al., 2018), average inflation targeting and policy communication (Jia and Wu, 2023), and the role of target credibility and expectation anchoring in shaping inflation dynamics (Arifovic et al., 2025; Bullard et al., 2025). Most closely related to our paper is Arifovic et al. (2023), which uses the evolutionary learning framework to replicate treatment differences observed in a learning-to-forecast experiment under alternative monetary policy regimes. We build on and extend the framework to capture the effects of different initial forecasting beliefs that are induced through different macroeconomic literacy, and rationalize the effects of providing the targets in macroeconomic training. Our work, therefore, add to the literature on heterogeneous-expectations models by using experimental and survey data to evaluate their empirical relevance.[1] In this literature, some New Keynesian frameworks feature endogenous switching across expectation rules.[2] Other

[1]Our approach builds in particular on the literature that models heterogeneity through evolutionary algorithms; see, for example, Anufriev and Hommes (2012); Anufriev et al. (2019).

[2]See, among others, Branch and McGough (2010); Branch and Evans (2011); Massaro (2013);

models incorporate endogenous credibility under inflation-targeting regimes (Hommes and Lustenhouwer, 2019; Kostyshyna et al., 2024; Ozden, 2025). Related recent contributions on heterogeneous expectations also include Andrade et al. (2019) and Evans et al. (2025). Moreover, our incorporation of cognitive bounds into the model bears resemblance to the treatment of complexity and cognition in Gabaix and Graeber (2024).

Methodologically, the contributions of this paper are two-fold. First, we contribute to the design of learning-to-forecast experiments by systematically examining how the informational environment shapes expectation formation in a multi-equation macroeconomic setting. Table 1 provides a non-exhaustive summary of the presentation of information in the literature. While the existing literature has largely relied on qualitative descriptions of the data-generating process—both to study how agents learn about an unknown environment and to reduce cognitive burden—this approach limits the ability to test theories that assume full-information rational expectations. By contrast, providing fully specified quantitative information allows for a direct assessment of whether subjects behave in line with such benchmarks. Our results show that even when subjects are given complete knowledge of the underlying model, their expectations deviate systematically from rational expectations, highlighting the limits of information provision alone. These findings—together with related evidence—suggest that simplifying the use of information, for example through projections (Mokhtarzadeh and Petersen, 2020; Kryvtsov and Petersen, 2021), may be more effective than increasing its completeness, underscoring the importance of how information is presented, not just how much is provided. Second, together with the experimental approach, our model contributes a computational testbed that complements central banks' existing toolkits for analyzing the effects of information on expectations. By allowing computational agents to learn from empirically observed information environments, it provides a framework that can be linked to survey data.

Gasteiger (2014); Busetti et al. (2017); Branch and Gasteiger (2019); Kostyshyna et al. (2025b).

Table 1: Instruction content about experimental data-generating process across learning-to-forecast experiments

Type	No Information	Qualitative Information	Quantitative Information
New Keynesian	Adam (2007)	Pfajfar and Žakelj (2014, 2016)	Petersen (2014)*
		Cornand and M'baye (2018a,b)	Kryvtsov and Petersen (2013)*
		Assenza et al. (2013)	Arifovic and Petersen (2017)
		Hommes et al. (2019)	Mokhtarzadeh and Petersen (2020)
		Hommes and Makarewicz (2021)	Kryvtsov and Petersen (2021)
		Ahrens et al. (2023)	Rholes and Petersen (2021)
		Mauersberger (2021)	Petersen and Rholes (2022)
		Arifovic et al. (2023)	Kostyshyna et al. (2025a)
		Lustenhouwer and Salle (2025)	Kronick and Petersen (2025)
Other	McMahon and Rholes (2023)	Hommes et al. (2005, 2007)	Marimon and Sunder (1993, 1994, 1995)
		Heemeijer et al. (2009)	Marimon et al. (1993)
		Sonnemans and Tuinstra (2010)	Lim et al. (1994)
		Bao et al. (2013)	Nagel (1995)
		Arifovic et al. (2019)	Bao and Duffy (2016)
		Bao et al. (2017)	Anufriev et al. (2022)
		Colasante et al. (2017, 2018)	Duffy et al. (2025)
		Hennequin and Hommes (2024)	Hanaki and Takahashi (2023)
		Afrouzi et al. (2023)	Evans et al. (2025)

Note: This table presents a non-exhaustive list of learning-to-forecast experiments where subjects are incentivized to forecast accurately. *Subjects were provided qualitative instructions during the instruction phase and able to look up quantitative instructions during the experiment.

3 Experimental Design and Hypotheses

The purpose of our experiment is to understand how qualitative and quantitative information about an economy's data-generating process influences forecasting heuristics. Our experiment economy follows the design of Mokhtarzadeh and Petersen (2020) and is modeled as a linearized system of equations based on a reduced-form version of the New Keynesian framework. We choose a simple version as a starting point, and leave a more complex and nonlinear data-generating process for future research.

The economy evolved according to a system of four equations:

$$x_t = \mathbb{E}_t x_{t+1} - \sigma^{-1}(i_t - \mathbb{E}_t \pi_{t+1} - r^n_t) \tag{1}$$

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

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

$$r^n_t = \rho_r r^n_{t-1} + \epsilon_{rt} \tag{4}$$

Eq. (1) is the Investment-Saving (IS) curve and describes the level of the output gap x_t, or aggregate demand relative to the steady state, which changes in response to the aggregate expected future output gap $\mathbb{E}_t x_{t+1}$, and the difference between the real interest rate, $i_t - \mathbb{E}_t \pi_{t+1}$ and the natural rate of interest, r_t^n. The difference between the real interest rate and natural interest rate is sensitive to households' intertemporal elasticity of substitution, σ^{-1}.

Eq. (2) is the New Keynesian Phillips Curve which describes the level of inflation, π_t in response to changes in aggregate expected future inflation, $\mathbb{E}_t \pi_{t+1}^*$ and current aggregate demand, x_t. In this equation, β is a parameter that represents the economy's discount rate and κ is a function of parameters that represents the sensitivity of firms' pricing behaviour in response to aggregate demand.

Eq. (3) is the Taylor rule equation which represents the central bank's policy reaction function. The nominal interest rate changes based on deviations of output gap and inflation from their respective steady states. The parameters ϕ_π and ϕ_x dictate the central bank's reaction to inflation and output gap, with the goal of keeping aggregate demand and inflation stable at their steady-state levels of 0.

Eq. (4) describes the natural rate of interest which is subject to random perturbations. For the purposes of this study, r_t^n is understood as a *shock* to the economy to aggregate demand while ϵ_{rt} represents an $i.i.d.$ distributed $N(0, \sigma_\epsilon)$ innovation.

The parameters of the data-generating process were chosen in accordance of moments of Canadian data following Kryvtsov and Petersen (2013); $\sigma = 1$, $\beta = 0.989$, $\kappa = 0.13$, $\phi_\pi = 1.5$, $\phi_x = 0.5$, $\rho_r = 0.57$, $\sigma_\epsilon = 1.13$, and steady-state values $\pi^* = x^* = i^* = 0$.

Each session of the experiment began with participants receiving a detailed common set of instructions about the task that they would be participating in, followed by four unpaid practice rounds with the computer interface.[3] Thereafter, participants repeatedly submitted forecasts over two sequential 30-period horizons. During the first 10 periods of the first sequence, participants had 65 seconds to submit their forecast, followed by 50 seconds thereafter. After all subjects had submitted their forecasts for the subsequent period, or time ran out, the median submitted forecasts for output and inflation for each group were selected as the aggregate expectations

[3]Instructions can be found in Online Appendix B.

Table 2: Summary of Treatments

Treatment	**Sequences**	**Subjects**	**Periods**	**Qualitative Relationships**	**Quantitative Relationships**	**CB Targets**
NoInfo	6	41	30 x 2	no	no	no
NoInfoTarget	6	41	30 x 2	no	no	yes
QualInfo	6	42	30 x 2	yes	no	no
QualInfoTarget	6	42	30 x 2	yes	no	yes
QuantInfo	6	42	30 x 2	yes	yes	yes

and directly used in the calculation of output, inflation, and the nominal interest rate. We selected the median forecast rather than the average to avoid significantly biased aggregate expectations driven by a small number of subjects.

Participants were incentivized to submit accurate forecasts. Subject i's score in each period t was calculated as:

$$Score_{i,t} = 0.3(2^{-0.01|E^*_{i,t-1}\pi_t - \pi_t|} + 2^{-0.01|E^*_{i,t-1}x_{i,t} - x_t|}) \tag{5}$$

where $E^*_{i,t-1}\pi_t - \pi_t$ and $E^*_{i,t-1}x_{i,t} - x_t$ are subject i's inflation and output gap forecast errors submitted in period *t-1* forecasting period *t*, respectively. This scoring continuously decreased subjects' payoffs as forecast errors grew larger. A subject would earn a maximum score per period of 0.6 for a forecast error of 0. For every 100 basis points error made for each variable, a subject's score would decrease by 50%. At the end of the two repetitions, the subjects' total scores were tallied, converted into dollars and paid out in cash in addition to a show-up fee of \$7. Finally, all subjects received common information about historical data to be presented on their screen and details about how their payoffs would be computed.

3.1 Treatments

We consider five different levels of information provided to participants about the economy's data-generating process. The treatments and their differences are summarized in Table 2. In all five treatments, participants were provided basic definitions about the key variables they would observe during the experiment (the output gap, inflation, nominal interest rate, and demand shocks). They were also informed that all values would be expressed and inputted in basis points.

Participants in the *NoInfo* treatment received no additional information about the data-generating process. They were not informed about the relationship between different macroeconomic variables or that their aggregated expectations would have an endogenous effect on the economy. Moreover, participants were not informed about the reaction function or objectives of the central bank.

The *NoInfoTarget* treatment provided the same basic information as the NoInfo treatment as well as precise information about the central bank's inflation and output targets of zero.

The *QualInfo* treatment involved presenting participants with a qualitative description of the data-generating process. The instructions described qualitatively the reaction of each variable to the other macroeconomic variables. The qualitative instructions also conveyed that aggregate expectations would have an effect on the economy. The central bank's objectives and reaction function were explained qualitatively.

The *QualInfoTarget* treatment extended the QualInfo treatment by additionally providing subjects with the central bank's precise quantitative inflation and output targets.

Finally, the *QuantInfo* treatment provided participants with a detailed quantitative description of the economy's data-generating process. Participants learned the economy's system of equations, including the values of all parameters and targets, i.e. β, σ, κ, ρ, σ_ϵ, ϕ_π, ϕ_x, π^* and x^*.

3.2 Procedures

The experiments were conducted in-person at the CRABE laboratory at Simon Fraser University from September 2016 to January 2020. A total of 415 undergraduate students were recruited on a first-come first-serve basis from a subject pool of over 3000 subjects from various disciplines. No subject had experience in a learning-to-forecast experiment. Each session, consisting of 7 participants[4], lasted approximately 90 minutes including 30 minutes for instructions and practice. We conducted 6 sessions per treatment consisting of two repetitions of 30 periods. We collected a total of 12,408 observations on forecasts. After dropping 72 outlier observations where the forecast

[4]NoInfo Session 6 and NoInfoTarget Session 3 only contained 6 participants

exceeded $\pm1500bps$, we had 12,336 observations for our analysis.

Within a treatment, sessions differed based on the randomly generated shock sequence. Shock sequences were pre-selected for the sake of consistency across treatments. The shocks were drawn from a normal distribution where two-thirds of the time, the shock took on a value between -138 and +138 basis points, and 95% of the time took on a value between -276 and +276 basis points. The standard deviations of the individual shock sequences ranged from 125 to 155 basis points. This was an additional dimension of exogenous variation that we are able to exploit in our analysis.

The experiment was programmed in *Redwood* (Pettit et al., 2014). Fig. 1 presents a screenshot of the experimental interface. Participants submitted numerical predictions for the subsequent period's inflation and output. They were told to submit their forecasts as integers in basis points. The user interface contained graphical time series of historical interest rates, shocks (including the current period shock), output, inflation and personal expectations over time. The screen also included a timer indicating the amount of time remaining in a period and their accumulating score. Subjects had access to their paper instructions and a computer calculator during the entire duration of the experiment.

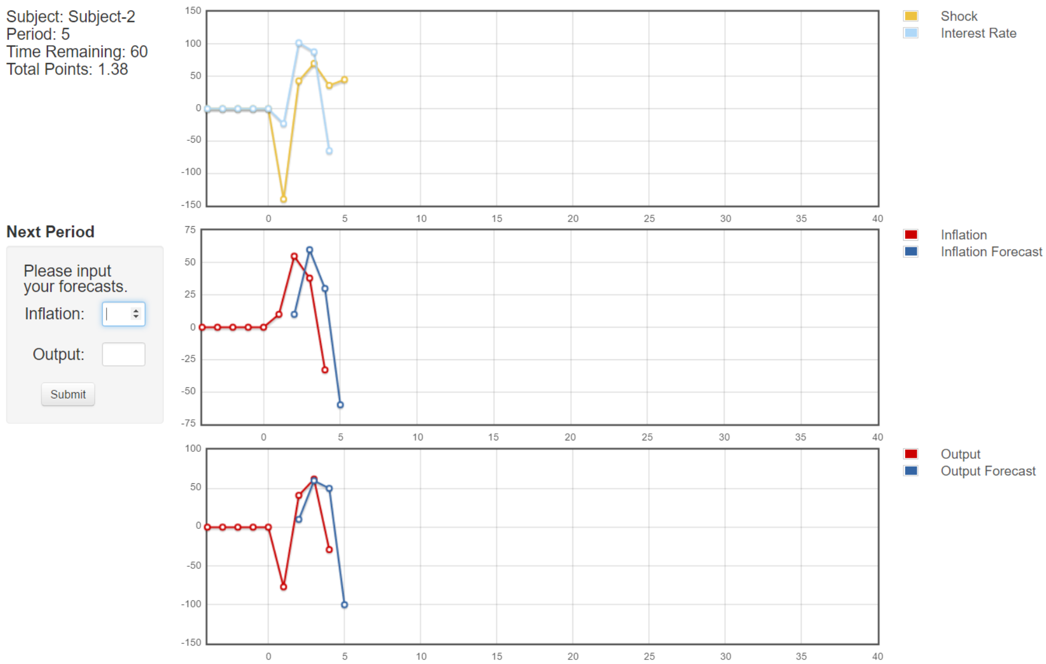
Participants were instructed not to communicate with each other during the experiment. They were allowed to ask clarifying questions, but were not allowed to ask questions regarding strategy. The average payment, including a CDN$7 show-up fee was CDN$18.6 and ranged from $14.9 to $21.4.

3.3 Testable Hypotheses

A standard assumption in macroeconomic theory is that the representative agent forms rational expectations over their stochastic environment. Under this assumption, agents' forecast errors would be on average zero and not systematically biased.

Without detailed information about the economy's data-generating process, participants in the NoInfo and QualInfo treatments were anticipated to have difficulty forming accurate forecasts. Thus, we hypothesized that increasing the precision of information about the central bank's policy objectives and the economy's data-generating

Figure 1: Experimental interface



process would reduce participants' forecast errors and disagreement.

Hypothesis 1a: Information about the central bank's targets reduces absolute forecast errors.

Hypothesis 1b: Information about the central bank's targets reduces disagreement.

Hypothesis 2a: Absolute forecast errors are lower with more information about the data-generating process.

Hypothesis 2b: Disagreement among forecasters - measured as the standard deviation of forecasts in lower with more information about the data-generating process.

More accurate and coordinated expectations are associated with more anchored expectations in both surveyed expectations of households and in the lab. Thus, we hypothesized that more detailed and precise information would also stabilize expectations and lead to greater welfare, measured as the weighted average of inflation and output gap deviations from steady state.

Hypothesis 3: Aggregate welfare is higher with more information about the data-generating process.

4 Experimental Results

We begin by evaluating how subjects' forecast errors are systematically influenced by the availability of information about the economy's data-generating process. We then proceed to examine the impact of information on aggregate dynamics and welfare.

Table 3: Summary statistics of individual forecast variables and aggregate outcomes

Treatment	Abs. FE		Disag.		Std. Dev.		Abs. Dev. from		Welfare
	x_{t+1}	π_{t+1}	x_{t+1}	π_{t+1}	x_t	π_t	x^*	π^*	Loss
NoInfo	109.3	33.2	63.9	24.0	123.4	53.3	101.6	43.1	2.330
	(29.43)	(5.97)	(18.22)	(6.16)	(11.29)	(19.37)	(10.58)	(16.06)	(0.619)
NoInfoTarget	105.0	56.6	61.8	36.5	124.0	69.8	102.9	56.0	3.911
	(13.70)	(17.75)	(9.89)	(8.93)	(12.83)	(21.02)	(10.93)	(17.23)	(0.977)
QualInfo	105.1	51.3	62.4	38.9	124.4	64.8	103.0	51.4	3.381
	(4.99)	(18.46)	(14.48)	(7.70)	(11.86)	(20.19)	(13.67)	(16.44)	(0.880)
QualInfoTarget	102.6	62.7	57.5	45.6	120.0	74.3	99.5	59.3	4.078
	(14.70)	(14.01)	(8.47)	(6.40)	(11.19)	(11.46)	(8.98)	(9.21)	(0.420)
QuantInfo	106.0	55.1	56.4	37.4	124.5	70.2	103.2	58.8	4.420
	(6.49)	(28.18)	(14.06)	(21.05)	(9.68)	(39.80)	(11.17)	(32.55)	(1.726)
REE	83.5	47.8	–	–	118.1	35.2	97.1	28.9	1.000
	(8.13)	(18.58)			(3.98)	(1.19)	(4.86)	(1.45)	(–)

Note: This table presents means and standard deviation for each variable by treatment. The REE statistics are calculated by using the model-implied REE path for each session, with forecast error calculated from the *ex-ante rational* forecasts. Units are given in basis points.

4.1 Individual Results

Forecast Errors and Disagreement

Fig. 2 presents the empirical cumulative distribution functions for absolute output and inflation forecast errors, by repetition and grouping, for all subjects and periods. The first four columns of Table 3 provide summary statistics of forecast precision and disagreement.

Absolute forecast errors are significantly different from zero in all treatments. Mean output forecast errors differ little across treatments, ranging from 102.6 to 109.3 bps across treatments. We observe more variability in inflation forecast performance, with a low of 33 bps in NoInfo and high of 62.7 bps in QualInfoTarget. We also observe notable increases in inflation forecast errors with information about the central bank's targets. Quantitative information about the economy's DGP leads to modestly higher forecast errors for output but much lower errors for inflation. Disagreement in forecasts follows similar patterns.

Figure 2: Empirical CDFs of output and inflation absolute forecast errors, by repetition

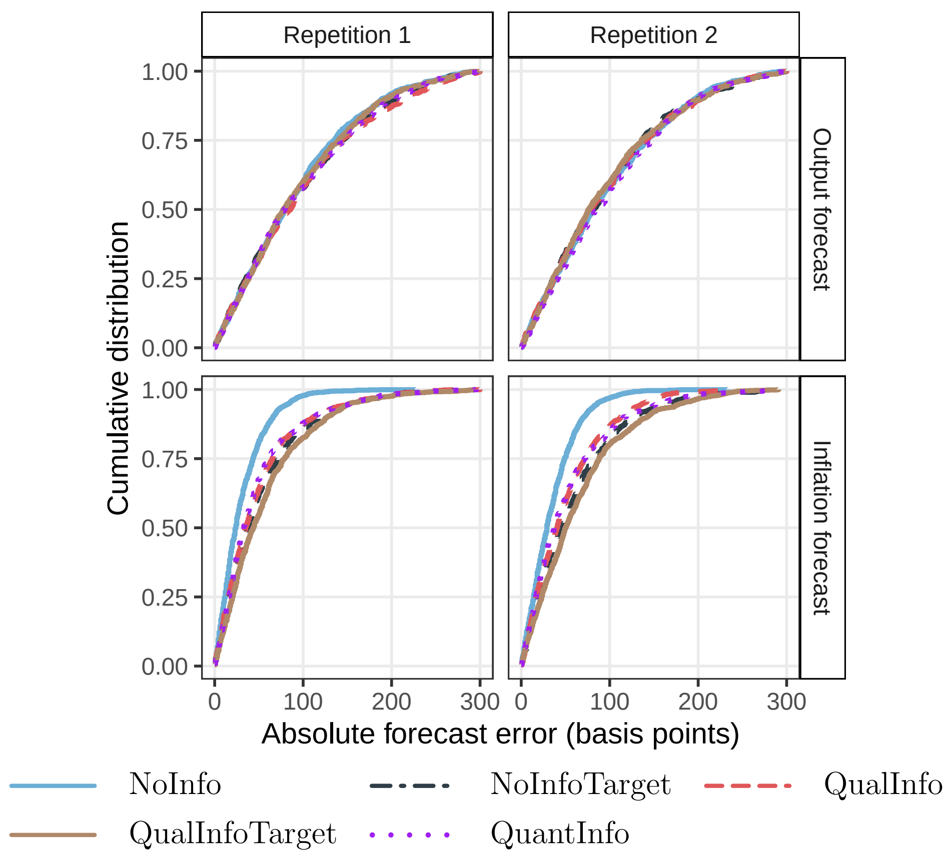


Table 4: Pairwise comparisons - Experiments

Panel A	Log absolute inflation forecast error						Log absolute inflation disagreement					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
NoInfoTarget	0.481***						0.456***					
	(0.053)						(0.049)					
QualInfo		0.391***						0.487***				
		(0.056)						(0.055)				
QualInfoTarget			0.224***	0.134***					0.202***	0.232***		
			(0.053)	(0.049)					(0.050)	(0.047)		
QuantInfo					-0.227***	0.388***					-0.317***	0.371***
					(0.057)	(0.052)					(0.057)	(0.055)
Constant	3.598***	3.500***	4.005***	4.193***	4.255***	3.526***	3.263***	3.298***	3.541***	3.475***	3.851***	3.407***
	(0.125)	(0.121)	(0.119)	(0.115)	(0.119)	(0.140)	(0.164)	(0.158)	(0.149)	(0.139)	(0.150)	(0.174)
Baseline	NoInfo	NoInfo	QualInfo	NoInfoTarget	QualInfoTarget	NoInfo	NoInfo	NoInfo	QualInfo	NoInfoTarget	QualInfoTarget	NoInfo
Num.Obs.	720	720	720	720	720	720	720	720	720	720	720	720
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B	Log absolute output forecast error						Log absolute output disagreement					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
NoInfoTarget	-0.205***						-0.318***					
	(0.060)						(0.073)					
QualInfo		-0.207***						-0.376***				
		(0.065)						(0.077)				
QualInfoTarget			-0.005	-0.007					-0.014	-0.071*		
			(0.055)	(0.053)					(0.048)	(0.043)		
QuantInfo					0.026	-0.186***					-0.072	-0.461***
					(0.054)	(0.063)					(0.050)	(0.075)
Constant	4.786***	4.802***	4.760***	4.747***	4.729***	4.775***	4.130***	4.170***	3.697***	3.715***	3.901***	4.387***
	(0.174)	(0.153)	(0.109)	(0.126)	(0.115)	(0.153)	(0.235)	(0.256)	(0.171)	(0.126)	(0.133)	(0.224)
Baseline	NoInfo	NoInfo	QualInfo	NoInfoTarget	QualInfoTarget	NoInfo	NoInfo	NoInfo	QualInfo	NoInfoTarget	QualInfoTarget	NoInfo
Num.Obs.	720	720	720	720	720	720	720	720	720	720	720	720
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Each column reports a separate random-effects regression estimated on the indicated treatment pair. The dependent variables are the log absolute one-period-ahead absolute forecast errors or period-level standard deviation of forecasts for inflation and output gap. Units are given in basis points. The panel unit is session-period, with session random effects and period fixed effects. α denotes the estimated constant. NoInfoTarget, QualInfo, QualInfoTarget, and QuantInfo are treatment-specific dummy variables. HAC robust standard errors are reported in parentheses. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

We construct a series of random-effects regressions that estimate the effects of the information treatments on forecast accuracy and forecast disagreement. We sequentially estimate the effect of qualitative and quantitative information about the targets and DGP on subjects' ex-ante one-period ahead absolute forecast errors and the standard deviation in forecasts. Specifically, we focus on two general regression specifications that make pairwise treatment comparisons:

$$\begin{aligned} log|E_{t,s}z_{t+1} - z_{t+1}| &= \alpha + \beta\mathbb{T} + \eta_{t,s}, \\ log(s.d.E_{t,s}z_{t+1}) &= \alpha + \beta\mathbb{T} + \eta_{t,s}, \end{aligned}$$

where $E_t z_{t+1}$ refers to period $t-1$ average forecast of period t output gap or inflation, z_t, in experimental session s. The dummy variable $\mathbb{T}$ takes the value of 1 for observations from NoInfoTarget, QualInfo, QualInfoTarget and QuantInfo depending on the specification and zero otherwise. The estimated coefficient $\hat{\alpha}$ is the estimates of the average log absolute forecast error or standard deviation in forecasts observed in the baseline treatment while the coefficient $\hat{\alpha} + \hat{\beta}$ is the estimate observed in the comparison treatment. Table 4 presents the results for each pairwise comparison. Data from the two repetitions are treated as one 60-period observation. We also conduct robustness checks where we include repetition fixed effects to control for learning (see Online Appendix Table A1.)

Consistent with our earlier findings, $\hat{\alpha}$ is positive and significantly different from zero in all specifications, indicating that forecast errors and aggregate disagreement are statistically significantly different from zero in all (baseline) treatments.

Observation 1: Information about the central bank's targets has relatively little impact on output gap forecast errors - except when participants have no information about the economy's data process. It does not improve forecast performance and coordination when participants already have qualitative information about the economy. Furthermore, information about the Bank's targets significantly increases inflation forecast errors and disagreement irrespective of other information available.

Comparing forecast errors in the NoInfo and NoInfoTarget treatments (Specifications (1) and (6)), we find that the additional provision of information about the central bank's targets when participants have no other information has very different effects for inflation and output gap forecasts. Additional information about the Bank's targets causes inflation forecast errors to increase significantly by 62% $((exp(0.481) - 1))$ and leads to a 58% increase in forecast disagreement. By contrast, output forecast errors decrease by 18% and disagreement decrease by 27%.

Comparing QualInfo to QualInfoTarget treatments in Specifications (3) and (9) indicates the value of providing additional quantitative information about the central bank's targets when participants already have qualitative information about the DGP. We observe significant increases in inflation forecast errors and disagreement (by 25% and 22%), but no change in output forecast accuracy or disagreement.

Observation 2: Qualitative information about the DGP worsens forecast accuracy and disagreement, irrespective of whether the central bank's targets are known. Output gap forecast accuracy and disagreement improve with qualitative information compared to a situation where no information about the DGP is known.

Comparing NoInfo to QualInfo treatments (Specifications (2) and (8)) indicates the value of providing qualitative information about the DGP (without information about the central bank's quantitative targets). Similarly, we find that qualitative information increases inflation forecast errors and disagreements (48% and 63%, respectively), while decreasing output forecast errors and disagreement (19% and 31%).

We observe a very similar result when we compare NoInfoTarget to QualInfoTarget treatments in Specifications (4) and (10), which indicates the value of providing additional qualitative information about the DGP when participants already have information about the targets. The additional qualitative information significantly increases inflation forecast errors and disagreement (by 14% and 26%), but has no effect on output gap forecasting.

Observation 3: Supplementary quantitative information about the DGP significantly reduces inflation forecast errors and disagreement, with no effect on output gap forecasts.

Comparing QualInfoTarget and QuantInfo treatments in Specifications (5) and (11) indicates the value of providing quantitative information above and beyond a qualitative description of the economy and precise quantitative information about the targets. We find that the additional quantitative information about the DGP leads to minimal improvements in output gap forecast accuracy but large and significant improvements in inflation forecast accuracy and disagreement (by 20% and 27%).

Finally, comparing QuantInfo and NoInfo (Specifications (6) and (12)), we find mixed effects of information on forecasts. For inflation forecasts, the comprehensive information treatment QuantInfo appears to increase both forecasting errors and disagreement. For output forecasts, the opposite occurs where subjects under QuantInfo make significantly less forecasting errors and disagreement.

Overall, we find limited evidence in support of **Hypotheses 1** and **2**, which posit a monotonic improvement in forecasts as more information is provided. Additional provision of information (informing the targets and data-generating process) appears to exacerbate inflation forecast errors and disagreement. Additional provision of information only yields improvement in forecasting accuracy and agreement from QualInfoTarget to QuantInfo. On the other hand, information about targets or qualitative details of the DGP only helps to improve output forecasts only when there is no other information to base forecasts on. There is no further improvement in forecasting performance or coordination once participants are informed of either type of information, or are provided more precise quantitative information about the DGP.

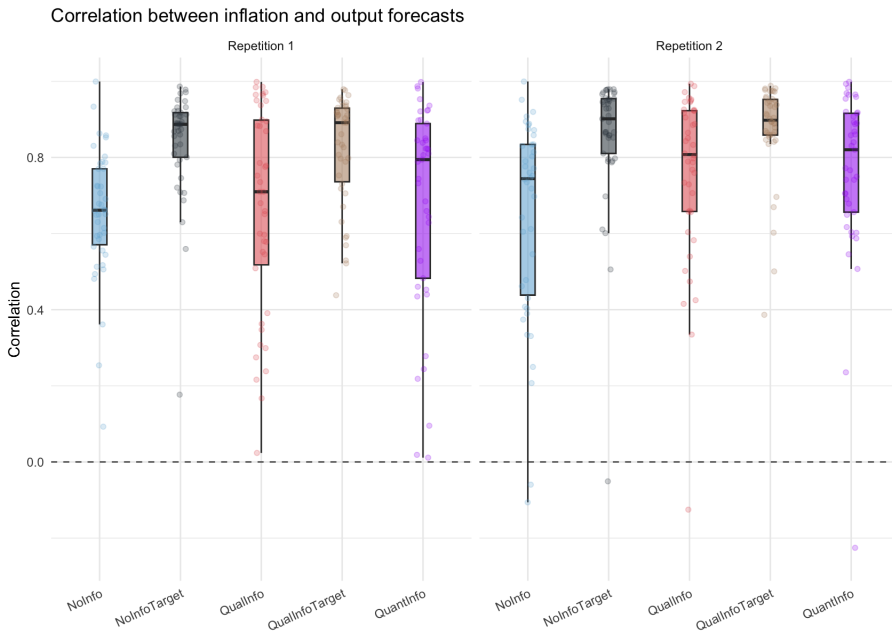
4.2 Macroeconomic Narratives

Participants come into our experiment with their own 'home-grown' views of how inflation and output co-evolve. Our data enables us to evaluate the impact that information and experience has on participants' macroeconomic narratives.

Figure 3 plots the the correlations in inflation and output gap expectations at the individual level. An agent who fully understands the underlying DGP would have a correlation coefficient of 1 given that the economy is only exposed to shocks to aggregate demand.

While most people anticipate that inflation and output gaps will co-move in the same direction, they do not believe this all the time. In the NoInfo treatment, where participants' perceptions are the most 'home-grown', the correlation in forecasts for the median subject is 0.65 (s.d. 0.17) for repetition 1, 0.64 (s.d. 0.27) for repetition 2, and 0.65 (s.d. 0.22) for both repetitions. Roughly one-quarter of forecasts are negatively correlated in a given period.

Figure 3: Correlation in inflation and output gap expectations

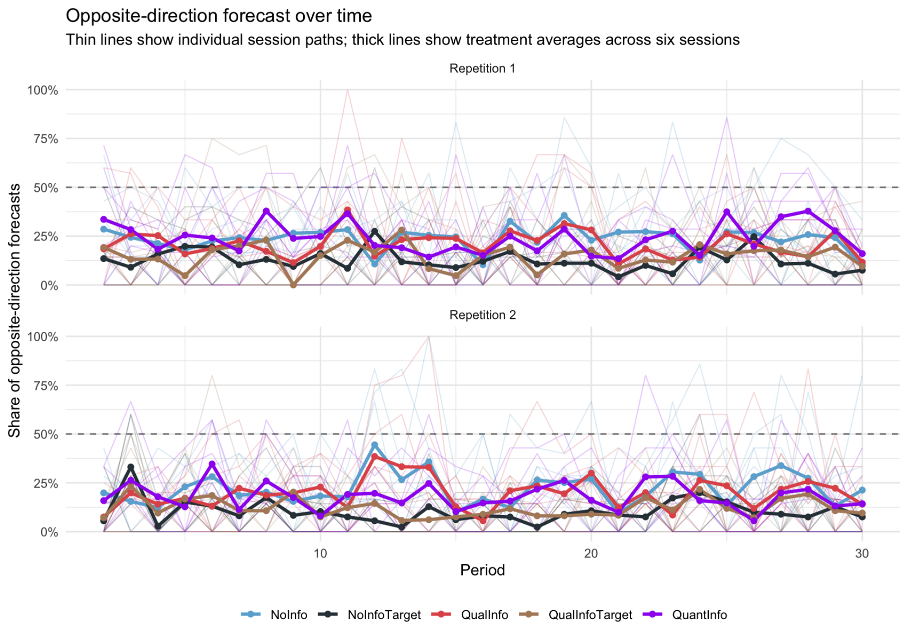


For inexperienced participants, qualitative information about the DGP marginally increases the correlation between inflation and output gap forecasts, but also creates more heterogeneity in this correlation, despite detailed information about the nature of shocks and the positive correlation between the two variables. Further quantitative information further raises the median correlation but also creates even more heterogeneity in perceptions.

Communication about the central bank's inflation and output gap targets are much more effective at shaping narratives, despite not providing any details about the true correlation. We speculate that information about the targets increases participants' attention - and thus BOTH forecasts - toward the targets, leading to more positively correlated beliefs.

Experience plays a less important role in shaping participants' narratives. While median perceived correlations between inflation and output gap increase in all treatments, the differences across repetitions is not statistically significant. Under Wilcoxon signed-rank tests comparing session-level median perceived correlations between repetitions 1 and 2, only QualInfo is marginally significant at the 10% level ($p = 0.0935$), while the remaining treatments are well above 0.10 (NoInfo: $p = 0.529$; NoInfoTarget:

Figure 4: Correlation in inflation and output gap expectations



p = 1.000; QualInfoTarget: p = 0.142; QuantInfo: p = 0.295). Moreover, people do not appear to start out with a supply-shock view of the economy and learn over time. Figure 4 shows that the share of participants with misperceptions about the correlation (i.e. negatively correlated forecasts) is relatively low, typically ranges between 10 and 35 percent, depending on the treatment, and does not change meaningfully over time.

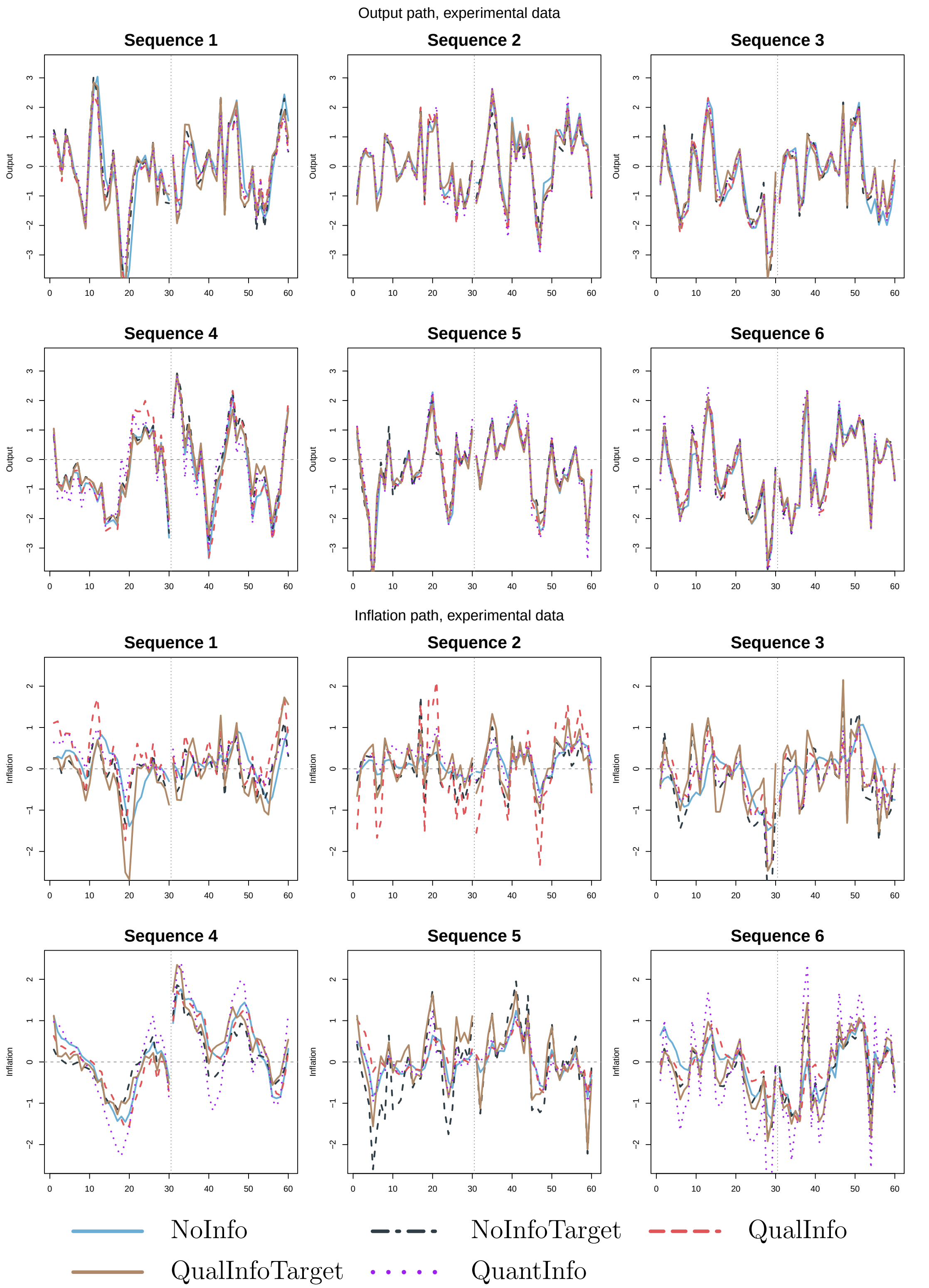
4.3 Aggregate Results

Does the provision of information about the DGP improve macroeconomic stability? To answer this, we begin by plotting the time series of output and inflation for all sequences and repetitions in Fig. 5.

First, we observe no explosive dynamics in any treatment despite being a theoretical possibility under rational expectations. The dynamics in NoInfo and QualInfo treatments are relatively stable despite subjects not knowing the targets of the central bank or the central bank's quantitative response to inflation and output.

The last five columns of Table 3 provide summary statistics of aggregate variables:

Figure 5: Time series of output (top) and inflation (bottom), by shock sequence, both repetitions



the mean variability and absolute deviations from target of output and inflation, and the mean welfare loss relative to the REE prediction. Mean variability of output and deviations from the output gap target is very close to the REE prediction. The high consistency across treatments suggests that providing additional details about the macroeconomy does not appear to have an important effect on median output forecasts.

We come to a very different conclusion when we look at the time series of inflation. Information appears to play a role in shaping median inflation expectations and aggregate dynamics. Inflation is 1.5 to 2.1 times more variable than in an environment with rational expectations (see, again, Table 3). We observe the lowest levels of inflation variability in the NoInfo treatment and the highest levels in the QualInfoTarget treatment. However, Wilcoxon rank-sum tests indicate that the differences in relative standard deviations across treatments are statistically insignificant in most treatment comparisons.

We compute the session-level central bank's relative welfare loss ratio as

$$\frac{var(\pi_t) + \omega var(x_t)}{var(\pi_t^{REE}) + \omega var(x_t^{REE})}, \tag{6}$$

where $\omega = \frac{\kappa}{\mu} = 0.013$ is a function of the price elasticity of demand parameterized to be $\mu = 10$. Summary statistics are reported in the last column of Table 3.

There are few statistically significant differences in welfare across treatments, except for NoInfo, which has the smallest welfare loss relative to the REE.

Overall, our information treatments appear to have statistically significant effects on forecasts, particularly inflation forecasts, while their effects on aggregate outcomes appear to be more limited. Contrary to our hypotheses, additional information about the underlying experimental economies does not monotonically improve subjects' forecasting accuracy or agreement. Instead, the results suggest higher forecast errors and greater disagreement in inflation forecasts. For output forecasts, by contrast, there appears to be some improvement, though it is more modest. In the next section, we present a learning model that rationalizes these experimental findings.

5 A behavioral model

5.1 Initial beliefs of lab participants

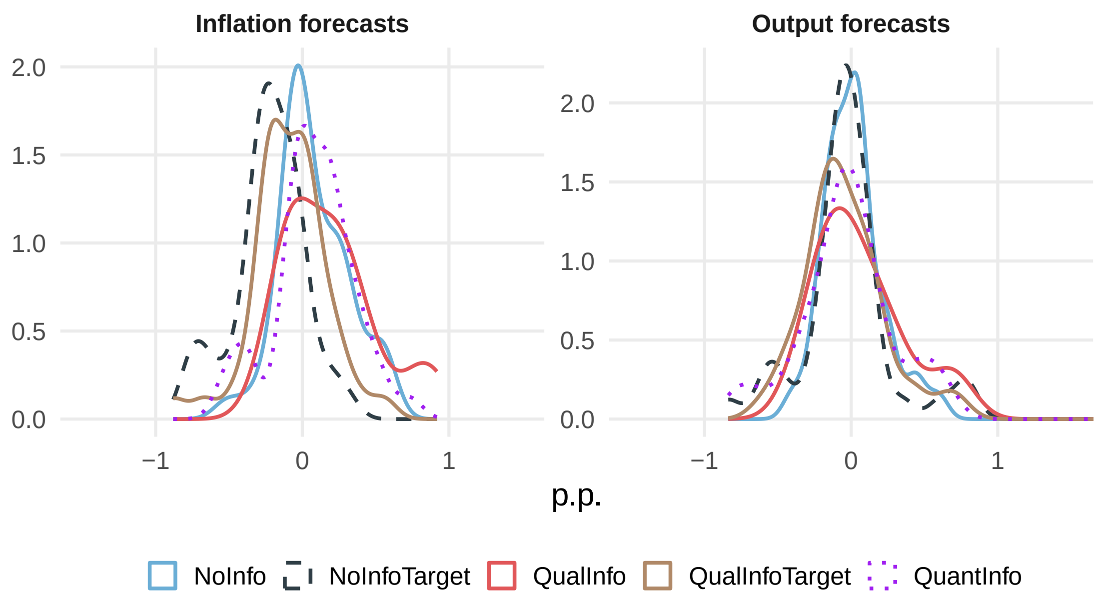
We first examine the empirical distributions of subjects' initial beliefs across treatments. This is a key step because the model is anchored in these observed *early-phase* forecast distributions rather than in arbitrary initial conditions. It also allows us to separate treatment differences that are already embedded in subjects' starting beliefs from those that must emerge through subsequent learning and behavioral responses to target communication. We define the *early/learning-phase* as the first eight periods of the first repetition and use each subject's average forecast over these periods as a measure of that subject's initial forecast.[5] Fig. 6 plots the resulting distributions by treatment.

The figure reveals treatment-specific patterns in the dispersion and skewness of initial expectations. To characterize these patterns more formally, we fit skew-normal distributions to the initial forecasts. Table 5 reports the maximum-likelihood estimates of the skew-normal parameters: the location parameter, which captures the central tendency of the distribution; the scale parameter, which reflects its dispersion; and the shape parameter, which determines its skewness.

Several patterns emerge for inflation forecasts. First, the QualInfo treatment exhibits the largest estimated scale parameter, indicating the greatest dispersion, in subjects' inflation forecasts during the learning-phase. Providing target communication substantially reduces this dispersion, as the corresponding QualInfoTarget treatment displays a smaller scale estimate. Second, the shape estimates reveal a pronounced shift in asymmetry across treatments. In the absence of target communication, the forecast distributions in NoInfo and QualInfo are right-skewed. Once target communication is introduced, however, these distributions become left-skewed, as reflected in the negative shape parameter estimates for NoInfoTarget and QualInfoTarget. The QuantInfo treatment also exhibits a negative shape estimate, placing it closer to the

[5] We demean forecasts by subtracting the mean forecast for participants exposed to the same shock sequence, which nets out sequence-specific variation common to all five treatments and isolates differences in initial beliefs. The ex-ante rational expectations are then always zero. Additionally, in the Appendix, we evaluate the robustness of the maximum likelihood estimates for different lengths of the learning-phase (Tables A2 and A3), our interpretations remain.

Figure 6: Distributions of initial (learning-phase) forecasts of experimental subjects



Note: An omnibus ANOVA test for equality of mean inflation forecasts across treatments during the learning-phase yields $F = 3.38$ and $p = 0.066$. For output forecasts, $F = 1.02$ and $p = 0.578$. Forecasts are residualized around common shock sequences to account for the difference in shocks across sessions. The learning-phase is defined as the first eight periods of the first repetition.

Table 5: Maximum likelihood estimates of skew-normal parameters of the learning-phase forecasts

	Treatment	Location-μ (s.e.)	Scale-ω (s.e.)	Shape-α (s.e.)	Implied mean	Implied SD
Inflation forecasts						
(I)	NoInfo	-0.14 (0.08)	0.32 (0.07)	1.65 (1.05)	0.08	0.23
(II)	NoInfoTarget	0.00 (0.07)	0.33 (0.06)	-1.78 (0.92)	-0.23	0.24
(III)	QualInfo	-0.21 (0.05)	0.51 (0.07)	6.14 (3.61)	0.18	0.31
(IV)	QualInfoTarget	0.12 (0.09)	0.33 (0.07)	-1.30 (0.78)	-0.09	0.25
(V)	QuantInfo	0.29 (0.12)	0.34 (0.09)	-1.23 (1.03)	0.08	0.27
Output forecasts						
(VI)	NoInfo	-0.32 (0.05)	0.68 (0.08)	8.54 (4.14)	0.21	0.41
(VII)	NoInfoTarget	-0.28 (0.10)	0.39 (0.08)	1.24 (0.71)	-0.03	0.31
(VIII)	QualInfo	-0.36 (0.06)	0.67 (0.09)	10.78 (9.75)	0.17	0.41
(IX)	QualInfoTarget	-0.32 (0.07)	0.39 (0.07)	2.16 (1.03)	-0.04	0.27
(X)	QuantInfo	0.19 (0.19)	0.38 (0.11)	-0.97 (1.14)	-0.03	0.32

Note: Entries report MLE estimates of skew-normal direct parameters. Implied mean and SD are computed from the estimations using standard skew-normal moments. The learning-phase length is $K = 8$. In the Appendix, we provide tables with different choices of K. Units are in percentage points.

target-communication treatments along this dimension.

For output forecasts, NoInfo and QualInfo display the largest scale estimates, suggesting greater dispersion in subjects' initial output forecasts. This dispersion falls noticeably in NoInfoTarget and QualInfoTarget, indicating that target communication also reduces forecast dispersion for output. In terms of asymmetry, output forecasts in NoInfo and QualInfo remain more strongly right-skewed, while target communication tends to dampen this skewness in NoInfoTarget and QualInfoTarget. Unlike the case of inflation, however, target communication does not shift output forecasts into left-skewness. QuantInfo again stands out, with a slightly negative shape estimate. Consistent with these patterns, the implied means for NoInfoTarget, QualInfoTarget, and QuantInfo lie closer to zero than those for NoInfo and QualInfo, suggesting that target communication and quantitative information help anchor output forecasts during learning. More generally, output forecasts exhibit less heterogeneity across treatments than inflation forecasts.

Overall, relative to NoInfo, providing qualitative instructions about the relationships among macroeconomic variables appears to increase the dispersion in initial forecasts. This pattern is descriptive of **Observation 2**, which shows that qualitative information about the data-generating process increases subjects' inflation forecast errors and disagreement. By contrast, the effect of supplementing this information with an announced target is more puzzling. Table 5 suggests that target communication reduces the initial dispersion of beliefs, particularly when comparing QualInfoTarget with QualInfo; however, **Observation 1** indicates that supplementary target information increases inflation forecast errors and disagreement for NoInfo and QualInfo subjects. This contrast suggests that the treatment effect of target communication does not operate solely through initial belief dispersion, but likely also through an additional distortion in beliefs. Table 5 points to an observation that target communication does more than compress the distribution of initial forecasts. Relative to treatments without target information, target communication shifts the distribution of inflation forecasts from right-skewed to left-skewed. Importantly, this pattern is not confined to the early-phase. When we estimate the skew-normal parameters using the full sample of periods, reported in Appendix Table A4, the negative skewness associated with the -Target treatments remains present.

A similar over-anchoring of inflation expectations following target communication is documented by Coibion et al. (2022). In their June 2018 survey, a randomized subset of respondents was informed of the Federal Reserve's inflation target. Mean inflation expectations fell immediately from 2.47% to 1.48%. That is, revised expectations not only overshot the target on the downside, but also ended up 12 basis points below realized inflation in June 2019, which was 1.6%. This is quantitatively on par with our experimental findings. In the learning phase, mean inflation expectations in the target treatments (QualInfo-Target and NoInfo-Target) lie between 9 and 23 basis points below the rational expectations equilibrium.

For output forecasts, the experimental evidence shows only limited differences in forecast errors and disagreement between NoInfo and QualInfo. This is broadly consistent with Table 5, which indicates that the initial belief distributions in these two treatments are relatively similar, particularly in terms of dispersion and skewness. Target communication also reduces the upward bias in initial output forecasts, but does not fully eliminate the upward skew.

Taken together, these patterns motivate the learning model developed in this section. In particular, they point to a puzzling observation: supplementary target information does not initially increase the dispersion in beliefs—and may even reduce it, especially for QualInfo subjects—yet it leads to higher forecast errors and disagreement later in the experiment. One important mechanism, which we develop below, is that target communication may induce a negative-skew effect in inflation forecasts that becomes consequential as beliefs evolve over time.

5.2 The model

In this environment, agents use *steady-state learning*, which is widely used in the adaptive learning literature (see, inter alia, Evans et al., 2008, 2022). Each agent $j = 1, \dots, N$ forms idiosyncratic one-step-ahead forecasts for output and inflation,

$$E^{\text{Evol}}_{j,t}(z_{t+1}) \equiv z^e_{j,t+1} = \xi^z_{j,t} \in \mathbb{R}, \tag{7}$$

where $z \in \{x, \pi\}$, and the superscript "Evol" indicates that expectations evolve under evolutionary learning. Such steady-state learning beliefs intuitively measure expectations as the distance of each variable to its respective fixed target (i.e., zero).

Following Arifovic et al. (2019, 2025), we model the endogenous credibility agents assign to communicated policy targets. Agents in the -Target treatments are additionally endowed with a target-credibility component, $c^z_{j,t} \in [0, 1]$. This component captures the subjective weight that agent j assigns to the announced target z^*, with the remaining weight, $(1 - c^z_{j,t})$, assigned to agent j's own belief, $\xi^z_{j,t}$. That is, the forecast made by agents in -Target treatments is:

$$E^{\text{Evol}}_{j,t}(z_{t+1}) = (1 - c^z_{j,t})\xi^z_{j,t} + c^z_{j,t} z^*, \tag{8}$$

For non-Target treatments, the learning variables of an agent are $\xi^x_{j,t}, \xi^\pi_{j,t}$, implying two learning tasks. For -Target treatments, the learning variables are $\xi^x_{j,t}, \xi^\pi_{j,t}, c^x_{j,t}, c^\pi_{j,t}$, implying four learning tasks.

Next period forecast candidates. At the beginning of each period, agents receive private signals, or "news," that perturb their previous forecasts. The private signals for each learning task are stacked in a column vector $\boldsymbol{\eta}^z_{j,t}$ of length $\mathcal{J}^z$. Let $\mathcal{J}$ denote the total length of news available to each agent in a period. A key behavioral consideration here is how this capacity must be allocated across learning tasks.[6] In non-Target treatments, capacity is split across output and inflation forecasts, $\mathcal{J}^x + \mathcal{J}^\pi = \mathcal{J}$. In -Target treatments, the same capacity must also be allocated to the credibility variables, $\mathcal{J}^x + \mathcal{J}^\pi + \mathcal{J}^{c^x} + \mathcal{J}^{c^\pi} = \mathcal{J}$. This reduces the length of the news vector that agents receive for each learning variable, thereby introducing a cognitive constraint that becomes more binding as agents face a greater number of learning tasks. The private signals are utilized as followed, for each $z \in \{x, \pi\}$, the news vector $\boldsymbol{\eta}^z_{j,t} = \left(\eta^z_{j,\iota,t}\right)_{\iota=1}^{\mathcal{J}^z}$ is applied to an agent's most recent belief and therefore generates a vector of candidate beliefs:

$$\boldsymbol{m}^z_{j,t} = \xi^z_{j,t-1} + \boldsymbol{\eta}^z_{j,t}. \tag{9}$$

In -Target treatments, a similar procedure applies to credibility,

$$\boldsymbol{m}^{c^z}_{j,t} = \text{clip}_{[0,1]}\left(c^z_{j,t-1} + \boldsymbol{\eta}^{c^z}_{j,t}\right), \tag{10}$$

[6] Finite $\mathcal{J}$ can be interpreted as an individual's cognitive capacity. We assume that all agents have the same $\mathcal{J}$ across treatments, reflecting the experimental design in which laboratory participants are controlled to have similar characteristics and therefore differ only by treatment, that is, by the level of macroeconomic training they receive.

where $\text{clip}_{[0,1]}(\cdot)$ truncates values outside the unit interval. Now, each agent has a set of belief candidates.

The news vectors are drawn from:

$$\boldsymbol{\eta}^{z}_{j,t} \sim \text{SN}(\text{Location-}\mu^{z}_{\tau},\, \text{Scale-}\omega^{z}_{\tau},\, \text{Shape-}\alpha^{z}_{\tau})\,, \tag{11}$$

for $1 \leq t \leq K$ indicating the learning-phase of length K periods, and a normal-phase given by $t > K$. SN indicates a skew-normal distributional form, and $(\mu^{z}_{\tau}, \omega^{z}_{\tau}, \alpha^{z}_{\tau})$ denote the location, scale, and shape parameters. τ indexes information treatment, i.e., from treatment-specific distributions disciplined by the experimental learning-phase presented in Table 5. In -Target treatments, initial credibility is drawn from a common Gaussian prior with variance $\sigma^2_{c^z}$:

$$\boldsymbol{\eta^{c^z}_{j,t}} \sim \mathcal{N}(0, \sigma^2_{c^z_0}), 1 \leq t \leq K. \tag{12}$$

After the learning-phase, i.e., normal-phase, agents continue to receive private signals, now in the form of Gaussian perturbations (in line with the literature), with the variances being disciplined by the volatility observed during the learning-phase:

$$\boldsymbol{\eta}^{z}_{j,t} \sim \mathcal{N}(0, \hat{\sigma}^2_{z}), \qquad \boldsymbol{\eta^{c^z}_{j,t}} \sim \mathcal{N}(0, \hat{\sigma}^2_{c^z}), \tag{13}$$

for $t > K$, and $\hat{\sigma}^2_{z}$ and $\hat{\sigma}^2_{c^z}$ are computed from the realized learning-phase paths. This specification allows the model to preserve the experimental discipline in the early periods while transitioning to a stable updating environment in the normal-phase.

Belief evaluation. Agents evaluate candidate beliefs retrospectively using forecast performance over the most recent observed period. For each candidate forecasts

$m \in \boldsymbol{m}^z_{j,t}$ obtained from Eq. (9) (and Eq. (10) if -Target), the fitness score is:[7]

$$F^z_{j,t}(m) = -\big(z_{t-1} - m\big)^2. \tag{14}$$

The updated forecast for the period is then selected as the best-performing candidate,

$$\xi^z_{j,t} \in \arg\max_{m\in\boldsymbol{m}^z_{j,t}} F^z_{j,t}(m), \tag{15}$$

with random tie-breaking. The forecasts used for the period by each agent j is then $E^{\text{Evol}}_{j,t}(z_{t+1}) = \xi^z_{j,t}$ for subjects in non-Target treatments, and $E^{\text{Evol}}_{j,t}(z_{t+1}) = c^z_{j,t}z^* + (1 - c^z_{j,t})\big(\xi^z_{j,t}\big)$ for agents in -Target treatments.

Target-induced over-anchoring in inflation forecasts. In the -Target treatments, we allow knowledge of the central bank's inflation objective to distort agents' inflation expectations. Specifically, we assume that knowledge of the target induces a downward bias in inflation forecasts whenever the agent's own forecast exceeds the target:

$$E^{\text{Evol}}_{j,t}(\pi_{t+1}) = c^\pi_{j,t}\pi^* + (1 - c^\pi_{j,t})\xi^\pi_{j,t} - c^\pi_{j,t}\gamma \max\big\{\xi^\pi_{j,t} - \pi^*,\, 0\big\}. \tag{16}$$

The last term introduces a target-induced over-anchoring bias, which introduces the downward (asymmetric) effect of communicating target. Its magnitude is given by $c^\pi_{j,t}\gamma(\xi^\pi_{j,t} - \pi^*)$ whenever $\xi^\pi_{j,t} > \pi^*$, where γ is a scaling parameter; when $\gamma = 0$, the bias disappears. The bias becomes stronger as the target becomes more credible, that is, as $c^\pi_{j,t}$ increases, and as the agent's own forecast rises further above the target. By contrast, when the agent's forecast is below the target, the bias term is zero. Hence, target communication generates only a downward distortion in inflation expectations, making the effect asymmetric by construction. This feature allows the model to capture the empirical left-skewness observed in the initial forecast distributions under

[7] More generally, the fitness function can be written as: $F^z_{j,t}(m) = -\sum_{\ell=1}^{L} \lambda^{\ell-1}\big(z_{t-\ell} - m\big)^2$, where L denotes the length of recalled history and $\lambda \in (0, 1]$ is a memory discount factor. The fitness of a belief therefore reflects its discounted forecast performance over a short memory window. In the main text, we consider the parsimonious case $L = 1$, consistent with Arifovic et al. (2023), who find that $L = 1$ is sufficient to explain treatment effects in a learning-to-forecast experiment featuring different monetary policy treatments. Also, Arifovic et al. (2019) suggests that laboratory subjects tend to disregard longer past information, with usage of information beyond the second lag being uncommon. Our results remain qualitatively robust for higher values of L; these results are available upon request.

target communication (see Table 5). In the limiting case where an agent assigns full credibility to the central bank's inflation objective, $c^{\pi}_{j,t} = 1$, her inflation expectation satisfies $E^{\text{Evol}}_{j,t}(\pi_{t+1}) \leq \pi^*$ regardless of the value of her own belief $\xi^{\pi}_{j,t}$. Intuitively, such an agent interprets the policy objective as exerting downward pressure on inflation, rather than as calling for symmetric adjustments around π^*. In addition to being consistent with Table 5 where -Target treatments introduce a negative skewness to the distributions of the initial inflation forecasts of experimental participants (the negative estimated shape parameters), this interpretation is also consistent with empirical evidence suggesting that households do not evaluate inflation symmetrically around the central bank's target, and have a downward *preferences* over the target level of inflation; or "lower is better," despite the positive bias in reported expectations documented in the literature (e.g., D'Acunto et al., 2023). For example, Afrouzi et al. (2024) show that U.S. consumers, on average, prefer inflation to be close to zero than the FED's 2% target (see, also, Pfajfar and Winkler, 2025).

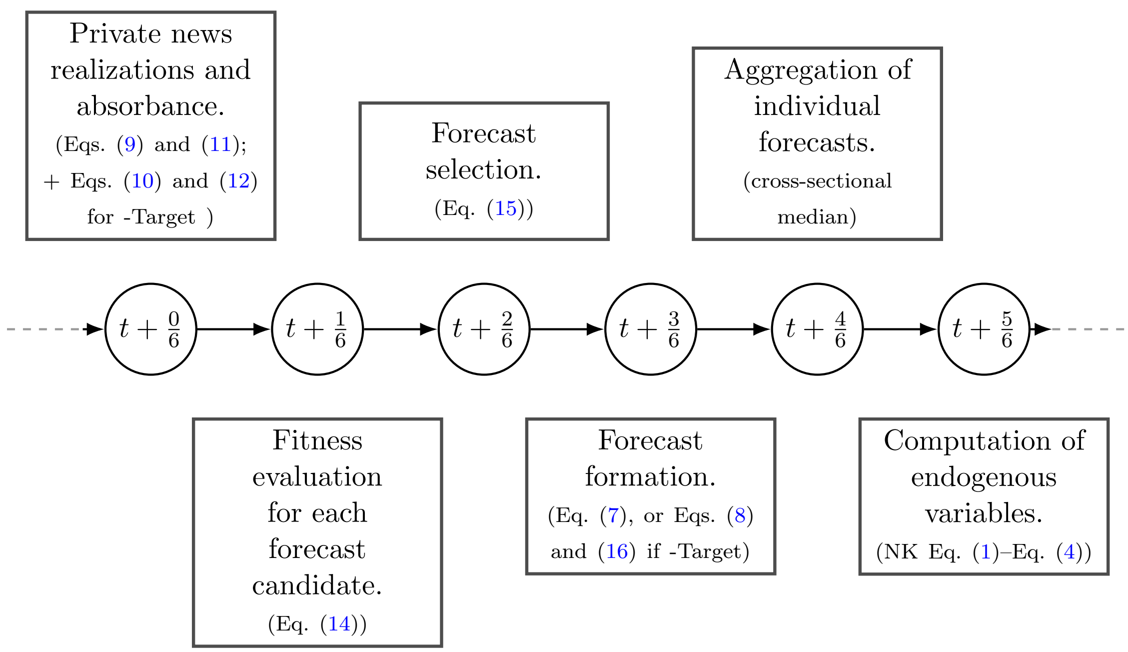
Regarding output forecasts, Table 5 suggests that target communication primarily dampens expectations toward zero, rather than inducing negative skewness. While we are not aware of comparable empirical evidence for household and firm expectations of output gaps, the existing firm-expectations literature points more toward optimistic or upward-biased expectations for firms' own sales or production (e.g., Bloom et al., 2025).

Motivated by these experimental and empirical evidence, our main specification allows the target-induced bias (the over-anchoring) to operate only on inflation forecasts, and not on output forecasts. That said, to clarify which features of the mechanism are essential for matching the data, we also consider several alternative specifications. Relative to the experimental evidence, denoted by specification (a), specification (b) is the baseline no-bias benchmark, obtained by setting $\gamma = 0$, so that target communication affects expectations only through the credibility term and not through any additional distortion. Specification (c) allows the bias to operate symmetrically around the target rather than asymmetrically, replacing the last term in Eq. (16) with $+\,c^{\pi}_{j,t}\gamma(\xi^{\pi}_{j,t} - \pi^*)$. This specification tests whether asymmetry is necessary to reproduce the treatment patterns observed in the data. Specification (d) is our main asymmetric negative-skew specification, given by Eq. (16). Finally, specifications (e) and (e′) provide robustness checks by extending the symmetric and asymmetric target-induced biases, respectively, to output forecasts as well.

Aggregation Each period's aggregate expectations are computed from the median of agents' forecasts, consistent with the experimental design. These aggregated expectations are then fed into the New Keynesian block together with the exogenous natural-rate disturbance.

In a diagram in Fig. 7, we summarize the sequence of events that occur within each period of the learning model. The figure links each step of this intra-period timing to the corresponding model equations.

Figure 7: Intra-period timing of events for each agent in the model



Note: In the learning-phase (i.e., $t \leq K$), events follow the sequence described above. In the normal-phase (i.e., $t > K$), Eq. (13) is used in place of Eq. (9) and Eq. (11) in the $(t + \frac{0}{6})$ box.

Taken together, the model extends the evolutionary learning framework of Arifovic et al. (2013) in two ways. First, it incorporates an empirically disciplined initialization of beliefs; in Arifovic et al. (2013), the algorithm is instead initialized with a history of REE path. Second, it introduces cognitive and behavioral constraints through finite information-processing capacity, modeled as a complexity penalty, and through a target-induced bias.

5.3 Simulation protocol and treatment mapping

Our objective is to reproduce the laboratory information treatments within the model. To this end, we conduct Monte Carlo simulations in which the learning-phase of each computerized economy is initialized using the estimated distributions of subjects' initial forecasts from the experiment, reported in Table 5. In this way, we construct simulated counterparts to the experimental treatments, discipline the model using the empirical learning-phase behavior observed in the lab, and then allow the model to generate implications for the subsequent belief dynamics.

As described above, each computerized economy is divided into two phases: a learning-phase followed by a normal-phase. During the learning-phase, the support of the news vectors in Eq. (11) is parameterized using the treatment-specific skew-normal estimates reported in Table 5, separately for inflation and output beliefs.

To avoid overfitting the model and to let it account for the effects of target provision endogenously, we use the estimated parameters from NoInfo, QualInfo, and QuantInfo to initialize the corresponding belief supports in the simulated economies (Table 5's Rows (I), (III), (V) for inflation forecasts, and Rows (VI), (VIII), (X) for output forecasts). In particular, NoInfo and NoInfoTarget are both initialized using the NoInfo estimates, QualInfo and QualInfoTarget are both initialized using the QualInfo estimates, and QuantInfo is initialized using its own estimates. This mapping is consistent with the experimental design: in the laboratory, NoInfo and NoInfoTarget differ only in whether the target is provided, and the same is true for QualInfo and QualInfoTarget, while subjects within each pair otherwise receive identical macroeconomic-literacy training. Since the model already incorporates the cognitive and behavioral effects associated with target communication, imposing the same initial belief distributions within each pair isolates the role of target provision rather than forcing its effects directly into the initialization. And, consistent to the laboratory environment, in our computerized environments, NoInfo/QualInfo agents differ than NoInfoTarget/QualInfoTarget agents only in the dimension of knowing the targets.

Overall, the resulting computerized treatments differ along the same dimensions as in the experiment, including information complexity and, for the -Target treatments, the additional cognitive and behavioral burden associated with learning the target.

Under this protocol, the model is then used to generate the evolution of agents' beliefs and the implied economic variables. We then assess whether the simulated treatment patterns are consistent with the experimental evidence. The simulation environment matches the laboratory design: each economy consists of $N = 7$ agents and runs for $T = 60$ periods, organized into two repetitions, with the initial $K = 8$ periods of the first repetition constituting the learning-phase. In the second repetition, no separate learning-phase is imposed; instead, the standard deviations of the news vectors are set using the realized inflation and output paths from the first repetition. The data-generating process is governed by the same New Keynesian parameters used in the experiment. The learning parameters are set to $J = 60$, $\sigma^2_{c_0^z} = 0.1$. For the -Target treatments, initial target credibility is set to $c^z_{j,1} = 0.35$, and the bias parameter $\gamma = 1.8$ for all agents in all -Target treatments.

5.4 Simulation results

We use the model to assess whether the behavioral mechanisms introduced above can reproduce the treatment patterns observed in the laboratory. The focus is on three facts from the experiment: first, treatment differences are modest for output but much more pronounced for inflation; second, target communication worsens inflation forecast accuracy and disagreement for agents with limited macroeconomic training; and third, QuantInfo improves on QualInfoTarget for inflation expectations. To evaluate these dimensions, we first compare simulated and experimental time series under the six experimental shock sequences, and then turn to broader Monte Carlo evidence based on randomly drawn shocks.

5.4.1 Model fit and treatment patterns

As a reality check, we simulate our main specification (d) under the six experimental shock sequences and compare the median simulated paths with the laboratory data. The results are presented in Fig. 8-Fig. 10.

Our main specification reproduces the broad output dynamics reasonably well across treatments and, importantly, matches the empirical finding that aggregate output paths differ relatively little across information treatments. By contrast, inflation

Figure 8: Dynamics of output, experiments (top) vs. simulations (bottom), main specification (d), all shock sequences, both repetitions

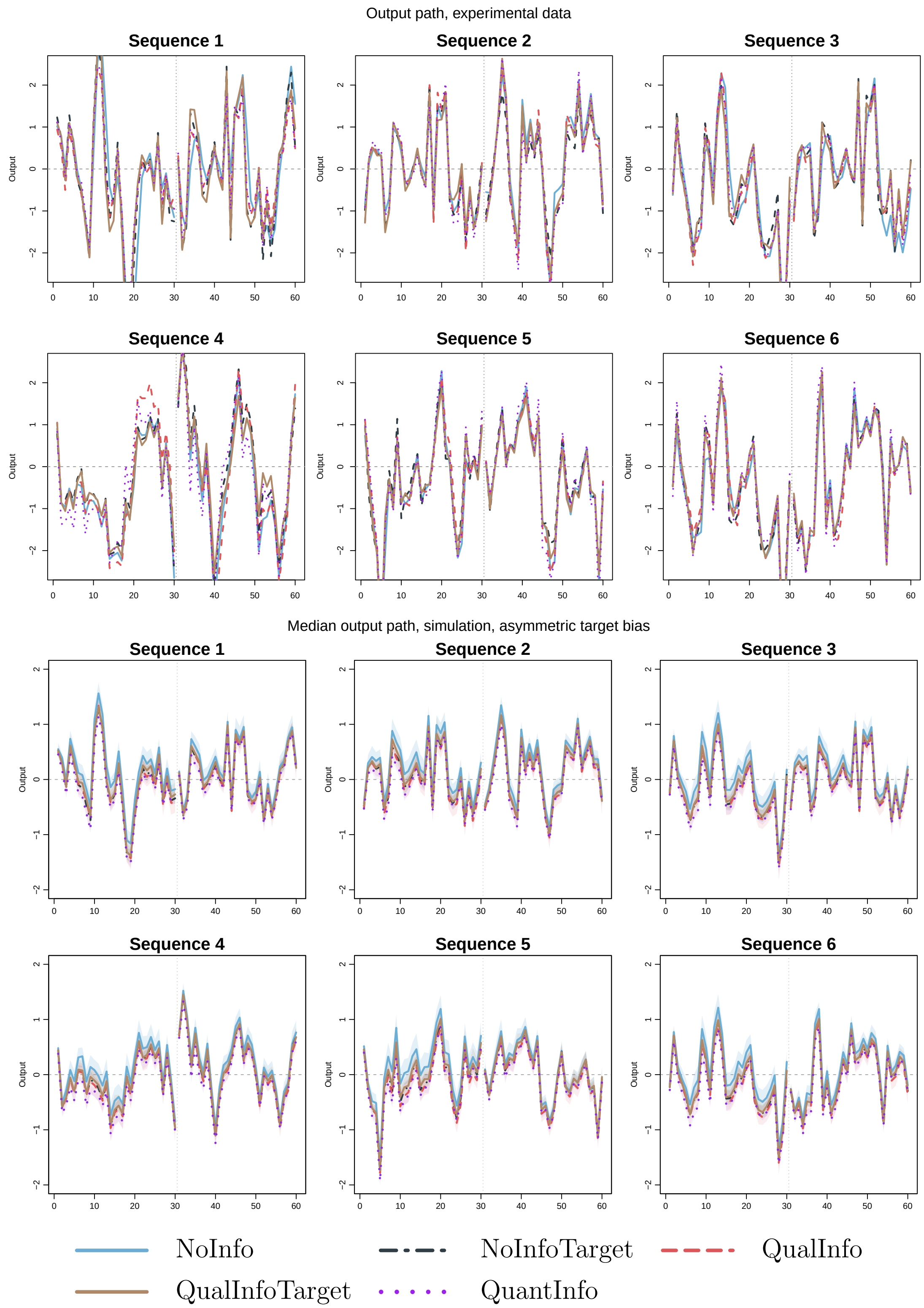


Figure 9: Dynamics of inflation, experiments (left) vs. simulations (right), main specification (d), shock sequences 1-3, both repetitions

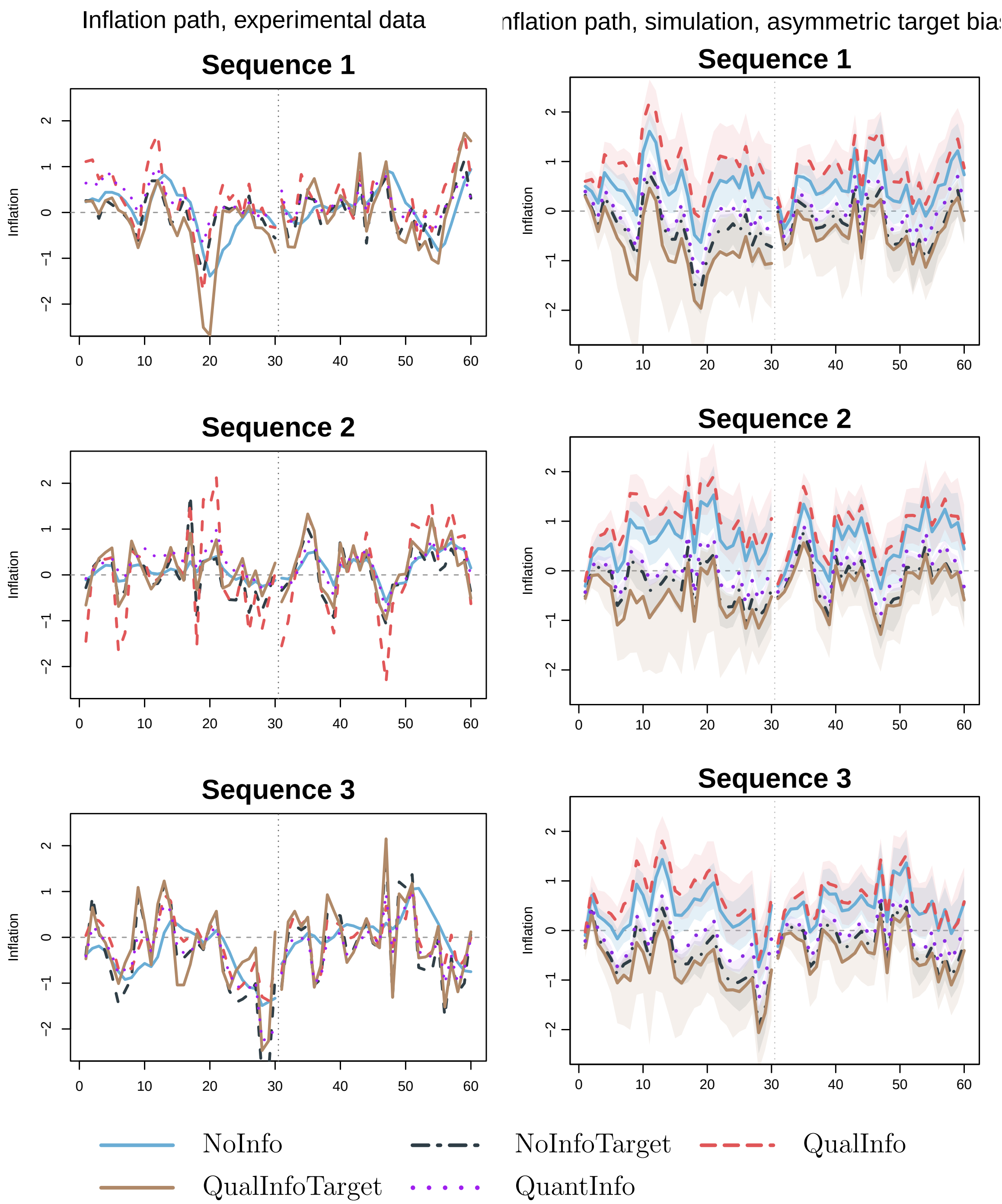
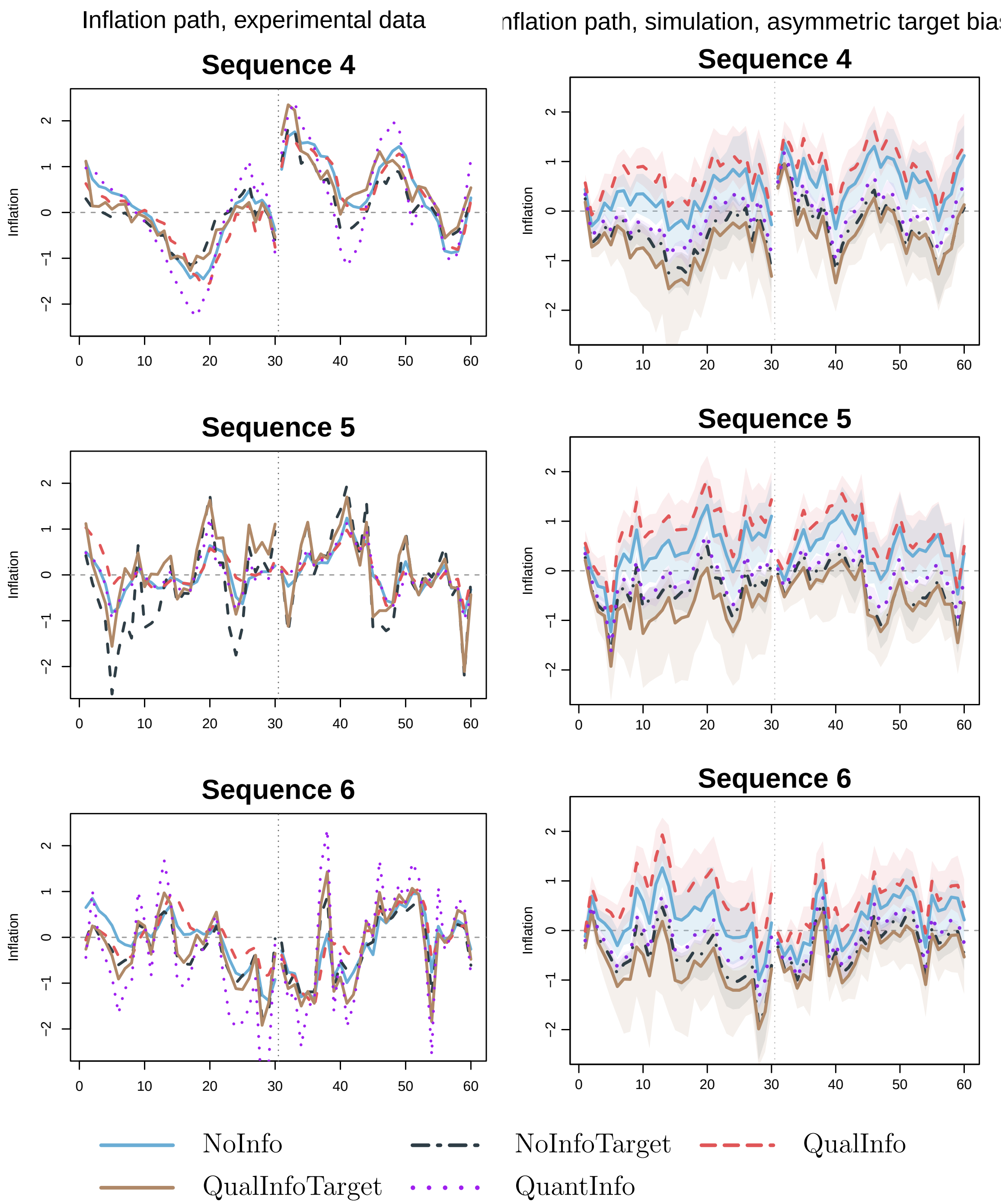


Figure 10: Dynamics of inflation, experiments (left) vs. simulations (right), main specification (d), shock sequences 4-6, both repetitions



displays clear treatment heterogeneity in both the data and the simulations. This asymmetry between output and inflation is a central feature of the experiment, and the model captures it well. In particular, under the main specification, the simulated inflation paths follow the treatment ordering observed in the laboratory more closely than the alternative specifications.

To compare specifications more systematically, we conduct 100 Monte Carlo simulations for each treatment, drawing a new shock path in each simulation and holding it fixed across treatments. We then estimate the same pairwise regressions used for the experimental data, i.e., reported in Table 4, for each of the abovementioned specifications. Respectively, the regression tables for specification (b)-(e′) are presented in Table 6-Table A6. We summarize the model fit by a treatment-effects replication score, $\mathcal{R}$. For each estimated coefficient $coef$ under specification $spec$, we assign:

$$\mathcal{R}_{spec,coef} = \begin{cases} 1 & \text{if the simulated estimate matches the experimental counterpart in both sign and statistical significance,} \\ 0.5 & \text{if the sign matches but at least one is not statistical,} \\ 0 & \text{if the sign is reversed relative to the experimental counterpart.} \end{cases}$$

We then define the overall replication score as $\mathcal{R}_{spec} = \sum_{j=1}^{24} \mathcal{R}_{spec,j}$, where the 24 comparisons in Table 4 consisting of 12 inflation-side and 12 output-side treatment effects. With respect to the experimental estimates in Table 4, the overall replication scores of the specifications are: $\mathcal{R}_b = 14$, $\mathcal{R}_c = 16.5$, $\mathcal{R}_d = 20.5$, $\mathcal{R}_e = 14$, and $\mathcal{R}_{e'} = 16$.

The baseline specification (b), Table 6—in which target communication affects expectations only through the additional credibility learning task and not through any bias—reproduces some features of the data: QualInfo yields worse inflation forecasts than NoInfo, and QuantInfo improves on QualInfoTarget. However, it fails on the key target-treatment comparison, because it predicts that adding targets should reduce inflation errors and disagreement in NoInfoTarget and QualInfoTarget relative to their non-target counterparts. In this specification, the announced target acts only as an anchor that dampens forecasts toward the zero targets.

Specification (c), Table 7—which introduces a symmetric inflation-target bias—improves on this dimension: it results in an improvement of fit ($\mathcal{R}_c > \mathcal{R}_b$) by generating higher inflation forecast errors and disagreement in NoInfoTarget and QualInfoTarget, consistent with the experimental data. However, it still misses an important distributional feature with respect to the inflation forecasts. That is, Table 5 shows that the -Target treatments subject to a negative skewness. Here, specification (c) is unable to generate that. To see this, we zoom in at an experimental session (Sequence 1) and plots the inflation paths by model specification in Fig. 11. It can be seen that in specification (c), inflation paths in NoInfoTarget and QualInfoTarget display an upward (positive) tendency. The reason for this pattern is: the initial inflation beliefs of simulated NoInfo and QualInfo agents are positively skewed (per their human counterpart); then once augmented with the target learning tasks, specification (c)'s symmetric target-induced distortion preserves or reinforces that skewness rather than reversing it. Overall, specification (c) matches the sign of some treatment effects, but not the observed shape of the inflation dynamics.

Our best performing specification is (d), Table 8—in which knowledge of the inflation target induces an asymmetric downward bias in inflation expectations. This specification matches the experimental evidence most closely. It reproduces the deterioration in inflation forecast accuracy and the increase in disagreement when targets are communicated to agents with limited macroeconomic training, while also preserving the improvement of QuantInfo relative to QualInfoTarget. It also aligns with the distributional evidence by generating the negative skewness observed in the inflation dynamics of the target treatments (see Fig. 11).

By contrast, extensions that impose target-induced biases on output forecasts, specifications (e) and (e′), Tables A5 and A6, perform less well in replicating the treatment effects to output forecasts: they tend to generate deteriorating output forecast performance with more information, which is not supported by the laboratory evidence. Taken together, the simulation evidence points to a bias mechanism that is specific to inflation, not output.

Table 6: Pairwise comparisons, simulations, baseline specification (b)

Panel A	Log absolute inflation forecast error						Log absolute inflation disagreement					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
NoInfoTarget	-0.665***						-1.118***					
	(0.028)						(0.061)					
QualInfo		0.062***						0.108***				
		(0.024)						(0.030)				
QualInfoTarget			-0.678***	0.049*					-1.177***	0.049		
			(0.029)	(0.027)					(0.065)	(0.087)		
QuantInfo					-0.083***	-0.699***					-0.144*	-1.213***
					(0.027)	(0.029)					(0.081)	(0.075)
Constant	3.899***	3.712***	4.025***	3.484***	3.568***	3.933***	3.646***	3.425***	3.990***	2.985***	3.146***	3.757***
	(0.051)	(0.041)	(0.045)	(0.055)	(0.058)	(0.051)	(0.039)	(0.029)	(0.042)	(0.048)	(0.053)	(0.048)
Baseline	NoInfo	NoInfo	QualInfo	NoInfoTarget	QualInfoTarget	NoInfo	NoInfo	NoInfo	QualInfo	NoInfoTarget	QualInfoTarget	NoInfo
Num.Obs.	11,800	11,800	11,800	11,800	11,800	11,800	11,800	11,800	11,800	11,800	11,800	11,800
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B	**Log absolute output forecast error**						**Log absolute output disagreement**					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
NoInfoTarget	-0.495***						-0.701***					
	(0.037)						(0.069)					
QualInfo		-0.063*						-0.023				
		(0.035)						(0.045)				
QualInfoTarget			-0.537***	-0.105***					-0.897***	-0.219**		
			(0.037)	(0.036)					(0.076)	(0.094)		
QuantInfo					-0.147***	-0.747***					-0.293***	-1.213***
					(0.028)	(0.033)					(0.090)	(0.080)
Constant	4.120***	4.033***	4.179***	3.833***	3.795***	4.186***	4.014***	3.909***	4.115***	3.542***	3.420***	4.111***
	(0.049)	(0.044)	(0.048)	(0.053)	(0.059)	(0.053)	(0.042)	(0.034)	(0.044)	(0.055)	(0.053)	(0.049)
Baseline	NoInfo	NoInfo	QualInfo	NoInfoTarget	QualInfoTarget	NoInfo	NoInfo	NoInfo	QualInfo	NoInfoTarget	QualInfoTarget	NoInfo
Num.Obs.	11,800	11,800	11,800	11,800	11,800	11,800	11,800	11,800	11,800	11,800	11,800	11,800
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Each column reports a separate random-effects regression estimated on the indicated treatment pair. With session random effects and period fixed effects. Robust standard errors are reported in parentheses. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively. 100 Monte Carlo simulations of the model. In each simulation, we draw a new shock path and hold it fixed across treatments. if the simulated estimate matches the experimental counterpart in sign and statistical significance; if the sign matches but at least one is not statistical; if the sign is reversed relative to the experimental counterpart.

Table 7: Pairwise comparisons, simulations, specification (c)

Panel A	Log absolute inflation forecast error						Log absolute inflation disagreement					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
NoInfoTarget	0.703***						0.915***					
	(0.038)						(0.045)					
QualInfo		0.062***						0.108***				
		(0.024)						(0.030)				
QualInfoTarget			0.647***	0.006					0.817***	0.011		
			(0.036)	(0.044)					(0.044)	(0.051)		
QuantInfo					0.038	0.747***					0.027	0.952***
					(0.043)	(0.034)					(0.051)	(0.040)
Constant	3.552***	3.712***	3.783***	4.263***	4.310***	3.593***	3.270***	3.425***	3.650***	4.302***	4.380***	3.338***
	(0.045)	(0.041)	(0.037)	(0.039)	(0.037)	(0.039)	(0.035)	(0.029)	(0.035)	(0.036)	(0.037)	(0.032)
Baseline	NoInfo	NoInfo	QualInfo	NoInfoTarget	QualInfoTarget	NoInfo	NoInfo	NoInfo	QualInfo	NoInfoTarget	QualInfoTarget	NoInfo
Num.Obs.	11,800	11,800	11,800	11,800	11,800	11,800	11,800	11,800	11,800	11,800	11,800	11,800
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B	Log absolute output forecast error						Log absolute output disagreement					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
NoInfoTarget	-0.193***						-0.220***					
	(0.037)						(0.048)					
QualInfo		-0.063*						-0.023				
		(0.035)						(0.045)				
QualInfoTarget			-0.117***	0.013					-0.210***	-0.012		
			(0.034)	(0.035)					(0.044)	(0.047)		
QuantInfo					-0.370***	-0.550***					-0.428***	-0.660***
					(0.030)	(0.030)					(0.043)	(0.044)
Constant	3.996***	4.033***	3.921***	3.754***	3.878***	4.107***	3.784***	3.909***	3.732***	3.409***	3.463***	3.850***
	(0.049)	(0.044)	(0.053)	(0.056)	(0.058)	(0.051)	(0.037)	(0.034)	(0.036)	(0.042)	(0.035)	(0.034)
Baseline	NoInfo	NoInfo	QualInfo	NoInfoTarget	QualInfoTarget	NoInfo	NoInfo	NoInfo	QualInfo	NoInfoTarget	QualInfoTarget	NoInfo
Num.Obs.	11,800	11,800	11,800	11,800	11,800	11,800	11,800	11,800	11,800	11,800	11,800	11,800
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

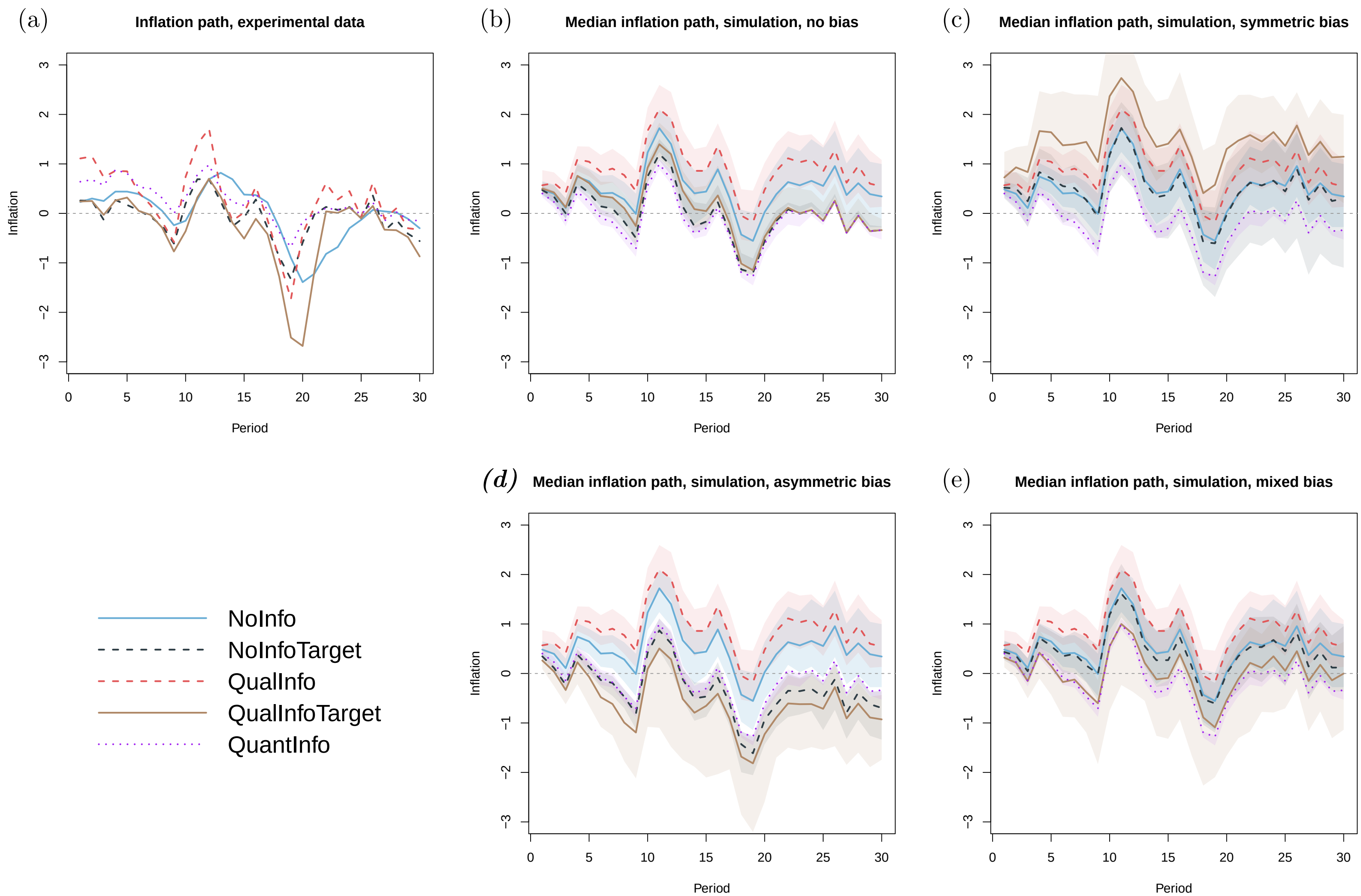
Note: Each column reports a separate random-effects regression estimated on the indicated treatment pair. With session random effects and period fixed effects. Robust standard errors are reported in parentheses. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively. 100 Monte Carlo simulations of the model. In each simulation, we draw a new shock path and hold it fixed across treatments. if the simulated estimate matches the experimental counterpart in sign and statistical significance; if the sign matches but at least one is not statistical; if the sign is reversed relative to the experimental counterpart.

Table 8: Pairwise comparisons, simulations, main specification (d)

Panel A	Log absolute inflation forecast error						Log absolute inflation disagreement					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
NoInfoTarget	0.143***						0.233***					
	(0.034)						(0.045)					
QualInfo		0.062***						0.108***				
		(0.024)						(0.030)				
QualInfoTarget			0.573***	0.492***					0.739***	0.614***		
			(0.044)	(0.050)					(0.053)	(0.062)		
QuantInfo					-0.490***	0.145***					-0.595***	0.252***
					(0.050)	(0.044)					(0.063)	(0.057)
Constant	3.515***	3.712***	3.514***	3.397***	3.892***	3.517***	3.043***	3.425***	3.245***	2.988***	3.660***	3.102***
	(0.050)	(0.041)	(0.044)	(0.053)	(0.058)	(0.053)	(0.041)	(0.029)	(0.041)	(0.053)	(0.061)	(0.047)
Baseline	NoInfo	NoInfo	QualInfo	NoInfoTarget	QualInfoTarget	NoInfo	NoInfo	NoInfo	QualInfo	NoInfoTarget	QualInfoTarget	NoInfo
Num.Obs.	11,800	11,800	11,800	11,800	11,800	11,800	11,800	11,800	11,800	11,800	11,800	11,800
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B	**Log absolute output forecast error**						**Log absolute output disagreement**					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
NoInfoTarget	-0.523***						-0.703***					
	(0.031)						(0.080)					
QualInfo		-0.063*						-0.023				
		(0.035)						(0.045)				
QualInfoTarget			-0.546***	-0.086***					-0.862***	-0.181*		
			(0.035)	(0.031)					(0.078)	(0.108)		
QuantInfo					-0.084***	-0.693***					-0.212**	-1.097***
					(0.027)	(0.032)					(0.097)	(0.069)
Constant	4.158***	4.033***	4.125***	3.789***	3.725***	4.180***	4.043***	3.909***	4.075***	3.528***	3.361***	4.057***
	(0.046)	(0.044)	(0.049)	(0.054)	(0.057)	(0.052)	(0.048)	(0.034)	(0.046)	(0.060)	(0.055)	(0.047)
Baseline	NoInfo	NoInfo	QualInfo	NoInfoTarget	QualInfoTarget	NoInfo	NoInfo	NoInfo	QualInfo	NoInfoTarget	QualInfoTarget	NoInfo
Num.Obs.	11,800	11,800	11,800	11,800	11,800	11,800	11,800	11,800	11,800	11,800	11,800	11,800
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Each column reports a separate random-effects regression estimated on the indicated treatment pair. With session random effects and period fixed effects. Robust standard errors are reported in parentheses. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively. 100 Monte Carlo simulations of the model. In each simulation, we draw a new shock path and hold it fixed across treatments. if the simulated estimate matches the experimental counterpart in sign and statistical significance; if the sign matches but at least one is not statistical; if the sign is reversed relative to the experimental counterpart.

Figure 11: Dynamics of inflation: experiments vs. simulations, zoom in



Note: Panel (a) displays the inflation paths under five treatments obtained from the lab. For visibility, dynamics under shock sequence 1 – repetition 1 are shown for comparisons with the simulated data. The simulations are conducted under four specifications. The baseline, i.e., specification (b), no target bias; (c) symmetric target bias on inflation forecasts, (d) main specification, asymmetric target bias on inflation forecasts, and (e) asymmetric target bias on inflation forecasts and symmetric target bias on output forecasts.

5.4.2 Interpretation

The simulations show that the treatment effects arise from three distinct ingredients that play different roles. The first is heterogeneity in initial beliefs. In the model, QualInfo agents begin with more dispersed inflation beliefs than NoInfo agents, consistent with the learning-phase evidence. This feature helps rationalize why qualitative information alone does not improve inflation forecasting and can instead worsen accuracy and increase disagreement: when descriptions are too imprecise to discipline beliefs, they introduce ambiguity rather than useful structure.

The second ingredient is bounded cognitive capacity. In the -Target treatments, agents allocate fixed learning capacity across more objects. They update not only inflation and output beliefs, but also the credibility assigned to announced targets. This increases complexity and slows adjustment. On its own, however, this mechanism cannot explain the main inflation result. Greater complexity and limited processing capacity can make beliefs more sluggish and error-prone, but it does not imply that target communication should systematically worsen inflation forecast performance relative to non-target treatments.

The third ingredient—the key behavioral mechanism of the model—is an asymmetric interpretation of the inflation target. Under the main specification, agents with limited macroeconomic understanding do not treat the target as a symmetric stabilization objective around π^*. Instead, they interpret it in a downward-biased way, as if lower inflation were always preferred.[8] In other words, target communication over-anchors inflation expectations. Absent this bias, the target would act as a stabilizing anchor, pulling beliefs toward π^* and reducing errors and disagreement—precisely why the no-bias benchmark cannot match the data. Once the asymmetric bias is introduced, target communication no longer merely anchors expectations; it pulls them below target. In NoInfoTarget and QualInfoTarget, this distortion pushes inflation beliefs downward, increasing forecast errors and disagreement in line with the laboratory evidence. A symmetric-bias specification also falls short, as it cannot replicate the directional and distributional features of the data.

[8] Figure A1 shows that agents in the -Target treatments place increasing weight on announced targets over time. Because the target-induced bias scales with this credibility weight, rising credibility amplifies the downward distortion in expectations and helps generate the deterioration in forecast accuracy and disagreement.

The contrast with output is informative. For output forecasts, target communication mainly plays an anchoring role and does not induce a comparable bias. This is consistent with the empirical finding that the deterioration under target communication is concentrated in inflation, not output. Taken together, the simulations imply that the adverse effects of target communication in low-literacy environments do not arise from transparency per se, but from how communication is processed—through heterogeneous beliefs, limited cognitive capacity, and, for inflation, an asymmetric downward interpretation of the target.

6 Discussion

Many countries have now implemented national strategies to improve financial literacy, often coordinated by central banks, finance ministries, or dedicated public agencies. Recent evidence suggests that this policy approach has become widespread, with dozens of economies adopting national strategies aligned with OECD guidance. These initiatives have also expanded in scope, frequently being integrated into school curricula and public outreach efforts. Despite this progress, their focus remains overwhelmingly on personal finance—budgeting, saving, and household financial decision-making—while systematic attention to macroeconomic literacy is largely absent.

This omission is notable. Macroeconomic literacy serves a distinct purpose: it equips individuals to understand aggregate dynamics, interpret policy actions, and form expectations about key variables such as inflation, interest rates, and unemployment. These expectations are central to monetary policy transmission and the broader functioning of the economy. Without a basic understanding of how the macroeconomy operates, individuals may struggle to process the implications of policy, limiting the effectiveness of central bank communication and, ultimately, policy itself.

The results from our experiment suggest that providing people more information about their economy does not necessarily improve their ability to forecast. Providing the central bank's targets when subjects have no information about the DGP improves experienced output forecast accuracy but worsens inflation accuracy. With already a qualitative understanding of the economy, providing information about targets worsens forecast accuracy. Quantitative information does significantly improve inflation forecasting and reduces disagreement about inflation, but only relative to qualitative information. Compared to having no information, quantitative information also worsens forecast performance.

Our results highlight that the effects of target communication depend critically on how the inflation target is perceived. In our data, announcing the target reduces the upward skew in inflation beliefs, consistent with evidence that communicating the target can strengthen credibility and move expectations toward the central bank's objective (see, e.g., Kostyshyna and Petersen, 2023; Ehrmann et al., 2025). However, our findings also show that anchoring can overshoot. Rather than serving solely as a symmetric focal point around which inflation stabilizes, the target can generate a downward bias in expectations and lower relative forecast accuracy. While most survey experiments find only modest and incomplete anchoring effects, Coibion et al. (2022) similarly document expectations that immediately overshoot the target. We attribute the over-anchoring results in both their survey and our experimental environment to the fact that inflation was already close to target and macroeconomic conditions were relatively stable, making the target especially salient as a focal point and encouraging participants to place excessive weight on it.

Improving macroeconomic literacy presents substantial challenges that remain largely unresolved. The effectiveness of quantitative training depends not only on the public's baseline education and interest, but also on difficult design choices about what to teach and how to teach it. Indeed, McMahon et al. (2026) find that a teaching approach can yield better understanding than giving households specific information to influence expectations. Another challenge is in selecting among competing models of the economy and translating them into forms that are both accurate and accessible inevitably involves a trade-off between fidelity and comprehensibility. These challenges point to a clear need for further research on how individuals process and internalize complex, interdependent economic relationships. Advancing this agenda is essential for understanding whether, and how, macroeconomic literacy can be meaningfully improved, and for designing communication strategies that enhance the public's ability to form well-grounded expectations.

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A Additional results

Table A1: Pairwise comparisons - Experiments, with repetition interactions

Panel A	Log absolute inflation forecast error						Log absolute inflation disagreement					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
NoInfoTarget	0.479***						0.397***					
	(0.078)						(0.074)					
QualInfo		0.434***						0.525***				
		(0.083)						(0.082)				
QualInfoTarget			0.184**	0.139**					0.162**	0.290***		
			(0.078)	(0.070)					(0.076)	(0.072)		
QuantInfo					-0.194**	0.423***					-0.265***	0.422***
					(0.079)	(0.075)					(0.084)	(0.079)
Repetition 2	0.145	0.145	0.060	0.149	0.140	0.145	0.073	0.073	-0.004	0.193	0.076	0.073
	(0.129)	(0.108)	(0.163)	(0.177)	(0.149)	(0.214)	(0.151)	(0.106)	(0.156)	(0.143)	(0.140)	(0.201)
Treat x Rep2	0.004	-0.085	0.080	-0.009	-0.066	-0.071	0.119	-0.077	0.080	-0.117	-0.104	-0.102
	(0.106)	(0.111)	(0.105)	(0.099)	(0.114)	(0.104)	(0.097)	(0.109)	(0.101)	(0.094)	(0.115)	(0.109)
Constant	3.526***	3.428***	3.975***	4.118***	4.185***	3.453***	3.226***	3.262***	3.543***	3.379***	3.813***	3.370***
	(0.137)	(0.130)	(0.147)	(0.146)	(0.139)	(0.179)	(0.177)	(0.164)	(0.171)	(0.161)	(0.168)	(0.201)
Baseline	NoInfo	NoInfo	QualInfo	NoInfoTarget	QualInfoTarget	NoInfo	NoInfo	NoInfo	QualInfo	NoInfoTarget	QualInfoTarget	NoInfo
Num.Obs.	720	720	720	720	720	720	720	720	720	720	720	720
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B	Log absolute output forecast error						Log absolute output disagreement					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
NoInfoTarget	-0.186**						-0.214**					
	(0.089)						(0.109)					
QualInfo		-0.150						-0.220*				
		(0.095)						(0.115)				
QualInfoTarget			-0.054	-0.019					-0.092	-0.099		
			(0.081)	(0.078)					(0.072)	(0.064)		
QuantInfo					0.013	-0.191**					-0.072	-0.385***
					(0.079)	(0.093)					(0.073)	(0.111)
Repetition 2	0.032	0.032	-0.082	-0.005	0.017	0.032	0.174	0.174	-0.136	-0.036	0.021	0.174
	(0.274)	(0.252)	(0.111)	(0.116)	(0.088)	(0.249)	(0.456)	(0.451)	(0.171)	(0.152)	(0.128)	(0.459)
Treat x Rep2	-0.037	-0.114	0.099	0.022	0.026	0.011	-0.210	-0.310**	0.157*	0.056	0.000	-0.153
	(0.121)	(0.129)	(0.111)	(0.106)	(0.109)	(0.127)	(0.145)	(0.153)	(0.095)	(0.086)	(0.100)	(0.150)
Constant	4.770***	4.786***	4.801***	4.750***	4.720***	4.759***	4.043***	4.083***	3.765***	3.732***	3.891***	4.300***
	(0.236)	(0.211)	(0.127)	(0.144)	(0.125)	(0.208)	(0.344)	(0.360)	(0.202)	(0.148)	(0.146)	(0.338)
Baseline	NoInfo	NoInfo	QualInfo	NoInfoTarget	QualInfoTarget	NoInfo	NoInfo	NoInfo	QualInfo	NoInfoTarget	QualInfoTarget	NoInfo
Num.Obs.	720	720	720	720	720	720	720	720	720	720	720	720
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Each column reports a separate random-effects regression estimated on the indicated treatment pair. The dependent variables are the log absolute one-period-ahead absolute forecast errors or period-level standard deviation of forecasts for inflation and output gap. Units are given in basis points. The panel unit is session-period, with session random effects and period fixed effects. α denotes the estimated constant. NoInfoTarget, QualInfo, QualInfoTarget, and QuantInfo are treatment-specific dummy variables. HAC robust standard errors are reported in parentheses. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

Table A2: Maximum likelihood estimates of skew-normal parameters of the learning-phase forecasts, learning-phase length $K = 7$

Treatment	Location-μ (s.e.)	Scale-ω (s.e.)	Shape-α (s.e.)	Implied mean	Implied SD
Inflation forecasts					
NoInfo	-0.14 (0.09)	0.33 (0.07)	1.52 (0.99)	0.08	0.24
NoInfoTarget	-0.01 (0.08)	0.33 (0.07)	-1.74 (1.05)	-0.24	0.24
QualInfo	-0.21 (0.05)	0.53 (0.08)	5.47 (2.83)	0.20	0.33
QualInfoTarget	0.10 (0.09)	0.33 (0.06)	-1.32 (0.75)	-0.11	0.26
QuantInfo	0.28 (0.15)	0.33 (0.10)	-1.08 (1.14)	0.09	0.27
Output forecasts					
NoInfo	-0.33 (0.05)	0.69 (0.08)	6.14 (2.22)	0.22	0.43
NoInfoTarget	-0.32 (0.10)	0.41 (0.08)	1.39 (0.73)	-0.05	0.31
QualInfo	-0.37 (0.06)	0.75 (0.10)	7.65 (4.26)	0.22	0.46
QualInfoTarget	-0.33 (0.09)	0.40 (0.08)	1.60 (0.90)	-0.06	0.29
QuantInfo	-0.21 (0.28)	0.38 (0.15)	0.86 (1.50)	-0.01	0.33

Note: Entries report MLE estimates of skew-normal direct parameters. Implied mean and SD are computed from the estimations using standard skew-normal moments. The learning-phase length is $K = 7$. Units are in percentage points.

Table A3: Maximum likelihood estimates of skew-normal parameters of the learning-phase forecasts, learning-phase length $K = 9$

Treatment	Location-μ (s.e.)	Scale-ω (s.e.)	Shape-α (s.e.)	Implied mean	Implied SD
Inflation forecasts					
NoInfo	-0.09 (0.19)	0.26 (0.11)	0.95 (1.62)	0.06	0.22
NoInfoTarget	-0.01 (0.06)	0.28 (0.05)	-1.83 (0.86)	-0.20	0.20
QualInfo	-0.23 (0.05)	0.50 (0.07)	6.44 (3.66)	0.17	0.31
QualInfoTarget	0.08 (0.25)	0.30 (0.12)	-0.73 (1.57)	-0.06	0.26
QuantInfo	-0.05 (0.29)	0.27 (0.13)	0.68 (1.90)	0.07	0.24
Output forecasts					
NoInfo	-0.39 (0.05)	0.70 (0.08)	11.42 (7.56)	0.17	0.43
NoInfoTarget	-0.23 (0.08)	0.35 (0.06)	1.41 (0.68)	-0.00	0.26
QualInfo	-0.31 (0.05)	0.57 (0.08)	5.65 (3.90)	0.13	0.35
QualInfoTarget	-0.31 (0.05)	0.39 (0.06)	2.59 (1.04)	-0.02	0.26
QuantInfo	0.20 (0.12)	0.37 (0.09)	-1.16 (0.86)	-0.03	0.30

Note: Entries report MLE estimates of skew-normal direct parameters. Implied mean and SD are computed from the estimations using standard skew-normal moments. The learning-phase length is $K = 9$. Units are in percentage points.

Table A4: Maximum likelihood estimates of skew-normal parameters of forecasts in all periods of repetition 1

Treatment	Location-μ (s.e.)	Scale-ω (s.e.)	Shape-α (s.e.)	Implied mean	Implied SD
Inflation forecasts					
NoInfo	-0.15 (0.02)	0.20 (0.03)	5.95 (4.22)	0.01	0.12
NoInfoTarget	0.01 (0.04)	0.17 (0.03)	-1.64 (1.04)	-0.11	0.12
QualInfo	-0.01 (0.08)	0.23 (0.05)	1.24 (0.91)	0.13	0.18
QualInfoTarget	0.13 (0.10)	0.27 (0.07)	-1.26 (1.09)	-0.04	0.21
QuantInfo	0.18 (0.12)	0.27 (0.08)	-1.18 (1.16)	0.02	0.22
Output forecasts					
NoInfo	-0.21 (0.02)	0.21 (0.03)	4.06 (1.78)	-0.04	0.14
NoInfoTarget	-0.22 (0.06)	0.28 (0.05)	2.33 (1.61)	-0.01	0.19
QualInfo	-0.17 (0.04)	0.37 (0.05)	5.28 (3.07)	0.12	0.23
QualInfoTarget	-0.19 (0.07)	0.26 (0.05)	1.51 (0.93)	-0.01	0.19
QuantInfo	-0.28 (0.02)	0.32 (0.04)	22.44 (22.83)	-0.02	0.19

Note: Entries report MLE estimates of skew-normal direct parameters. Implied mean and SD are computed from the estimations using standard skew-normal moments. Units are in percentage points.

Table A5: Pairwise comparisons, simulations, specification (e)

Panel A	Log absolute inflation forecast error						Log absolute inflation disagreement					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
NoInfoTarget	0.583***						0.521***					
	(0.035)						(0.043)					
QualInfo		0.062***						0.108***				
		(0.024)						(0.030)				
QualInfoTarget			0.853***	0.332***					0.869***	0.456***		
			(0.044)	(0.052)					(0.052)	(0.061)		
QuantInfo					-0.686***	0.229***					-0.680***	0.298***
					(0.053)	(0.041)					(0.067)	(0.056)
Constant	3.435***	3.712***	3.448***	3.691***	4.166***	3.578***	2.956***	3.425***	3.203***	3.147***	3.811***	3.163***
	(0.048)	(0.041)	(0.046)	(0.053)	(0.053)	(0.051)	(0.038)	(0.029)	(0.044)	(0.051)	(0.054)	(0.043)
Baseline	NoInfo	NoInfo	QualInfo	NoInfoTarget	QualInfoTarget	NoInfo	NoInfo	NoInfo	QualInfo	NoInfoTarget	QualInfoTarget	NoInfo
Num.Obs.	11,800	11,800	11,800	11,800	11,800	11,800	11,800	11,800	11,800	11,800	11,800	11,800
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B	Log absolute output forecast error						Log absolute output disagreement					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
NoInfoTarget	0.901***						1.022***					
	(0.036)						(0.043)					
QualInfo		-0.063*						-0.023				
		(0.035)						(0.045)				
QualInfoTarget			0.988***	0.024					1.112***	0.068		
			(0.043)	(0.043)					(0.047)	(0.046)		
QuantInfo					-0.449***	0.477***					-0.391***	0.698***
					(0.050)	(0.035)					(0.053)	(0.043)
Constant	3.885***	4.033***	3.813***	4.630***	4.749***	3.980***	3.815***	3.909***	3.765***	4.715***	4.827***	3.860***
	(0.039)	(0.044)	(0.038)	(0.033)	(0.038)	(0.036)	(0.035)	(0.034)	(0.034)	(0.033)	(0.041)	(0.031)
Baseline	NoInfo	NoInfo	QualInfo	NoInfoTarget	QualInfoTarget	NoInfo	NoInfo	NoInfo	QualInfo	NoInfoTarget	QualInfoTarget	NoInfo
Num.Obs.	11,800	11,800	11,800	11,800	11,800	11,800	11,800	11,800	11,800	11,800	11,800	11,800
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Each column reports a separate random-effects regression estimated on the indicated treatment pair. With session random effects and period fixed effects. Robust standard errors are reported in parentheses. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively. 100 Monte Carlo simulations of the model. In each simulation, we draw a new shock path and hold it fixed across treatments. if the simulated estimate matches the experimental counterpart in sign and statistical significance; if the sign matches but at least one is not statistical; if the sign is reversed relative to the experimental counterpart.

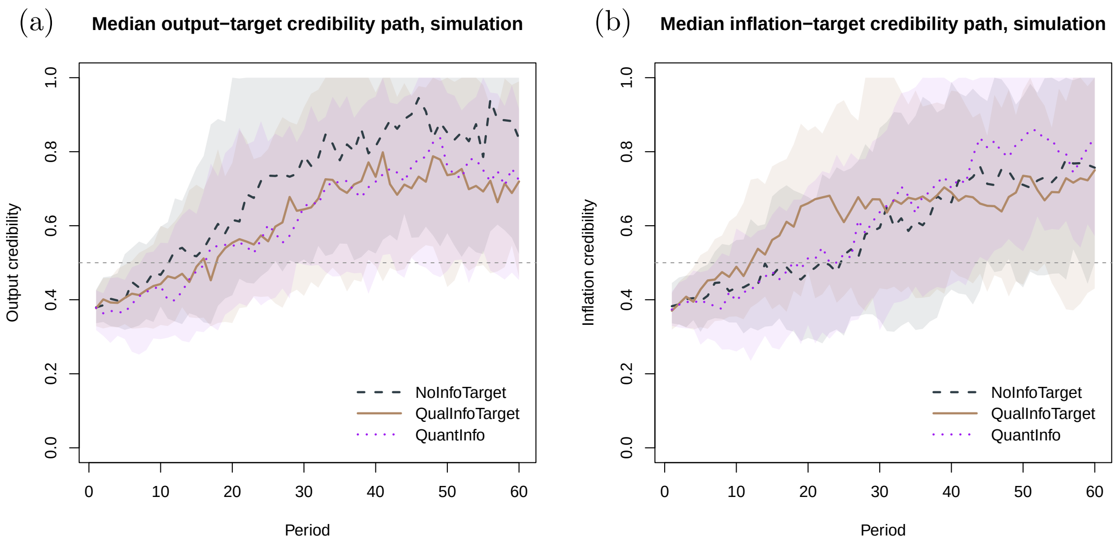
Table A6: Pairwise comparisons - Simulations, asymmetric target bias on both output and inflation forecasts, specification (e′)

Panel A	Log absolute inflation forecast error						Log absolute inflation disagreement					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
NoInfoTarget	0.131***						0.215***					
	(0.039)						(0.054)					
QualInfo		0.062***						0.108***				
		(0.024)						(0.030)				
QualInfoTarget			0.537***	0.468***					0.698***	0.591***		
			(0.043)	(0.054)					(0.053)	(0.070)		
QuantInfo					-0.568***	0.031					-0.724***	0.083
					(0.051)	(0.038)					(0.065)	(0.055)
Constant	3.544***	3.712***	3.545***	3.446***	3.975***	3.605***	3.087***	3.425***	3.292***	3.061***	3.778***	3.213***
	(0.050)	(0.041)	(0.049)	(0.063)	(0.052)	(0.049)	(0.041)	(0.029)	(0.046)	(0.051)	(0.054)	(0.046)
Baseline	NoInfo	NoInfo	QualInfo	NoInfoTarget	QualInfoTarget	NoInfo	NoInfo	NoInfo	QualInfo	NoInfoTarget	QualInfoTarget	NoInfo
Num.Obs.	11,800	11,800	11,800	11,800	11,800	11,800	11,800	11,800	11,800	11,800	11,800	11,800
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B	Log absolute output forecast error						Log absolute output disagreement					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
NoInfoTarget	0.551***						0.867***					
	(0.052)						(0.061)					
QualInfo		-0.063*						-0.023				
		(0.035)						(0.045)				
QualInfoTarget			0.577***	-0.036					0.838***	-0.052		
			(0.045)	(0.054)					(0.055)	(0.068)		
QuantInfo					-0.903***	-0.389***					-1.261***	-0.446***
					(0.041)	(0.037)					(0.059)	(0.051)
Constant	3.751***	4.033***	3.693***	4.024***	4.244***	4.006***	3.484***	3.909***	3.431***	3.895***	4.058***	3.699***
	(0.044)	(0.044)	(0.044)	(0.055)	(0.060)	(0.052)	(0.042)	(0.034)	(0.041)	(0.056)	(0.052)	(0.040)
Baseline	NoInfo	NoInfo	QualInfo	NoInfoTarget	QualInfoTarget	NoInfo	NoInfo	NoInfo	QualInfo	NoInfoTarget	QualInfoTarget	NoInfo
Num.Obs.	11,800	11,800	11,800	11,800	11,800	11,800	11,800	11,800	11,800	11,800	11,800	11,800
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Each column reports a separate random-effects regression estimated on the indicated treatment pair. With session random effects and period fixed effects. Robust standard errors are reported in parentheses. *, **, and *** denote $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively. 100 Monte Carlo simulations of the model. In each simulation, we draw a new shock path and hold it fixed across treatments. ■ if the simulated estimate matches the experimental counterpart in sign and statistical significance; ■ if the sign matches but at least one is not statistical; ■ if the sign is reversed relative to the experimental counterpart.

Figure A1: Evolutions of target credibility, simulations, specification (d) – asymmetric target bias on inflation forecasts



Note: Data is obtained from 100 Monte Carlo simulations of the model with asymmetric target bias on inflation forecasts (i.e., main specification (d)). In each simulation, we draw a new shock path and hold it fixed across treatments.

Evolution of target credibility. Fig. A1 plots the simulated paths of the endogenous target-credibility coefficients under the main specification. In all -Target treatments, credibility rises over time, indicating that agents increasingly place weight on the announced targets as they gain experience in the environment. This is important for the mechanism of the model, because the target-induced bias in inflation expectations is scaled by the credibility weight: as agents assign greater credibility to the inflation target, the downward distortion in their inflation forecasts becomes quantitatively more relevant. The figure therefore shows that the bias operates jointly with endogenous target credibility, rather than as an isolated behavioral wedge. At the same time, the inflation-credibility paths remain somewhat noisier than those for output, which is consistent with the broader finding that inflation expectations are harder to coordinate and more susceptible to distortion under target communication.

B Experimental Instructions

Instructions are provided below. For conciseness, we consolidated instructions into one set. Treatments differed in terms of the information provided about the economy. We highlight the different information sets in yellow (NoInfo, QualInfo, and QuantInfo) and green (target treatments).

Experimental Instructions

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

Each participant is paid CDN$7 for attending. Throughout this experiment you will also earn points based on the decisions you make. Every point you earn is worth $0.50. We reserve the right to improve 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. If you have any questions, the experimenter will be glad to answer them privately. If you do not comply with these instructions, you will be excluded from the experiment and deprived of all payments aside from the minimum payment of CDN $7 for attending.

The experiment is based on a simple simulation that approximates fluctuations in the real economy. Your task is to serve as private forecasters and provide real-time forecasts about future output and inflation in this simulated economy. The instructions will explain what output, inflation, and the interest rate are. You will also have a chance to try it out in a practice demonstration.

Your earnings in this experiment will depend on the accuracy of your individual forecasts.

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

The Experiment

You will submit forecasts for the next period's inflation and output, measured in basis points:

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

These are just a handful of examples of how basis points work. You can submit any forecast you wish, positive or negative or zero, but please only submit integers.

The economy consists of four main variables: inflation, output, the interest rate, and shocks. Each period, you will receive the following information that will help you make forecasts.

NoInfo description of the economy

Shock

A shock is a random "event" that directly affects the economy.

Interest Rate - NoInfo

The interest rate is the rate at which consumers and firms borrow and save in this experimental economy.

Interest Rate - NoInfo Target

The interest rate is the rate at which consumers and firms borrow and save in this experimental economy. The central bank's objective is to keep the economy stable. The central bank sets the target for output and inflation at zero.

You will be making forecasts about what you believe inflation and output will be in the next period.

1. ***Inflation***

Inflation is the rate at which overall prices change between two periods.

2. ***Output***

Output refers to a measure of the quantity of goods produced in a given period.

QualInfo description of the economy

Each period, you will receive the following information to help you make forecasts.

Current Shock

A shock is a random "event" that directly affects output. E.g. A natural disaster can suddenly destroy crops, or a technological discovery immediately improves productivity.

Depends on: **Random Draw (+)**

The shock will be relatively small most of the time. Every shock takes some time to dissipate from the system. As the past shock dissipates, new random draws randomly increase or decrease the current period's shock.

Interest Rate

The interest rate is the rate at which consumers and firms borrow and save in this experimental economy. The central bank's objective is to keep the economy stable. It responds to changes in the current level of output and inflation and in some cases this means the interest rate can become negative.. (QualInfo)

The interest rate is the rate at which consumers and firms borrow and save in this experimental economy. The central bank's objective is to keep the economy stable. It responds to changes in the current level of output and inflation. The central bank sets the target for output and inflation at zero. In order to achieve its targets it will adjust the interest rate and in some cases this means the interest rate can become negative. (QualInfoTarget)

Depends on: **Inflation in the current period (+)**

Depends on: **Output in the current period (+)**

Question: If inflation and output are -10 and -20, respectively, what sign will the interest rate be? _________. What if inflation is -10 and output is 20?________

Note that you will only be able to view the previous period's interest rate. This is because the current period's interest rate cannot be calculated until we know the current period's inflation and output.

HOW INFLATION AND OUTPUT ARE DETERMINED

You will be making forecasts about what you believe inflation and output will be in the next period.

1. ***Inflation***

Inflation is the rate at which overall prices change between two periods.

Inflation is determined largely by aggregate forecasts about future inflation. The idea behind this is simple: If the professional forecasters communicate to the public that inflation is likely to rise in the future, consumers will spend more immediately to avoid paying relatively higher prices in the future. This increase in demand will cause prices to start rising, ie. Current inflation will increase. Current output will also have a small positive effect on current inflation.

The median of each of the forecasts will be employed as the aggregate forecast in the given period and play an important role in determining the current level of output and inflation. The median, rather than the average forecast, is used so that a small number of subjects cannot have a significant effect on the economy. However, if the majority of forecasters expect relatively high inflation or output in the future, the aggregate forecast will be higher.

Depends on: **Forecasted inflation in the next period (+)**

Question: Holding all else constant, will current inflation be positive or negative if the median forecast for future inflation is -20? _________________.

Depends on: **Current output (+)**

Question: Holding all else constant, what sign is current inflation if current output is 50?______0?_________

2. ***Output***

Output refers to a measure of the quantity of goods produced in a given period.

The amount of output that will be produced in any given period will also depend on the median forecaster's expectation, formed that period, about future output and inflation. If the forecasters predict that the future economy will be producing more output and there will be more inflation, consumers will want to spend more in the current period. Firms will then produce more to meet consumer demand. Likewise, positive shocks to consumer demand will have a positive effect on how much will be produced. Increases in the nominal interest rate will make it more expensive for consumers to borrow and will create more incentive for them to save. With higher interest rates, consumers will decrease their demand for goods, leading to lower production, which will indirectly reduce inflation.

Depends on: **Forecasted output in the next period (+)**

Question: Holding all else constant, will output be positive or negative if the median subject forecasts output to be -15 points next period?_____________. What sign will inflation have? ______________.

Depends on: **Forecasted inflation in the next period (+)**

Question: Holding all else constant, what sign will output be if the median subject forecasts inflation to be 250 points next period?____________
What sign will inflation have? ___________.

Depends on: **Current interest rate (-)**

Question: Holding all else constant, what sign will output be if interest rates are 10? ______________
What sign will inflation have? _____________

Depends on: **Random Shocks (+)**

Question: Holding all else constant, what sign will output be if the shock is -50?_________
What sign will inflation have? ________________

- Expectations are self-fulfilling in this economy. If the median subject forecasts higher inflation and output in the future, both inflation and output will grow higher in the current period. Similarly, median forecasts of negative inflation and output will cause the economy to recede in the current period.

QuantInfo description of the economy

Each period, you will receive the following information to help you make forecasts.

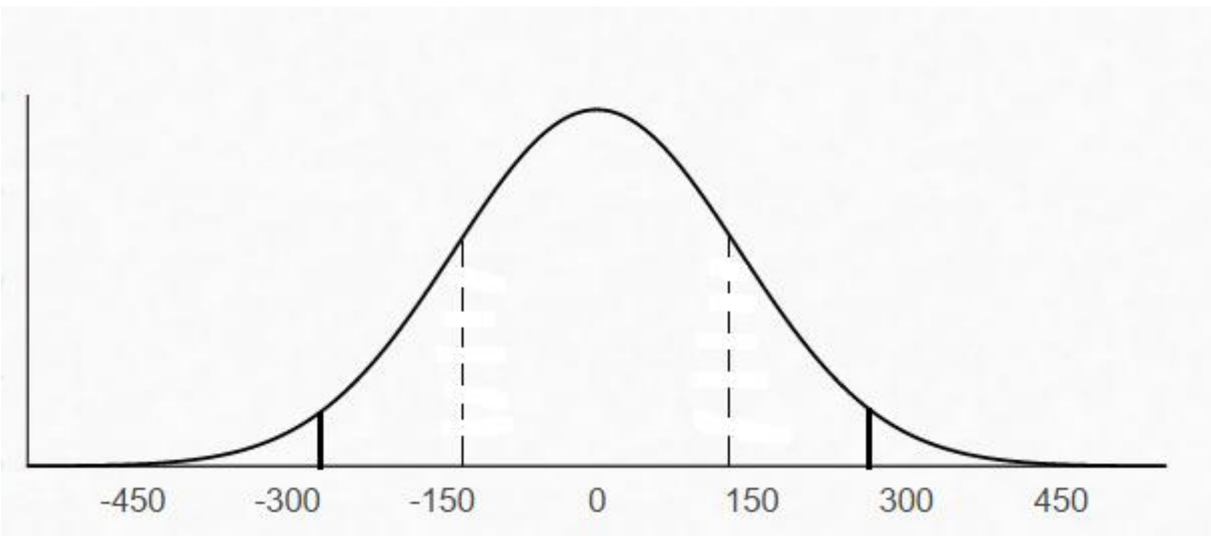
Current Shock

A shock is a random "event" that directly affects output. E.g. A natural disaster can suddenly destroy crops, or a technological discovery immediately improves productivity.

At any time, *t*, the value of the shock will be calculated as follows:

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

The random component averages 0.
About 2/3 of the time shocks lie between -138 and 138.
About 95% of the time shocks lie between -276 and 276.



Consider the following example. Suppose in Period 1 the shock was 30.

$$Shock_1 = 30$$

Now suppose the next draw was 30. In Period 2, the shock would be:

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

Alternatively, if the next draw was -150, then the shock in Period 2 would be

$$\begin{aligned} Shock_2 &= 17.1 + (-150) \\ &= -132.9 \end{aligned}$$

Interest Rate

The interest rate is the rate at which consumers and firms borrow and save in this experimental economy. The central bank's objective is to keep the economy stable. It responds to changes in the current level of output and inflation. The central bank sets the target for output and inflation at zero. In order to achieve its targets it will adjust the interest rate and in some cases this means the interest rate can become negative.

More precisely, the interest rate in period *t* will be calculated as:

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

Depends on: **Inflation in the current period (+)**

Depends on: **Output in the current period (+)**

Question: If inflation and output are -10 and -20, respectively, what sign will the interest rate be? _________. What if inflation is -10 and output is 20?________

Note that you will only be able to view the previous period's interest rate. This is because the current period's interest rate cannot be calculated until we know the current period's inflation and output.

HOW INFLATION AND OUTPUT ARE DETERMINED

You will be making forecasts about what you believe inflation and output will be in the next period.

1. ***Inflation***

Inflation is the rate at which overall prices change between two periods. It is calculated as follows:

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

Inflation is determined largely by aggregate forecasts about future inflation. The idea behind this is simple: If the professional forecasters communicate to the public that inflation is likely to rise in the future, consumers will spend more immediately to avoid paying relatively higher prices in the future. This increase in demand will cause prices to start rising, ie. Current inflation will increase. Current output will also have a small positive effect on current inflation.

The median of each of the forecasts will be employed as the aggregate forecast in the given period and play an important role in determining the current level of output and inflation. The median, rather than the average forecast, is used so that a small number of subjects cannot have a significant effect on the economy. However, if the majority of forecasters expect relatively high inflation or output in the future, the aggregate forecast will be higher.

Depends on: **Forecasted inflation in the next period (+)**

Question: Holding all else constant, will current inflation be positive or negative if the median forecast for future inflation is -20? _________________.

Depends on: **Current output (+)**

Question: Holding all else constant, what sign is current inflation if current output is 50?______0?_________

2. Output

Output refers to a measure of the quantity of goods produced in a given period. It is calculated as follows:

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

The amount of output that will be produced in any given period will also depend on the median forecaster's expectation, formed that period, about future output and inflation. If the forecasters predict that the future economy will be producing more output and there will be more inflation, consumers will want to spend more in the current period. Firms will then produce more to meet consumer demand. Likewise, positive shocks to consumer demand will have a positive effect on how much will be produced. Increases in the nominal interest rate will make it more expensive for consumers to borrow and will create more incentive for them to save. With higher interest rates, consumers will decrease their demand for goods, leading to lower production, which will indirectly reduce inflation.

Depends on: **Forecasted output in the next period (+)**

Question: Holding all else constant, will output be positive or negative if the median subject forecasts output to be -15 points next period?_____________. What sign will inflation have? ______________.

Depends on: **Forecasted inflation in the next period (+)**

Question: Holding all else constant, what sign will output be if the median subject forecasts inflation to be 250 points next period?____________
What sign will inflation have? ___________.

Depends on: **Current interest rate (-)**

Question: Holding all else constant, what sign will output be if interest rates are 10? ______________
What sign will inflation have? _____________

Depends on: **Random Shocks (+)**

Question: Holding all else constant, what sign will output be if the shock is -50?_________
What sign will inflation have? ________________

- Expectations are self-fulfilling in this economy. If the median subject forecasts higher inflation and output in the future, both inflation and output will grow higher in the current period. Similarly, median forecasts of negative inflation and output will cause the economy to recede in the current period.

ALL TREATMENTS:

Score

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

Absolute Forecast Error = absolute (Your Forecast – Actual Value)
Total Score = 0.30(2^-0.01(Forecast Error for Output)) + 0.30(2^-0.01 (Forecast Error for Inflation))

The maximum score you can earn each period is 0.6 points.
Your score will decrease as your forecast error increases. Suppose your forecast errors for each of output and inflation are:

0	-Your score will be 0.6	300	-Your score will be 0.075
50	-Your score will be 0.42	500	-Your score will be 0.02
100	-Your score will be 0.3	1000	-Your score will be 0
200	-Your score will be 0.15	2000	-Your score will be 0

Information about the Interface, Actions, and Payoffs

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

At the top left of the screen, you will see your subject number, the current period, time remaining, and the total number of points earned. You will also see three history plots. The top history plot displays past interest rates and past and current shocks. The second plot displays your past forecasts of inflation and realized inflation levels. The final plot displays your past forecast of output and realized output levels. The difference between your forecasts and the actual realized levels constitutes your forecast errors. Your forecasts will always be shown in blue while the realized value will be shown in red. You can see the exact value for each point on a graph by placing your mouse at that point.

When the first period begins, you will have 65 seconds to submit new forecasts for the next period's inflation and output levels. After the first 10 rounds, you will have 50 seconds to submit new forecasts. You may submit both negative and positive forecasts. Please review your forecasts before pressing the SUBMIT button. Once the SUBMIT button has been clicked, you will not be able to revise your forecasts until the next period. You will earn zero points if you do not submit both forecasts.

You will make forecasts for two sequences of 30 periods each. Your score, converted into Canadian dollars, plus the show up fee will be paid to you in cash at the end of the experiment.