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What to Target? Insights from a Lab Experiment

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Abstract

This paper compares alternative monetary policy regimes within a controlled lab environment, where groups of participants are tasked with repeatedly forecasting inflation in a simple macroeconomic model featuring only the dynamics of interest rates, inflation and inflation expectations. Average-inflation targeting can approximate the price path observed under price-level targeting in the presence of disinflationary shocks and enable subjects to coordinate on simple heuristics that reflect the concern of the central bank for past inflation gaps. However, this depends on the exact specification of the policy rule. In particular, if the central bank considers more than two lags, subjects fail to form expectations that are consistent with the monetary policy rule, which results in greater inflation volatility. Reinforcing communication around the target helps somewhat anchor longrun inflation expectations.

Topics: Monetary policy framework; Inflation targets; Monetary policy communications
JEL codes: E31; E52; E7; C92

1 Introduction

This paper compares alternative monetary policy regimes within a controlled lab environment, where groups of participants are tasked with repeatedly forecasting inflation in a simple macroeconomic model featuring only the dynamics of interest rates, inflation and inflation expectations.

Over the last decade, inflation-targeting (IT) regimes have had difficulties delivering the targeted levels of inflation in the many countries that have adopted an explicit inflation target. Persistently low inflationary pressures, exacerbated by the effective lower bound (ELB) constraint on interest rates, have resulted in price levels falling behind the paths consistent with the inflation target. This is illustrated in Figure 1: if inflation is persistently below the target (blue dotted line), the price grows further apart from the path consistent with the target (thick black line). Even if inflation eventually returns to the target, the resulting price level (dashed black line) remains permanently lower than this path. This is because, under IT, past failures of achieving the target are not compensated by temporary future deviations from this target. This state of affairs has eventually put the long-run anchorage of inflation expectations at risk (Mertens and Williams, 2019).

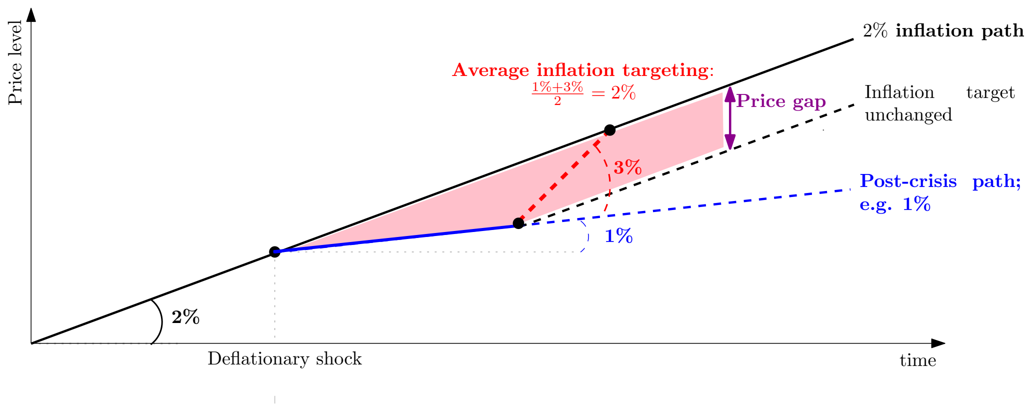
Consequently, both practitioners and academics have suggested adjustments to the IT framework, referred to as 'make-up' strategies; see the discussion in Svensson (2019). Two commonly discussed alternatives are average-inflation targeting and price-level targeting (hereafter, respectively, AIT and PLT). AIT emphasizes deviations of an average past inflation rate from the target (red dashed line on Figure 1), while, with PLT, the central bank (hereafter, CB) reacts to the price gap (pink-shaded area), which is the difference between the current price and the price level it would have been had it grown in line with the target. Under both alternatives, as illustrated in Figure 1, the price eventually returns to the level consistent with the target, even after a deflationary shock.

Mathematically, AIT and PLT are similar because they both involve introducing lagged endogenous variables into the equilibrium law of motion of the economy. However, from a practical point of view, PLT is considered too extreme.[1] In this context, in August 2020, the US Federal Reserve Bank (Fed) announced an adjustment of its monetary policy framework towards AIT (Powell, 2020). First analyses of survey expectations fail to report any subsequent increase in households' inflation expectations (Coibion et al., 2020).

In fact, the merits of these make-up strategies crucially depend on how expectations are modeled. We provide a discussion of the literature below. The two key elements of any newly announced policy are *credibility* and *understanding*. These ensure that agents' expectations align with how monetary policy is conducted and, hence, are *model-consistent*.

Whether these two elements reflect real-world expectations is an empirical issue. In the 1980s, it took a long time for inflation expectations to eventually decrease, while

[1] AIT, however, may facilitate CB transparency and accountability, essentially because the CB's objective remains framed in terms of the inflation rate. The closest to a PLT experiment that has ever been implemented, albeit in a different historical context, would be Sweden in the 1920s and 1930s, in line with the advice from Knut Wicksell, first discussed in 1898.



Notes: Let us assume that the price level rises at the targeted inflation rate (2% in this figure). Following a deflationary shock, prices rise at a slower pace than before (1% in this example), so that the price level gradually falls below the path that it was following before the shock (i.e. the dashed blue line gradually diverges from the solid black one). Once the shock has dampened out and inflation returns to its 2% target, the price level will permanently remain below the pre-crisis targeted path, resulting in a negative price gap (the dotted black line never converges back to the solid black one). Under PLT, the CB would target the 2% price-growth path and would aim to bring the price level back to this path and to keep it there (i.e. would aim to close the price gap, represented by the shaded pink area). PLT would imply an inflation rate above 2% in the short run (to catch up with the path). The AIT alternative would also require allowing the inflation rate overshoot the target to catch up with the 2% path (3% in this example, so average inflation over two periods equals 2%). One may also conceive AIT with more than two lags.

Figure 1: Make-up strategies following a deflationary shock

the disinflation was arguably credible among professionals (Erceg and Levin, 2003). After more than a decade of low inflation rates, one may equally question the credibility of future higher inflation when current inflation is low.

A number of additional practical issues are posed by the adoption of a make-up strategy, and we argue that a laboratory experiment can usefully address some of them; e.g. would the public understand a price-level target since IT has framed CB communication in terms of inflation for almost three decades? Could a state-dependent communication of the inflation target be a sufficient fix to dampen the effect of deflationary pressures on short-run expectations and keep long-run expectations anchored? We focus on the understanding of the subjects, as we conjecture that expectations need not align with the way monetary policy is conducted if, for instance, some subjects fail to exactly understand the monetary policy framework.

Laboratory experiments are ideal for assessing alternative make-up strategies. Real-world expectations, albeit a key part of the monetary policy performances, are hard to observe and cannot easily be isolated from the policy environment in which the agents make their economic decisions. Survey data are useful in this respect but may be prone to substantial noise and confounding factors. In contrast, so-called learning-to-forecast experiments allow the researcher to collect 'clean' data on expectations.

In this class of experiments, the expectation formation process is left to the human subjects and is not imposed *a priori*. The researcher is then agnostic about how expectations are formed and observes them *ex post*, as the product between the subjects' interactions and the underlying economic model, which is fully specified to ensure a control on the fundamentals. Naturally occurring expectations are endogenous to the policies in place, and the lab environment allows us to reproduce this key feature by jointly emulating a given policy regime and eliciting forecasts.[2]

The laboratory setup presents further advantages: it enables us to elicit expectations at various horizons to assess the long-run anchorage of expectations and to manipulate the information presented to the subjects to test how communication may influence how each monetary policy regime performs. In this respect, we envision the lab as a 'wind tunnel' that provides a necessary but non-sufficient condition for the empirical success of a policy: theories that have no explanatory power in the stylized lab environment are unlikely to perform well in the admittedly more complex real economies.

This paper reports on a laboratory experiment to empirically compare the CB's ability to smooth price fluctuations under each policy alternative. We use the simplest macroeconomic model one can think of to describe the inflation dynamics, inflation expectations and interest rates in the lab, namely a frictionless model. The lab implementation is already far from trivial within this one-dimensional system. Subjects are tasked with predicting short- and long-run inflation and receive detailed information about inflation and monetary policy. They also have to grasp concepts such as 'price gap.'

We compare six specific monetary policy regimes, corresponding to six randomized treatments: IT (referred to as Tr. `IT`), IT with a state-dependent communication of the target (referred to as Tr. `ITcomm`), AIT where the CB targets average inflation over two periods (referred to as Tr. `AIT`), the same AIT regime with a stronger reaction coefficient (referred to as Tr. `AITstrong`), this same AIT regime where the CB targets average inflation over four periods (referred to as Tr. `AIT4`) and a PLT regime (referred to as Tr. `PLT`). The fundamental shocks are the same in all treatments and simulate persistent deflationary pressures in the first half of the experiment that fade away in the second half. Those shocks, as well as the monetary policy regime, are made common knowledge to the subjects.

The two IT experimental economies experience a liquidity trap during the first half of the exercise and gradually converge back to the target, albeit from below, in the second half. In line with the benchmark theory under rational expectations (hereafter RE), we find that PLT overall outperforms IT. In particular, PLT allows the subjects to coordinate on simple forecasting heuristics that reflect the concern of the CB for past inflation performances. From a practical point of view, we then look at which AIT alternatives may come closest to the PLT performances. It turns out that the stabilizing properties of AIT are sensitive to the exact design of the monetary policy rule and require a strong reaction coefficient. Interestingly, adding more lags makes it more challenging for the subjects to coordinate their expectations formation process and correctly incorporate the past inflation rates into their inflation forecasts. Nonetheless, no AIT design tested in the experiment fully closes the price gap after an episode of deflationary pressures.

We further explore a scenario of CB communication under a standard IT regime using simple messages recalling the inflation target every time expectations fall at a predetermined low level. Only when this communication is consistent with inflation

[2] Lab experiments as the ones described here allow researchers to test different policies. See Duffy (2016); Cornand and Heinemann (2019); Hommes (2021, Sec. 3) for surveys and, *inter alia*, Hommes et al. (2019); Assenza et al. (2020); Kryvtsov and Peterson (2020); Mokhtarzadeh and Petersen (2021); Mauersberger (2021); Baeriswyl et al. (2021); Hommes et al. (2021) for most recent applications.

actually rising back to target is this communication effective at shaping short-run expectations. In other words, we find that subjects ‘need to see it to believe it.’ Nevertheless, communication does have an anchoring effect, albeit of modest magnitude, on long-run expectations.

The rest of the paper is organized as follows. After a brief literature review, Section 2 describes the model under IT, AIT and PLT; Section 3 explains the experimental design; the results are discussed in Section 4; and Section 5 concludes.

Literature review

Macroeconomic models are usually studied under the assumption of RE. Under RE, it is well known that PLT constitutes optimal monetary policy in many standard macroeconomic models. A strand of the macroeconomic literature has also studied how model predictions are affected if agents instead learn how to form expectations in a recursive manner, which may be arguably more realistic (see Evans and Honkapohja (2001) for an introduction). Under this type of learning, Honkapohja and Mitra (2014, 2015, 2018) show that the performances of PLT with respect to IT crucially depend on whether the agents form expectations that are consistent with the policy rule. If they fail to do so, PLT is less robust than IT in the sense that the basin of attraction of the targeted steady state is smaller than under IT. If agents instead can form rule-consistent expectations, PLT always delivers convergence to the target, even when inflation expectations are initially pessimistic. Hommes and Makarewicz (2017) conduct a lab experiment that broadly corroborates these results. Our experiment also reproduces an environment of initial pessimism induced by the shock, but our underlying model and the policy options that are tested substantially differ from theirs.

Arifovic and Petersen (2017) report on a learning-to-forecast experiment in a New Keynesian model with a liquidity trap and a state-dependent target as in Eggertsson and Woodford (2003), which may be understood as a make-up strategy. While they are effective at mitigating the drop in expectations that results from adverse shocks under RE, they show that state-dependent targets fail to nudge inflation expectations out of the liquidity trap in the lab. This is because state-dependent monetary policy objectives lack credibility in low-inflation environments. In other words, if subjects have adaptive expectations rather than RE, actual inflation first needs to increase to drive inflation expectations up to the target. The state-dependent target otherwise grows disconnected from the macroeconomic outcomes, and subjects start discarding it. Their important contribution highlights the difference between transparency in theoretical models, which implies credibility, and announcements in an experiment with human subjects, where delays in understanding and processing information may make these announcements irrelevant. In our experiment, we also report on the effectiveness of communication of the inflation target when expectations are particularly low.

In a learning-to-forecast experiment, Mokhtarzadeh and Petersen (2021) study how various CB communication strategies may affect subjects’ expectations in a way that nudges them towards RE. Among others, they emphasize that the CB should communicate easy-to-process information. In line with this previous conclusion, we test here a simple communication strategy.

There have been a few contributions specifically regarding AIT. Nessen and Vestin

(2005) show that AIT outperforms PLT if inflation involves backward-looking components, but PLT is the best option if inflation is purely forward-looking. Their framework allows one to study optimal policy and the trade-off between the output gap and inflation gap stabilization but leaves out the ELB. We overlook the interaction with the output gap stabilization as we focus on the evolution of the nominal variables and the anchorage of the related expectations, but our framework is subject to the ELB.

Mertens and Williams (2019) compare PLT and AIT, where AIT is modeled as a standard IT rule with a lower intercept so as to create higher-than-target inflation in normal times to compensate for the ELB episodes. However, their analysis hinges entirely upon RE. Amano et al. (2020) consider a dynamic stochastic general equilibrium (DSGE) model where some agents use rules of thumb rather than purely forward-looking behaviors. In this context, AIT and PLT perform equally better than IT at the ELB. Yet, their analysis assumes model-consistent expectations from the forward-looking agents, which implies that at least a substantial share of the agents fully understand and believe how monetary policy is conducted and form expectations accordingly. On the contrary, if learning agents form their expectations using simple adaptive rules, Honkapohja and McClung (2021) show that AIT is unstable under learning and, hence, undesirable from a practical point of view as real-world agents are then unlikely to be able to learn how to adjust their expectations to this new regime. Our experiment partly corroborates their result: we show that subjects may be able to use more sophisticated learning rules and somewhat pay attention to the right amount of lags but fail to integrate this information in a model-consistent way into their expectations, resulting in excess deviations from the target under AIT with more than two lags.

2 The model under different monetary policy regimes

In this section, we provide an underlying model for the experiment. We use the simplest workhorse model in macroeconomics one can think of, namely a classical, frictionless DSGE model, as described in, *inter alia*, Woodford (2003, Chap. 2) and (Galí, 2015, p. 26).[3] To develop the model, we need to make an assumption on the expectation formation. The most obvious benchmark is RE, but we also consider the most common alternative of adaptive learning. Both mechanisms assume that agents know the form of the model and are able to form expectations accordingly. In other words, agents are supposed to include the exact state variables that are relevant for forecasting next period's inflation in their forecasting rules.[4] Adaptive learning is less stringent than RE as agents are only required to know the form of the optimal forecasting rule, not the exact parameter values. They instead update them over time as more information comes in.

Of course, both RE and adaptive learning may appear quite demanding for human subjects, and the behaviors of the participants in the experiment in fact differ, sometimes greatly, from these special cases, as shown in Section 4.4. Yet, determinacy under

[3] Appendix A provides the micro-foundations of the model under IT.

[4] Hence, we call this type of behavior 'MSV-type' of expectations hereafter, for Minimum-State-Variable solution; see Section 4.4. For instance, under AIT with one lag, RE agents or adaptive learners forecast inflation by only using an intercept and the last period's inflation rate $(t-1)$. They may not include further lags or other variables, such as the price level.

RE and stability under learning are seen as prerequisites for any policy regime to be considered as a credible option. This is because systems that are indeterminate under RE usually imply excess volatility in the endogenous variables and, hence, are considered undesirable. Adaptive learning is a particularly useful additional benchmark because systems that are unstable under this type of learning are regarded as empirically implausible. Therefore, the uniqueness (that is, determinacy) conditions under RE and the stability conditions under learning of the equilibrium consistent with the inflation target provide restrictions on the policy parameter values that we may use in the lab. We then systematically present these conditions along with the equations of the model under each monetary policy regime considered.

Let us now turn to the model. For the lab implementation, we consider point expectations, which does not affect our theoretical results on determinacy and stability as long as shocks have a small enough support, which will be the case in the experiment. All variables with a hat are expressed in log-deviation from their steady-state values, while all variables in capital letters denote their gross counterparts. The Euler equation reads as:

$$i_t - r_t^\star \equiv \widehat{\imath}_t = \hat{\pi}_{t+1}^e - \nu_t \tag{1}$$

where i denotes the nominal interest rate, $r^\star$ is the natural rate of interest, possibly subject to shocks, with an equilibrium value equal to $r^\star \equiv \rho + \pi^T$, which depends on the households' discount factor β *via* $\rho = -\ln(\beta)$ and the inflation target π^T (assumed to be small but possibly non-zero), while variable $\hat{\pi}_{t+1}^e \equiv \pi_{t+1}^e - \pi^T$ refers to the expected inflation gap. The shock ν_t, which support is to be specified later, is the only source of fundamental disturbance in the model. The exact definition of the shock is unimportant because its only function is to introduce deflationary pressures in the experimental economies: it may be understood as a technology or a preference shock that affects the natural rate $r_t^\star$ in Eq. (1) (as derived in Appendix A), a monetary policy shock or, more broadly, anything that influences inflation besides expectations and monetary policy but absent from this simple model.[5]

We now develop the model under alternative policy regimes. To ease the notation, the policy parameter that tunes the reaction function of the CB is denoted by $\phi > 0$ in all regimes.

2.1 Inflation targeting (IT)

When monetary policy follows an IT regime that is constrained at the ELB, the following non-linear Taylor rule ensues:

$$\widehat{\imath}_t = \max\{-r^\star, \phi\widehat{\pi}_t\} \tag{2}$$

Due to the non-linearity introduced by the ELB, we solve the system in a piecewise manner, as detailed in Appendix A. First, when the ELB is not binding, the law of

[5]As written in Eq. (1), a positive realization of the shock pushes inflation downwards, but the sign is not restrictive. To keep the environment as intuitive as possible to the subjects, the shocks are displayed with a minus sign. The subjects are then provided with instructions that negative shocks tend to decrease inflation and *vice-versa*; see Appendix G and Section 3.

motion of inflation is simply given by:

$$\hat{\pi}_t = \frac{1}{\phi}\hat{\pi}^e_{t+1} - \frac{1}{\phi}\nu_t \tag{3}$$

It is trivial to establish the following proposition, which is discussed, *inter alia*, in Galí (2015):

Proposition 1 *The targeted steady state is locally determinate under rational expectations and locally stable under recursive learning if* $\phi > 1$.

In the sequel and in the experiment, we assume that ν follows an AR(1) process with autocorrelation $\rho_\nu \in (0,1)$ and is realized at the beginning of period t so that it is part of the information set of the agents in period t. In the experiment, it will be displayed to the subjects before they submit their inflation forecasts (see Section 3.3). The equilibrium law of motion of the inflation gap is then (assume that $\phi \neq \rho_\nu$):

$$\hat{\pi}_t = -\frac{1}{\phi - \rho_\nu}\nu_t \tag{4}$$

We can express the price level as:

$$p_t \equiv p_{t-1} + \pi_t = p_{t-1} + \pi^T - \frac{1}{\phi - \rho_\nu}\nu_t \tag{5}$$

where we see that non-fully neutralized shocks ν_t have a permanent effect on the price path under IT, as explained in the introduction.

Second, besides the targeted steady state, where $\hat{\pi} = 0$, it is well-known that the ELB on nominal interest rates implies a second, low-inflation steady state (see, e.g., Galí (2015, pp. 25–26)). To see this, consider the case where the nominal rate is pegged to zero.[6] Inflation expectations are trivially pinned down by exogenous factors, i.e. $\hat{\pi}^e_{t+1} = -r^\star + \nu_t$, but this is not the case for inflation. Any inflation gap path satisfying $\hat{\pi}_t = -r^\star + \nu_{t-1} + \zeta_t$, where $E_{t-1}(\zeta_t) = 0$ is a solution of the system. The price level then evolves as $p_t = p_{t-1} + \nu_{t-1} + \zeta_t - r^\star + \pi^T$, which is also indeterminate. We note that the unconditional mean of ν being zero, any solution implies a negative inflation rate (deflation). We explain in Section 3.3 how we implement the ELB constraint in the lab.

2.2 Price-level targeting (PLT)

Under PLT, the CB adjusts the nominal interest rate so as to target a price path consistent with a constant inflation rate of π^T, i.e. $\frac{\bar{P}_t}{\bar{P}_{t-1}} = \Pi^T \geq 1$, where Π^T is the gross inflation target and $\bar{P}_t$ is the price target in any period t. To facilitate the exposition of the model, we may introduce an additional state variable, namely the price gap, i.e. the gap between the actual and the targeted price level. We denote the price gap by

[6] Another way to look at the indeterminacy and instability under learning of the ELB equilibrium is to see that it corresponds to an inactive monetary policy rule, i.e. $\phi \to 0$, which violates the determinacy and learnability condition of the targeted equilibrium.

$X_t \equiv \frac{P_t}{\bar{P}_t}$. We then have the following relation between the price gap and the inflation gap:

$$X_t = X_{t-1}\left(\frac{\Pi_t}{\Pi^T}\right) \tag{6}$$

At the targeted non-linear steady state, we have $X^T = 1$, $P_t = \bar{P}_t$ and $\Pi_t = \Pi^T$, $\forall t$. We further express the price gap in deviation from its steady-state values and take the logs from $x_t \equiv \frac{X_t - X^T}{X^T} = X_t - 1 = \frac{P_t - \bar{P}_t}{\bar{P}_t}$ so that $x_t \simeq \ln P_t - \ln(\bar{P}_t)$.

We consider a Wicksellian rule, which states that the CB increases (resp. decreases) the instrument when the current price gap is above (resp. below) its targeted level, subject to the ELB. The corresponding log-linearized rule reads as:

$$\widehat{\imath}_t = \max(-r^\star, \phi x_t) \tag{7}$$

The model is given by the log-linearization of Eq. (6):

$$x_t = x_{t-1} + \widehat{\pi}_t \tag{8}$$

together with Eq. (1) in which the interest rate is given by Eq. (7). Note that x is not a predetermined variable as π_t is not part of the information set of the agents when forming their forecasts at the beginning of any period t.

First, when the ELB is not binding, inflation under PLT evolves as:

$$\hat{\pi}_t = \frac{\hat{\pi}^e_{t+1}}{\phi} - x_{t-1} - \frac{\nu_t}{\phi} \tag{9}$$

We obtain the following proposition:

Proposition 2 *The targeted steady state under PLT is locally determinate and E-stable for any value $\phi > 0$ of the reaction coefficient of the CB.*

Proof 1 *See Appendix B.1.*

Under the assumption of AR(1) shocks, the law of motion of the price gap is given by:

$$x_t = -\frac{1}{\phi + 1 - \rho_\nu}\nu_t \tag{10}$$

where a tightening of monetary policy naturally reduces the price gap.

In terms of inflation, Eq. (10) gives:

$$\hat{\pi}_t = x_t - x_{t-1} = \frac{1}{\phi + 1 - \rho_\nu}(\nu_{t-1} - \nu_t) = -x_{t-1} - \frac{1}{\phi + 1 - \rho_\nu}\nu_t \tag{11}$$

and, in terms of price level:

$$p_t \equiv p_{t-1} + \pi_t = p_{t-1} + \pi^T - x_{t-1} - \frac{1}{\phi + 1 - \rho_\nu}\nu_t \tag{12}$$

Under RE and in the absence of the ELB, the inflation rate is set, *via* the interest rate, so as to fully offset previous shocks (contained in x_{t-1}) and take the current price level on average back to its targeted path.

It is well-known from multi-variate models that, analogue to the low-inflation steady state under IT, an additional state persists under any PLT rule at the ELB (see, e.g., Honkapohja and Mitra 2018). In our univariate model, this state is the same as under IT: imposing the ELB pins down inflation expectations as a sole function of exogenous factors, i.e. $\hat{\pi}^e_{t+1} = -r^\star + v_t$ and any inflation gap process $\hat{\pi}_t = -r^\star + v_{t-1} + \zeta_t$, where $E_{t-1}(\zeta_t) = 0$ is a solution of the system, which implies deflation.

In terms of price gap, the ELB translates into a quasi steady state as the variable x is not constant but as t grows, the price level P_t falls towards zero, while the targeted price path $\bar{P}_t$ grows to infinity at a rate π^T (or stays constant at P_0 in the special case of a zero-inflation target). This implies that x decreases towards -1 at an average rate $-r^* - \pi^\star$. Hence, the ELB on i eventually binds and this state is a deflationary spiral that may not represent a stationary determinate rational expectation equilibrium (REE) or a stable path under recursive learning.

2.3 Average-inflation targeting (AIT)

An alternative to PLT where 'bygones are not bygones' either is AIT. Under AIT, the CB targets the average inflation rate over $\ell + 1$ periods. In the special case of $\ell = 0$, AIT boils down to IT as described in Section 2.1. When $\ell > 0$, a log-approximation exactly as in the case of IT presented in Appendix A results in the following the Taylor rule:

$$\hat{\imath}_t = \max\left(-r^\star, \phi\left(\frac{\hat{\pi}_t + \hat{\pi}_{t-1} + \cdots + \hat{\pi}_{t-\ell}}{\ell+1}\right)\right) = \max\left(-r^\star, \frac{\phi}{\ell+1}\sum_{s=0}^{\ell}\hat{\pi}_{t-s}\right) \tag{13}$$

which adds ℓ state variables to the system.

We first detail the case of $\ell = 1$ and then turn to the general case $\ell > 1$.

2.3.1 Case of $\ell = 1$

The system is the Fisher relation (1) together with the following interest rate rule:

$$\widehat{\imath_t} = \max\left(-r^\star, \frac{\phi}{2}(\hat{\pi}_t + \hat{\pi}_{t-1})\right) \tag{14}$$

Let us first consider the case where the ELB is not binding. The law of motion for inflation is:

$$\hat{\pi}_t = \frac{2}{\phi}\hat{\pi}^e_{t+1} - \frac{2}{\phi}v_t - \hat{\pi}_{t-1} \tag{15}$$

We establish the following two propositions:

Proposition 3 *The targeted steady state is locally determinate if $\phi > 1$.*

Proof 2 *See Appendix B.2.*

Proposition 4 *The targeted steady state is locally E-stable when $\phi > 1$.*

Proof 3 *See Appendix B.3.*

Appendix B.2 shows that the MSV solution with the AR(1) shock reads as:

$$\hat{\pi}_t = \left(\frac{\phi}{4} - \frac{\sqrt{\phi(\phi+8)}}{4}\right)\hat{\pi}_{t-1} - \frac{2}{\phi - 2(b+\rho_\nu)}\nu_t \equiv b\hat{\pi}_{t-1} + c\nu_t \tag{16}$$

with $\phi > 1$. The negative sign on b is intuitive: under AIT, negative inflation gaps yesterday should result in positive inflation gaps today, so the average inflation gap over the two periods is equal to zero, on average.

Again, when the ELB is binding, analogue to the low-inflation steady state under IT, an additional state persists under AIT and the ELB binds whenever $\pi_t < -\frac{2}{\phi}r^\star - \pi_{t-1}$. Any inflation gap process $\hat{\pi}_t = -r^\star + \nu_{t-1} + \zeta_t$, where $E_{t-1}(\zeta_t) = 0$ is a solution of the system, which corresponds to deflation and an indeterminate equilibrium.

2.3.2 General case of $\ell \in \mathcal{N}$

When the ELB is not binding, the law of motion of inflation reads as:

$$\hat{\pi}_t = \frac{\ell+1}{\phi}\hat{\pi}^e_{t+1} - \sum_{s=1}^{\ell}\hat{\pi}_{t-s} - \frac{\ell+1}{\phi}\nu_t \tag{17}$$

Next, we derive the determinacy and stability conditions of the targeted steady state:

Proposition 5 *The targeted steady state is locally determinate if $\phi > 1$.*

Proof 4 *See Appendix B.4.*

Proposition 6 *The targeted steady state is locally E-stable if $\phi > 1$.*

Proof 5 *See Appendix B.5.*

The MSV solution takes the form:

$$\hat{\pi}_t = \sum_{s=1}^{j} b_s\hat{\pi}_{t-s} + c\nu_t \tag{18}$$

where the coefficients are given in Appendix B.4.

It can also be shown in the exact same way as for $\ell = 1$ that AIT with $\ell > 1$ does not eliminate the issue of a second deflationary and indeterminate steady state at the ELB.

Deriving the model under RE is a prerequisite to the lab implementation. However, the point of this paper is not to investigate the differences between the lab outcomes and the RE counterpart or to assess to what extent subjects may be or learn to be rational forecasters. Following the wind-tunnel approach discussed in the introduction, we prefer to take an agnostic approach to the expectation process and conduct an observational comparative study of the resulting inflation dynamics emerging in the lab under the different monetary policy regimes. We now detail how we implement this underlying model in the lab.

3 The experimental design

The experiment is a so-called learning-to-forecast experiment with a between-subject design and is programmed in oTree (Chen et al., 2016). A total of 247 subjects were recruited from the CREED pool at the lab of the University of Amsterdam where the experiment was run, and no subject participated more than once. Participants were students of various fields, not limited to economics. Using non-economic experts as participants reinforces the external validity of the experiment.

Pilots were conducted in-person in fall 2019, while the sessions discussed in this paper were run in a 'virtual lab' in 2020 due to the COVID-19 pandemic. We now detail the procedures in this virtual lab as, to the best of our knowledge, such procedures have not been described earlier and may be useful to the reader.

3.1 Implementation in a 'virtual lab'

Subjects were recruited using the usual CREED database but were informed that the experiment would take place in a 'virtual lab' *via* the Zoom platform. Twenty minutes before the start of the experiment, the 'door' opened and they received the corresponding Zoom link that was unique to each session. Upon clicking the link, subjects entered the virtual lab's waiting room. The experimenter then checked each subject in by admitting them one by one into the main room, checking their university ID, renaming them in an anonymous way (by assigning them a number) and sending them back into the waiting room. This procedure took about 10 more minutes than the regular check-in in the 'physical' lab for a group of about 15 subjects.

After the start of the experiment, the 'door' of the virtual lab was locked, and all subjects were admitted into the main room. If too many subjects showed up, the required number was sent away in the following way. First, volunteers to be sent away could raise their virtual hand to receive the show-up fee and re-enroll in a later session. If not enough, the experimenter would share their screen with the subjects and randomly draw the required number of sent-away participants using a statistical program such as R. The participants who were renamed during the check-in by the chosen numbers were asked to leave the experiment. All sent-away subjects would then have to send their names and IBAN to the experimenter *via* email for payment of the fee.

Once the required number of subjects was obtained, participants were divided into groups (experimental economies). The composition of the groups did not change during the experiment. Each group was composed of seven subjects, which guarantees a minimum of six participants in case of a drop-out.[7] Groups of six are usual in related experiments; see, e.g., Assenza et al. (2020). Each subject then received a unique oTree link *via* the Zoom's private chat that they could open with the browser of their choice.

[7] Participation in an experiment is always voluntary. Drop-outs, whether involuntary due to internet connection issues, or voluntary, due to boredom or loss of interest in the experiment, may happen somewhat more frequently in online experiments. It happened six times during the experiment. In contrast, the show-up rate in the virtual lab was up to 50% higher than in the physical lab, probably due to the greater flexibility of online environments: the virtual lab is not tied to the opening times of the campus (usually 9–5) and does not require the students to travel and spend several extra hours on campus. The lack of alternative activities due to the COVID-19-related restrictions might also explain the greater engagement of students.

Regime	IT	ITcomm	AIT	AITstrong	AIT4	PLT
ϕ	1.8	1.8	1.8	7.6	7.6	1.8
Independent observations	6	6	6	6	6	6

Table 1: Number of independent observations per treatment

The Zoom meeting was configured such that participants could not communicate with each other.

Subjects had the opportunity to read the instructions privately, at their own pace. Before starting the group experiment, they had to correctly answer a quiz in order to make sure that they had a good understanding of the experimental environment and their tasks. Subjects could request the assistance of the experimenter to fill out the quiz. In this case, communication would take place *via* the private chat, where subjects could send a screen shot of their quiz or a list of answers to the experimenter, who could then provide guidance on the answers. The instructions and the quiz were designed so as to visually guide the subjects towards the most critical pieces of information (see Appendix G).

The experiment could only start once all the participants had correctly answered all the questions. The participants were aware of this feature in order to make the instructions and the answers of the quiz common knowledge. At the end of the experiment, a questionnaire collected additional information from the subjects, such as demographics and background, and subjects had an opportunity to provide us feedback. They would also leave their IBAN for payment of their earnings, which were sent through anonymous bank transfers by the university's financial administration.

With such a rigorous implementation of the virtual lab, we hope to convince the reader that we have successfully approximated the controlled conditions of the physical lab despite the COVID-19 restrictions on in-person gatherings. Failure to notice any sizable difference, neither in the implementation nor in the results, between the earlier in-person pilot sessions and the actual virtual ones comforts our claim.

3.2 Experimental treatments

Table 1 summarizes the experimental treatments. We ran six independent groups for each of the six treatments: a baseline inflation-targeting treatment (referred to as Tr. IT), an inflation-targeting treatment with a reinforced communication, which we detail below (referred to as Tr. ITcomm), average-inflation targeting with one lag (referred to as Tr. AIT), average-inflation targeting with a stronger reaction coefficient and one lag (referred to as Tr. AITstrong), average-inflation targeting with this stronger reaction coefficient and three lags (referred to as Tr. AIT4) and price-level targeting (referred to as Tr. PLT). We now detail the implementation and rationale for these treatments.

First, we adopted the following calibration. The experiment was run for 60 periods. We chose a unique sequence of the shock ν to be used in every experimental economy, from an AR(1) process with persistence $\rho = 0.95$ and standard deviation 1%.[8] The per-

[8] The time series of the shock is reproduced in Appendix E.

sistence of the shock process is chosen so the exogenous deflationary pressures last over the first half of the experiment and fade away in the second half. The inflation target was set to $\pi^T = 2.5\%$, which was conveniently chosen not to correspond to the European Central Bank (ECB) target to avoid creating an *ad-hoc* focal point for the participants, but low enough to allow for the ELB to bind if inflation expectations were to substantially fall short of the target. Furthermore, we use $r^\star = 3\%$, which corresponds to a natural rate of $\rho = 0.5\%$. For all treatments except AITstrong and AIT4, we use $\phi = 1.8$.

In Tr. AITstrong, we use $\phi = 7.6$. This value was chosen because it is high enough to deliver an average squared deviation from target (which, hereafter, represents volatility) of similar magnitude under AIT with one lag as under PLT with $\phi = 1.8$. Hence, Tr. AITstrong allows for a fairer comparison between AIT and PLT than Tr. AIT.

To further explore alternatives to PLT, we consider an AIT treatment with $\ell = 3$ lags, which corresponds to the CB targeting the average inflation over *four* periods, hence Tr. AIT4. In this treatment, we keep $\phi = 7.6$ to ease the comparison with respect to Tr. AITstrong. This treatment is particularly interesting as it may come closer to what the Federal Reserve implemented in August 2020, although the corresponding monetary policy rule has not been officially specified. Moreover, theoretically, under RE, PLT may be seen as the limit case where the CB includes the whole past history into its reaction function (i.e. $\ell \to \infty$). Indeed, for a fixed reaction coefficient, increasing the lags under RE results in lower inflation volatility.

However, with at least two lags, as shown in Appendix B.5, the backward-looking dynamics with $\ell > 1$ are unstable. This means that if we consider simpler expectation mechanisms than recursive learning, such as naive or steady-state expectations, inflation fails to converge to the target with more than two lags in the policy rule. This does not contradict our stability result in Prop. 6: stability under learning in the theory part only refers to the so-called criterion of weak E-stability insofar as stability holds only if the perceived law of motion of the learning agents is of the same form as the actual law of motion of the economy. In other words, if the forecasting rules of the agents is misspecified and does not include as many lags as involved in the MSV solution, the target may not be stable. In particular, if subjects use some form of adaptive expectations involving only the information of period $t-1$, the target is unstable under AIT with more than two lags. This is particularly interesting because we know from previous learning-to-forecast experiments that subjects typically only look at a few lags, at best up to two, to form their expectations (see, e.g., Arifovic et al. 2019). Whether seven independent subjects may coordinate on a forecasting rule involving more lags in the context of our experiment remains a policy-relevant but open question that Tr. AIT4 is designed to address.

Finally, Tr. ITcomm explores the role of CB communication with respect to the baseline IT treatment. It is well-known from survey and experimental work that simple messages have a greater impact on people's expectations than complex announcements and that they need to be repeated, as their effect fades away quickly (see, e.g., Candia et al. 2020; Mokhtarzadeh and Petersen 2021). We then design a communication policy that is state-dependent and emphasizes the value of the inflation target, rather than the actual inflation, whenever inflation expectations fall substantially below the target. Specifically, a subject would receive a communication from the CB *via*

Figure 2: Central bank's communication in the treatment `ITcomm`

the pop-up window reproduced in Figure 2 every time their latest submitted short-run forecast fell short of the target by more than 1% *and* the latest average short-run forecast of the group also lies below 1.5%.

We complete this section by detailing the execution of the experimental economies.

3.3 The experimental game

In the lab, as under any form of learning, the underlying economic model is implemented sequentially and the endogenous variables are obtained from the elicited expectations of the subjects. This process facilitates the implementation of the non-linearity induced by the ELB. Yet, it is well-known from previous experimental and learning work that recursive dynamics yield deflationary spirals where inflation diverges away into negative territory because the ELB steady state is unstable under learning (Hommes et al., 2019). Such dynamics are well-known but not realistic and, hence, not attractive for the purpose of this study.

A common solution to circumvent this issue, which we implement here, is to introduce a lower bound on inflation, which creates an additional, stable steady state and may be motivated by the presence of nominal rigidities, fiscal policy or unconventional monetary policies that are voluntarily left out of the present framework (see, e.g., Evans et al. 2020). We implement such a lower bound to represent a liquidity trap in the lab economy, as illustrated on Figure 3. As clear from the figure, and from the lab results, this implementation allows for persistently below-target inflation while avoiding explosive deflationary dynamics.

For all treatments, the timing of events in each period $t = 1, \cdots, 60$ is then as follows:[9]

1. The shock is realized, and v_t is displayed.

2. Each subject has to simultaneously submit a one-period-ahead (i.e. for $t+1$, referred to later as 'short run') and an eight-period-ahead (i.e. for period $t+7$, referred to later as 'long run') forecast of inflation.

3. The seven short-run inflation forecasts are aggregated using the arithmetic mean into $\bar{\pi}^e_{t+1}$.[10]

[9] Note that, under PLT and AIT, the past initial values of inflation are assumed to be at the steady state, i.e. the inflation gap in $t = 0, -1, -2$ is 0.

[10] A usual interpretation consistent with the micro-foundations of the underlying model is that the

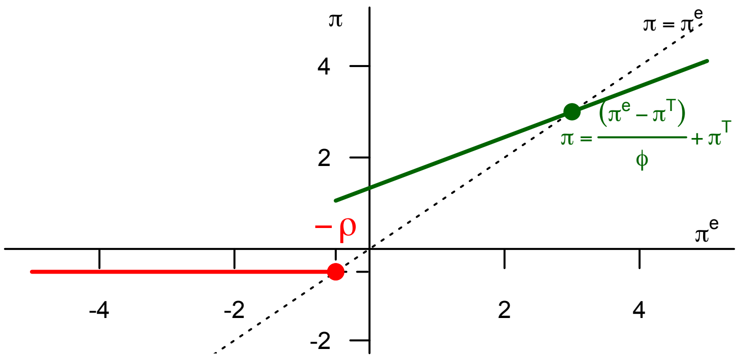


Figure 3: Learning map under IT, $\phi = 1.8$, $\pi^T = 2.5\%$, $\rho = 0.5\%$ so $r^\star = 3\%$

Notes: For any regime, plugging the corresponding reduced-form solution for inflation into the monetary policy gives the nominal interest rate. For any regime, the ELB binds whenever $\pi^e_{t+1} < -\rho + \nu_t$. The figure abstracts from the shock for simplicity.

4. Inflation is computed per the reduced-form equation (i.e. Eq. (3) under IT, (13) under AIT and (9) under PLT), together with the associated shadow interest rate $\hat{\imath}_t$ per the corresponding monetary policy rule (i.e. Eq. (2) under IT, (13) under AIT and (7) under PLT).

5. If the resulting shadow rate is negative, i.e. $\hat{\imath}_t \leq -r^\star$, the ELB binds, we set $\hat{\imath}_t = -r^\star$ and inflation is recomputed as $\pi_t = -\rho$ (see Figure 3).

6. A small *i.i.d.* shock of a standard deviation of 0.05% is added to the inflation realization,[11] and inflation, the interest rate and the price level are displayed to the subjects, along with their forecasting errors and forecasting score obtained from their corresponding past forecasts.

In the lab, information is conveyed to the subjects *via* the instructions and the graphical user interface (see Appendix F). We provide the same amount of information in all treatments. In particular, the instructions provided qualitative information about the main variables in the experimental economy, namely the inflation rate, the price level, the corresponding price gap, the shock and the interest rate, and the relationships between them. The instructions explained in plain English the important concepts such as persistent shock, inflation gap and price gap. We detailed the objective of the CB and the resulting determinants of inflation, which depend on the treatment. In particular, subjects were informed about the inflation target, and the target was explicitly displayed on the inflation plot of the graphical user interface (GUI).

The pre-experiment quiz was quite extensive (see Appendix G) and focused on the key parts of the instructions to minimize confusion. On the GUI, past realizations of all variables, up until period $t-1$, including the average past inflation over the last ℓ

representative agent uses the average forecast formed by all the statistical bureaus in the economy; see, e.g., Assenza et al. (2020).

[11]The same sequence of noise is used for all groups. Such a small noise is common in these experiments because it avoids perfect predictions. In the context of this experiment, it is also consistent with indeterminate inflationary paths when interest rates are pegged, as is the case at the ELB.

periods, were displayed both in a table and on plots and subjects could choose between a representation of the price gap or the price level (see Appendix F).

The participants were informed that inflation was partly determined by the average short-run forecasts of their group. As usual in these types of experiments, subjects were told that they were advisors for statistical institutes and had to provide inflation forecasts. Their payoff depended on their forecast accuracy. They received one cumulative score over all the periods of the experiment for short-run forecasting and one cumulative score for long-run forecasting. Because long-run forecasting is more challenging than short-run forecasting and because subjects received fewer scores for long-run forecasting (as forecasts beyond period 54 do not realize),[12] we designed two separate payoff functions. For each forecasting task, in each period, subjects collect a number of points given by:

$$\max\left(\frac{Y}{1+\text{absolute forecast errors in p.p.}},0\right) \tag{19}$$

where Y corresponds to the maximum possible payoff, equal to 100 for a perfect short-run forecast and 140 for a perfect long-run forecast.

To provide equal incentives between the two forecasting tasks, participants were informed that only one of the two cumulative scores would be randomly drawn at the end of the experiment, with equal probabilities, for payment and exchange into euros at a rate of 0.5 euro for 100 points. Each session lasted about two hours, and the average payoff was 22.4 euros, with a standard deviation of 4. We now turn to the results.

4 Experimental results

Section 4.1 and Section 4.2 contrast, respectively, the inflation performances and expectations anchorage and coordination in the different treatments. Section 4.3 focuses on the dynamics of long-run expectations, while Section 4.4 documents how subjects formed their short-run forecasts.

4.1 Inflation performances in the experimental economies

Figure 4 summarizes the inflation dynamics across the six independent experimental economies in the six treatments. We defer to Appendix C the plots of each individual group.

A first glance at the data indicates substantial treatment differences. Let us first describe what happens under IT. Deflationary pressures strikingly lock inflation into a below-target regime during the first half of the experiment (blue area), which results in occasionally binding ELB.[13] In the second half of the experiment, once the deflationary shock has dampened, inflation increases back to target from below, along smooth oscillations. The introduction of a reinforced communication under Tr. `ITcomm` (green line) seems to make virtually no difference with respect to the inflation dynamics under Tr. `IT` (red line).

[12] In the analysis in Section 4, these non-incentivized forecasts are discarded.

[13] The details of the number of ELB episodes are given in Table 4 in Appendix D.

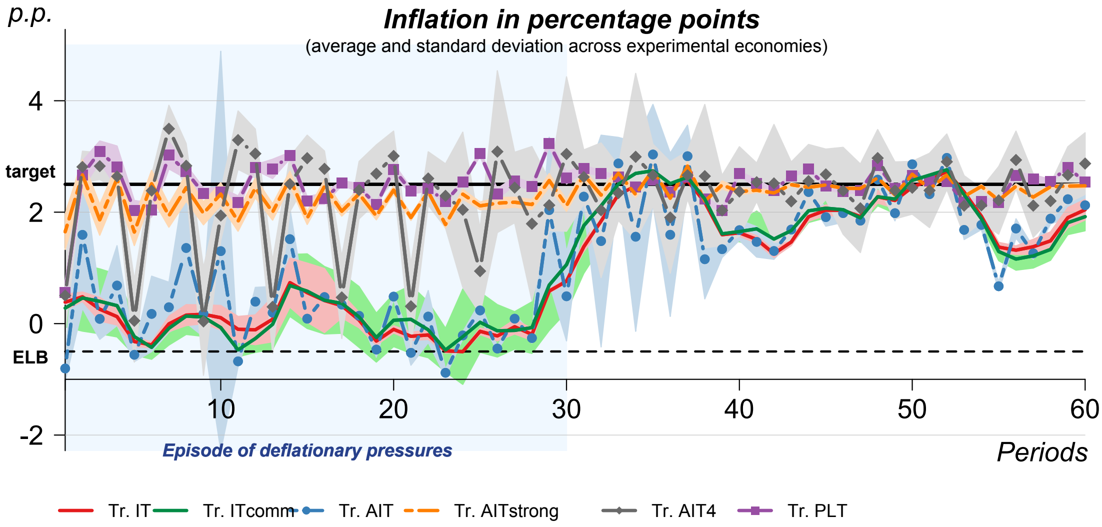


Figure 4: Inflation time series in the baseline experiment economies

Notes: Average inflation (lines) and standard deviation (shaded areas) across the six independent groups of each treatment. The horizontal bold plain line is the inflation target in the experiment (2.5%). The first half of the experiment is characterized by deflationary pressures.

The baseline AIT treatment (blue line), with one lag and $\phi = 1.8$, is also initially subject to below-target inflation, albeit less severe but clearly more volatile than under IT. The transition between the deflationary episodes and the second half of the experiment where the fundamental shocks have faded away is particularly volatile. Over the last 20 periods, inflation converges back to target in a way that appears similar to what it does under IT. The only difference is a 'hiccup' pattern in inflation that is due to the negative autocorrelation introduced in the inflation time series under AIT, in particular with one lag – as a below-target data point has to be compensated by an above-target realization in the next period under Tr. `AIT` (blue line).

A similar 'hiccup' pattern also naturally arises under Tr. `AITstrong` (orange line), in particular in the first half of the experiment. Yet, the much higher ϕ coefficient allows the CB to dampen deflationary pressures so inflation remains below but close to the target in the first half of the experiment, without hitting the ELB. Tr. `PLT` achieves an even better result, as inflation always fluctuates around the target (purple line). More lags in the CB's reaction function simply result in more fluctuations in inflation that somewhat persists in the second half of the experiment, albeit in a smoother pattern than with a single lag (gray line).

We now turn to a formal comparison of the six regimes. Table 2 summarizes the cross-treatment comparisons in the experiment. In this subsection, we focus on the inflation level, measured by the average inflation gap and the inflation volatility, computed with the usual mean squared inflation gap (see Panel A). The detailed statistics per group are given in Table 4 in Appendix D.

First, regarding the inflation level, PLT outperforms all alternatives because the price gap is fully closed after 60 periods, i.e. inflation is on average equal to the target in the experiment. While this first-best alternative may be hard to deploy in practice, as discussed in the introduction, AIT, if accompanied by a strong reaction coefficient, appears as a second best, where inflation falls short of the target by about 20 basis points and the resulting price gap is about 10% after 60 periods. This result holds whether the CB targets the average inflation over two or four periods.

The effect of the deflationary shocks is most visible in the three other treatments. In particular, IT delivers an inflation gap of about 150 basis points and is prone to the ELB, with the price gap ending up on average 42% of what it would have been had it grown at 2.5% throughout the experiment. We summarize this first result as follows:

Result 1 (Ranking in terms of average inflation gap) *: AIT with a strong reaction coefficient approximates the average inflation performances of PLT, while the deflationary pressures have lasting effects under IT.*

The second result concerns inflation volatility. AIT with a strong reaction coefficient delivers the most stable inflation, although the absolute difference in the squared inflation gap with respect to PLT is not large. In these two regimes, inflation volatility is particularly low compared to the four other alternatives.

AIT with more lags (Tr. `AIT4`) falls short of replicating the stability performances of PLT. Figure 4 and the values reported in Table 4 indicate that the increased volatility when the number of lags increases is substantial, while it should be the other way around under RE.[14] The highest volatility is observed under IT and under AIT with one lag and a weaker coefficient (Tr. `AIT`) due to the occurrence of the ELB in these three treatments. Here again, adding a reinforced communication (Tr. `ITcomm`) does not make any difference with respect to Tr. `IT`.

Result 2 (Ranking in terms of inflation volatility) *: Increasing the reaction coefficient on inflation under AIT with one lag successfully replicates the low inflation volatility under PLT. However, increasing the amount of lags does not. Moreover, considering a smaller reaction coefficient or reinforcing communication of the target does not improve inflation volatility with respect to IT.*

To conclude, AIT may replicate the inflation performances under PLT but is sensitive to the exact design of the rule. In particular, very few lags with a particularly strong reaction coefficient seem necessary. It should be further noted that performing the comparisons separately on each half of the experiment leads to the same results. This indicates that the performances of each regime are robust whether confronted with deflationary pressures or whether operating in normal times. We now turn to the properties of the individual forecasts under each regime.

[14]Although the goal of the experiment is not to compare each regime with the RE predictions, under RE, `AIT4` should deliver a similar magnitude of inflation volatility as under PLT, while it should be about twice larger under `AITstrong`. Section 4.4 below sheds further light on the reasons behind this result.

Panel A. **Ranking in terms of macroeconomic performances**

Average inflation level (the target is 2.5%):

$$\underset{(0.62)}{\texttt{IT} = \texttt{AIT} = \texttt{ITcomm}} \underset{(0.002)}{<} \underset{(0.22)}{\texttt{AITstrong} = \texttt{AIT4}} \underset{(0.002)}{<} \texttt{PLT}$$

Inflation volatility:

$$\underset{(0.59)}{\texttt{IT} = \texttt{AIT} = \texttt{ITcomm}} \underset{(0.004)}{<} \texttt{AIT4} \underset{(0.002)}{<} \texttt{PLT} \underset{(0.08)}{<} \texttt{AITstrong}$$

Panel B. **Ranking in terms of forecasting performances of the subjects**

Earnings efficiency ratio for short-run forecasting:

$$\underset{(0.33)}{\texttt{AIT} = \texttt{AIT4}} \underset{(0.002)}{<} \underset{(0.84)}{\texttt{IT} = \texttt{ITcomm}} \underset{(0.002)}{<} \texttt{PLT} \underset{(0.004)}{<} \texttt{AITstrong}$$

Earnings efficiency ratio for long-run forecasting:

$$\underset{(0.10)}{\texttt{IT} = \texttt{AIT} = \texttt{ITcomm}} \underset{(0.08)}{<} \texttt{AIT4} \underset{(0.004)}{<} \underset{(0.95)}{\texttt{AITstrong} = \texttt{PLT}}$$

Panel C. **Ranking in terms of expectation dynamics**

Coordination of short-run forecasts:

$$\underset{(0.70)}{\texttt{AIT} = \texttt{AIT4}} \underset{(0.002)}{<} \underset{(0.84)}{\texttt{IT} = \texttt{ITcomm}} \underset{(0.002)}{<} \underset{(0.94)}{\texttt{PLT} = \texttt{AITstrong}}$$

Coordination of long-run forecasts:

$$\underset{(0.10)}{\texttt{IT} = \texttt{AIT} = \texttt{ITcomm}} \underset{(0.009)}{<} \texttt{AIT4} \underset{(0.02)}{<} \underset{(0.78)}{\texttt{AITstrong} = \texttt{PLT}}$$

Anchorage of short-run forecasts:

$$\underset{(0.80)}{\texttt{IT} = \texttt{ITcomm} = \texttt{AIT}} \underset{(0.002)}{<} \underset{(0.18)}{\texttt{PLT} = \texttt{AITstrong} = \texttt{AIT4}}$$

Anchorage of long-run forecasts:

$$\texttt{IT} \underset{(0.02)}{<} \texttt{ITcomm} \underset{(0.24)}{=} \texttt{AIT} \underset{(0.009)}{<} \underset{(0.14)}{\texttt{PLT} = \texttt{AITstrong} = \texttt{AIT4}}$$

Notes: `regime A = regime B` means that the difference between treatments A and B is not statistically significant, while `regime A < regime B` indicates that regime B significantly outperforms regime A. Unless otherwise stated, the reported p-values in brackets correspond to tests at the matching-group level with exact rank-sum tests. When multiple two-by-two comparisons are involved, we report the lowest p-value when the differences are not significant and the highest p-value when they are.
Panel B uses the *earnings efficiency ratio* (EER), expressed in percentage points, which measures the number of points earned on average per subject with respect to the maximum amount of points possible (in case of perfect predictions).
Panel C measures the disagreement between the subjects about the short- and the long-run inflation forecasts computed, respectively, as the average cross-sectional variance of individual forecasts $\frac{1}{60}\sum_{s=1}^{60} V(\pi^e_{j,s+1})$ and $\frac{1}{60}\sum_{s=1}^{60} V(\pi^e_{j,s+7})$. Expectations anchorage is measured as the average distance per period of individual forecasts (long- and short-horizon ones) to the target, aggregated over all subjects. We discard non-incentivized forecasts, i.e. short-run forecasts submitted in period 60 and long-run forecasts submitted from period 54 on, as no realization and, hence, no payoff may be computed for these submissions.

Table 2: Ranking of the regimes in the experiment

4.2 Expectation dynamics in the experimental economies

Panels B and C of Table 2 concern expectation formation in the experiment. The detailed statistics are given in Table 5 in Appendix D. Panel B reports on the forecasting performances of the participants for, respectively, the short-run and long-run forecasting task, using the so-called earning efficiency ratios (EERs).[15] The higher the ratios, the smaller the forecast errors and the better the forecasting performances of the subjects.

EERs greatly vary across treatments. As forecasting is easier in a more stable environment, regimes associated with lower inflation volatility also display higher EERs, in particular for the short-run forecasting task. Again, subjects earn the highest amount of money in Tr. `PLT` and `AITstrong`. The only difference with respect to the inflation-volatility ranking previously discussed concerns short-run forecasting performances that are worse in Tr. `AIT4` than in the treatments involving IT or AIT with one lag. Below, we discuss the dynamics of short-run expectations further. Moreover, as anticipated, forecasting at a longer horizon is more challenging than forecasting the next period's realizations, and the EERs are higher for the short-run than for the long-run forecasts, in all treatments.

Panel C of Table 2 reports a measurement of the disagreement between subjects as the average of the cross-sectional dispersion of their short- and long-run forecasts across the 60 periods and a measurement of expectation anchorage, as the average distance of the individual forecasts to the target across the whole experiment.

Again, the cross-treatment differences are substantial. PLT and AIT with a strong reaction coefficient and one lag globally outperform the four other alternatives considered. Yet, the effects of AIT with four lags on the expectation dynamics, in particular long-run expectations, is quite striking: inflation expectations, whether in the short run or in the long run, are as well-anchored to the target as in Tr. `PLT` or `AITstrong`, despite a more volatile environment. This is also somewhat true when it comes to coordination of long-run expectations. However, AIT with more lags falls short of coordinating short-run forecasts: they are the most heterogeneous in this treatment.

In echo to the two preceding results, we conclude:

Result 3 (Ranking in terms of expectation stabilization) *: PLT and AIT with one lag but a strong reaction coefficient are associated with the highest level of coordination and anchorage of both short-run and long-run inflation expectations. Considering more lags under AIT also stabilizes long-run expectations compared with IT but makes short-term forecasting more challenging.*

There is a dimension, however, where we find a significant difference between IT with and without a state-dependent communication of the target, namely the anchoring of the long-run expectations. These expectations are on average about 20 basis points closer to the target when the CB recalls the target when inflation expectations drift away from it than without this state-dependent communication (see again Table

[15] EERs are the ratios between the amount of points earned on average by the subjects across the 60 periods of the experiment and the maximum amount of points available in the experiment (i.e. 100 in case of a perfect short-run prediction and 140 for a perfect long-run prediction, see Eq. (19)).

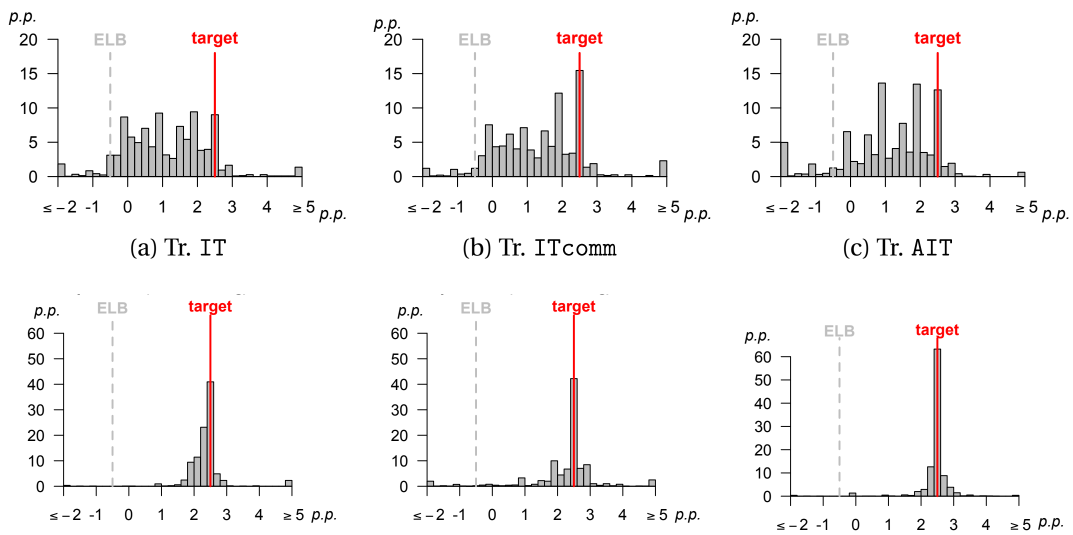
5 in Appendix D). We now dig further into the determinants of long-run expectations. The short-run forecasts are analyzed in a separate section hereafter, as these are the ones that have the potential to shed light on the aggregate inflation dynamics through the expectation feedback of the underlying model.

4.3 Determinants of long-run expectations

Figure 5 displays the empirical distributions of the long-run inflation forecasts of the participants in each treatment by pooling all groups, subjects and periods together. It is striking to see how well-anchored long-run expectations are under PLT and AIT with a strong coefficient. By contrast, under IT and AIT with a weaker coefficient, long-run expectations are spread between 0 and the target, in line with weaker inflation in the first half of the experiment. Furthermore, a K-S test over the entire distribution of long-run forecasts confirms the better anchorage of long-run expectations with than without announcements under IT (p-value < 0.001).

To identify the role of the communication of the target, we isolate Tr. `ITcomm` and use panel regression models on the individual long-run forecasts, which are presented in Table 3. As deflationary pressures during the first half of the experiment push long-run expectations downward and the communication has been engineered when expectations drop more than 1% short of the target, it is natural to use as the dependent variable the dummy equal to one if the subject increases their long-run expectation between period $t-1$ and t and 0 otherwise.

These regression results reveal that communication does increase long-run expectations, independently from the level of inflation (see Column I), but it does so in par-



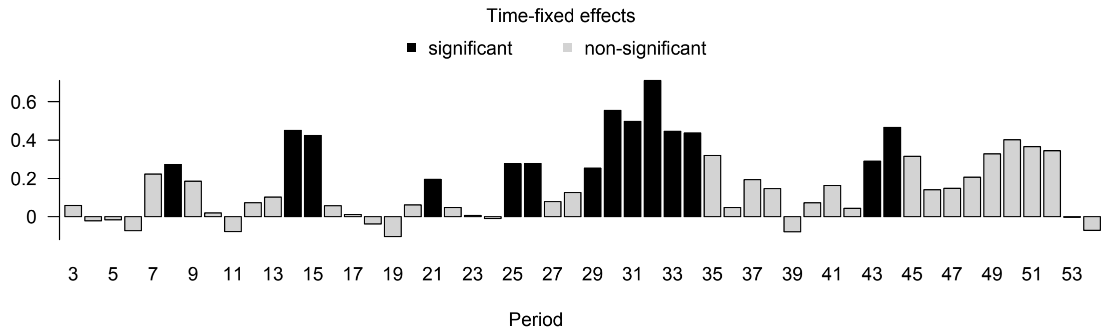
(a) Tr. `IT` (b) Tr. `ITcomm` (c) Tr. `AIT`

(d) Tr. `AITstrong` (e) Tr. `AIT4` (f) Tr. `PLT`

Figure 5: Distribution of the individual eight-period-ahead inflation forecasts in the baseline experiment economies

Notes: All data are pooled together across groups, participants and periods. Because long-run expectations in Tr. `AITstrong`, Tr. `AIT4` and Tr. `PLT` are particularly well-anchored to the target, the y-axis is wider than for the three other treatments.

Dependent variable: increasing the long-run prediction between $t-1$ ***and*** t			
	(I)	(II)	(III)
$comm$	0.11	0.36^{**}	0.20^{***}
	(0.08)	(0.11)	(0.06)
π_{t-1}	0.07^{*}	0.02	-0.04
	(0.03)	(0.02)	(0.08)
$comm \times \pi_{t-1}$	-	0.15^{**}	0.10^{**}
		(0.05)	(0.04)
Time fixed-effects	No	No	Yes
# of observations	57,996	57,996	2,143
F-stat	$< 0.001^{***}$	$< 0.001^{***}$	$< 0.001^{***}$



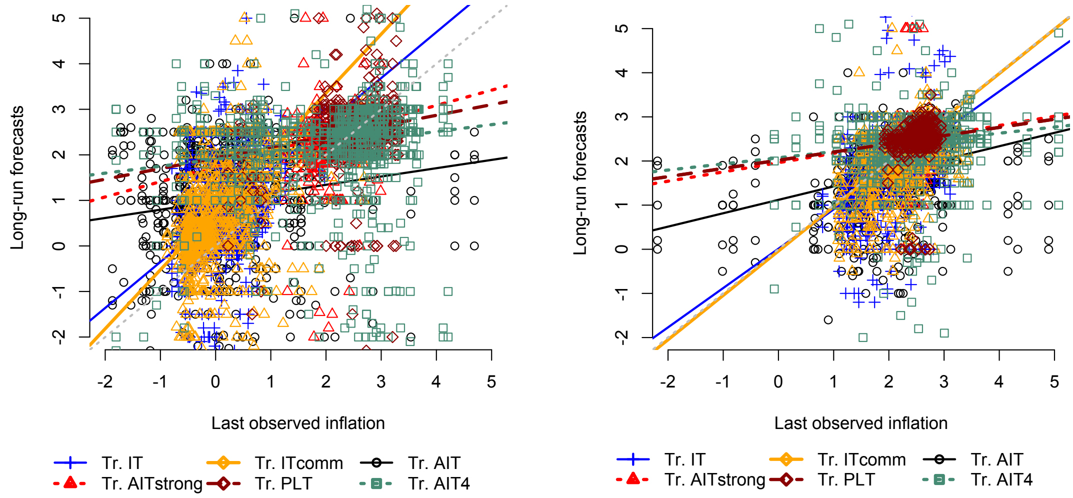
Notes: *** indicates significant at the 1% level, ** indicates significant at the 5% level and * indicates significant at the 10% level. Standard errors, reported below the coefficients in parentheses, are clustered by group and obtained using bootstrapping to account for the small numbers of clusters. $comm_{j,t} = 1$ if the CB communication was displayed to subject j in period t, 0 otherwise.

Table 3: Effects of CB communication on the likelihood to increase long-run inflation expectations in tr. `ITcomm`

ticular in conjunction with upward-sloping inflation (Column II). A Breusch-Pagan test indicates that time-fixed effects should be introduced (Column III). These effects of communication are robust to their introduction. In particular, these time-fixed effects are particularly strong and statistically significant around period 30, namely when the deflationary pressures dampen out and inflation is driven closer to target. These observations suggest that the effects of CB communication are state-dependent and are more likely to drive inflation expectations back towards the target when actual inflation is simultaneously increasing.

Result 4 (State-dependent effect of CB communication on long-run expectations) *: Reinforcing communication of the target contributes to increase long-run inflation expectations towards the target, in particular when inflation is simultaneously increasing back closer to it.*

This result recalls the conclusion from Arifovic and Petersen (2017): as subjects 'need to see it to believe it,' state-dependent inflation targets are not credible in a liquidity trap and fail to drive inflation expectations up before fundamentals actually start driving inflation back on target.



(a) First half of the experiment ($t < 31$)

(b) Second half of the experiment ($t > 30$)

Figure 6: Long-run forecasts as a function of lagged inflation

Notes: All data pooled together across groups, participants and periods. Only data from period 30 on are used for clarity, but the pattern remains the same whether only the first half of the experiment is considered or its entire course.

Finally, Figure 6 represents scatter-plots of the long-run forecasts elicited from the subjects in any period t against the last observable inflation value, i.e. inflation in any period $t-1$ over the first 30 periods of the experiment (see Figure 6a) and the last 30 periods (see Figure 6b). Linear regression lines are added for clarity. These two figures provide two main insights.

First, AIT anchors long-run expectations better than IT as long-run forecasts are more immune to movements in contemporaneous inflation than under IT. To see that, notice the flatter black, red, brown and green regression lines on both figures, compared to the yellow and blue lines under IT that even lie above the 45-degree line.

Second, long-run expectations clearly move towards the upper-right corner of the plot, closer to the 2.5% target, from Figure 6a to Figure 6b, reflecting an anchoring of the long-run expectations to the target once the deflationary pressures dampen out. Still, long-run expectations remain more immune to movements in recent inflation under AIT and PLT than under IT. In this respect, PLT, AIT with a strong coefficient with one lag or four (brown, red and green lines, respectively) appear indistinguishable. Long-run expectations under PLT are closest to the $(2.5, 2.5)$ point than in any other regime, reflecting the best convergence towards the target in the second half of the experiment.

The next section is dedicated to the estimation of short-run forecasting rules because these forecasts are at the core of the inflation dynamics in the experiment economies *via* the expectation feedback of the underlying model.

4.4 Short-run forecasting behaviors of the participants

We estimate short-run forecasting rules on each of the 247 subjects who participated in one of the six treatments of the experiment. We proceed as follows. For each subject separately, we run the following step-wise regression:

$$\pi^e_{j,t+1} = \alpha + \sum_{k=1}^{3} \beta_k \pi_{t-k} + \sum_{k=1}^{3} \gamma_k \pi^e_{j,t-k} + \delta_\nu \nu_t + \epsilon_t \tag{20}$$

where the dependent variable $\pi^e_{j,t+1}$ is the one-period-ahead inflation forecast of subject j for period $t+1$, formed at the beginning of period t, based on the latest observable pieces of information, namely the past inflation rates π_{t-k}, their past own forecasts $\pi^e_{j,t-k}$ up to $t-1$ and the shocks ν up to period t. Non-significant variables are removed until only significant ones remain.[16]

We include up to three lags for two main reasons. First, three lags are sufficient to nest the rational forecasts based on the MSV solution of each treatment. Second, previous forecasting experiments have demonstrated that subjects tend to quickly discard past information, and using information beyond two lags is not common (Arifovic et al., 2019).

Indeed, Specification (20) only includes observable pieces of information but is general enough to allow for the identification of several particular forecasting rules that are commonly estimated in related experiments. In the sequel, we define the following rules:[17]

- The *MSV-consistent forecast* includes all the state variables and only these, with the right corresponding coefficient signs. With the chosen calibration, we have:[18]
  - For Tr. `IT` and Tr. `ITcomm`, $\hat{\alpha} = \pi^T = 2.5$, $\hat{\delta_\nu} = -1.12$ and all other coefficients equal to zero;
  - For Tr. `AIT`, $\hat{\alpha} = 1.6$, $\hat{\beta}_1 = 0.36$ and $\hat{\delta_\nu} = -0.63$ and all other coefficients equal to zero;
  - For Tr. `AITstrong`, $\hat{\alpha} = 0.81$, $\hat{\beta}_1 = 0.68$ and $\hat{\delta_\nu} = -0.03$ and all other coefficients equal to zero;
  - For Tr. `AIT4`, $\hat{\alpha} = 0.25$, $\hat{\beta}_1 = 0.05$, $\hat{\beta}_2 = 0.21$, $\hat{\beta}_3 = 0.64$ and $\hat{\delta_\nu} = 0.02$ and all other coefficients equal to zero;
  - For Tr. `PLT`, $\hat{\alpha} = \pi^T = 2.5$, $\hat{\delta_\nu} = -1.05$ and all other coefficients equal to zero.
- *Adaptive expectations*, i.e. $\hat{\beta}_1, \hat{\gamma}_1 \in (0,1)$ with $\hat{\beta}_1 + \hat{\gamma}_1 = 1$ and all other coefficients equal to zero, where $\hat{\beta}_1 = 1$ and $\hat{\gamma}_1 = 0$ is the special case of *naive expectations*.

[16] Robust standard errors are obtained with the heteroscedasticity and autocorrelation consistent covariance matrix estimation of the `sandwich` R-package. Results are robust to removing the first 5 observations to allow for a burn-in phase. Yet, as we are interested in capturing the learning dynamics of subjects, we chose to use all the incentivized forecasts.

[17] Coefficients with hats refer to the estimated values as displayed in Figure 14 in Appendix D.

[18] It is easy to obtain these by taking the next period's expectation from the MSV solution and accounting for the AR(1) nature of the shock.

- *Extrapolative expectations*, i.e. $\hat{\beta}_1 > 1$, $\hat{\beta}_2 < 0$ and $\hat{\beta}_1 + \hat{\beta}_2 = 1$ and all other coefficients equal to zero.

- *Constant expectations*, namely $\hat{\alpha} > 0$ and all other coefficients equal to zero.

Figure 7 reports the proportion of subjects using each of these forecasting rules in each of the six treatments, while the distributions of the estimated coefficients are deferred to Figure 14 in Appendix D. It is particularly revealing to look at these rules in light of the inflation dynamics discussed in the previous sections. We obtain three main results.

First, let us look at the two IT treatments. Behaviors of participants in Tr. `IT` and Tr. `ITcomm` are virtually identical.[19] Extrapolative and adaptive (even naive) expectations are found to be prevalent, which are compatible with driving inflation away from the target into a below-target regime during the first half of the experiment. Once the deflationary pressures fade away, these forms of expectations contribute to gradually return inflation to target, as observed along the oscillations previously discussed under IT.

Second, it is striking to see that subjects forecast in the same way in the two most stable Tr. `PLT` and `AITstrong` (i.e. AIT with one lag and a strong reaction coefficient), despite the monetary policy framework being different.[20] Participants in these two treatments coordinate on simple forecasting heuristics that are not perfect predictors and that are not in line with the MSV solution, but reflect the CB's concern for past failures to meet the target.

In particular, at least half of the participants use a simple arithmetic average of the last two inflation rates to form their one-step-ahead inflation forecast. This simple rule of thumb had not been previously systematically identified in the related literature, hence it is not part of the special cases that we fleshed out above. It is interesting to notice that such a forecasting rule creates an initial uptrend in inflation that nurtures rising expectations despite the deflationary shocks; see, again, Figure 4 or the individual plots in Appendix C. Later, higher expectations are not offset by tighter monetary policy because they gradually contribute to close the price gap.

Note also that the diversity of behaviors is limited in these two treatments, as the vast majority of subjects may be classified into one of the highlighted categories of forecasting heuristics. This reflects the better coordination of beliefs associated with a more stable inflation environment under PLT or AIT with a strong reaction coefficient, in contrast with the other regimes.

Third, in line with previously established results, AIT performances are sensitive to the exact specification of the policy rule. With a weaker coefficient (Tr. `AIT`), shocks have a much larger impact on expectations than under all the other treatments, which is line with the MSV solution highlighted above. As a result, inflation adjustments under AIT are more challenging for subjects to understand. To see that, notice that we identify up to seven categories of forecasters in this treatment and about a quarter of the subjects do not fit into any of the predefined categories of rules. By contrast, in Tr. `AITstrong`, the reaction coefficient on the average inflation gap is large enough to

[19] The lowest p-value of the Chi-squared test for pair comparisons is 0.256.
[20] The lowest p-value of the Chi-squared test for pair comparisons is 0.111.

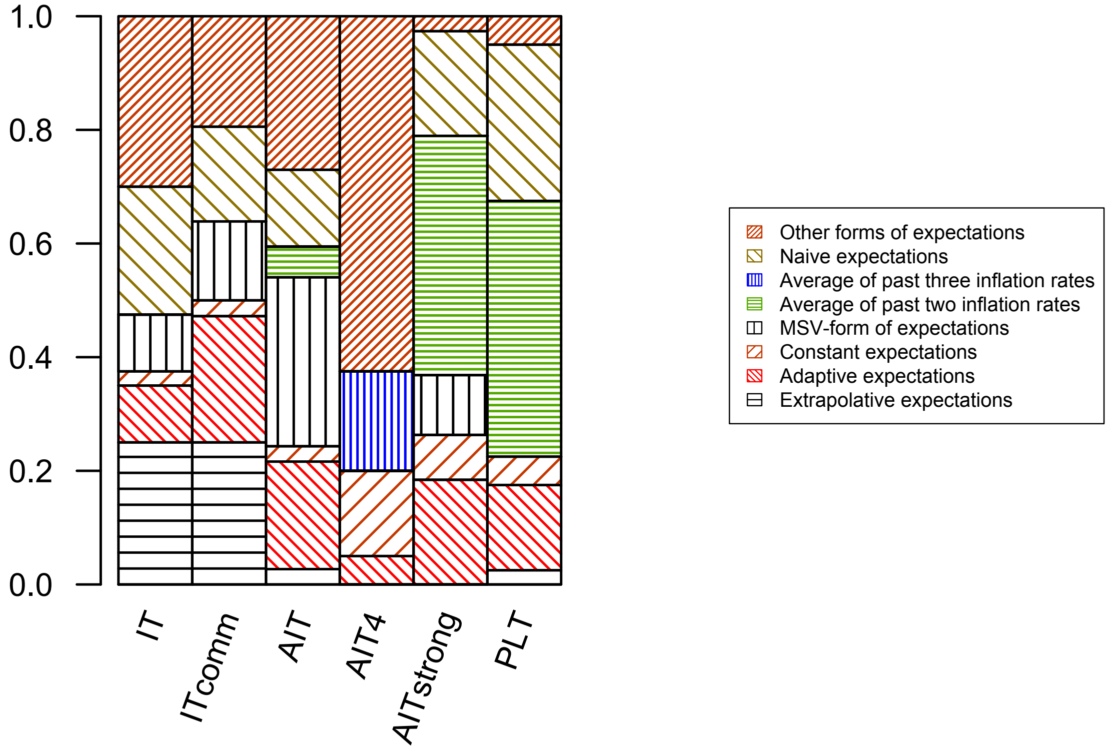


Figure 7: Forecasting rules used by the subjects in the experimental treatments

Notes: The definition of each forecasting rule is given in the main text, derived from Specification (20).

almost fully mute the effects of the shocks on inflation, which favors the coordination on simple converging heuristics, as just discussed.

In Tr. `AIT`, even once the shock has vanished, volatility is persistent as participants carry over the unstable pattern into their expectations. The transition towards the second part of the experiment where the shock fades away is particularly volatile (see, again, Figure 4).

Tr. `AIT4` displays the greatest heterogeneity in behaviors, which implies the weakest coordination between subjects, as found in Section 4.2. Indeed, 60% of the subjects do not fall into any of the pre-established categories. They instead use various linear combinations of the past variables. Only a small minority adopts a rule similar to what is observed in the two stable treatments, namely an average of the past three lags. Moreover, almost all instances of this simple heuristic are observed in Group 4, which is the most stable group (see, again, Appendix C).

A closer look at the estimated values, in Figure 14d, in fact reveals that about half of the participants use inflation up to lag three, which is uncommon in this class of experiments. This result speaks for the participants being able to grasp at least qualitatively the monetary policy framework. While already demanding, such an understanding is not enough to stabilize inflation as well as in Tr. `PLT` and Tr. `AITstrong`. This is because subjects clearly fail to correctly integrate these lags into their expectations. For instance, the information on lag two is totally discarded by more than 80% of the participants. Failing to coordinate subjects' expectations with the CB's objective results in the observed swings in inflation. This is our last result:

Result 5 (Short-run forecasting behaviors) *: PLT goes hand-to-hand with forecasting rules that reflect the CB's concern for bygones. AIT delivers the same outcome only if it involves a single lag and a strong reaction coefficient. In particular, the law of motion of inflation with more lags appears hard to grasp for the subjects.*

5 Conclusion

For make-up strategies to be effective, agents' expectations need to be in line with the strategy of the CB. Failure to fully integrate the policy framework into expectations may result in more volatile inflation. However, real-world expectations are not directly observable from the field and may be policy-dependent. This paper therefore reports on a stylized forecasting lab experiment to compare alternative monetary policy regimes.

We find that PLT outperforms the other regimes, as predicted by the theory under RE. Under PLT, subjects coordinate on simple forecasting heuristics that reflect the concern of the CB for past inflation performances. However, bearing in mind that PLT may not be a practical alternative, the experiment explores several designs of AIT that could reproduce the inflation performances under PLT.

We find that AIT can produce price dynamics similar to PLT but depends critically on the exact design of the AIT rule, namely the number of lags and the magnitude of the reaction coefficient. In particular, a strong reaction coefficient is required, which may be undesirable in light of the other concerns of monetary policy that are absent from this simple model. Adding more lags does not hurt the long-run anchorage of inflation expectations. It does, however, introduce inflation volatility, which is at odds with the predictions under RE but tends to comfort those under simple adaptive rules. In particular, it appears challenging for the subjects to coordinate their expectation rules and correctly incorporate the past inflation rates into their inflation forecasts in an environment with more lags. Nonetheless, it is worth mentioning that no AIT design tested in the experiment fully closes the price gap after an episode of deflationary pressures, contrary to PLT.

We further explore an IT regime where the CB reinforces its communication of the target using simple messages every time expectations fall too low. Only when this communication is consistent with inflation actually returning to target is this communication effective at shaping short-run expectations. In other words, we find that subjects 'need to see it to believe it.' Yet, communication does have an anchoring effect, albeit of small magnitude, on long-run expectations.

Of course, the wind-tunnel approach to the lab only provides us with a best-case scenario: information is controlled, fully displayed in a didactic way, using tables and plots, percentages and levels, etc. Subjects' attention is monopolized by the forecasting task during the experiment, and their incentives are in line with minimizing forecast errors. In the real world, communicating to the public about an inflation target has already proven non-trivial. One may then reasonably wonder how realistic it is to hope to be able to communicate on a price gap or even an average of inflation rates across time.

Yet, the stylized lab experiment developed in this paper provides a self-contained, ready-to-use and easily implementable framework for performing a first test on policies. For instance, one may test a communication policy around AIT that would be accompanied by announcements such as ‘inflation will be higher in the future because it’s too low now!’ One may test alternative designs of the Taylor rule or the implementation of bands around a point target. These perspectives are left for future research.

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A Micro-foundations of the inflation model

The model is the endowment economy with flexible prices and a fixed perishable output. The households' first order condition gives the Euler equation:

$$U'(c_t) = \beta \frac{R_t}{\hat{E}_t(\Pi_{t+1})} U'(\hat{E}_t(c_{t+1})) \tag{21}$$

where $\hat{E}_t(\cdot)$ denotes (possible non rational) expectations, and Π and R are inflation and interest expressed in gross value.

Nominal interest is given by a monetary policy rule encompassing the ELB and continuously increasing in Π, with a reaction coefficient $\phi > 0$:

$$R(\Pi_t) = 1 + \Theta_t f(\Pi_t) = 1 + \Theta_t (R^T - 1) \left(\frac{\Pi_t}{\Pi^T} \right)^{\frac{\phi R^T}{R^T - 1}} \tag{22}$$

with Θ_t a random shock, R^T the equilibrium nominal interest and Π^T the gross inflation target.

In equilibrium, consumption c is constant and the dynamics of inflation are given by:

$$\hat{E}_t(\Pi_{t+1}) = \beta R(\Pi_t) \Leftrightarrow \Pi_t = R^{-1}\left(\hat{E}_t(\Pi_{t+1})\beta^{-1}\right) \tag{23}$$

and, more explicitly, with the function (22):

$$\Pi_t = \Pi^T \left(\frac{\hat{E}_t(\Pi_{t+1})\beta^{-1} - 1}{\Theta_t (R^T - 1)} \right)^{\frac{R^T - 1}{\phi R^T}} \tag{24}$$

We assume that fiscal policy is Ricardian (or passive) and do not specify here the government budget constraint, which amounts to assuming that bonds are zero in every period.

Log-linearizing the Fisher relation around a steady state (R, Π) gives:

$$-\beta R \Pi^{-2} E_t \pi_{t+1} + \beta \hat{\pi}^{-1} r_t = 0 \Leftrightarrow E_t \hat{\pi}_{t+1} = \beta \hat{\pi}_t \tag{25}$$

remarking that $\beta R \Pi^{-1} = 1$ and, at the steady state, we have $\Pi^{ss} = \beta R(\Pi^{ss})$.

Assuming that the shock Θ is small with mean one, we can consider point expectations, and the system (23) can be linearized around the two steady states, denoted by 'T' for the target and 'L' for the liquidity trap arising from the ELB as follows:

$$\hat{\pi}^e_{t+1} = \beta f'(\Pi_{ss}) \hat{\pi}_t + \beta f(\Pi^{ss}) \nu_t \text{ , with } ss = T, L \tag{26}$$

with $\hat{\pi}_t \equiv \frac{\Pi_t - \Pi^{ss}}{\Pi^{ss}}$ and $\nu_t \equiv \Theta_t - 1$.

Or, equivalently:

$$\hat{\pi}_t = \left[\beta f'(\Pi^{ss})\right]^{-1} \hat{\pi}^e_{t+1} - f(\Pi^{ss}) \left[f'(\Pi^{ss})\right]^{-1} \nu_t \text{ , with } ss = T, L \tag{27}$$

which is of the same form as the law of motion (3) under IT. Under AIT, a version of rule (22) that includes lagged inflation shall be considered and log-linearized around the two steady states. Under PLT, one may introduce an rule involving an additional variable X representing the price gap and log-linearize the corresponding law of motion for inflation as in Section 2.2.

B Proofs

B.1 Proof of Proposition 2

We may rewrite the model under PLT in terms of the price gap x only:

$$x_t - x_{t-1} = \frac{x^e_{t+1} - x_t}{\phi} - \frac{\nu_t}{\phi} - x_{t-1} \Leftrightarrow x_t = \frac{x^e_{t+1}}{\phi+1} - \frac{\nu_t}{\phi+1} \tag{28}$$

For determinacy under RE and E-stability under recursive learning, we need $\frac{1}{1+\phi} < 1$, which is true for all $\phi > 0$.

B.2 Proof of Proposition 3

Let us use the simplifying case of white noise shocks. $\hat{\pi}_{t-1}$ is the only state variable of the model, and the MSV-REE solution reads $\hat{\pi}_t = b\hat{\pi}_{t-1}$, where the intercept has been dropped as the model is in gaps. Using the method of undetermined coefficients, take $\hat{\pi}^e_{t+1} = b^2\hat{\pi}_{t-1}$ from the MSV solution, replace inflation expectations in the model (15) and identify the coefficients: we find that b is solution of $\frac{2}{\phi}b^2 - b - 1 = 0$, which admits two solutions, i.e. $\frac{\phi}{4} \pm \frac{\sqrt{\phi(\phi+8)}}{4}$. The MSV-REE solution is the root with the minus sign as this is the one that provides zero in the special case where (15) would not depend on the lagged inflation gap. So we have $b = \frac{\phi}{4} - \frac{\sqrt{\phi(\phi+8)}}{4} \in (-1, 0)$.

We can then rewrite the system (15) in vectorial form:

$$\begin{pmatrix} x_{1,t+1} \\ \pi^e_{t+1} \end{pmatrix} = \begin{pmatrix} 0 & 1 \\ \frac{\phi}{2} & \frac{\phi}{2} \end{pmatrix} \begin{pmatrix} x_{1,t} \\ \pi_t \end{pmatrix} + \begin{pmatrix} 0 \\ \nu_t \end{pmatrix} \Leftrightarrow \begin{pmatrix} x_{1,t+1} \\ \pi^e_{t+1} \end{pmatrix} = A \begin{pmatrix} x_{1,t} \\ \pi_t \end{pmatrix} + \begin{pmatrix} 0 \\ \nu_t \end{pmatrix}$$

with $x_{1,t} \equiv \hat{\pi}_{t-1}$ a predetermined variable in time t. As the other variable π is free, we need one eigenvalue of the matrix A to be inside the unit circle and the other one outside for determinacy of the target. The characteristic polynomial of A reads as $P_A(\lambda) = \lambda^2 - \lambda\frac{\phi}{2} - \frac{\phi}{2}$ with $\Delta = \left(\frac{\phi}{2}\right)^2 + 2\phi > 0$, so both eigenvalues are real. Notice that $P_A(-1) = 1 > 0$ and $P_A(0) = -\frac{\phi}{2} < 0$, so P_A changes sign and hence has one zero on $(-1, 0)$. For the other zero to be outside $(-1, 1)$, we need that the P_A changes sign for $\lambda > 1$, i.e. we need $P_A(1) = 1 - \phi < 0 \Leftrightarrow \phi > 1$. Hence, the targeted steady state is determinate if and only if $\phi > 1$.

B.3 Proof of Proposition 4

The condition for E-stability of the target in a univariate system are given in Evans and Honkapohja (2001, Proposition 8.3, p. 202). Provide that the MSV is stationary and E-stable it is then stable under recursive learning. Let us denote here $a = \frac{\phi}{2}$, $c = -1$, and b the MSV solution, then the targeted steady state is E-stable if the following two conditions hold: $a(1-ab)^{-1} < 1$ and $ca(1-ab)^{-2} < 1$.

The first condition may be rewritten as $4 < \phi + \sqrt{\phi(\phi+8)}$. Let us define $f(\phi) = \phi + \sqrt{\phi(\phi+8)}$ for any $\phi > 0$, which is strictly increasing in ϕ, with $f(0) = 0$ and $f(1) = 4$. Hence, the first inequality is verified for any $\phi > 1$.

The second condition may be rewritten as:

$$\frac{-8\phi}{\left(\phi+\sqrt{\phi(\phi+8)}\right)^2} < 0 < 1 \tag{29}$$

Hence, the targeted steady state is E-stable when $\phi > 1$.

B.4 Proof of Proposition 5

Let us first define s additional state variables, such as $x_{s,t} = \pi_{t-s}$, for $s = 1, \cdots, \ell$, and rewrite the law of motion (13) in a matrix form:

$$\begin{pmatrix} x_{1,t+1} \\ \vdots \\ x_{\ell,t+1} \\ \hat{\pi}^e_{t+1} \end{pmatrix} = \begin{pmatrix} 0 & \cdots & 0 & 1 \\ & & 0 & 0 \\ & I_{\ell-1} & \vdots & \vdots \\ & & 0 & 0 \\ \frac{\phi}{\ell+1} & \cdots & \cdots & \frac{\phi}{\ell+1} \end{pmatrix} \begin{pmatrix} x_{1,t} \\ \vdots \\ x_{\ell,t} \\ \hat{\pi}_t \end{pmatrix} + \begin{pmatrix} 0 \\ \vdots \\ 0 \\ \nu_t \end{pmatrix}$$

Let us denote the $(\ell+1)$-by-$(\ell+1)$ matrix by A_ℓ and $\{a_{ij}\}$, $i, j = 1, \cdots \ell+1$ its terms. This is the matrix relevant for determinacy. As all x_t-variables are predetermined in t and $\hat{\pi}$ is the only free variable, we need exactly all but one eigenvalue of A inside the unit circle for the target to be determinate (Blanchard and Kahn, 1980, Prop. 1).

First, we need to prove that the characteristic polynomial of A is of the form: $\lambda^{\ell+1} - \frac{\phi}{\ell+1}\sum_{s=0}^{\ell}\lambda_s$, $\forall \ell \geq 2$. Let us write matrix $B \equiv \lambda I - A$ for some $\lambda \in \mathscr{C}$, where I in the identity matrix of dimension $\ell+1$:

$$B = \begin{pmatrix} \lambda & 0 & \cdots & \cdots & 0 & -1 \\ -1 & \lambda & 0 & \cdots & \cdots & 0 \\ 0 & -1 & \lambda & 0 & \cdots & 0 \\ \vdots & \ddots & \ddots & \ddots & \ddots & \vdots \\ 0 & \dots & 0 & -1 & \lambda & 0 \\ -\frac{\phi}{\ell+1} & & \cdots & & -\frac{\phi}{\ell+1} & -\frac{\phi}{\ell+1}+\lambda \end{pmatrix}$$

The characteristic polynomial of A is the determinant of B. First notice that B is almost lower triangular except for the last term of the first row $-1 \neq 0$. Using the co-factors, the first term of the determinant of B is the co-factor $M_{1,1}$, i.e. the determinant of the matrix obtained by removing the first column and the first row of B. The resulting ℓ-by-ℓ matrix is triangular, and all its diagonal terms are equal to λ except the last one, which is $\frac{\phi}{\ell+1}+\lambda$, so that the co-factor $C_{1,1} = \lambda\lambda^{\ell-1}(-\frac{\phi}{\ell+1}+\lambda) = \lambda^{\ell+1} - \frac{\phi}{\ell+1}\lambda^{\ell}$. All the other entries of the first row of B are zero except the last one so that the other non-zero co-factor associated to the first row is $C_{1,\ell+1} = (-1)(-1)^{\ell+2}\det(BB)$, where BB is the ℓ-by-ℓ matrix obtained by removing the last row and the last column of matrix B:

$$BB \equiv \begin{pmatrix} -1 & \lambda & 0 & \cdots & 0 \\ 0 & -1 & \lambda & \cdots & 0 \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ 0 & \dots & 0 & -1 & \lambda \\ -\frac{\phi}{\ell+1} & & \cdots & & -\frac{\phi}{\ell+1} \end{pmatrix}$$

Again, the determinant of BB can be obtained from its co-factors and decomposed into two terms. We now use the co-factor obtained from the first column as it contains only two non-zero entries. One co-factor is $M_{\ell,1} = \left(-\frac{\phi}{\ell+1}\right)^{\ell+1}(-1)^{\ell+1}\lambda^{\ell-1}$, which results from the fact that the matrix obtained from removing the last row and the first column of BB is triangular with all $\ell-1$ diagonal terms equal to λ. The other non-zero co-factor is $M_{1,1}$, which is obtained from the matrix resulting when we remove the first row and the first column of BB. The resulting $\ell-1$-by-$\ell-1$ matrix is:

$$BBB \equiv \begin{pmatrix} -1 & \lambda & \cdots & 0 \\ \vdots & \ddots & \ddots & \vdots \\ 0 & 0 & -1 & \lambda \\ -\frac{\phi}{\ell+1} & \cdots & \cdots & -\frac{\phi}{\ell+1} \end{pmatrix}$$

which is exactly of the same form as BB with one fewer dimension. To sum up, so far the determinant of M is equal to $\lambda^{\ell+1}-\frac{\phi}{\ell+1}\lambda^{\ell}+(-1)^{\ell+3}\left(-\frac{\phi}{\ell+1}(-1)^{\ell+1}\lambda^{\ell-1}-\det(BBB)\right) = \lambda^{\ell+1}-\frac{\phi}{\ell+1}\lambda^{\ell}-\frac{\phi}{\ell+1}\lambda^{\ell-1}+(-1)^{\ell+3}\det(BBB)$. Let us repeat this process $\ell-2$ times until we arrive at the 3×3 matrix:

$$\begin{pmatrix} -1 & \lambda & 0 \\ 0 & -1 & \lambda \\ -\frac{\phi}{\ell+1} & -\frac{\phi}{\ell+1} & -\frac{\phi}{\ell+1} \end{pmatrix}$$

Its determinant $-\left(\frac{\phi}{\ell+1}+\frac{\phi}{\ell+1}\lambda\right)-\frac{\phi}{\ell+1}\lambda^2$ multiplied by $(-1)^{\ell+3}(-1)^{\ell-1}=1$ is equal to the last three terms of the determinant of M.

Hence the characteristic equation associated to A_ℓ is $P_{A,\ell}(\lambda) = \lambda^{\ell+1} - \frac{\phi}{\ell+1}\sum_{s=0}^{\ell}\lambda^s$, $\forall \ell \geq 1$.[21]

From there, various theorems help us show how many eigenvalues of A_ℓ are within the unit circle.

Decompose $P_{A,\ell}$ into two polynomials f and g such as $g(\lambda)=\lambda^n$, $f(\lambda) = -\frac{\phi}{\ell+1}\sum_{s=0}^{\ell}\lambda^s$ and $P_{A,\ell}(\lambda) \equiv g(\lambda)+f(\lambda)$. The Rouché's theorem states that if $\mid g(1) \mid < \mid f(1) \mid$, then $f+g = P_{A,\ell}$ and f have the same number of zeros inside the unit circle. This condition corresponds to $\phi > 1$.

Let us now look at the eigenvalues of f. Per the theorem of Eneström-Kayeka, a polynomial that satisfies $a_n \geq a_{n-1} \geq \cdots \geq a_0 \geq 0$ has all its zeros satisfying $\mid \lambda \mid < 1$. This condition is satisfied (with equality) for f as $\phi > 0$. So f has all its ℓ zeros inside the unit circle. Hence, if $\phi > 1$, $P_{A,\ell}$ has also exactly $n-1$ eigenvalues inside the unit circle. This implies that $P_{A,\ell}$ has exactly one eigenvalue outside the unit circle when $\phi > 1$.

One thing remains to be checked: to rule out the degenerate case where eigenvalues may lie exactly on the unit circle. For this, we will first show that A_ℓ is primitive. To see that, we need to see that each product of the matrix by itself adds a strictly positive row so that $A_\ell^n > 0$ for $n > \ell+1$. First notice that $a_{ij} \geq 0$, $\forall i, j$ no row or column contains only zero entries, the last row contains only strictly positive entries and the last term of the first row is strictly positive (i.e. 1). Then, the first and the last rows of matrix A^2 are strictly positive (i.e. do not contain any zero entries). Then, the first term

[21] Note that for $\ell = 1$, we find the result of Section B.2.

of the second row of A is one, so that multiplying A^2 by A results in A^3 having a second row with strictly positive terms, besides the first and the last ones. Similarly, the second term of the third row of A is one, so that multiplying A^3 by A results in A^4 having a third row with strictly positive terms, besides the first, second and the last ones, etc. $A^{\ell+1}$ is then composed of ℓ strictly positive rows on the top of the last one, so $A^n > 0, n \geq \ell+1$.

We can then remark that the eigenvalue of A that lies out of the unit circle is the Perron eigenvalue. Indeed, per the Perron-Frobenius theorem applied to any primitive matrix, it exists a real positive eigenvalue, which is simple and higher (in absolute value) than all other eigenvalues of the matrix. Let us denote $r > 0$ this eigenvalue. As a corollary, we have $\min_i \sum_j a_{ij} \leq r \leq \max_i \sum_j a_{ij}$. For any $\ell > 1$, it is straightforward to see that all rows except the last one are always composed of ℓ zeros and one term equal to 1, hence the sum of the terms in each of the rows of A except the last one is always equal to one. The sum of the terms of the last row equals $\phi > 0$. When $\phi > 1$, we have $1 < r < \phi$ (where the strict inequality rules out the case of r being on the unit circle).

We finally use the Gershgorin circle theorem that states that all eigenvalues of a matrix lie at the union of the disks associated to each row, where the center in the imaginary plane is the diagonal term and the radius is the sum of all other terms of the row. In the case of matrix A, all first ℓ rows define the same disk $D(0,1)$, which is the unit circle and the last row define $D\left(\frac{\phi}{\ell+1}, \frac{\ell}{\ell+1}\phi\right)$. If a matrix is primitive, then no eigenvalues lie exactly on the circle, unless they all do. But this is not the case as $1 < r < \phi$, r does not lie on either of the two disks. Therefore no eigenvalues of A lie exactly on the unit circle, ℓ lie inside and one outside as soon as $\phi > 1$. Hence, the targeted steady state under the AIT rule is determinate for any lag ℓ for $\phi > 1$.

RE solution (method of undetermined coefficients) The MSV-REE solution takes the form (ignoring intercepts as the model is in gaps):

$$\hat{\pi}_t = \sum_{s=1}^{\ell} b_s \hat{\pi}_{t-s} + c v_t \tag{30}$$

Taking expectations and isolating π_t yields:

$$\hat{\pi}^e_{t+1} = b_1 \hat{\pi}_t + \sum_{s=2}^{\ell} b_s \hat{\pi}_{t-s+1} + c\rho_v v_t \tag{31}$$

Replacing π_t by the MSV solution (30) and rewriting the index of the sum gives:

$$\hat{\pi}^e_{t+1} = b_1 \left(\sum_{s=1}^{\ell} b_s \hat{\pi}_{t-s} \right) + \sum_{s=1}^{\ell-1} b_{s+1} \hat{\pi}_{t-s} + c v_t (b_1 + \rho_v) \tag{32}$$

or, equivalently:

$$\hat{\pi}^e_{t+1} = \left(\sum_{s=1}^{\ell-1} (b_1 b_s + b_{s+1}) \hat{\pi}_{t-s} \right) + b_1 b_\ell \hat{\pi}_{t-\ell} + c v_t (b_1 + \rho_v) \tag{33}$$

Replacing π^e_{t+1} in (13) with (33):

$$\hat{\pi}_t = \sum_{s=1}^{\ell-1} \left(\frac{\ell+1}{\phi} (b_1 b_s + b_{s+1}) - 1 \right) \hat{\pi}_{t-s} + \left(\frac{\ell+1}{\phi} b_1 b_\ell - 1 \right) \hat{\pi}_{t-\ell} + \frac{\ell+1}{\phi} v_t \left(c(b_1 + \rho_v) - 1 \right) \tag{34}$$

Identify the terms between (34) and the MSV solution (30) gives:

$$b_s = \left(\frac{\ell+1}{\phi}(b_1 b_s + b_{s+1}) - 1\right), \forall s = 1, \dots \ell - 1. \tag{35}$$

and $\left(\frac{\ell+1}{\phi} b_1 b_\ell - 1\right) = b_\ell$, which pins down b_ℓ as a function of b_1, which then uniquely determines all b_s, $s = 1, \dots, \ell - 1$ and $c = \frac{\ell+1}{(\ell+1)(b_1+\rho_v)-\phi}$.

B.5 Proof of Proposition 6

To study E-stability, let us first spell out the MSV-REE solution in matrix form with the variables x_ℓ, $\ell \geq 2$, as defined in Section B.4:

$$\begin{pmatrix} \hat{\pi}_t \\ x_{1,t} \\ \vdots \\ x_{\ell-1,t} \end{pmatrix} = \begin{pmatrix} b_1 & \cdots & \cdots & b_\ell \\ & & & 0 \\ & I_{\ell-1} & & \vdots \\ & & & 0 \end{pmatrix} \begin{pmatrix} \hat{\pi}_{t-1} \\ x_{1,t-1} \\ \vdots \\ x_{\ell-1,t-1} \end{pmatrix} \equiv \Omega \begin{pmatrix} \hat{\pi}_{t-1} \\ x_{1,t-1} \\ \vdots \\ x_{\ell-1,t-1} \end{pmatrix}$$

remarking that $x_{\ell-1,t-1} = \hat{\pi}_{t-\ell}$ and Ω is a ℓ-by-ℓ matrix. We also rewrite the equation (13) as follows:

$$\begin{pmatrix} \hat{\pi}_t \\ x_{1,t} \\ \vdots \\ x_{\ell-1,t} \end{pmatrix} = \begin{pmatrix} -1 & \cdots & \cdots & -1 \\ & & & 0 \\ & I_{\ell-1} & & \vdots \\ & & & 0 \end{pmatrix} \begin{pmatrix} \hat{\pi}_{t-1} \\ x_{1,t-1} \\ \vdots \\ x_{\ell-1,t-1} \end{pmatrix} + \begin{pmatrix} \frac{\ell+1}{\phi} & 0 & \cdots & 0 \\ 0 & 0 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & 0 \end{pmatrix} \begin{pmatrix} \hat{\pi}^e_{t+1} \\ x_{1,t+1} \\ \vdots \\ x_{\ell-1,t+1} \end{pmatrix}$$

$$\Leftrightarrow \begin{pmatrix} \hat{\pi}_t \\ x_{1,t} \\ \vdots \\ x_{\ell-1,t} \end{pmatrix} = \delta \begin{pmatrix} \hat{\pi}_{t-1} \\ x_{1,t-1} \\ \vdots \\ x_{\ell-1,t-1} \end{pmatrix} + N \begin{pmatrix} \hat{\pi}^e_{t+1} \\ x_{1,t+1} \\ \vdots \\ x_{\ell-1,t+1} \end{pmatrix}$$

The conditions for E-stability is that matrices $(I - N\Omega)^{-1}N$ and $[(I - N\Omega)^{-1}\delta]' \otimes [(I - N\Omega)^{-1}N]$ have all the real parts of their eigenvalues lower than one strictly Evans and Honkapohja (2001, Prop. 10.3, p. 238). As long as the AR(1) process is stable ($|\rho| < 1$), the result holds under persistent shocks. Recall that the eigenvalues of a Kronecker product of two matrices is the product of their eigenvalues.

If the REE is stationary, $[(I - N\Omega)^{-1}\delta] \equiv \Omega$ has all eigenvalues within the unit circle and so has its transpose. It is easy to see that $(I - N\Omega)^{-1}N$ is diagonal, so its eigenvalues are the diagonal terms that are 0 (with multiplicity $\ell - 1$) and $-\frac{\ell+1}{\phi} b_\ell$. If this later term is lower than one strictly, the targeted steady state is E-stable. We remark that $b_\ell = \det(\Omega)$, which is then the product of the eigenvalues of Ω. So, if $b_\ell > 0$, the E-stability condition is satisfied whenever the MSV solution is stationary.

If $b_\ell < 0$, the eigenvalues of $(I - N\Omega)^{-1}$ (which is an upper triangular matrix) are 1 ($\ell - 1$ times) and $\frac{\phi}{\phi - b_1(\ell+1)}$ and the eigenvalues of $(I - N\Omega)^{-1}N$ are 0 ($\ell - 1$ times) and $\frac{\ell+1}{\phi}\frac{\phi}{\phi - b_1(\ell+1)} = \frac{\ell+1}{\phi - b_1(\ell+1)}$ as the first term of matrix N is the only non-zero term. If b_1 is negative, the only non-zero eigenvalue of $(I - N\Omega)^{-1}N$ is lower than 1. And if $b_1 < 0$, so is b_ℓ per the definition of the MSV solution.

So, either $b_1 < 0$ and $b_\ell < 0$ and the E-stability condition is verified as $\frac{\ell+1}{\phi - b_1(\ell+1)} < 1$, or $b_1 > 0$ and $b_1 > \phi/(\ell+1)$ with $b_\ell > 0$, so the E-stability condition is verified as $-\frac{\ell+1}{\phi} b_\ell < 1$.

It remains to examine the case where $0 < b_1 < \frac{\phi}{\ell+1}$, which implies $b_\ell < 0$. But is that case possible? We recall that b_ℓ solve the equation $b_\ell = \frac{\ell+1}{\phi} b_1 b_\ell - 1$, and b_ℓ is also the determinant of Ω, which is the product of its eigenvalues that are all within the unit circle per stationarity of the MSV solution. So $-1 < b_\ell < 1$ and if $0 < b_1 < \frac{\phi}{\ell+1}$, we have $0 < b_1 \frac{\ell+1}{\phi} < 1$ and $-1 < b_1 b_\ell \frac{\ell+1}{\phi} < 0$ and $-2 < b_1 b_\ell \frac{\ell+1}{\phi} - 1 = b_\ell < -1$, which is not possible if $b_\ell \in (-1, 1)$.

Hence, provide that the MSV is stationary, it is *weakly* E-stable.

Note that this result does not contract the result obtained in Honkapohja and McClung (2021), which states that the target is unstable under AIT with more than $\ell = 2$ lags. A way to see that is to recall that our stability result concerns weak E-stability, i.e. our agents must have a forecasting rule of the same form as the MSV solution. Under a simpler rule, such as naive expectations or steady-state learning, the stability condition depends on the eigenvalues of the matrix $N + \delta$ being within the unit circle. It is easy to show that this is not the case. Indeed, we have:

$$N + \delta = \begin{pmatrix} \frac{\ell+1}{\phi} - 1 & -1 & \cdots & -1 \\ & I_{\ell-1} & & 0 \\ & & & 0 \end{pmatrix}$$

We may compute the determinant of $N + \delta$ using the co-factors in a similar way as for matrix B in Section B.4. The first co-factor is always zero as the resulting sub-matrix is a triangular matrix with diagonal terms equal to zero. The only non-zero co-factor is the term on the second row, first column, namely -1. The associated co-factor gives a matrix $(\ell - 1, \ell - 1)$ as:

$$\begin{pmatrix} \frac{\ell+1}{\phi} - 1 & -1 & \cdots & -1 \\ & I_{\ell-2} & & 0 \\ & & & 0 \end{pmatrix}$$

again, where the first co-factor is zero. Reducing the problem further leads to $\det(N + \delta) = (-1)^{\ell-1}$, which is either equal to 1 or -1 depending on ℓ. As the determinant of a matrix is the product of its eigenvalues, either all eigenvalues are on the unit circle or at least some are not. We rule out the former possibility by showing that neither 1 nor -1 is a solution of the deterministic equation, which we can obtain for any lag $\ell \geq 2$ in a similar manner:[22]

$$\sum_{j=0}^{\ell-1} (-1)^j (-\lambda)^{\ell-j} + (-\lambda)^{\ell-1} \left(\frac{\ell+1}{\phi} \right) (-1)^{\ell-2}$$

where the last term 1 or -1 is the determinant of $N + \delta$. It is then easy to see that, for any $\phi > 1$, neither 1 nor -1 can be a root. Indeed, if ℓ is odd, 1 gives $-\frac{\ell+1}{\phi} + \ell(-1)^\ell$,

[22] Note that the system is stable under naive or steady-state expectations with $\ell = 1$ if $\phi > 1$.

which cannot equal zero if $\phi \neq \frac{\ell+1}{\ell}$ and if ℓ is even, 1 gives $\frac{-1-\phi-\ell}{\phi} \neq 0$. Similarly, with -1 and ℓ even, we have $\frac{\ell+1}{\phi} \neq 0$ and $\frac{\phi-\ell-1}{\phi} \neq 0$ if $\phi \neq \ell + 1$. Hence, outside these non-generic cases, some of the eigenvalues have to be outside the unit circle, which makes the target unstable under simple backward-looking expectations involving one lag.

C Experimental time series per group

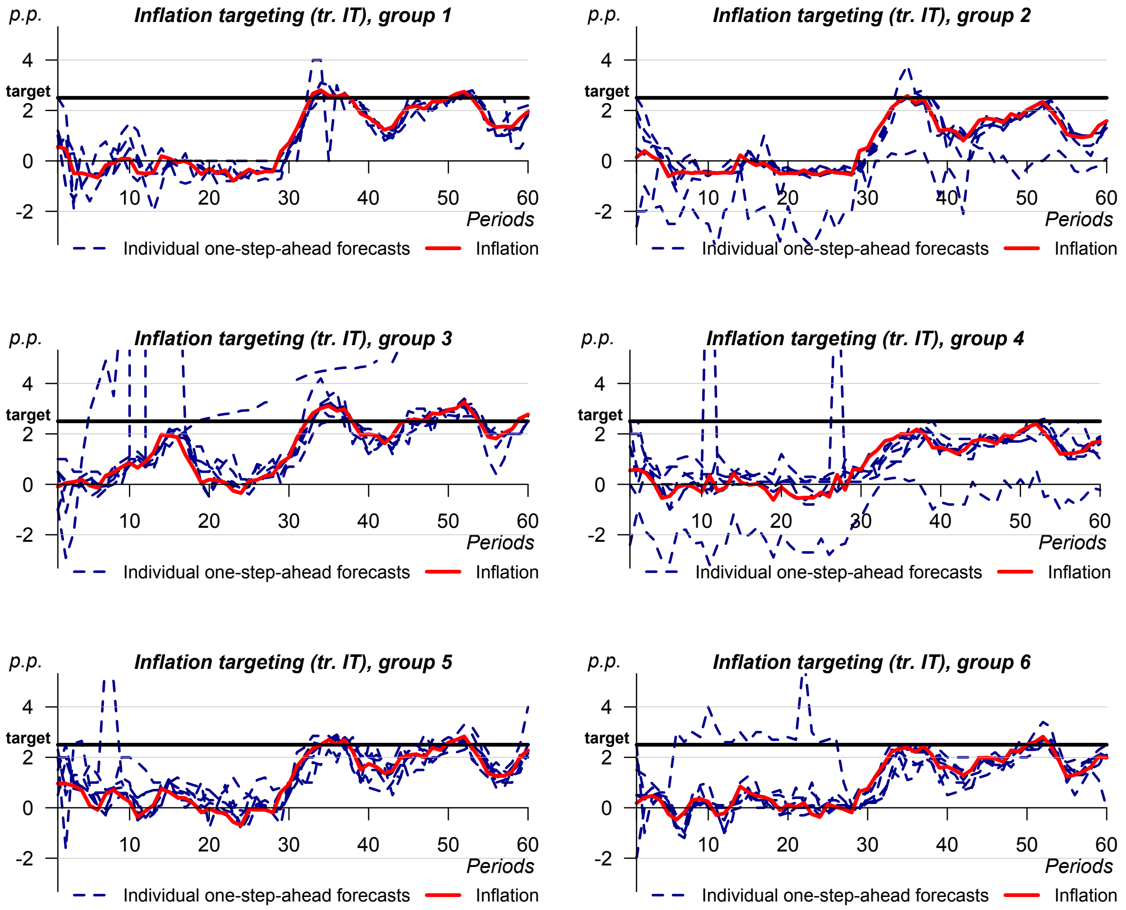


Figure 8: Inflation targeting experimental economies (Tr. IT)

Notes: Each plot is a group. The solid red line is inflation (as also depicted on Figure 4 in the main text, the six dashed blue lines are the individual one-step-ahead inflation forecasts of the six participants. The solid black line is the target in the experiment (2.5%).

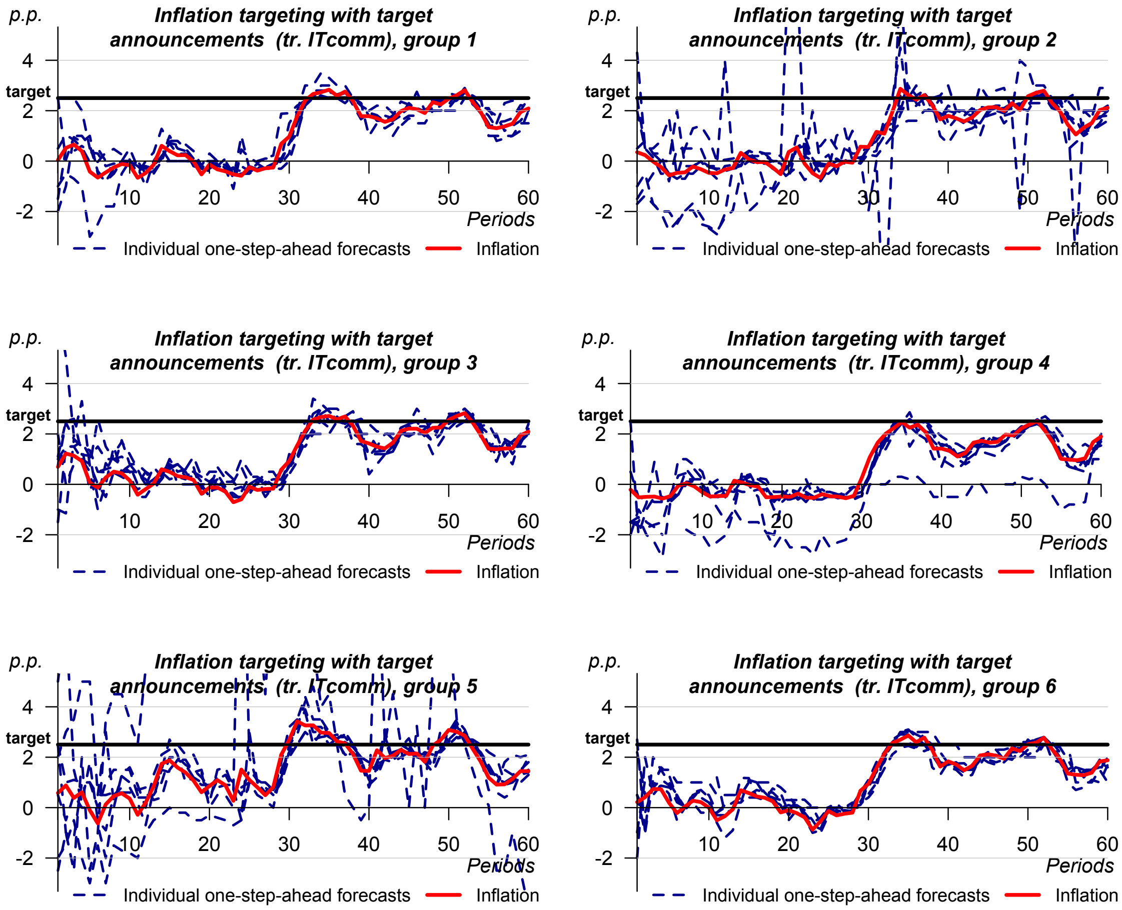


Figure 9: Inflation targeting experimental economies (Tr. ITcomm)

Notes: See Figure 8.

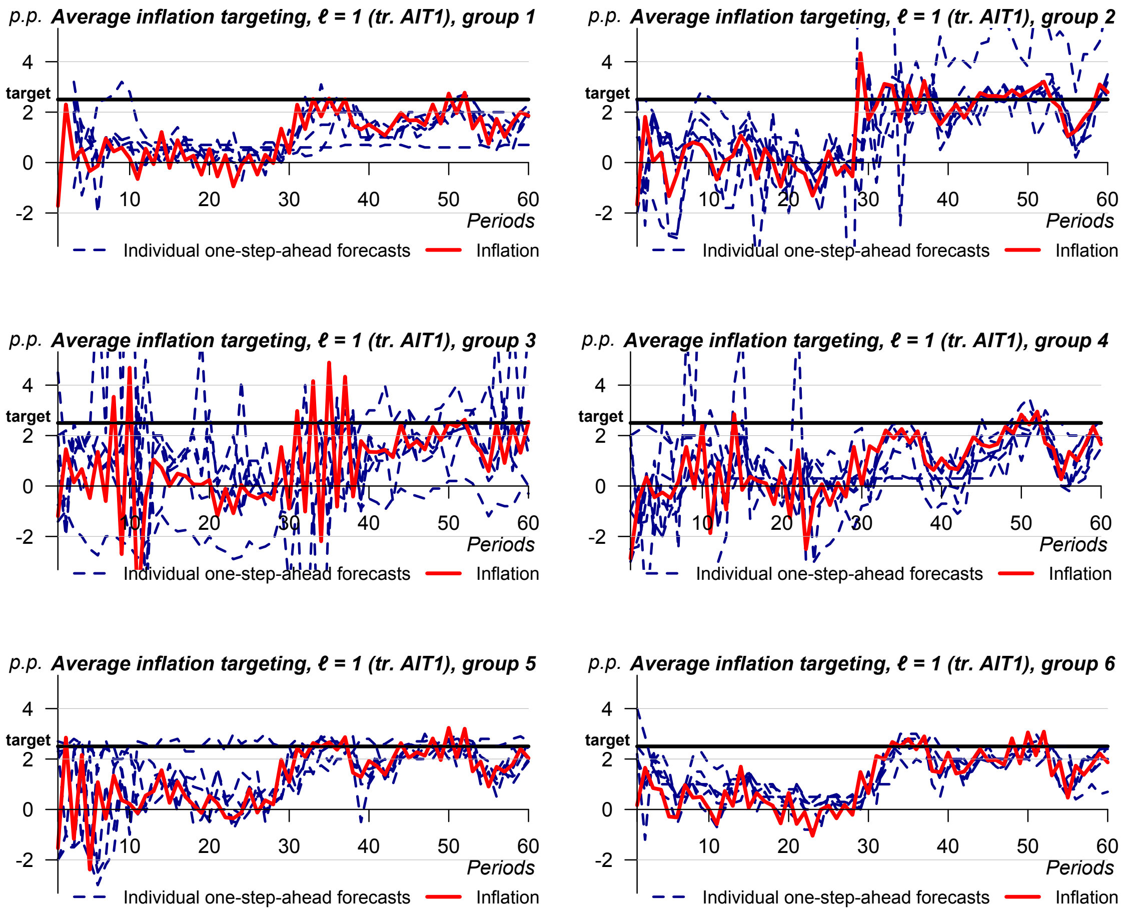


Figure 10: Average inflation targeting experimental economies with $\ell = 1$, (Tr. AIT1)

Notes: See Figure 8.

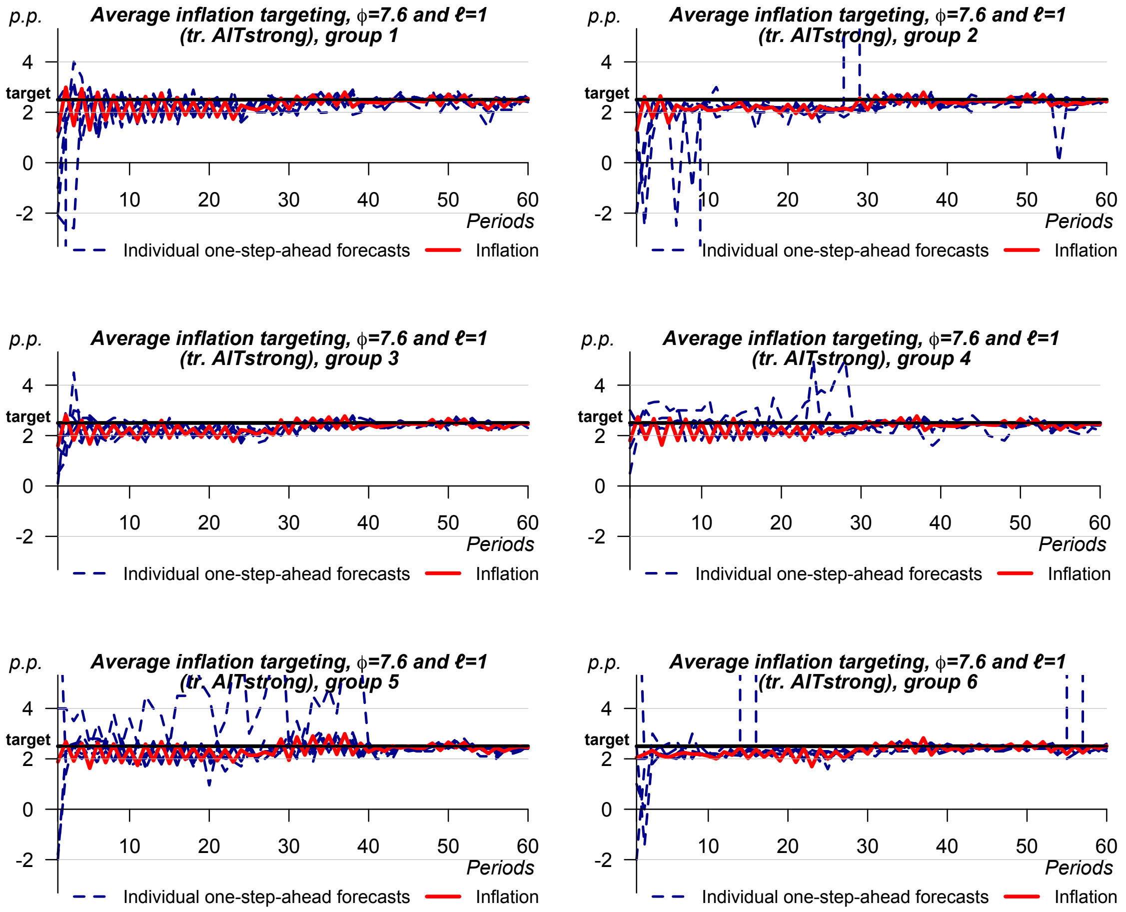


Figure 11: Average inflation targeting experimental economies with $\ell = 1$, $\phi = 7.6$ (Tr. AITstrong)

Notes: See Figure 8.

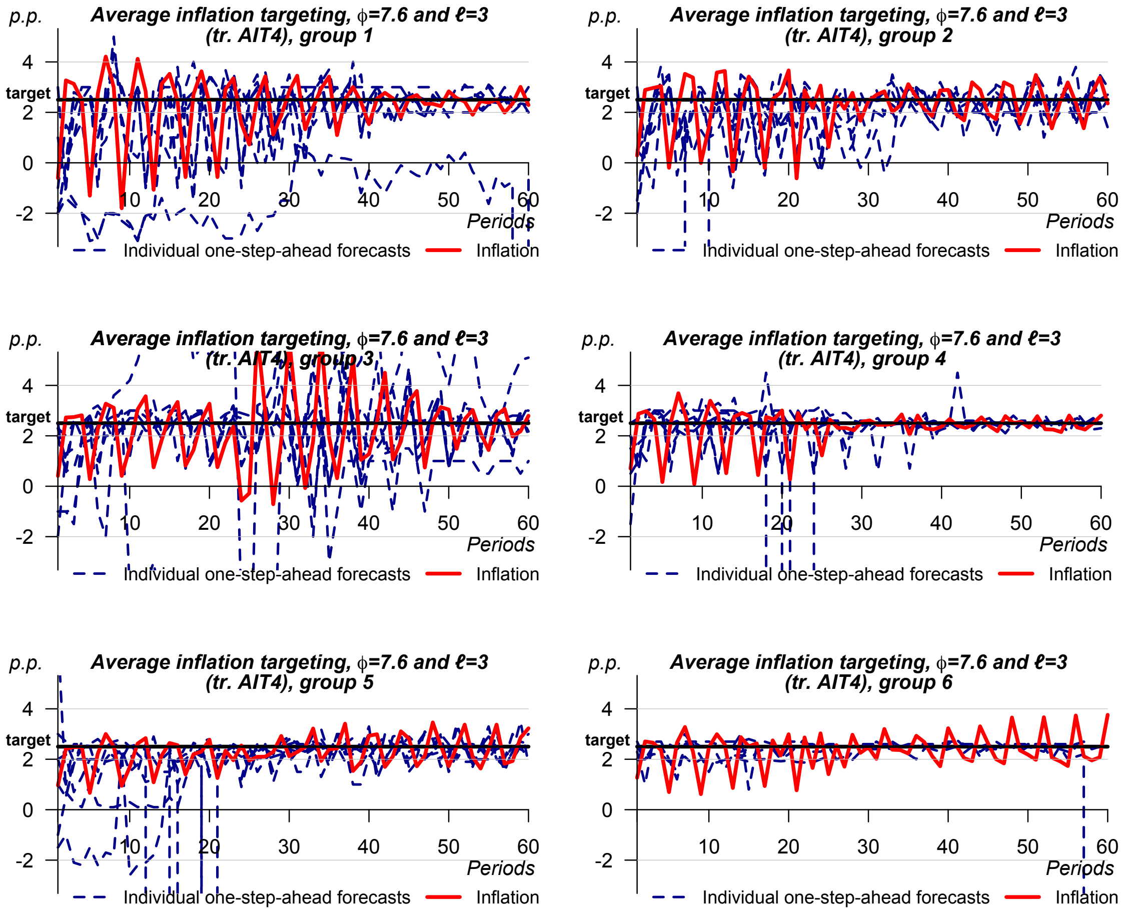


Figure 12: Average inflation targeting experimental economies with $\ell = 3$, $\phi = 7.6$ (Tr. AIT4)

Notes: See Figure 8.

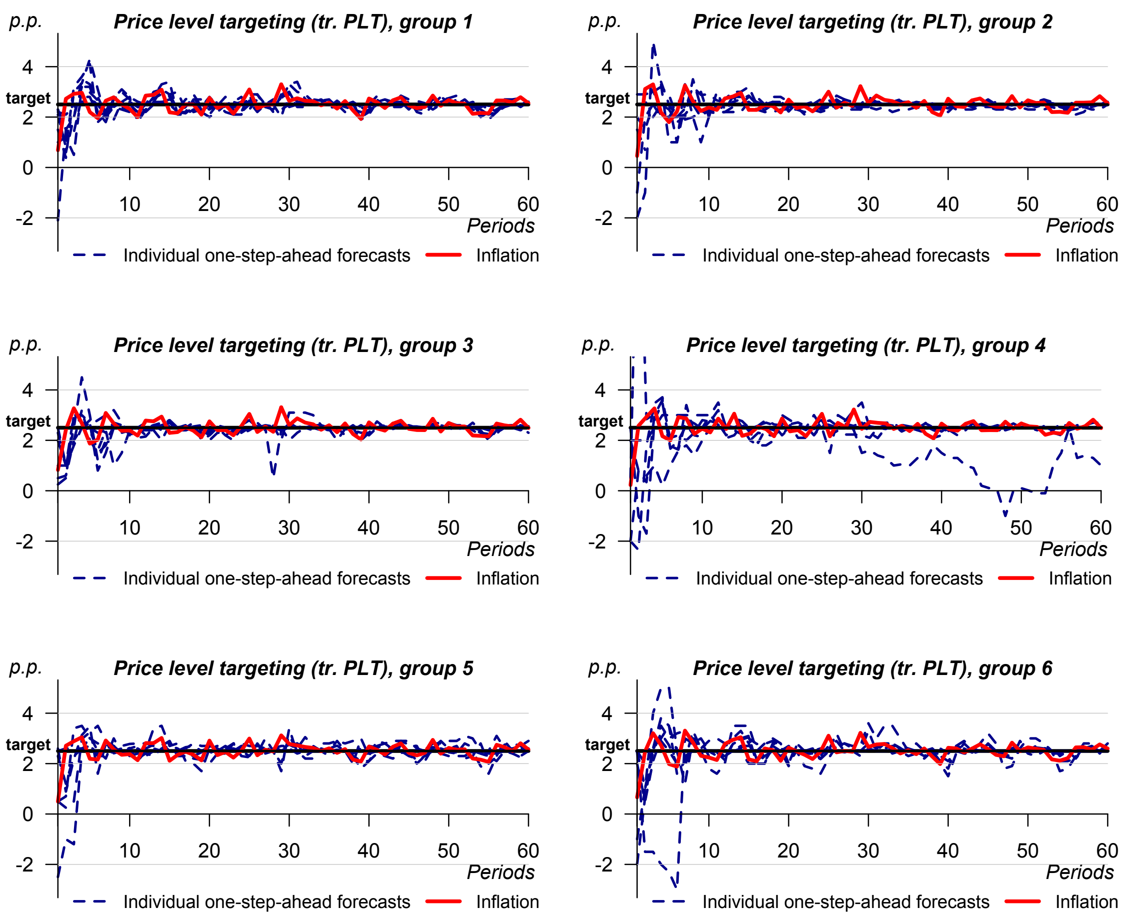


Figure 13: Price level targeting experimental economies (Tr. PLT)

Notes: See Figure 8.

D Experimental results

Group	*1*	*2*	*3*	*4*	*5*	*6*	*average (sd)*
	Inflation targeting (Tr. `IT`)						
mean(π)	0.92	0.69	1.51	0.81	1.13	1.05	1.02 (0.29)
$\frac{P_{60}}{\bar{P}_{60}}$	0.39	0.34	0.55	0.37	0.45	0.42	0.42 (0.07)
mean$(\pi - \pi^T)^2$	3.95	4.37	2.25	3.75	2.92	3.06	3.38 (0.78)
Freq. $i_t = 0$	3	7	0	0	0	0	1.67 (2.88)
	Inflation targeting with target announcements (Tr. `ITcomm`)						
mean$(\pi - \pi^T)$	0.98	0.94	1.13	0.71	1.52	1.07	1.06 (0.27)
$\frac{P_{60}}{\bar{P}_{60}}$	0.41	0.40	0.44	0.34	0.56	0.43	0.43 (0.07)
mean$(\pi - \pi^T)^2$	3.68	3.72	3.02	4.41	1.94	3.22	3.33 (0.83)
Freq. $i_t = 0$	1	1	0	8	0	1	1.83 (3.06)
	Average inflation targeting (Tr. `AIT`)						
mean(π)	0.96	1.27	0.87	0.81	1.25	1.16	1.05 (0.20)
$\frac{P_{60}}{\bar{P}_{60}}$	0.41	0.48	0.38	0.37	0.48	0.45	0.43 (0.05)
mean$(\pi - \pi^T)^2$	3.39	3.57	5.79	4.50	3.02	2.96	3.87 (1.09)
Freq. $i_t = 0$	1	4	2	3	1	0	1.85 (1.47)
	Average inflation targeting with $\phi = 7.6$ (Tr. `AITstrong`)						
mean(π)	2.31	2.3	2.31	2.33	2.34	2.31	2.32 (0.02)
$\frac{P_{60}}{\bar{P}_{60}}$	0.89	0.89	0.89	0.90	0.91	0.90	0.90 (0.01)
mean$(\pi - \pi^T)^2$	0.18	0.11	0.11	0.11	0.13	0.08	0.12 (0.03)
Freq. $i_t = 0$	0	0	0	0	0	0	0.00 (0.00)
	Average inflation targeting with $\phi = 7.6$ and $\ell = 3$ (Tr. `AIT4`)						
mean(π)	2.21	2.29	2.26	2.33	2.30	2.34	2.29 (0.05)
$\frac{P_{60}}{\bar{P}_{60}}$	0.84	0.88	0.86	0.90	0.88	0.90	0.88 (0.03)
mean$(\pi - \pi^T)^2$	1.68	1.12	2.21	0.58	0.44	0.56	1.10 (0.72)
Freq. $i_t = 0$	0	0	0	0	0	0	0.00 (0.00)
	Price level targeting (Tr. `PLT`)						
mean(π)	2.49	2.50	2.50	2.50	2.49	2.50	2.50 (0.00)
$\frac{P_{60}}{\bar{P}_{60}}$	1.00	1.00	1.00	1.00	1.00	1.00	1.00 (0.00)
mean$(\pi - \pi^T)^2$	0.14	0.15	0.13	0.16	0.14	0.15	0.15 (0.01)
Freq. $i_t = 0$	0	0	0	0	0	0	0 (0.00)

Notes: For each experimental group, the table reports the following statistics, computed over the 60 periods of the experiment unless otherwise stated: the average inflation mean(π); the final price gap, defined as the ratio between the price level observed in $t = 60$, assuming $P_0 = 100$, and the level consistent with a growth of 2.5% over the 60 periods, namely 440, and the variance of inflation var(π).

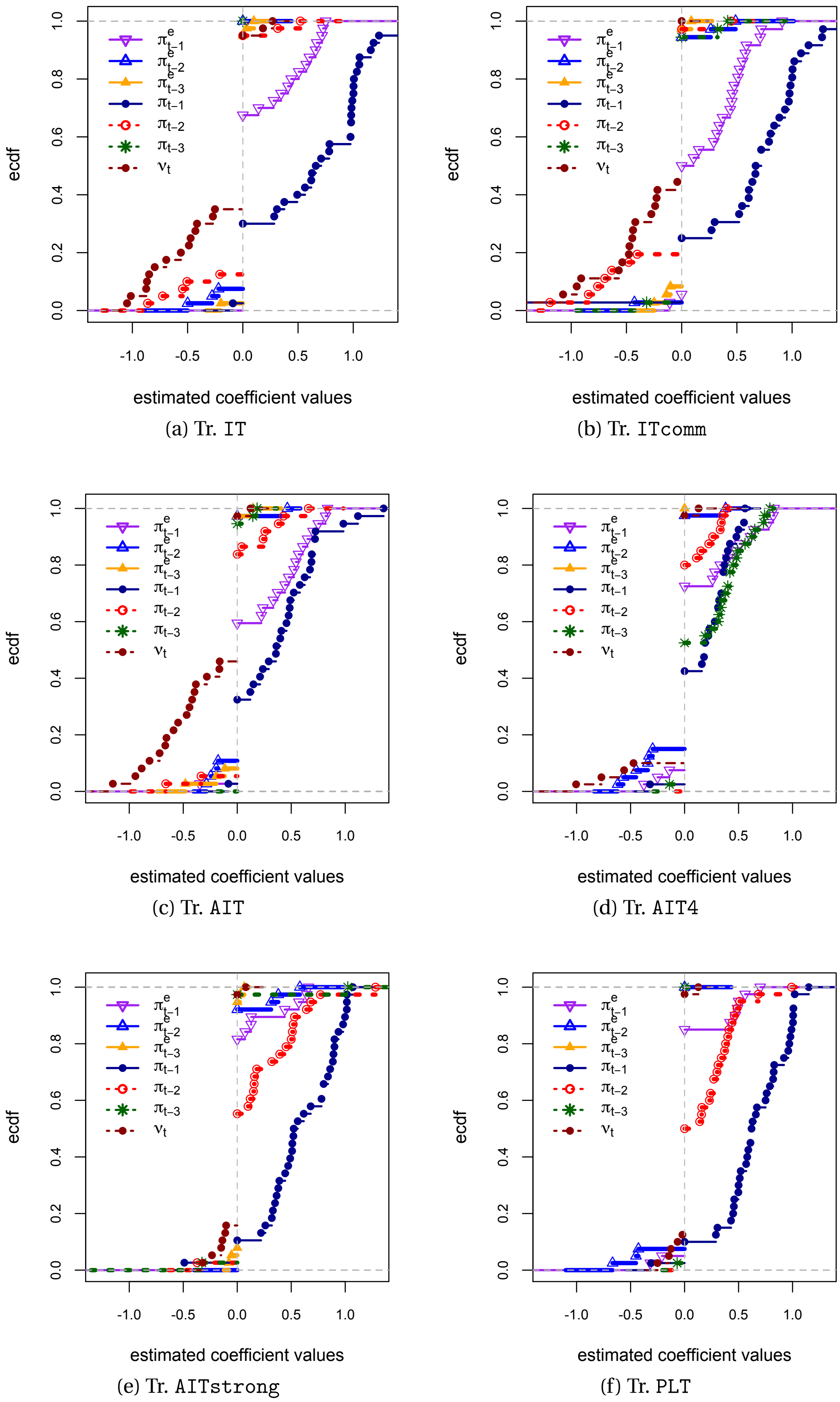
Table 4: Summary of macroeconomic statistics in the baseline experimental economies

Group	*1*	*2*	*3*	*4*	*5*	*6*	*average (sd)*
	Inflation targeting (Tr. `IT`***)***						
EER-short	0.71	0.67	0.64	0.65	0.68	0.7	0.68 (0.03)
EER-long	0.48	0.50	0.45	0.49	0.50	0.53	0.49 (0.03)
$\frac{1}{60}\sum_{s=1}^{60} V(\pi^e_{j,s+1})$	0.38	0.81	1.38	1.04	0.50	0.65	0.79 (0.37)
$\frac{1}{60}\sum_{s=1}^{60} V(\pi^e_{j,s+7})$	0.82	0.79	1.98	1.08	0.57	0.48	0.95 (0.55)
$\frac{1}{420}\sum_{s=1}^{60}\sum_{j=1}^{7} \mid \pi^e_{j,s+1} - \pi^T \mid$	1.66	2.15	1.42	1.92	1.30	1.44	1.64 (0.33)
$\frac{1}{420}\sum_{s=1}^{60}\sum_{j=1}^{7} \mid \pi^e_{j,s+7} - \pi^T \mid$	1.40	1.43	1.24	1.49	1.12	1.31	1.33 (0.13)
	Inflation targeting with target announcements (Tr. `ITcomm`***)***						
EER-short	0.71	0.66	0.70	0.66	0.58	0.71	0.67 (0.05)
EER-long	0.49	0.51	0.49	0.48	0.44	0.45	0.48 (0.03)
$\frac{1}{60}\sum_{s=1}^{60} V(\pi^e_{j,s+1})$	0.42	0.84	0.42	0.72	1.96	0.35	0.79 (0.61)
$\frac{1}{60}\sum_{s=1}^{60} V(\pi^e_{j,s+7})$	0.60	0.76	0.59	0.78	3.20	0.45	1.06 (1.05)
$\frac{1}{420}\sum_{s=1}^{60}\sum_{j=1}^{7} \mid \pi^e_{j,s+1} - \pi^T \mid$	1.52	1.74	1.32	2.08	1.67	1.39	1.62 (0.28)
$\frac{1}{420}\sum_{s=1}^{60}\sum_{j=1}^{7} \mid \pi^e_{j,s+7} - \pi^T \mid$	0.97	0.89	0.99	1.62	1.47	0.75	1.12 (0.35)
	Average inflation targeting (Tr. `AIT`***)***						
EER-short	0.63	0.55	0.47	0.54	0.59	0.63	0.57 (0.06)
EER-long	0.51	0.45	0.41	0.44	0.47	0.49	0.46 (0.04)
$\frac{1}{60}\sum_{s=1}^{60} V(\pi^e_{j,s+1})$	0.57	1.32	1.83	1.02	0.88	0.43	1.00 (0.51)
$\frac{1}{60}\sum_{s=1}^{60} V(\pi^e_{j,s+7})$	0.59	0.81	1.31	1.32	0.85	0.37	0.97 (0.38)
$\frac{1}{420}\sum_{s=1}^{60}\sum_{j=1}^{7} \mid \pi^e_{j,s+1} - \pi^T \mid$	1.47	1.65	2.03	1.85	1.09	1.20	1.55 (0.37)
$\frac{1}{420}\sum_{s=1}^{60}\sum_{j=1}^{7} \mid \pi^e_{j,s+7} - \pi^T \mid$	1.11	1.08	1.47	1.60	0.88	0.93	1.18 (0.29)
	Average inflation targeting with $\phi = 7.6$ ***(Tr.*** `AITstrong`***)***						
EER-short	0.80	0.83	0.84	0.80	0.79	0.84	0.82 (0.02)
EER-long	0.69	0.70	0.73	0.70	0.64	0.74	0.70 (0.04)
$\frac{1}{60}\sum_{s=1}^{60} V(\pi^e_{j,s+1})$	0.36	0.27	0.17	0.32	0.60	0.24	0.33 (0.15)
$\frac{1}{60}\sum_{s=1}^{60} V(\pi^e_{j,s+7})$	0.40	0.42	0.17	0.46	1.73	0.22	0.57 (0.58)
$\frac{1}{420}\sum_{s=1}^{60}\sum_{j=1}^{7} \mid \pi^e_{j,s+1} - \pi^T \mid$	0.32	0.33	0.24	0.26	0.41	0.24	0.30 (0.07)
$\frac{1}{420}\sum_{s=1}^{60}\sum_{j=1}^{7} \mid \pi^e_{j,s+7} - \pi^T \mid$	0.22	0.22	0.05	0.19	0.69	0.07	0.24 (0.23)
	Average inflation targeting with $\phi = 7.6$ ***and*** $\ell = 3$ ***(Tr.*** `AIT4`***)***						
EER-short	0.55	0.57	0.48	0.72	0.65	0.66	0.57 (0.09)
EER-long	0.50	0.53	0.42	0.67	0.60	0.58	0.55 (0.09)
$\frac{1}{60}\sum_{s=1}^{60} V(\pi^e_{j,s+1})$	1.59	0.73	2.30	0.34	0.69	0.18	0.97 (0.81)
$\frac{1}{60}\sum_{s=1}^{60} V(\pi^e_{j,s+7})$	1.55	0.72	1.85	0.24	0.58	0.24	0.86 (0.68)
$\frac{1}{420}\sum_{s=1}^{60}\sum_{j=1}^{7} \mid \pi^e_{j,s+1} - \pi^T \mid$	1.25	0.69	1.53	0.25	0.55	0.11	0.73 (0.56)
$\frac{1}{420}\sum_{s=1}^{60}\sum_{j=1}^{7} \mid \pi^e_{j,s+7} - \pi^T \mid$	1.05	0.55	1.12	0.12	0.40	0.15	0.57 (0.43)

	Price level targeting (Tr. PLT)						
EER-short	0.75	0.79	0.78	0.73	0.76	0.74	0.76 (0.02)
EER-long	0.71	0.72	0.72	0.69	0.72	0.69	0.71 (0.02)
$\frac{1}{60}\sum_{s=1}^{60} V(\pi^e_{j,s+1})$	0.23	0.24	0.20	0.67	0.31	0.39	0.34 (0.18)
$\frac{1}{60}\sum_{s=1}^{60} V(\pi^e_{j,s+7})$	0.23	0.23	0.18	0.70	0.20	0.51	0.34 (0.21)
$\frac{1}{420}\sum_{s=1}^{60}\sum_{j=1}^{7} \mid \pi^e_{j,s+1} - \pi^T \mid$	0.24	0.19	0.16	0.43	0.26	0.29	0.26 (0.09)
$\frac{1}{420}\sum_{s=1}^{60}\sum_{j=1}^{7} \mid \pi^e_{j,s+7} - \pi^T \mid$	0.17	0.15	0.11	0.35	0.14	0.29	0.20 (0.10)

Table 5: Summary of forecast statistics of the baseline experimental economies

Notes: For each experimental group, the table reports the following statistics, computed over the 60 periods of the experiment unless otherwise stated: the *earnings efficiency ratio* (EER), expressed in percentage points, which measures the number of points earned on average per subject w.r.t. the maximum amount of points possible (in case of perfect prediction), where *EER – short* refers to the one-period-ahead prediction score and *EER – long* to the eight-period-ahead prediction score; a measure of the disagreement between subjects about the one-period-ahead and the eight-period-ahead inflation forecasts computed, resp., as the average cross-sectional variance of individual forecasts $\frac{1}{60}\sum_{s=1}^{60} V(\pi^e_{j,s+1})$ and $\frac{1}{60}\sum_{s=1}^{60} V(\pi^e_{j,s+7})$; the average distance per period of individual forecasts (long- and short-horizon ones) to the target, aggregated over all subjects, as a measure of expectations anchorage. We discard non-incentivized forecasts, i.e. short-run forecasts submitted in period 60 and long-run forecasts submitted from period 54 on, as no realization and there no payoff may be computed for these submissions.



(a) Tr. `IT`

(b) Tr. `ITcomm`

(c) Tr. `AIT`

(d) Tr. `AIT4`

(e) Tr. `AITstrong`

(f) Tr. `PLT`

Figure 14: Distribution of estimated coefficients for each participants across all groups

Notes: See Equation (20).

E The exogenous shock process

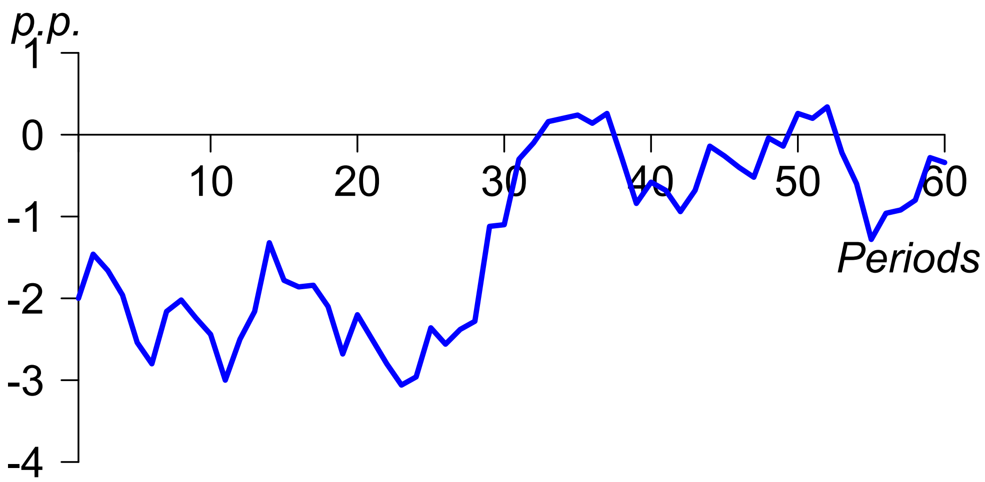


Figure 15: Time series of the shock process used in the experiment:
$\nu_t = 0.95\nu_{t-1} + \epsilon_t$ with $\sigma_\epsilon^2 = 1\%$, $\nu_0 = -2$.

F Graphical user interface (GUI)

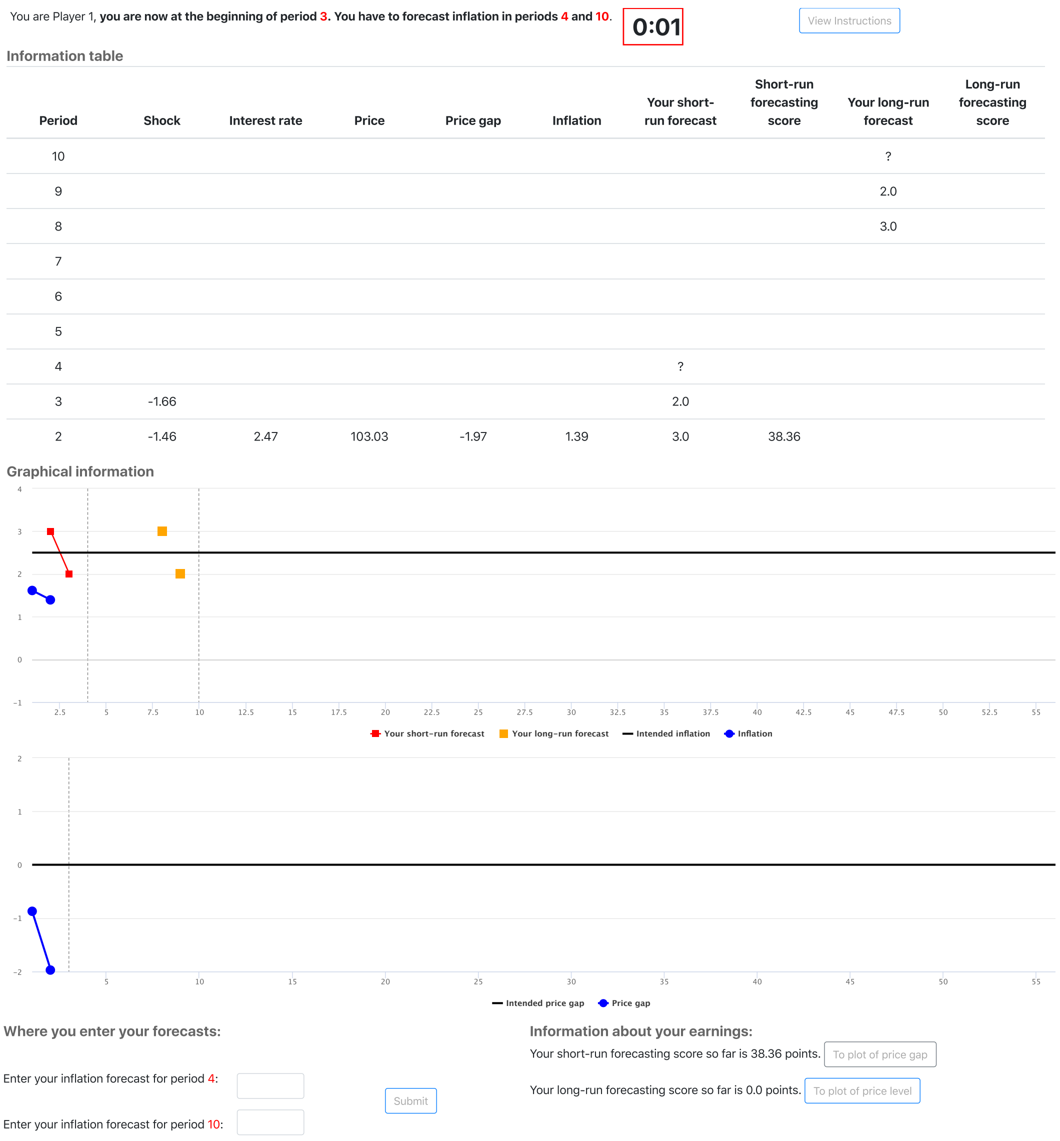
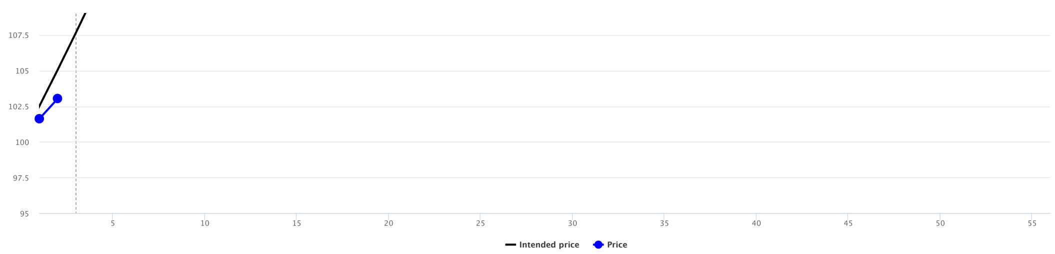


Figure 16: Graphical user interface (decision screen)

Upon clicking on 'to plot of price level,' subjects can see the following graph instead of the price gap:



G Instructions and quizzes

G.1 Tr. IT

Welcome to our experiment!

Thank you for your participation!

Welcome to this experiment! The experiment is anonymous, the data from your choices will only be linked to your anonymous participant code, never to your name. During the experiment you are not allowed to communicate with other participants. If you have a question at any time, please raise your virtual hand on the zoom meeting and we will assist you in the private chat.

Please read these instructions carefully as each participant has to answer the quiz before we can start the experiment. After the experiment, you will also be asked to fill out a short questionnaire and provide your IBAN (but not your name) for payment. You can use a simple calculator and scratch paper during the experiment but it is not necessary to complete your experimental tasks. Good luck!

Next

Figure 17: Welcome screen (common to all treatments)

Instructions

Next

General information about the experimental economy

All participants have been randomly divided into **groups of seven**. The group composition will not change during the experiment. You and all other participants will take the ***roles of statistical research bureaus making predictions of inflation***. The experiment consists of **60 periods**. In each period you will be asked to predict inflation **in the short run *(next period)* and in the long run *(in 8 periods)***.

The economy is described by **three main variables**: ***inflation***, the ***price level***, and the ***interest rate***.
Inflation measures the percentage change in the price level between two consecutive periods. The ***intended level of inflation is 2.5%*** in this economy. This means that the price level ***should*** grow at a rate of 2.5% per period. The initial price is 100. In period 1, the intended price level should be 100*(1+0.025) = 102.5. In period 2, the intended price level should be 102.5*(1+0.025) = 105.06, etc. The **difference between the price and its intended level** is called the ***price gap***.

The interest rate measure the cost of borrowing money and is the instrument of the central bank to achieve the intended inflation level. **The central bank cares about the *current level of inflation*** and adjusts the interest rate so as ***current inflation* to be in line with the intended level of inflation of 2.5%**. In each period, if ***current inflation* is higher (resp. lower) than 2.5%, the central bank increases (resp. decreases) the interest rate. However, *the interest rate cannot take negative values.***

Inflation depends on **short-run inflation predictions** and **shocks**. **If the *average short-run inflation prediction* of all statistical research bureaus in your group *increases*** (that is if the mean of your inflation prediction for the next period and the ones of the other participants in your group increases), actual inflation is likely to **increase**. If the average prediction for the next period **decreases**, inflation is likely to **decrease**.
Note that **only your short-run predictions**, ***not your long-run predictions for 8 periods in the future***, influence inflation.

Shocks represent all other elements that influence inflation on top of short-run inflation predictions. **Positive values** of shocks **increase** inflation, **negative** shocks **decrease** inflation. **The shocks across periods depend on each other**: if the **past shocks were mostly positive** (resp. negative), the next shock is **highly likely be positive** (resp. negative).

To summarise, current inflation :

- ***depends positively on shocks***. Positive (resp. negative) shocks increase (resp. decrease) inflation. If past shocks have been mostly upcoming ones are likely to be positive (resp. negative) as well.
- ***depends positively* on the average short-run inflation predictions in your group**. Higher (resp. lower) than 2.5% average predict decrease) inflation.
- ***does not depend on long-run predictions.***

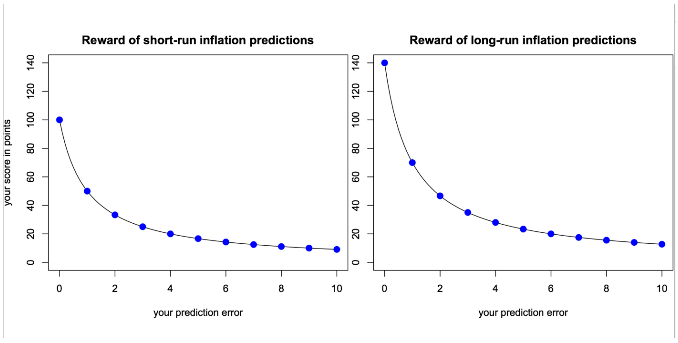
Your prediction tasks

Your task in each period of the experiment is to predict inflation in the **next period** and in **8 periods from now**. When the experiment starts, you enter **period 1** and have to forecast inflation in the short-run, that is **for period 2** and in the long run, that is **for period 8**. Once all participants have submitted their two predictions, the **average prediction for period 2** and the **shock in period 1** determines **inflation in period 1**. You then enter period 2 and have to submit inflation predictions for period 3 and 9. Shock in period 2 and the average prediction for period 3 gives inflation in period 2. You then can see your first short-run prediction error, that is for inflation in period 2 based on the prediction you made in period 1. This process repeats itself for 60 periods. In period 9, you will see your first long-run prediction error, that is for inflation in period 8 based on your prediction made in period 1.

Hence, in any period t, you make predictions of inflation for the next period t + 1 and t+7.

Your payment

Your payment will depend on the **accuracy of your predictions**, measured as the **absolute distance between your predictions and the actual values** (this distance is the prediction error). For each period, the prediction errors are calculated as soon as the actual values are known. Your prediction **score decreases as the prediction error increases**. The left-hand side graphic below gives your prediction score for the short-run forecasts. For any error, you make ***100/(1+error)*** points. Hence, in case of perfect prediction (zero prediction error), you get a maximum of 100 points. The right-hand side graphic below gives your prediction score for the long-run forecasts. For any error, you make ***140/(1+error) points***. Hence, in case of perfect prediction, you get a maximum of 140 points. Note that **you get more points for predicting long-run than short-run inflation because you will get fewer prediction scores for long-run predictions** (as you get the first one in period 9 only as opposed to period 3 for short-run scores).



Example: If you predict 2% and the actual inflation turns out to be 3%, your prediction error is 3%−2% = 1%. Therefore you get a prediction score of 50 if it was a short-run prediction and 70 if it was a long-run prediction. If you predict 1% and the actual inflation turns out −2%, your error is 1% − (−2%) = 3% and you get a prediction score of 35 if it was a long-run prediction and 25 if it was a short-run prediction.

After the 60 periods of the experiment, you will have two total scores, one for short-run and one for long-run inflation predictions. These total scores simply consist of the sum of all prediction scores you got during the experiment, **separately for short and long-run inflation predictions.**

When the experiment has ended, you will be paid ***either*** **for predicting short-run *or* long-run inflation**. One of the two scores will be ***randomly selected with equal probability*** for payment at a rate of **0.5 euro for each 100 points**. The selected score is the same for all participants and the random draw is independent from how well you did in the two tasks. This will be the only payment from this experiment, i.e. you will not receive a show-up fee on top of it.

Computer interface and information

The computer interface is mainly self-explanatory. The **top table** will show you:

- Up to and including the last period t − 1: i) **inflation in every period, including the last one, which influences current inflation**, ii) the **price level**, iii) the difference between the realised prices and the intended price levels, that is the **price gap** and iv) the **interest rates**;
- Up to and including the current period t: the **shocks**.
- Up to 7 periods in the future: your **short and long-run inflation predictions**;
- Up to and including the last period t − 1: your **short and long-run prediction scores**.

The **first graph** will show you the time series of ***inflation, which is the concern of the central bank***, your short- and long-run predictions next to the intended inflation level (black thick line).

The **second graph** will show you the **price next to its intended level**. You will be able to display the **price gap in percentage points** instead of the plot of the price. If the price equals its intended level, the price gap equals zero (thick black line on the plot). You will be able to switch back and forth between the two plots. The horizontal axes give the periods in the experiment and the vertical axis shows the corresponding values in percentage points for inflation and the price gap (for instance, 3 corresponds to 3%).

All this information **may be relevant to form your predictions** but ***this is up to you to make use of it or not***.

In the bottom left part of the screen you will be asked to enter your predictions. The sum of the short- and long-run prediction scores over the different periods are shown separately in the bottom right of the screen. You can input positive or negative numbers and several digits, using commas or dots.

There is a timer on each decision page. It is not enforced but please focus on your experimental task not to unnecessarily delay the experiment! Thank you!

Next

Quiz

1. Upon entering period 6, for which periods are you asked to submit inflation predictions? **(again check the red parts in the instructions)**

- for periods 6 and 12
- for periods 6 and 13
- for periods 7 and 13
- for periods 7 and 12

2. If you enter a prediction for inflation in period 10, which period's inflation may be influenced by your prediction? **(today is influenced by predictions for tomorrow, only type in the number of the period)**

3. The central bank sets the interest rate to **(check the red parts in the instructions)**

- Keep current inflation around 2.5%;
- Keep the price gap positive;
- Keep the price gap around zero.

4. Suppose the past shocks all have negative values. Which ones are true? **(again, check the red parts in the instructions)**

- The current shock is likely to be positive;
- The current shock is likely to be negative;
- We cannot say anything about the current shock.

5. Is inflation likely to ... **(USE THE THREE ITEMS IN THE GREY BOX!)**

(a) If the current shock is negative:

- increase
- decrease
- can't tell

(b) If the average prediction for the next period is below 2.5:

- increase
- decrease
- can't tell

(c) If the average prediction in 8 periods is higher than 2.5%:

- increase
- decrease
- can't tell

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Figure 18: Quiz

Notes: The correct answers are 1.c; 2.9; 3.a; 4b; 5(a)b; 5(b)b; 5(c)b.

G.2 Tr. AIT

Notes: for higher numbers of lags, the defining of the "average past inflation" is adjusted accordingly.

Instructions

Next

General information about the experimental economy

All participants have been randomly divided into **groups of seven**. The group composition will not change during the experiment. You and all other participants will take the ***roles of statistical research bureaus making predictions of inflation***. The experiment consists of **60 periods**. In each period you will be asked to predict inflation **in the short run *(next period)* and in the long run *(in 8 periods)***.

The economy is described by **three main variables**: ***inflation***, the ***price level***, and the ***interest rate***.
Inflation measures the percentage change in the price level between two consecutive periods. The ***intended level of inflation is 2.5%*** in this economy. This means that the price level ***should*** grow at a rate of 2.5% per period. The initial price is 100. In period 1, the intended price level should be 100*(1+0.025) = 102.5. In period 2, the intended price level should be 102.5*(1+0.025) = 105.06, etc. The **difference between the price and its intended level** is called the ***price gap***.

The interest rate measure the cost of borrowing money and is the instrument of the central bank to achieve the intended inflation level. **The central bank cares about the *average past inflation, that is the average inflation over today and yesterday*** and adjusts the interest rate so as ***average past inflation* to be in line with the intended level of inflation of 2.5%**. In each period, if ***average past inflation* is higher (resp. lower) than 2.5%, the central bank increases (resp. decreases) the interest rate. However, *the interest rate cannot take negative values.***

This implies that ***inflation (in period t)*** depends on ***past inflation*** **(that is inflation in period t-1)**: if **past inflation has been below 2.5%** (resp. above 2.5%), **current inflation is likely to be higher than 2.5%** (resp. lower than 2.5%) so as **inflation to be on average around 2.5%**.

Inflation depends also on **short-run inflation predictions** and **shocks**. **If the *average short-run inflation prediction* of all statistical research bureaus in your group *increases*** (that is if the mean of your inflation prediction for the next period and the ones of the other participants in your group increases), actual inflation is likely to **increase**. If the average prediction for the next period **decreases**, inflation is likely to **decrease**.
Note that **only your short-run predictions**, ***not your long-run predictions for 8 periods in the future***, influence inflation.

Shocks represent all other elements that influence inflation on top of short-run inflation predictions. **Positive values** of shocks **increase** inflation, **negative** shocks **decrease** inflation. **The shocks across periods depend on each other**: if the **past shocks were mostly positive** (resp. negative), the next shock is **highly likely be positive** (resp. negative).

To summarise, current inflation :

- ***depends negatively on the past inflation (in t-1)***. If past inflation was above 2.5%, current inflation is likely to be lower than 2.5%. T has been below 2.5%, current inflation is likely to be higher than 2.5%.
- ***depends positively on shocks***. Positive (resp. negative) shocks increase (resp. decrease) inflation. If past shocks have been mostly upcoming ones are likely to be positive (resp. negative) as well.
- ***depends positively* on the average short-run inflation predictions in your group**. Higher (resp. lower) than 2.5% average predict decrease) inflation.
- ***does not depend on long-run predictions.***

Your prediction tasks

Your task in each period of the experiment is to predict inflation in the **next period** and in **8 periods from now**. When the experiment starts, you enter **period 1** and have to forecast inflation in the short-run, that is **for period 2** and in the long run, that is **for period 8**. Once all participants have submitted their two predictions, the **average prediction for period 2** and the **shock in period 1** determines **inflation in period 1**. You then enter period 2 and have to submit inflation predictions for period 3 and 9. Shock in period 2 and the average prediction for period 3 gives inflation in period 2. You then can see your first short-run prediction error, that is for inflation in period 2 based on the prediction you made in period 1. This process repeats itself for 60 periods. In period 9, you will see your first long-run prediction error, that is for inflation in period 8 based on your prediction made in period 1.

Hence, in any period t, you make predictions of inflation for the next period t + 1 and t+7.

Your payment

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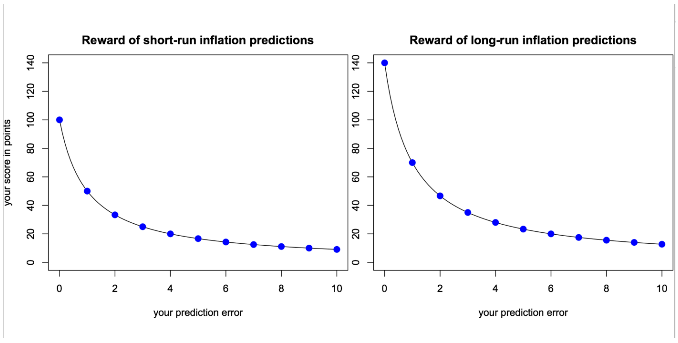

Example: If you predict 2% and the actual inflation turns out to be 3%, your prediction error is 3%–2% = 1%. Therefore you get a prediction score of 50 if it was a short-run prediction and 70 if it was a long-run prediction. If you predict 1% and the actual inflation turns out –2%, your error is 1% – (–2%) = 3% and you get a prediction score of 35 if it was a long-run prediction and 25 if it was a short-run prediction.

After the 60 periods of the experiment, you will have two total scores, one for short-run and one for long-run inflation predictions. These total scores simply consist of the sum of all prediction scores you got during the experiment, **separately for short and long-run inflation predictions.**

When the experiment has ended, you will be paid ***either*** **for predicting short-run *or* long-run inflation**. One of the two scores will be ***randomly selected with equal probability*** for payment at a rate of **0.5 euro for each 100 points**. The selected score is the same for all participants and the random draw is independent from how well you did in the two tasks. This will be the only payment from this experiment, i.e. you will not receive a show-up fee on top of it.

Computer interface and information

The computer interface is mainly self-explanatory. The **top table** will show you:

- Up to and including the last period t – 1: i) **inflation in every period, that is the central bank's objective**, ii) the **price level**, iii) the difference between the realised prices and the intended price levels, that is the **price gap** and iv) the **interest rates**;
- Up to and including the current period t: the **shocks**.
- Up to 7 periods in the future: your **short and long-run inflation predictions**;
- Up to and including the last period t – 1: your **short and long-run prediction scores**.

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The **second graph** will show you the **price next to its intended level**. You will be able to display the **price gap in percentage points** instead of the plot of the price. If the price equals its intended level, the price gap equals zero (thick black line on the plot). You will be able to switch back and forth between the two plots. The horizontal axes give the periods in the experiment and the vertical axis shows the corresponding values in percentage points for inflation and the price gap (for instance, 3 corresponds to 3%).

All this information **may be relevant to form your predictions** but ***this is up to you to make use of it or not***.

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There is a timer on each decision page. It is not enforced but please focus on your experimental task not to unnecessarily delay the experiment! Thank you!

Quiz

1. Upon entering period 6, for which periods are you asked to submit inflation predictions? **(again check the red parts in the instructions)**

- for periods 6 and 12
- for periods 6 and 13
- for periods 7 and 13
- for periods 7 and 12

2. If you enter a prediction for inflation in period 10, which period's inflation may be influenced by your prediction? **(today is influenced by predictions for tomorrow, only type in the number of the period)**

3. The central bank sets the interest rate to **(check the red parts in the instructions)**

- Keep current inflation around 2.5%;
- Keep the average past inflation around 2.5%;
- Keep the price gap positive

4. Suppose the past shocks all have negative values. Which ones are true? **(again, check the red parts in the instructions)**

- The current shock is likely to be positive;
- The current shock is likely to be negative;
- We cannot say anything about the current shock.

5. Is inflation likely to ... **(USE THE FOUR ITEMS IN THE GREY BOX! each ullet point is an answer, in the same order as the subquestions below!)**

(a) If the last inflation was above 2.5%:

- increase
- decrease
- can't tell

(b) If the current shock is negative:

- increase
- decrease
- can't tell

(c) If the average prediction for the next period is below 2.5:

- increase
- decrease
- can't tell

(d) If the average prediction in 8 periods is higher than 2.5%:

- increase
- decrease
- can't tell

Figure 19: Quiz

Notes: The correct answers are 1.c; 2.9; 3.b; 4b; 5(a)b; 5(b)b; 5(c)b; 5(d)d.

G.3 Tr. PLT

Instructions

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General information about the experimental economy

All participants have been randomly divided into **groups of seven**. The group composition will not change during the experiment. You and all other participants will take the ***roles of statistical research bureaus making predictions of inflation***. The experiment consists of **60 periods**. In each period you will be asked to predict inflation **in the short run *(next period)* and in the long run *(in 8 periods)***.

The economy is described by **three main variables**: ***inflation***, the ***price level***, and the ***interest rate***.
Inflation measures the percentage change in the price level between two consecutive periods. The ***intended level of inflation is 2.5%*** in this economy. This means that the price level ***should*** grow at a rate of 2.5% per period. The initial price is 100. In period 1, the intended price level should be 100*(1+0.025) = 102.5. In period 2, the intended price level should be 102.5*(1+0.025) = 105.06, etc. The **difference between the price and its intended level** is called the **price gap**.

The interest rate measure the cost of borrowing money and is the instrument of the central bank to achieve the intended inflation level. **The central bank cares about the *price gap*** and adjusts the interest rate so as ***the price* to be in line with the level it would reach if it were to always grow at 2.5%.** In each period, if ***the price gap* is higher (resp. lower) than 0%**, that is if the price is higher (resp. lower) than its intended level, **the central bank increases (resp. decreases) the interest rate. However, *the interest rate cannot take negative values.***

This implies that ***inflation*** depends on the ***last* price gap**: if the **last price gap has been positive** (resp. negative), that is if the price was higher (resp. lower than its intended level), **current inflation is likely to be lower** (resp. higher) than 2.5% so as the **price to increase less** (resp. more) and **catch up with its intended level**.

Inflation also depends on **short-run inflation predictions** and **shocks**. **If the *average short-run inflation prediction* of all statistical research bureaus in your group *increases*** (that is if the mean of your inflation prediction for the next period and the ones of the other participants in your group increases), actual inflation is likely to **increase**. If the average prediction for the next period **decreases**, inflation is likely to **decrease**.
Note that **only your short-run predictions**, ***not your long-run predictions for 8 periods in the future***, influence inflation.

Shocks represent all other elements that influence inflation on top of short-run inflation predictions. **Positive values** of shocks **increase** inflation, **negative** shocks **decrease** inflation. **The shocks across periods depend on each other**: if the **past shocks were mostly positive** (resp. negative), the next shock is **highly likely be positive** (resp. negative).

To summarise, current inflation :

- ***depends negatively on the last price gap***. If the last price gap has been positive (i.e. the price was above its intended level), curre
2.5%. The opposite is true: if the last price gap has been negative, current inflation is likely to be higher than 2.5%.
- ***depends positively on shocks***. Positive (resp. negative) shocks increase (resp. decrease) inflation. If past shocks have been mostly
upcoming ones are likely to be positive (resp. negative) as well.
- ***depends positively* on the average short-run inflation predictions in your group**. Higher (resp. lower) than 2.5% average predict
decrease) inflation.
- ***does not depend on long-run predictions.***

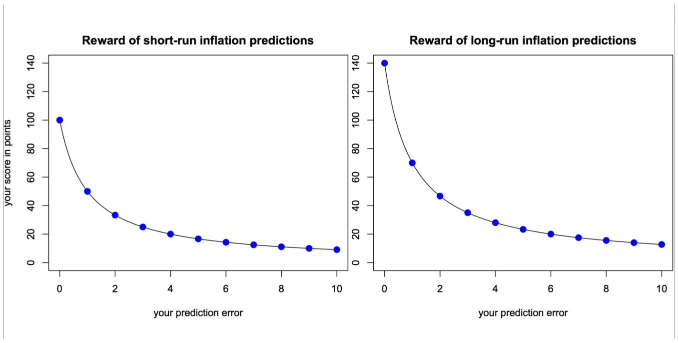
Your prediction tasks

Your task in each period of the experiment is to predict inflation in the **next period** and in **8 periods from now**. When the experiment starts, you enter **period 1** and have to forecast inflation in the short-run, that is **for period 2** and in the long run, that is **for period 8**. Once all participants have submitted their two predictions, the **average prediction for period 2** and the **shock in period 1** determines **inflation in period 1**. You then enter period 2 and have to submit inflation predictions for period 3 and 9. Shock in period 2 and the average prediction for period 3 gives inflation in period 2. You then can see your first short-run prediction error, that is for inflation in period 2 based on the prediction you made in period 1. This process repeats itself for 60 periods. In period 9, you will see your first long-run prediction error, that is for inflation in period 8 based on your prediction made in period 1.

Hence, in any period t, you make predictions of inflation for the next period t + 1 and t+7.

Your payment

Your payment will depend on the **accuracy of your predictions**, measured as the **absolute distance between your predictions and the actual values** (this distance is the prediction error). For each period, the prediction errors are calculated as soon as the actual values are known. Your prediction **score decreases as the prediction error increases**. The left-hand side graphic below gives your prediction score for the short-run forecasts. For any error, you make ***100/(1+error)*** points. Hence, in case of perfect prediction (zero prediction error), you get a maximum of 100 points. The right-hand side graphic below gives your prediction score for the long-run forecasts. For any error, you make ***140/(1+error) points***. Hence, in case of perfect prediction, you get a maximum of 140 points. Note that **you get more points for predicting long-run than short-run inflation because you will get fewer prediction scores for long-run predictions** (as you get the first one in period 9 only as opposed to period 3 for short-run scores).



Example: If you predict 2% and the actual inflation turns out to be 3%, your prediction error is 3%–2% = 1%. Therefore you get a prediction score of 50 if it was a short-run prediction and 70 if it was a long-run prediction. If you predict 1% and the actual inflation turns out –2%, your error is 1% – (–2%) = 3% and you get a prediction score of 35 if it was a long-run prediction and 25 if it was a short-run prediction.

After the 60 periods of the experiment, you will have two total scores, one for short-run and one for long-run inflation predictions. These total scores simply consist of the sum of all prediction scores you got during the experiment, **separately for short and long-run inflation predictions.**

When the experiment has ended, you will be paid ***either* for predicting short-run *or* long-run inflation**. One of the two scores will be ***randomly selected with equal probability*** for payment at a rate of **0.5 euro for each 100 points**. The selected score is the same for all participants and the random draw is independent from how well you did in the two tasks. This will be the only payment from this experiment, i.e. you will not receive a show-up fee on top of it.

Computer interface and information

The computer interface is mainly self-explanatory. The **top table** will show you:

- Up to and including the last period t – 1: i) **inflation in every period**, ii) the **price level**, iii) the difference between the realised prices and the intended price levels, that is the **price gap, that is the central bank's objective** and iv) the **interest rates**;
- Up to and including the current period t: the **shocks**.
- Up to 7 periods in the future: your **short and long-run inflation predictions**;
- Up to and including the last period t – 1: your **short and long-run prediction scores**.

The **first graph** will show you the time series of ***inflation***, your short- and long-run predictions next to the intended inflation level (black thick line).

The **second graph** will show you the **price next to its intended level**, which is the concern of the central bank. You will be able to display the **price gap in percentage points** instead of the plot of the price. If the price equals its intended level, the price gap equals zero (thick black line on the plot). You will be able to switch back and forth between the two plots. The horizontal axes give the periods in the experiment and the vertical axis shows the corresponding values in percentage points for inflation and the price gap (for instance, 3 corresponds to 3%).

All this information **may be relevant to form your predictions** but ***this is up to you to make use of it or not***.
In the bottom left part of the screen you will be asked to enter your predictions. The sum of the short- and long-run prediction scores over the different periods are shown separately in the bottom right of the screen. You can input positive or negative numbers and several digits, using commas or dots.
There is a timer on each decision page. It is not enforced but please **focus on your experimental task not to unnecessarily delay the experiment!** Thank you!

Quiz

1. Upon entering period 6, for which periods are you asked to submit inflation predictions? **(again check the red parts in the instructions)**

- ◯ for periods 6 and 12
- ◯ for periods 6 and 13
- ◯ for periods 7 and 13
- ◯ for periods 7 and 12

2. If you enter a prediction for inflation period 10, which period's inflation may be influenced by your prediction? **(today is influenced by predictions for tomorrow, only type in the number of the period)**

3. The central bank sets the interest rate to **(again check the red parts in the instructions)**

- ◯ Keep current inflation around 2.5%;
- ◯ Keep the price gap positive;
- ◯ Keep the price gap around zero.

4. Suppose the past shocks all have negative values. Which ones are true? **(again, check the red parts in the instructions)**

- ◯ The current shock is likely to be positive;
- ◯ The current shock is likely to be negative;
- ◯ We cannot say anything about the current shock.

5. Is inflation likely to ... **(USE THE FOUR ITEMS IN THE GREY BOX!)**

(a) If the last price gap was negative:

- ◯ increase
- ◯ decrease
- ◯ can't tell

(b) If the current shock is negative:

- ◯ increase
- ◯ decrease
- ◯ can't tell

(c) If the average prediction for the next period is below 2.5:

- ◯ increase
- ◯ decrease
- ◯ can't tell

(d) If the average prediction in 8 periods is higher than 2.5%:

- ◯ increase
- ◯ decrease
- ◯ can't tell

Figure 20: Quiz

Notes: The correct answers are 1.c; 2.9; 3.c; 4b; 5(a)a; 5(b)b; 5(c)b; 5(d)c.