Inflation Expectations and Monetary Policy Design: Evidence from the Laboratory*

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Abstract

Using laboratory experiments within a New Keynesian macro framework, we explore the interaction between the formation of inflation expectations and monetary policy design. The central question in this paper is how to design monetary policy in an environment characterized by heterogeneous expectations. Rules that use actual rather than forecasted inflation produce lower inflation variability and reduce expectational cycles. Inflation forecast targeting rule where a reaction coefficient equals 4 produces lower inflation variability than rules with reaction coefficients 1.5 and 1.35. The difference between the latter two is not significant. However, this result heavily depends on the subjects’ predominant expectation formation mechanism.

JEL: C91, C92, E37, E52

Key words: Laboratory Experiments, Inflation Expectations, New Keynesian Model, Monetary Policy Design.

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1 Introduction

With the development of explicit microfounded models, expectations have become pivotal in modern macroeconomic theory. Friedman’s proposals (1948 and 1960) for economic stability postulate that the relationship between monetary policy and expectations is crucial for promoting economic stability. Friedman argues in favor of simple rules, because they are easier to learn and facilitate the coordination of agents’ beliefs. Several leading macroeconomists and policy makers, including the Chairman of the Federal Reserve Bernanke (2007), stress the importance of improving understanding of the relationship between economic policies (monetary policy), agents’ expectations, and equilibrium outcomes. While the theoretical literature has expanded rapidly in the last two decades, less attention has been paid to empirical assessment of the relationship between (inflation) expectations and monetary policy. Laboratory experiments provide suitable environments to test these relationships as one can control for the underlying model, shocks and forecasters’ information sets.

This paper analyzes the effectiveness of alternative monetary policy rules in stabilizing the variability of inflation in a setting where inflation expectation formation processes are potentially heterogeneous across subjects.\(^1\) We study this question by employing several simple instrumental monetary policy rules in different treatments and examine the relationship between the design of monetary policy and inflation forecasts. Firstly, we find that the variability of inflation is significantly affected by the degree of aggressiveness of the monetary policy. Secondly, regarding the form of the instrumental rules, those that respond to contemporaneous inflation perform better than those that respond to inflation expectations.

As pointed out by Marimon and Sunder (1995) the actual dynamics of an economy is the product of a complex interaction between the underlying stability properties of the model and the agents’ behavior. We define the Rational Expectations Equilibrium (REE) and various potential Restricted Perception Equilibria (RPE) along with their stability properties and compare them with the aggregate behavior in the experiment. The results suggest that different expectation formation mechanisms are used for forecasting, thus no one RPE or REE best describes the behavior of all independent groups. Therefore, it is imperative to design a monetary policy that is robust to different expectation formation mechanisms, i.e., to determine a rule that will produce the lowest variability of inflation in this environment characterized by heterogeneous expectations. However, both inflation expectations and monetary policy (the underlying model) determine the variability. To extract the effect of the monetary policy, we have to determine how individuals form inflation expectations. We find that subjects form expectations in

\(^1\)In this paper we consider heterogeneity with respect only to different rules used for forecasting and not heterogeneity with respect to e.g., information sets as all subjects observe the same macroeconomic variables relevant to produce inflation forecasts.
accordance with different theoretical models. The most popular rules are trend extrapolation and a general model that in some treatments is of the form of REE and includes all relevant information to forecast inflation in the next period. A significant share of the subjects also uses adaptive expectations, adaptive learning, and sticky information type models.\(^2\) Even when controlling for the expectation formation mechanism, we are still able to identify significant effects of the monetary policy. Furthermore, the interaction between monetary policy and inflation expectations is important as well. The design of monetary policy significantly affects the composition of forecasting rules used by subjects in the experiment (heterogeneity) – especially the proportion of trend extrapolation rules – and thus influences the stability of the main macroeconomic variables. The proportion of trend extrapolation rules increases in an environment characterized by excessive inflation variability and expectational cycles and then further amplifies the cycles.

Our experiment relates to previous studies that investigate the expectation formation process. Learning-to-forecast experiments have been conducted before within a simple macroeconomic setup (e.g., Williams, 1987; Marimon et al., 1993; Evans et al., 2001; Arifovic and Sargent, 2003) and also within an asset pricing framework (see Hommes et al., 2005 and Anufriev and Hommes, 2012).\(^3\) Marimon and Sunder (1995) and Bernasconi and Kirchkamp (2000) find that most subjects behave adaptively, although the latter provide evidence that adaptive expectations are not of first-order degree as argued by the former. So far, these two studies are also the only one that investigate the effects of different monetary policies on inflation volatility. Marimon and Sunder (1995) compare different monetary rules in an overlapping generations (OLG) framework to see their influence on the stability of inflation expectations. In particular, they focus on a comparison between Friedman’s k-percent money rule and the deficit rule where the government fixes the real deficit and finances it through seigniorage. They find little evidence that Friedman’s rule could help to coordinate agent beliefs and help to stabilize the economy. The inflation process might be even more volatile in an economy where the Friedman rule is announced and maintained compared to an economy where the inflation target is not announced, but the REE is more stable under learning dynamics. A similar analysis is performed in Bernasconi and Kirchkamp (2000). They argue that Friedman’s money growth rule produces less inflation volatility but higher average inflation compared to a constant real deficit rule.\(^4\)

Closer to our framework is the experiment by Adam (2007). He conducts experiments in a sticky price environment where the inflation and output depend on the expected inflation, and analyzes the resulting cyclical patterns of inflation around its steady state.

\(^2\)Adaptive learning assumes that the subjects are acting as econometricians when forecasting, i.e., reestimating their models each time new data become available. See Evans and Honkapohja (2001).

\(^3\)See Duffy (2008) and Hommes (2011) for a survey of experimental macroeconomics.

\(^4\)The effects of monetary policy design on expectations were also examined by Hazelett and Kernen (2002), who search for hyperinflationary paths in the laboratory.
These cycles exhibit significant persistence, and he argues that they closely resemble an RPE where subjects make forecasts with simple underparametrized rules. In our experiment we also detect the cyclical behavior of inflation and the output gap in some treatments. However, we show that these phenomena are not associated only with the parametrization of the rule but also with the heterogeneity of expectations, the design of monetary policy, and (its influence on) the way subjects form expectations. Recently, a setup similar to ours has been used by Assenza et al. (2011), who focus on an analysis of switching between different forecasting rules.

This paper is organized as follows: Section 2 describes the underlying experimental economy. Section 3 studies the properties of equilibria under different expectation formation mechanisms, and Section 4 outlines the experimental design. In Section 5 we study the relationship between the monetary policy design and expectation formation; Section 6 provides concluding remarks.

2 A Simple New Keynesian Economy

In our experiment we use a simplified version of a forward-looking sticky price New Keynesian (NK) monetary model. The model consists of a forward-looking Phillips curve (PC), an IS curve, and a monetary policy reaction function. In this paper, we focus on the reduced form of the NK model, where we can clearly elicit forecasts and study their relationship with monetary policy. There is a trade-off between using the model from "first principles" and employing a reduced form. The former has the advantage of setting the objectives (payoff function) exactly in line with the microfoundations since subjects act as producers and consumers and interact on both the labor and final product markets (for this approach, see Noussair et al., 2011). However, forecasts are difficult to elicit in such an environment, where subjects do not explicitly provide their forecasts. Therefore, an appropriate framework for the question that we address in this paper is the "learning-to-forecast" design, where incentives are set in order to induce forecasts that are as accurate as possible. In this framework we do not assign the subjects a particular role in the economy; rather they act as "professional" forecasters.

The forecasts for period $t + 1$ are made in period $t$ with the information set consisting of macro variables up to $t - 1$. Mathematically, we denote this as $E_t (\pi_{t+1} | I_{t-1})$, or simply

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5 This small-scale NK model successfully reproduces several stylized facts about major economies and is also widely used for policy analysis. Used in an experimental setup it has potential drawbacks. It requires forecasting two periods ahead. In addition, in standard NK models agents have to forecast both inflation and the output gap. We simplify this experiment by asking only for expectations of inflation.

6 The argument is similar to that of Marimon and Sunder. Bao et al. (2011) actually show that within the same model convergence to REE occurs much faster in the "learning-to-forecast" design than in the "learning-to-optimize" design.

7 One way to think about the relationship between professional forecasters and consumers/firms is that these economic subjects employ professional forecasters to provide them with forecasts of inflation.
In our case, $E_t \pi_{t+1}$. In our case, $E_t$ might not be restricted to just rational expectations. The IS curve is specified as follows:

$$y_t = -\varphi (i_t - E_t \pi_{t+1}) + y_{t-1} + g_t,$$  \(1\)

where the interest rate is $i_t$, $\pi_t$ denotes inflation, $y_t$ is the output gap, and $g_t$ is an exogenous shock.\(^8\) The parameter $\varphi$ is the intertemporal elasticity of substitution in demand. We set $\varphi$ to 0.164.\(^9\) One period represents one quarter. Note that we do not include expectations of the output gap in the specification. Instead, we have a lagged output gap.\(^10\) Compared to purely forward-looking specifications, our model displays more persistence in the output gap. The supply side of the economy is represented by the PC:

$$\pi_t = \beta E_t \pi_{t+1} + \lambda y_t + u_t.$$  \(2\)

The longer prices are fixed on average, i.e., the smaller $\lambda$ is. McCallum and Nelson (1999) suggest the value 0.3. The parameter $\beta$ is the subjective discount rate and set to 0.99. The shocks $g_t$ and $u_t$ are unobservable to subjects and follow the following process:

$$\begin{bmatrix} g_t \\ u_t \end{bmatrix} = \begin{bmatrix} g_{t-1} \\ u_{t-1} \end{bmatrix} + \begin{bmatrix} \gamma_t \\ \tilde{u}_t \end{bmatrix}; \quad \Omega = \begin{bmatrix} \kappa & 0 \\ 0 & \nu \end{bmatrix},$$

where $0 < |\kappa| < 1$ and $0 < |\nu| < 1$. $\gamma_t$ and $\tilde{u}_t$ are independent white noises, $\gamma_t \sim N(0, \sigma^2_g)$ and $\tilde{u}_t \sim N(0, \sigma^2_u)$. $g_t$ could be seen as a government spending shock or a taste shock, and the standard interpretation of $u_t$ is a technology shock. In particular, $\kappa$ and $\nu$ are set to 0.6, while their standard deviations are 0.08.\(^11\) All these shocks are found to be quite persistent in the empirical literature (see e.g., Cooley and Prescott, 1995 or Ireland, 2004). In the experimental context it is important to have some exogenous unobservable component in the law of motion for endogenous variables, so we avoid the extreme case where all agents coordinate on forecasts identical to the inflation target.\(^12\)

To close the model, the interest rate rule has to be specified. We use two alternative forms of Taylor-type rules in different treatments. We study three parametrizations of inflation forecast targeting rule where the interest rate is set in response to inflation expectations and investigate how different degrees of central bank aggressiveness in sta-

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\(^8\)Detailed derivations can be found in e.g., Walsh (2003) or Woodford (2003).

\(^9\)We implement McCallum and Nelson’s (1999) calibration.

\(^10\)One could argue that this specification of the IS equation corresponds to the case where subjects have naive expectations about the output gap or where an extreme case of habit persistence is assumed. The main reason for including a lagged output gap in our specification is that we want another endogenous variable to influence the law of motion for inflation.

\(^11\)Parameterization of these shocks is quite important. Increasing $\kappa$ and $\nu$ would increase the variability of inflation and of the output gap. $\kappa$ and $\nu$ higher than 0.6 (and closer to empirical estimates) were avoided as the frequency of the cycles drops and raises the possibility of having only one big recession (expansion) over the whole time span considered.

\(^12\)Without AR(1) shocks this would represent the dominant strategy. This is an especially relevant concern as we initialize the model in a REE.
bilizing inflation influence inflation expectations. In addition, we analyze whether it is better for the central bank to respond to the current rather than to expected inflation, and therefore we also analyze inflation targeting. *Inflation Forecast Targeting* interest rate rule is specified as:

\[ i_t = \gamma (E_t \pi_{t+1} - \bar{\pi}) + \bar{\pi}, \] (3)

where the central bank responds to deviations in inflation from the target, \( \bar{\pi} \). To ensure positive inflation for most of the periods we set the inflation target to \( \pi = 3 \). We vary \( \gamma \) in different treatments. The second alternative specification is *Inflation Targeting*, where the monetary authority responds to deviations in current inflation from the inflation target:

\[ i_t = \gamma (\pi_t - \bar{\pi}) + \bar{\pi}. \] (4)

The different treatments are summarized in Table 1.

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Parameter</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inflation forecast targeting (1)</td>
<td>( \gamma = 1.5 )</td>
</tr>
<tr>
<td>Inflation forecast targeting (2)</td>
<td>( \gamma = 1.35 )</td>
</tr>
<tr>
<td>Inflation forecast targeting (3)</td>
<td>( \gamma = 4 )</td>
</tr>
<tr>
<td>Inflation targeting (4)</td>
<td>( \gamma = 1.5 )</td>
</tr>
</tbody>
</table>

Table 1: Treatments

The first three treatments, which are shown in Table 1, deal with the parametrization of the inflation forecast targeting given in Eq. (3). In this setup, the coefficient \( \gamma \) determines the central bank’s aggressiveness in response to deviations of inflation from its target. It is of our key interest to see how subjects react to more and less aggressive interest rate policies. We chose \( \gamma = 1.5 \) as a baseline specification in line with the majority of empirical findings and the initial proposal of Taylor (1993), \( \gamma = 1.35 \) as a case with a lower stabilization effect and \( \gamma = 4 \) as a parametrization with a high stabilizing effect. Initially, we planned to perform a treatment with \( \gamma < 1 \) to check whether this leads to instability, but the findings from the pilot treatment convinced us this was not a suitable choice as subjects quickly reached extremely high levels of inflation, leading to explosive behavior of the system.\(^{13}\)

\(^{13}\)Under these circumstances inflation never returned to the target inflation but just kept growing. Therefore, the effect of the output gap on inflation never outweighed the expected inflation effect. This suggests that under heterogeneous expectations the Taylor principle is still required in order to produce an E-stable and determinate outcome. Assenza et al. (2011) perform a treatment where \( \gamma = 1 \). In their economy with i.i.d. shocks this results in a convergence to values of inflation that are different from the target value.
3 Properties of the Model under Different of Expectation Formation Mechanisms

The actual dynamics of endogenous variables in the model is a result of the interaction between the underlying model and the expectation formation mechanism. Several recent papers, using both experimental and survey data, have shown that the expectations of individuals are heterogeneous. In this section we outline the properties of the underlying model under different expectation formation mechanisms in order to compare these properties with the observed aggregate behavior in the experiment. Rational expectations are defined first as they represent a benchmark, followed by several other forecasting rules that are used for the analysis in Section 5.

3.1 Rational Expectations

When all agents in the economy are rational, their perceived law of motion (PLM) is equal to the actual law of motion (ALM) of the minimum state variable (MSV) form. There exists a unique evolutionary stable REE in our economy, which has the following form:

$$\begin{bmatrix} y_t \\ \pi_t \end{bmatrix} = B \begin{bmatrix} 1 \\ y_{t-1} \end{bmatrix} + C \begin{bmatrix} y_{t-1} \\ u_{t-1} \end{bmatrix} + D \begin{bmatrix} \tilde{y}_t \\ \tilde{u}_t \end{bmatrix}, \quad B = \begin{bmatrix} b_y & b_{yy} \\ b_\pi & b_{py} \end{bmatrix}, \quad C = \begin{bmatrix} c_\pi & c_{yy} \\ c_{\pi\pi} & c_{xy} \end{bmatrix}. $$

$B$ is the matrix of coefficients specific to each treatment. It is presented in the first column of Table 3 below along with the other properties of possible equilibria in this framework. $C$ and $D$ are matrices of coefficient values for the exogenous variables. $D$ is specific to the form of the Taylor rule employed. Note that $\pi_{t-1}$ does not enter the REE solution. To solve this model for rational expectations we use the method of undetermined coefficients. The corresponding expectations (PLM) of the REE form (representation 1) are:

$$E_t\pi_t = b_\pi + b_{\pi y}y_{t-1} + c_{\pi y}g_{t-1} + c_{\pi\pi}u_{t-1},$$

$$E_t\pi_{t+1} = b_\pi + b_{\pi y}E_t y_t + c_{\pi y}E_t g_t + c_{\pi\pi}E_t u_t,$$

$$= (b_\pi + b_{\pi y}b_y) + b_{\pi y}b_{yy}y_{t-1} + (b_{\pi y}c_{yy} + c_{\pi\pi}k) g_{t-1} + (b_{\pi y}c_{y\pi} + c_{\pi\pi}\nu) u_{t-1}. \quad (5)$$

We insert these into the IS equation (1), where we substitute in the monetary policy rule, and the PC equation (2). We thus obtain the ALM. By comparing the PLM and the ALM we solve this model for the MSV-REE. The parameters of the RE forecasting rule ($B$ and $C$) can be found in Table A3 in Appendix. Note that for inflation forecast targeting

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14Support in survey data is found in e.g., Branch (2004) and Pfajfar and Santoro (2010). For a survey of experimental support see Hommes (2011). Fehr and Tyran (2008) and Arifovic and Sargent (2003) also suggest that the expectations of individuals are heterogeneous.
treatments there exist an alternative representation of the MSV-REE (representation 2), which is actually more useful in our case where subjects do not directly observe the shocks:\(^\text{15}\)

\[
E_t \pi_{t+1} = (a_\pi + b_\pi a_y) - \pi \left( \frac{\gamma - 1}{\gamma} \right) \left( \varphi \left( b_\pi c_{yy} + c_{\pi y} \right) + \beta \left( b_\pi c_{y\pi} + c_{\pi y} \nu \right) \right)
\]

\[
+ \left( b_\pi c_{y\pi} + c_{\pi y} \right) \pi_{t-1} + \left( b_\pi b_{yy} + \left( b_\pi c_{yy} + c_{\pi y} \right) - \lambda \left( b_\pi c_{y\pi} + c_{\pi y} \right) \right) y_{t-1}
\]

\[
- \left( b_\pi c_{yy} + c_{\pi y} \right) y_{t-2} + \left( b_\pi c_{yy} + c_{\pi y} \right) \varphi \left( \frac{\gamma - 1}{\gamma} \right) + \frac{1}{\gamma} \beta \left( b_\pi c_{y\pi} + c_{\pi y} \nu \right) i_{t-1}.
\]

In this representation REE also depends on \(\pi_{t-1}, i_{t-1}, \) and \(y_{t-2}\). If we would use similar procedure in the inflation targeting treatment we would find that the REE is dependent on the initial values of the shocks and the whole history of \(\pi\) and \(y\).

In Table A3 we also present the detailed E-stability and determinacy properties of the model, while the summary is in Table 3. E-stability is the asymptotic stability of an equilibrium under least squares learning. By determinacy we mean the existence of a unique dynamically-stable equilibrium. Note that for the system to be locally E-stable all eigenvalues of the T-map associated with a particular solution have to be less than one (see Evans and Honkapohja, 2001). A T-map is a mapping between the PLM and the ALM, where a fixed point of this mapping represents a solution of the model.\(^\text{16}\)

The NK literature shows that when \(\gamma > 1\) the model produces a determinate outcome (Taylor principle) under RE and is E-stable. When \(\gamma \leq 1\) it is E-unstable and indeterminate. Note that the models that we analyze retain these stability properties although we replace the expectations of the output gap by the lagged output gap in the IS equation. Since \(\gamma\) is greater than one in all treatments of our experiment, the Taylor principle holds, and they all yield a determinate and E-stable REE (for both representations). We report the eigenvalues of the determinacy and E-stability conditions for these treatments in the first and second columns of Table A3.\(^\text{17}\) As Marimon and Sunder (1995) point out, higher eigenvalues result in a greater variability of inflation. Generally, under RE, higher \(\gamma\) results in a lower variability. Thus, among the first three treatments the variability in inflation is the lowest in treatment 3 where \(\gamma = 4\). Comparing treatments 1 and 4, under RE the inflation targeting rule stabilizes inflation better than does the inflation forecasting targeting rule.\(^\text{18}\)

\(^\text{15}\)In order to obtain this representation it is crucial that the instrumental rule incorporates expectations of inflation. In order to derive it we replace the \(g_{t-1}\) and \(u_{t-1}\) in (5) by lagged (1) and (2) and then use (3) to substitute \(E_{t-1} \pi_t\).

\(^\text{16}\)Simulations of inflation under RE in different treatments are plotted in Figures A3 and A4.

\(^\text{17}\)Note that the \(B\) matrix of the equilibrium solution for REE (representation 1) is the same as the equilibrium solution of the underparametrized rule without shocks (\(C = 0\)). The latter is presented in the second column of Tables 3 and A3. In the first column there is representation 2.

\(^\text{18}\)In a more standard NK model, the results are usually the opposite. See, e.g., Orphanides and Williams (2005).
experiment.

3.2 Other models

This subsection considers that agents use alternative expectation formation mechanisms to rational expectations. We assume that agents choose between twelve models of expectation formation that have support in the empirical literature. They choose both the rule and its parameters. These models are summarized in Table 2. Shocks were not directly observable in our experiment, so these models do not include them.\textsuperscript{19}

<table>
<thead>
<tr>
<th>Model (Eq.)</th>
<th>Specification</th>
</tr>
</thead>
<tbody>
<tr>
<td>AR(1) process (M1)</td>
<td>$\pi_{t+1}^k = \alpha_0 + \alpha_1 \pi_{t</td>
</tr>
<tr>
<td>Sticky information type (M2)</td>
<td>$\pi_{t+1}^k = \lambda_1 y_t + \lambda_1 \eta_{t-1} + (1 - \lambda_1) \pi_{t</td>
</tr>
<tr>
<td>Adaptive expectations CGL (M3)</td>
<td>$\pi_{t+1}^k = \pi_{t-1}^k + \theta^k (\pi_{t-1} - \pi_{t-2}^{k-1})$</td>
</tr>
<tr>
<td>Adaptive expectations DGL (M4)</td>
<td>$\pi_{t+1}^k = \pi_{t-1}^k + 1 (\pi_{t-1} - \pi_{t-2}^{k-1})$</td>
</tr>
<tr>
<td>Trend extrapolation (M5)</td>
<td>$\pi_{t+1}^k = \tau_0 + \pi_{t-1} + \tau_1 (\pi_{t-1} - \pi_{t-2}); \tau_1 \geq 0$</td>
</tr>
<tr>
<td>General model (M6)</td>
<td>$\pi_{t+1}^k = \alpha_0 + \alpha_1 \pi_{t-1} + \alpha_2 y_{t-1} + \alpha_3 y_{t-1} + \alpha_4 i_{t-1}$</td>
</tr>
<tr>
<td>Recursive - lagged inflation (M7)</td>
<td>$\pi_{t+1}^k = \phi_{0,t-1} + \phi_{1,t-1} \pi_{t-1}$</td>
</tr>
<tr>
<td>Recursive - lagged output gap (M8)</td>
<td>$\pi_{t+1}^k = \phi_{0,t-1} + \phi_{1,t-1} y_{t-1}$</td>
</tr>
<tr>
<td>Recursive - trend extrapolation (M9)</td>
<td>$\pi_{t+1}^k = \phi_{0,t-1} + \pi_{t-1} + \phi_{1,t-1} (\pi_{t-1} - \pi_{t-2})$</td>
</tr>
<tr>
<td>Recursive - AR(1) process (M10)</td>
<td>$\pi_{t+1}^k = \phi_{0,t-1} + \phi_{1,t-1} \pi_{t</td>
</tr>
<tr>
<td>Lagged output gap (M11)</td>
<td>$\pi_{t+1}^k = \phi_{0} + \phi_{1} y_{t-1}$</td>
</tr>
<tr>
<td>Lagged inflation (M12)</td>
<td>$\pi_{t+1}^k = \phi_{0} + \phi_{1} i_{t-1}$</td>
</tr>
</tbody>
</table>

Table 2: Models of inflation expectation formation. Notes: $\pi_t$ is inflation at time $t$, $y_t$ is the output gap, $i_t$ is the interest rate, and $\pi_{t+1}^k$ is the $k^{th}$ forecaster’s inflation expectation for time $t+1$ made at time $t$ (with information set $t-1$).

M1 is a simple AR(1) model, while model M2 represents a weighted average model similar in formulation to the sticky information model of Carroll (2003).\textsuperscript{20} We estimate this model stated in terms of observable variables with restrictions on the coefficients, where $\eta_0 = b_x + b_{xy} y_t$ and $\eta_1 = b_{xy} y_{t-1}$ are REE coefficients. Forecasts according to model M11 are based on the last observed output gap, and M12 is a model that takes into account only the most recent development in inflation.

To test for adaptive behavior, we apply a constant gain learning (CGL) model (M3), where agents revise their expectations according to the last observed error; $\theta$ is the constant gain parameter. In model M4 we check whether they use decreasing gain learning.

\textsuperscript{19} However, they could infer the values of the shocks as explained in the section above.

\textsuperscript{20} As in Carroll (2003), the model is a convex combination between the rational forecast and the forecast made in the previous period.
is the decreasing gain parameter. Next, we evaluate simple trend extrapolation rules (M5). These are identified in Hommes et al. (2005) as particularly important rules for expectation formation processes. Simple rules do not capture all the macroeconomic factors that can affect inflation forecasts. Therefore, we estimate a general model (M6) which coincides with the REE form for treatments 1-3.\footnote{The models in groups 19 – 24 do not have the interest rate as a dependent variable because this would imply multicollinearity due to the design of the monetary policy in our framework.}

We also allow agents to reestimate rules whenever new information becomes available, as postulated in the adaptive learning literature. In the following specifications, we test whether agents update their coefficients with respect to the last observed error. We use this estimation procedure for models M7–M10. When agents estimate their PLM they exploit all the available information up to period \( t - 1 \). As new data become available they update their estimates according to a stochastic gradient learning (see Evans et al., 2010) with a constant gain. Let \( X_t \) and \( \hat{\phi}_t \) be the vectors of variables and coefficients, respectively, specific to each rule; for example, for model M7, \( X_t = \left( 1 \ 
abla \right) \) and \( \hat{\phi}_t = \left( \phi_{0,t} \ 
abla \right)^\prime \). In this version of CGL agents update the coefficients according to the following stochastic gradient learning rule:

\[
\hat{\phi}_t = \hat{\phi}_{t-2} + \xi X_{t-2} \left( \nabla - X_{t-2} \hat{\phi}_{t-2} \right).
\] (7)

### 3.2.1 Stability Properties of Restricted Perceptions

Not only the monetary policy, but also the expectation formation mechanism may alter the stability properties of the model and thus the variability of inflation. Some of the most common reasons for the excessive volatility are misspecification of the PLM, rules with nonoptimal coefficients, and adaptive learning with constant gain. We assess these rules based on individual data in Section 5. In general, the stability of the model can be summarized by the determinacy and E-stability properties. If the system is indeterminate or E-unstable the inflation volatility could be higher. Therefore, it is important to analyze the stability properties of the equilibria in all four underlying models under different expectation formation mechanisms.

It is not possible to use the undetermined coefficients technique to calculate the optimal coefficients in adaptive expectation models (M3 and M4): in our setting there are no solutions for the coefficients \( \vartheta \) and \( \kappa \). Therefore, only temporary equilibria exist.\footnote{Strictly speaking, there might exist an equilibrium with a different (nonfundamental) representation using alternative methods to the undetermined coefficients, e.g., common factor representation.} In the case of the sticky information type model (M2) this technique shows that the optimal coefficient is \( \lambda_1 = 1 \), thus the model reduces to the lagged output gap rule in M11 and is studied in the second column of Table 3. Also, the AR(1) process model (M1) in equilibrium has a coefficient \( \alpha_1 = 0 \) and thus reduces to forecasting the steady state. This is
also the case in the lagged inflation model (M12), which thus exhibits the same equilibrium dynamics as M1. Of course, recursive representations of the models have optimal coefficients equal to the static counterparts. In general, we can write all the remaining forecasting models using \( \pi_{t+1} = \phi X_t \), where \( X_t = \begin{bmatrix} 1 & y_t & \pi_{t-1} & \pi_{t-2} & \pi_{t-1} \end{bmatrix}' \). But first we define the RPE, which exists for all models except M3 and M4:

**Definition 1** Restricted Perception Equilibria in Models \( M^* \) (\( M^* \in \{ M1, M2, M5, \ldots, M12 \} \)) are stationary sequences \( \{ y_t, \pi_t \}_{t=0}^{\infty} \) generated by (1), (2) and either (3) or (4) depending on the treatment where agents use Model \( M^* \left( \pi_{t+1|t} = \phi X_t \right) \) with parameters \( \phi_M^* \) to forecast inflation at time \( t \) for time \( t+1 \) where \( \phi_M^* \) is the orthogonal projection of \( \pi_t \) on \( X_t \).

**Definition 2** There exist four classes of Restricted Perception Equilibria in Model \( M^* \):

1. If \( M^* \in \{ M2, M8, M11 \} \), \( \phi_M^* \) is the orthogonal projection of \( \pi_t \) on \( \begin{bmatrix} 1 & y_t \end{bmatrix} \), the dynamics is characterized as a Underparameterized Perception Equilibrium level 1 (UPE1).

2. If \( M^* \in \{ M1, M7, M10, M12 \} \), \( \phi_M^* \) is the orthogonal projection of \( \pi_t \) on \( \begin{bmatrix} 1 \end{bmatrix} \), the dynamics is characterized as a Underparameterized Perception Equilibrium level 2 (UPE2).

3. If \( M^* = M6 \) and \( \alpha_3 = 0 \), \( \phi_M^* \) is the orthogonal projection of \( \pi_t \) on \( \begin{bmatrix} 1 & y_t \end{bmatrix} \), the dynamics is characterized as a Misspecified Perception Equilibrium level 1 (MPE1).

4. If \( M^* \in \{ M5, M9 \} \), \( \phi_M^* \) is the orthogonal projection of \( \pi_t \) on \( \begin{bmatrix} 1 & \pi_{t-1} & \pi_{t-2} \end{bmatrix} \), the dynamics is characterized as a Misspecified Perception Equilibrium level 2 (MPE2).

In Table 3 we present the REE and different RPEs and the summary of their determinacy and E-stability properties across all treatments. For the parameter of the ALM, \( B \), under each expectation formation mechanism, the corresponding eigenvalues of the determinacy condition, and values of the eigenvalues of the T-map see Table A3 in Appendix.

The second column in the table presents a UPE1, which has the same form as the REE (5) except that we omit shocks from the representation because they were not directly observable by the subjects in our experiment. Its determinacy and E-stability properties

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23\ It is worth pointing out that in general our stochastic gradient models M7–M10 converge to a path around the RPE.

24\ M2 is misspecified, but the inclusion of past forecasts does not alter the properties of the equilibrium.

25\ Table A3 reports numerical values for different treatments. In the case of indeterminacy we report both solutions and their corresponding eigenvalues of the E-stability condition. The analytical solutions can be obtained upon request from the authors. We also omit the eigenvalues of the E-stability condition corresponding to the shocks because they are always less than one and specific only to treatments (thus C and D are omitted as well) and not to the expectation formation rules for the cases under scrutiny.
are the same as those of the RE. The third column of Table 3 represents UPE2. In this case only a constant (equal to inflation target) is used for the forecasting. The models in these two columns are determinate and E-stable.

The fourth column of Table 3 contains the stability results for a MPE1. As in the previous case, the optimal coefficient on the lagged inflation is always zero (see Table A3 in Appendix). Note that the difference between UPE1 and MPE1 is a result of the inclusion of $\pi_{t-1}$ in M6. Comparing these results with those for the UPE1 in the first column, it can be observed that the inclusion of a lagged inflation causes indeterminacy and different values for the ALM. Furthermore, this causes the eigenvalues of the T-map to be complex in all treatments, and only the $B_1$ solutions are E-stable. As Marimon and Sunder (1995) observe, if the eigenvalues are complex, then the convergence is cyclical.

The MPE2 in the last column yields a determinate outcome only in treatment 3. The other treatments have two evolutionary stable solutions (thus indeterminacy), which could result in higher inflation volatility. Furthermore, solutions in all treatments are E-unstable. The trend extrapolation rule (M5) is restricted to positive coefficients $\tau_1$, so only solution $B_1$ is sensible in treatments 1, 2 and 4, while no evolutionary stable solution with positive $\tau_1$ exists in treatment 3 (they exist only for $\gamma < 2.99$).

To further study the relationship between $\gamma$ and the variability in inflation under different expectation formation mechanisms, we perform simulations of different equilibria and compute the root mean squared deviation of inflation from its target\(^{26}\) while varying

\(^{26}\)In the case of rational expectations this would correspond to the standard deviation of inflation
\( \gamma \) between 1 and 4. Results are reported in Figure 1. When all agents have rational expectations, a higher \( \gamma \) leads to less variability in inflation. The lagged output gap (M11), UPE1, and the general model (M6), under solution \( B_1 \), MPE2, produce less variability for higher \( \gamma \). Furthermore, they all produce less variability than the REE. This is a somehow surprising result because restricted perceptions usually generate more volatility. Higher volatility is produced by the lagged inflation model (M12), UPE2, and the trend extrapolation rule (M5) under \( B_1 \), MPE2. In fact, the relationship with \( \gamma \) is nonmonotonic in these cases: the minimum for the M12 is at \( \gamma = 1.03 \) and for the M5 at \( \gamma = 1.98 \). After these thresholds the volatility increases with higher \( \gamma \) for both rules. Note that UPE2 under inflation forecast targeting is characterized by a unit root in the determinacy condition.\(^{27}\)

![Figure 1: Equilibrium dynamics of inflation under different expectation formation rules in inflation forecast targeting. Notes: RMSD \( \pi_t \) is root mean squared deviation of inflation from its target. Figure is based on a simulation over 1000 periods.](image)

because the mean of inflation is equal to its target. However, under the trend extrapolation rule, the mean depends on \( \gamma \) and e.g., for \( \gamma = 4 \) reaches values around 7.1.

\(^{27}\)We perform an additional simulation where the agents use OLS to estimate the coefficients in their respective rules based on the past data, and compute the standard deviation of inflation while varying \( \gamma \) between 1 and 4 (see Figure A11). When all the agents employ a sticky information type model, a higher \( \gamma \) leads to less variability in inflation. Several other expectation formation mechanisms produce a U-shaped inflation variability. In particular, trend extrapolation rules lead to U-shaped behavior and eventually higher variability with increasing \( \gamma \). The minimum variability of inflation with sticky information and a trend extrapolation rule is achieved at \( \gamma = 1.1 \). Therefore, under certain expectation formation mechanisms, a lower \( \gamma \) could result in less inflation variability.
A comparison between the inflation forecast targeting and the inflation targeting rule at $\gamma = 1.5$ (a comparison between treatments 1 and 4) suggests that under treatment 4 the REE produces about 25% less variability (0.52) than under treatment 1.\textsuperscript{28} This is already suggested by a comparison of the eigenvalues of the determinacy condition but not by the eigenvalues of the E-stability condition. A difference of a similar order of magnitude is seen for UPE1 and MPE2. In treatment 4 UPE2 results in inflation variance that is only 5% of a variance produced by the same rule in treatment 1. The reason for this can be observed in Table A3: under treatment 4 only, this equilibrium does not exhibit a unit root. In contrast, in treatment 4 the variability of M6 (MPE1) is 3% higher than in treatment 1. Note that the eigenvalues of the T-map suggest that the variability under stochastic gradient learning is higher under treatment 4 than in treatment 1.\textsuperscript{29}

Generally, we can conclude that the stability and determinacy of the system crucially depend on the expectation formation mechanism. A system that is E-stable and determinate under RE might not be so under different expectation rules. In E-stable models under RE a higher value of $\gamma$ will result in lower eigenvalues of both the determinacy and E-stability conditions.\textsuperscript{30} On the contrary, under some expectation rules, e.g., trend extrapolation rules (M5), a higher value of $\gamma$ can produce higher eigenvalues of the determinacy and E-stability conditions and thus more volatile inflation. We label these expectation formation mechanisms as potentially destabilizing. Another type of forecasting rules that we classify as potentially destabilizing are those that do not have a MSV solution. In our case, this holds for adaptive expectations (M3) as seen in the simulations in Figures A3 and A4. Therefore, the relationship between the variability of inflation and different forecasting rules is nontrivial. We confirm the results of Marimon and Sunder (1995), that the stability properties of the system, especially the eigenvalues of the determinacy condition, provide a good explanation for inflation volatility but only with respect to stable expectation formation mechanisms (mechanisms that always produce less variability of inflation when we increase $\gamma$).

\textsuperscript{28}Calculations from Figure 1 are reproduced for treatment 4 in Figure A12 in Appendix A.

\textsuperscript{29}Indeed, if we simulate the REE under stochastic gradient learning the volatility is 55% higher under treatment 4 than under treatment 1.

\textsuperscript{30}Increasing $\gamma$ has two effects on the dynamic behavior of inflation: i) it always increases the frequency of cycles regardless of the expectation formation mechanism, and ii) it affects the amplitude of the cycle, depending on the expectation formation mechanism. For models that have a decreasing pattern in Figure 1, the amplitude is lower when $\gamma$ is higher, while in the other cases, most notably for the lagged inflation model, the relationship is not monotonic.
4 Experimental Design

The experimental subjects participate in a simulated economy with 9 agents. Each participant is an agent who makes forecasting decisions, and each simulated economy is an independent group. All the participants were recruited through recruitment programs for undergraduate students at the Universitat Pompeu Fabra and the University of Tilburg. The participants were invited from a database of approximately 1300 students at Pompeu Fabra (in May 2006) and 1200 students at Tilburg (in June 2009). They were predominantly economics and business majors. On average, the participants earned around €15 (≈$20), depending on the treatment and individual performance.

There are 4 treatments in the experiment, each based on a different specification of the monetary policy reaction function. The experiment consists of 24 independent groups of 9 subjects, 216 subjects in total. Each subject was randomly assigned to one group; each group is exposed to only one treatment. Therefore, there are 6 independent groups per treatment. The subjects forecast inflation for 70 periods. We scaled the length of each decision sequence and the number of repetitions in such a way that each session lasted approximately 90 to 100 minutes, including the time for reading the instructions and 5 trial periods at the beginning. The program was written in z-Tree (Fischbacher, 2007). We gathered 15,120 point forecasts of inflation from the 216 subjects.

The subjects are presented with a simple fictitious economy setup. The economy is described with three macroeconomic variables: inflation, the output gap, and the interest rate. The participants observe time series of these variables in a table up to period $t - 1$. Ten initial values (periods $-9, \ldots, 0$) are generated by the computer under the assumption of rational expectations. The subjects’ task is to provide inflation forecasts for period $t + 1$. The underlying model of the economy is qualitatively described to them. We explain the meaning of the main macroeconomic variables and inform them that their decisions have an impact on the realized output, inflation, and interest rate at time $t$.

This is the predominant strategy in learning-to-forecast experiments (see Duffy, 2008, and Hommes, 2011). All the treatments have exactly the same shocks.

---

31 Most learning-to-forecast experiments are conducted with 5 – 6 subjects, e.g., Hommes et al. (2005), Adam (2007), Fehr and Tyran (2008).

32 The experimental instructions can be found in Appendix B.

33 In learning-to-forecast experiments it is not possible to achieve the REE simply by introspection. This holds even if we provide the subjects with the data generating process, because there exists uncertainty as to how other participants forecast, so the subjects have to engage in a number of trial-and-error exercises, or in other words adaptive learning. It has been analytically proven by Marcet and Sargent (1989) and further formalized in a series of papers by Evans and Honkapohja (see their book: Evans and Honkapohja, 2001) that agents will achieve the REE if they observe all the relevant variables in the economy and update their forecasts according to the adaptive learning algorithm (their errors). Bao et al. (2011) show that convergence to the REE actually occurs faster in the learning-to-forecast design than in the learning-to-optimize design. For further discussion see Duffy (2008) and Hommes (2011). Kelley and Friedman (2008) provide a survey of experiments that support the theoretical result above. Examples of learning-to-forecast experiments are Marimon and Sunder (1993, 1994), Adam (2007), and Hommes et al. (2005).
In every period \( t \), there are two decision variables that subjects have to input: \( i) \) a prediction of the \( t + 1 \) period inflation; and \( ii) \) the 95\% confidence interval of their inflation prediction.\(^{34}\) After each period, the subjects receive information about the realized inflation in that period, their inflation expectations, and the payoff they have gained. The subjects’ payoffs depend on the accuracy of their predictions. The accuracy benchmark is the actual inflation rate computed from the underlying model on the basis of the predictions made by all the agents in the economy. We replace \( E_t \pi_{t+1} \) in Eqs. (1), (2), and (3) by \( \frac{1}{K} \sum_{k}^{K} \pi_{t+1|t}^k \), where \( \pi_{t+1|t}^k \) is subject \( k \)’s point forecast of inflation (\( K \) is the total number of subjects in the economy). In the subsequent rounds the subjects are also informed about their past forecasts. They do not observe the forecasts of other individuals or their performance. The payoff function, \( W \), is the sum of two components:

\[
W = W_1 + W_2, \quad W_1 = \max \left\{ \frac{100}{1 + f} - 20, \ 0 \right\}, \quad f = |\pi_t - \pi_{t+1|t}^k|.
\]

The first component, \( W_1 \), depends on the subjects’ forecast errors and is designed to encourage them to give accurate predictions. It gives subjects a payoff if their forecast errors, \( f \), are less than four.\(^{35}\) The second component, \( W_2 \), represents an independent incentive which refers to their confidence intervals and is not the focus of this paper. It is detailed in Pfajfar and Žakelj (2011). We accompanied the payoff function with a careful explanation and a payoff matrix on a separate sheet of paper to ensure that all the participants understood the incentives. The participants received detailed instructions which were read aloud. They also filled in a short questionnaire after they had read the instructions, answering questions about the procedure to demonstrate that they understood it.

5 Results: Monetary Policy and Heterogeneous Expectations

Summary statistics of the inflation and inflation expectations for each of the 24 independent groups are presented in Table 4. These statistics are used in the analysis below to establish whether the differences across treatments are significant. Unconditionally, the mean inflation forecast for all treatments is around 3.06\% while the mean inflation is 3.02\% when the inflation target is set to 3\%. The average inflation forecast is sig-

\(^{34}\)In this paper we focus on inflation expectations, while our companion paper Pfajfar and Žakelj (2011) studies the behavior of confidence intervals.

\(^{35}\)Compared to more standard quadratic payoff functions, ours gives a greater reward for more accurate predictions and provides an incentive to think also about small variations in inflation, which may be important. Since this experiment can potentially produce quite different variations in inflation between different sessions, it is important to keep the incentive scheme fairly steep. A similar approach is used in Adam (2007).
nificantly higher than the inflation realizations. Moreover, if we compare the means of
the inflation forecasts in treatments 1 and 4 we find that the median value in the later
treatment is significantly higher than in the former treatment (at 10% significance with
the Kruskal-Wallis rank test, see Conover, 1999).36 Similar results are obtained when
comparing treatments 2 and 3: the mean inflation is lower in the latter treatment. Ac-
tually, if we compute the trend of means of inflation expectations in inflation forecasting
treatments using Jonckheere-Terpstra test for ordered alternatives we find that the mean
is decreasing with higher γ.

The standard deviations of inflation and the inflation expectations vary considerably
across the independent groups. The largest standard deviation of inflation expectations
is 6.31 and the smallest 0.23, while the largest standard deviation of inflation is 5.83
and the smallest is 0.24. The differences across treatments are analyzed in the following
subsections.

5.1 Inflation Variability and Monetary Policy

Woodford (2003) pointed out that within a standard NK model monetary policy should
minimize the variability in inflation and the output gap around its targets as this cor-
responds to maximizing the utility of consumers. In our setup the monetary authority
cares only about inflation, so we focus our analysis on the variability in inflation. We
graph the evolution of inflation for all independent groups in Figure 2.37

As can be seen in Figure 1, simulations under rational expectations show that an
inflation forecast targeting rule with a lower γ produces a higher standard deviation of
inflation. In our case, when γ = 1.35 the standard deviation is 0.46, and when γ = 4 it re-
duces to 0.15. Table 5 also shows that when γ = 1.5 the inflation targeting rule produces
a slightly lower standard deviation of inflation than the inflation forecast targeting rule,
although the stability properties of the two models under different expectation formation
mechanisms (see Table A3) are very similar. In every group in our experiment the stan-
dard deviation of inflation is higher than that simulated under rational expectations. The
difference between the average standard deviation and that under RE is significant for
all treatments (p-value: 0.0110). The average standard deviation among the treatments
with the inflation forecasting rule is lowest when γ = 4 (0.42) and the highest when
γ = 1.5 (2.24). In the treatment with the inflation targeting rule the average standard
deviation is 0.64.

Does monetary policy have an influence on the inflation variability? When we test for

36 As we deal with small samples, in the analysis of the experimental data with nonparametric tests
10% is a commonly acceptable threshold.

37 Replication on a varying scale for different panels can be found in Figure A12. Detailed graphs
showing the evolution of inflation and the inflation forecasts in each treatment are presented in Appendix
A (Figures A1 and A2).
<table>
<thead>
<tr>
<th></th>
<th>Treatment 1</th>
<th>Treatment 2</th>
<th>Treatment 3</th>
<th>Treatment 4</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Inflation forecast targeting, $\gamma=1.5$</td>
<td>Inflation forecast targeting, $\gamma=1.35$</td>
<td>Inflation forecast targeting, $\gamma=4.0$</td>
<td>Inflation targeting, $\gamma=1.5$</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
</tr>
<tr>
<td>Mean</td>
<td>2.94</td>
<td>3.00</td>
<td>3.04</td>
<td>3.01</td>
</tr>
<tr>
<td>StdDev</td>
<td>6.31</td>
<td>3.48</td>
<td>2.02</td>
<td>0.73</td>
</tr>
<tr>
<td>Min</td>
<td>-13.9</td>
<td>-6.10</td>
<td>-2.50</td>
<td>0.40</td>
</tr>
<tr>
<td>Max</td>
<td>24.0</td>
<td>52.0</td>
<td>7.50</td>
<td>3.98</td>
</tr>
<tr>
<td>Inflation Expectations</td>
<td>Mean</td>
<td>2.85</td>
<td>2.88</td>
<td>2.92</td>
</tr>
<tr>
<td></td>
<td>StdDev</td>
<td>5.83</td>
<td>2.89</td>
<td>1.95</td>
</tr>
<tr>
<td></td>
<td>Min</td>
<td>-9.53</td>
<td>-5.27</td>
<td>-0.84</td>
</tr>
<tr>
<td></td>
<td>Max</td>
<td>16.7</td>
<td>10.5</td>
<td>6.51</td>
</tr>
</tbody>
</table>

Table 4: Preliminary statistics by independent groups
differences in the median variances of inflation across the treatments, the null hypothesis that the median variances are the same in all the treatments is rejected at 1% level with the Kruskal-Wallis test. Table 5 shows a comparison of the median standard deviations of inflation in treatments 2, 3, and 4 with the baseline treatment 1 (p-values from the Kruskal-Wallis test are reported).  

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Groups</th>
<th>Standard deviation under RE</th>
<th>Mean standard deviation</th>
<th>Median standard deviation</th>
<th>Comparison with treat. 1 (p-value)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1: Inf. forc. targ. $\gamma = 1.5$</td>
<td>1–6</td>
<td>0.37</td>
<td>2.24</td>
<td>1.52</td>
<td>–</td>
</tr>
<tr>
<td>2: Inf. forc. targ. $\gamma = 1.35$</td>
<td>7–12</td>
<td>0.46</td>
<td>2.17</td>
<td>1.35</td>
<td>0.6310</td>
</tr>
<tr>
<td>3: Inf. forc. targ. $\gamma = 4$</td>
<td>13–18</td>
<td>0.15</td>
<td>0.42</td>
<td>0.29</td>
<td>0.0104</td>
</tr>
<tr>
<td>4: Inf. targeting $\gamma = 1.5$</td>
<td>19–24</td>
<td>0.33</td>
<td>0.64</td>
<td>0.50</td>
<td>0.0250</td>
</tr>
</tbody>
</table>

Table 5: Standard deviation of inflation for each treatment and Kruskal-Wallis test of differences between treatments using group-level standard deviations.

According to a pairwise comparison, the standard deviation of inflation in treatment 3 is significantly lower than the standard deviation of inflation in both treatments 1 (p-value: 0.0104) and 2 (p-value: 0.0250). However, as can be seen in Figure 2, the frequency of cycles is higher in treatment 3, where the monetary authority responds stronger to deviations of inflation expectations from the inflation target. Under RE it is expected that treatment 2 produces higher variability in inflation than treatment 1, while we found that the median (and mean) standard deviation is lower, although not significantly different. We can also jointly compare the three inflation forecasting treatments and investigate the trend in the standard deviation of inflation. Using Jonckheere-Terpstra test we find that there is a descending standard deviation of inflation when we increase $\gamma$. Thus, we can argue that the size of the policy instrument ($\gamma$) is important.

Regarding the form of the policy rule, inflation targeting (treatment 4) produces a significantly lower standard deviation of inflation (and the inflation forecasts) than inflation forecast targeting with the same reaction coefficient (treatment 1); see Table 5. At the same time, higher mean inflation expectations (and possibly inflation because the average inflation in treatment 4 is 3.10 compared to 3.00 in treatment 1, although it is not significantly different) are detected in treatment 4. This is similar to Bernasconi and Kirchkamp (2000), who suggest that Friedman’s money growth rule produces less inflation volatility but higher average inflation compared to a constant real deficit rule.

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38 Results are identical if we consider just the last 40 periods of our sample.
Figure 2: Group comparison of inflation realized by treatment. Each line represents one of the 24 independent groups. Treatment 1 has inflation forecast targeting (IFT) with $\gamma = 1.5$. Treatment 2 has IFT with $\gamma = 1.35$. Treatment 3 has IFT with $\gamma = 4$. Treatment 4 has inflation targeting with $\gamma = 1.5$.

Now that we have established that there is a difference in the variability of inflation between treatments, we further analyze the roots of these differences between and within treatments. There are two possible explanations: monetary policy and inflation expectations. To proceed with the analysis and disentangle the two effects, we have to first establish how the subjects form expectations.

### 5.2 Formation of Individual Expectations

In this subsection we evaluate all twelve models introduced in Table 2 to find the one that best fits the actual expectations. The models are estimated using OLS. We consider an individual to use the model that produces the lowest RMSE among all competing models. In the case of the recursive models (M7–M10) we search for the parameter $\theta$ and initial values that minimize the RMSE between the simulated forecast under adaptive learning and the subjects’ forecasts (see Pfajfar and Santoro, 2010).

We can reject the rationality under the assumption of homogeneous expectations for each of 216 subjects.\textsuperscript{39} In addition, models M4 and M10–M12 never outperform the other

\textsuperscript{39}However, in experiments it is possible to go one step further as we are able to control the subjects’ information sets. The RE hypothesis postulates that rational agents use the correct distribution in
models. Detailed discussion on expectation formation in this experiment can be found in Pfajfar and Zakelj (2012).

<table>
<thead>
<tr>
<th>Model (Eq.)</th>
<th>Treatments</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>All</th>
</tr>
</thead>
<tbody>
<tr>
<td>AR(1) process (M1)</td>
<td></td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>1.9</td>
<td>0.5</td>
</tr>
<tr>
<td>Sticky information type (M2)</td>
<td></td>
<td>5.6</td>
<td>7.4</td>
<td>11.1</td>
<td>1.9</td>
<td>6.5</td>
</tr>
<tr>
<td>Adaptive expectations CGL (M3)</td>
<td></td>
<td>11.1</td>
<td>1.9</td>
<td>7.4</td>
<td>14.8</td>
<td>8.8</td>
</tr>
<tr>
<td>Adaptive expectations DGL (M4)</td>
<td></td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>Trend extrapolation (M5)</td>
<td></td>
<td>33.3</td>
<td>29.6</td>
<td>13.0</td>
<td>29.6</td>
<td>26.4</td>
</tr>
<tr>
<td>General model (M6)</td>
<td></td>
<td>33.3</td>
<td>29.6</td>
<td>55.6</td>
<td>29.6</td>
<td>37.0</td>
</tr>
<tr>
<td>Recursive - lagged inflation (M7)</td>
<td></td>
<td>3.7</td>
<td>13.0</td>
<td>3.7</td>
<td>13.0</td>
<td>7.8</td>
</tr>
<tr>
<td>Recursive - lagged output gap (M8)</td>
<td></td>
<td>0.0</td>
<td>1.9</td>
<td>1.9</td>
<td>1.9</td>
<td>1.4</td>
</tr>
<tr>
<td>Recursive - trend extrapolation (M9)</td>
<td></td>
<td>13.0</td>
<td>16.7</td>
<td>7.4</td>
<td>9.3</td>
<td>11.6</td>
</tr>
<tr>
<td>Recursive - AR(1) process (M10)</td>
<td></td>
<td>0.0</td>
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<td>0.0</td>
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<tr>
<td>Lagged output gap (M11)</td>
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<td>0.0</td>
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Table 6: Inflation expectation formation across treatments (percentage of subjects using a given rule).

In Table 6 we compare the empirical models across all the treatments. Eight of the models best represent the behavior of at least one subject. The behavior of about 37% of the subjects is best described by the general model (M6), using all the relevant information to forecast inflation. About 26% of the subjects simply extrapolate the trend (M5) and another 12% extrapolate the trend while updating their coefficients recursively (M9). About 9% employ adaptive expectations (M3), while the remaining 16% mostly behave in accordance with adaptive learning and sticky information type models. However, there are considerable differences across the treatments, especially in the proportion of subjects using the trend extrapolation rule (M5) and subjects using the general model. Treatment 3 has the lowest proportion of trend extrapolating subjects and the highest proportion of subjects using the general model (M6).

### 5.3 Inflation Variability and Expectations

In the exercise in Section 3 we learned that different expectation formation mechanisms can have different implications for the stability of the system. The analysis in the previous section shows that several forecasting mechanisms are used, and their structure varies across the treatments. In the present section we analyze these differences and establish predicting the variables relevant to their decisions. Note that strictly speaking this does not require the agents to know the model. When all the agents know the macroeconomic model and behave accordingly, the form of the RE solution is (??): the actual coefficient values are presented in the first column of Table 3. However, when one subject departs from this behavior, the other subjects must take this departure into account in order to be rational when they make forecasts. Strictly speaking, they have to know his exact PLM so that they can implement this information into their PLMs. For an assessment of this form of rationality see Pfajfar and Zakelj (2012).
the relationship between the observed expectation formation mechanisms and the inflation variability. In particular, we focus on disentangling the effects of the expectation formation mechanism and the monetary policy design.

The results from Section 5.1 demonstrate that the inflation volatility in every group in our experiment is significantly higher than that simulated on the basis of REE and RPEs considered in Section 3.2.1, possibly with the exception of UPE2 in treatments 1-3. Possible reasons for this discrepancy are (i) misspecification of the PLM, (ii) the use of nonoptimal coefficients, and (iii) the use of adaptive learning with a constant gain. In the existing literature the evidence for these temporary equilibria dynamics is not very abundant. In a forecasting experiment, Adam (2007) argues that subjects rely on simple underparameterized rules to forecast inflation and thus the equilibrium dynamics resembles the RPE. We observe a similar dynamics. In addition, many subjects in our experiment use misspecified models as they include inflation in their specifications of the forecasting rules, e.g., the general model (M6). As discussed above this has important consequences for the inflation dynamics.

We first focus on (i), the role of the specification of the PLM. It has been already suggested that the proportion of trend extrapolation subjects plays a particularly important role in the stability of the system. We observe that there is a considerable degree of heterogeneity across the treatments (see Table 6) and that there is a strong correlation between the variability of inflation and the degree of trend extrapolation behavior. We use panel data regressions to test these conjectures regarding the relationship between the variability and the proportions of different categories of subjects:

$$sd_{s,t} = \eta_0sd_{s,t-1} + \eta_1p_{js,t} + \eta_2T + \varepsilon_{s,t},$$  \hspace{1cm} (8)

where $sd_{s,t}$ is the standard deviation of inflation in group $s$ up to time $t$, $p_{js,t}$ is a vector of the proportions of agents in group $s$ that use forecasting rules $j$ (M2–M7 and M9 from Table 6) in time $t$, and $T$ is a vector of treatment dummies. The results are reported in Table 7.

A higher proportion of trend extrapolation agents increases the standard deviation of inflation. The proportion of these agents probably plays the most important role for the stability of inflation.\(^{41}\) In contrast, having more agents that behave according to the adaptive expectations models (M3 and M4) (and the sticky information model) decreases

\(^{40}\) To obtain the panel data for the standard deviation of inflation and the proportion of different rules, we compute for each period $t$ the standard deviation of inflation and determine the best forecasting rule for each individual by estimating all the forecasting rules recursively. For details see Pfajfar and Žakej (2012). Results for cross sectional models are reported in the Appendix in Table A1, with both robust and clustered standard errors as clustered standard errors might not have good properties for small samples.

\(^{41}\) It also helps to explain the differences among groups within the same treatment. Generally, we note that groups with a lower proportion of trend extrapolation rules are more stable than groups with a higher proportion in the same treatment.
Table 7: Influence of the decision model on the standard deviation of inflation. Notes: Estimations are conducted using the system GMM estimator of Blundell and Bond (1998) for dynamic panels. Arellano-Bond robust standard errors in parentheses. */**/*** denotes significance at 10/5/1 percent level.

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the standard deviation of inflation and thus has a stabilizing effect on the experimental economy. From the treatment dummies we learn that both treatments 3 and 4 produce effects that are significant and independent of the subjects’ alternative forecasting rules. These effects are negative, which confirms that compared to treatment 1 the monetary policies in treatments 3 and 4 have a stabilizing effect on the inflation variability. So far in this paper, this is a first evidence that both the expectation formation mechanism and the monetary policy have a significant effect on the inflation variability.

The second reason (ii) for the increased volatility in inflation is non-optimal parameter estimates of certain rules, as demonstrated in the simulations in Figures A3 and A4. Especially for the trend extrapolation and adaptive expectations, higher updating
coefficients are related to higher inflation variability. Hommes et al. (2005) show that coefficients in the trend extrapolation rules that are above one can severely compromise the dynamic stability of the model. The coefficients of individuals that use a given rule in our experiment are quite different across treatments.

We observe that the average coefficient of the trend extrapolation rule (τ) in M5 is higher in the treatments where inflation is more volatile on average. It is the highest in treatment 1 (0.53) and the lowest in treatment 3 (0.38). Sticky information type rules (M2) also exhibit significant differences across the treatments. The subjects in treatment 3 had the highest average λ (0.37), while those in treatment 2 had the lowest (0.11). Therefore, these expectation rules produce a less destabilizing effect in treatment 3 than in treatment 2. Similar evidence to that for the trend extrapolation rule is also found for the adaptive expectation rule (M3), where rules with a coefficient (τ or θ) larger than 1 represent another threat to stability. In fact, updating coefficients of the trend extrapolation rule that are higher than 0.6 could induce severe instability. As can be seen in Figure A9, most of the estimates are above this value. Furthermore, if τ > 0.4, treatment 3 produces the highest volatility among all the treatments, and for τ > 0.6 treatment 2 results in a lower volatility than treatment 1.42

It is possible to evaluate those effects more formally, by estimating the effects of the average coefficient of the trend extrapolation rule in each group on the standard deviation of inflation (see Table A3). The coefficient is positive and significant; the higher it is, the higher is inflation variability. Furthermore, we also investigate the joint effect of the proportion of agents using the trend extrapolation rule and their average coefficients, and we find the same results. Compared to the previous two regressions for the trend extrapolation rule, this one explains the most variability of the standard deviation of inflation. In all these regressions, the treatment dummies have a significant effect, emphasizing the importance of the monetary policy (see Table A3).

The third issue (iii) that is worth investigating is the relationship between the gain parameter in adaptive learning PLMs and the stability of the system: constant gain learning produces greater variability of the underlying series then does decreasing gain learning. Marcet and Nicolini (2003) show that this relationship could explain the evolution of inflation in Latin America. Furthermore, the variability increases with the level of the (constant) gain parameter. If this represented an important source of volatility, we would expect higher average gains in more volatile treatments. However, we find higher average (and median) gains for more stable treatments (3 and 4) than for more volatile treatments (1 and 2). This suggests that constant gain learning cannot explain the differences in volatility across the treatments.

42results in this paragraph are based on estimations of all models in Table 2 for each individual. For further details see Figures A5–A10, where we plot these results for different expectation formation mechanisms.
In the last part of this section we outline how the monetary policy design can influence the choice of expectation formation mechanism. The link between the realized inflation and the expectation formation mechanism can be represented by the expectational feedback, which is determined by the underlying model (monetary policy). This is the effect of a change in the average expectations in period $t$ for period $t+1$, $E_t \pi_{t+1}$, on the change in the realization of inflation in period $t$, $\pi_t$, formally $\frac{\partial \pi_t}{\partial E_t \pi_{t+1}}$. It can be calculated by substituting the monetary policy rule into the IS equation (1) and then substituting the resulting equation into the PC equation (2). The expectational feedback for the inflation forecasting targeting rule is $\beta + \lambda \varphi$, while for the inflation targeting rule it is $\beta + \lambda \varphi (1 - \gamma)$. We see that this derivative is decreasing in $\gamma$ for both rules. When we compare treatments 1 and 4, we see that the derivative is higher for inflation targeting than for inflation forecast targeting.

By changing the monetary policy, we augment the degree of positive feedback from the inflation expectations to the current inflation. In an environment with a higher expectational feedback, the inflation expectations (the PLM of inflation) have a larger influence on the realized ALM of inflation. Consequently, expectations are relatively more important than the output gap for the realization of inflation. This makes inflation more vulnerable to the presence of potentially destabilizing expectation formation mechanisms such as the trend extrapolation rule. When at least one subject extrapolates the trend, the first and second lags of inflation also enter the ALM for inflation. This has at least two effects. The inflation variability increases, and it becomes optimal for others to use the two lags of inflation as well, which results in a further increase in the inflation variability. If we compare systems with higher and lower expectational feedbacks, the former will require fewer subjects that use potentially destabilizing expectation formation mechanisms (with given coefficients) to produce the same inflation variability. Alternatively, if the number of subjects is the same, the coefficients must be higher to achieve the same effect. Therefore, the design of the monetary policy is important for the expectation formation mechanism and vice versa. We found that both the percentage of the potentially destabilizing expectation formation mechanisms (e.g., trend extrapolation rules or adaptive expectations) and the variability of inflation are the lowest in treatment 3, where the expectational feedback is the lowest.

In addition to the effect of the monetary policy that was evident from the significance of the treatment dummies in regressions (8) (see Table 7), it seems plausible that the monetary policy also partly contributed to the structure of the different rules used in each treatment. The relationship between the underlying model and the expectation formation has recently been studied by Heemeijer et al. (2009) and Bao et al. (2012). They compare experimental results from positive and negative expectation feedback models.\footnote{If they want to have the PLM of the same form as the ALM.} \footnote{Fehr and Tyran (2008) also compare the two environments, although in a different context.}
In a positive expectation system, e.g., an asset pricing model, they observe a similar cyclical behavior of prices to our behavior of inflation, and they note that when there is stronger positive feedback more agents resort to trend following rules. Therefore, we can argue that not only the monetary policy and the expectation formation mechanism but also the interaction between them determine the stability properties of the model.

6 Conclusion

In a macroeconomic experiment where the subjects are asked to forecast inflation we study the effectiveness of alternative monetary policy designs. The underlying model of the economy is a simplified version of the standard New Keynesian model that is commonly used for the analysis of monetary policy. In different treatments we employ various modifications of Taylor-type instrumental rules. We compare two forms of the Taylor-type rules responding to either deviations of the inflation expectations or inflation from the target, and study the effects of varying the degree of responsiveness to deviations of the inflation expectations from the target level.

Under rational expectations we expect inflation targeting to result in a lower variability in inflation than under the inflation forecast targeting. Also the higher is the reaction coefficient attached to deviations of the inflation expectations from the target level ($\gamma$) the lower variability in inflation. However, these policy prescriptions are altered under certain potentially destabilizing expectations formation mechanisms, especially the trend extrapolation rule and adaptive expectations. Generally, the eigenvalues of the determinacy condition under rational expectations are good indicators of the stability of the model under expectation formation mechanisms that produce less variability of inflation when we increase $\gamma$. In contrast, for potentially destabilizing forecasting rules eigenvalues derived under rational expectations may not be a suitable proxy. In the latter, a higher $\gamma$ may result in a higher volatility of inflation. The degree of expectational feedback also plays an important role in reducing the likelihood of ending up in the self-enforcing effect of potentially destabilizing expectations.

In all treatments of our experiment we observe the cyclical behavior of inflation and the output gap around their steady states. The variance of inflation in all the groups in the experiment is higher than that under rational expectations. We find that monetary policy matters in our environment and that there are sizeable differences in the inflation variability across the alternative designs under scrutiny. The effectiveness of the monetary policy crucially depends on the expectation formation mechanism. Our experiment is characterized by heterogeneous expectations as most subjects use either some version of adaptive expectations, a general model with both lagged inflation and output gap, a sticky information type model, or trend extrapolation rules.

Among the monetary policy rules that react to deviations of the inflation expectations
from inflation target, the one with a reaction coefficient 4 results in a lower inflation variability compared to those with reaction coefficients 1.35 and 1.5. Between the latter two there is no statistical difference. However, this result depends on the forecasting behavior of subjects. The proportion of subjects that use potentially destabilizing rules (such as trend extrapolation) plays an important role in the stability of the system, especially if the subjects’ trend extrapolation coefficients are high. Then the results might well be that the policy rule with reaction coefficient 1.35 produces lower variation than the one with 1.5.

We also explore inflation targeting, an instrumental rule that reacts to inflation rather than the inflation expectations, as in the inflation forecasting treatments. The results show that the inflation variance under inflation targeting is significantly lower than that under inflation forecast targeting at the same level of sensitivity of the interest rate to the deviation of the inflation (expectations) from the target.\footnote{Also Bernanke and Woodford (1997) suggest that inflation forecast targeting might entail undesirable properties.} One obvious reason is that the variability of interest rates is generally lower under inflation targeting. It is noteworthy that the lower inflation variance is not accompanied by a significantly smaller proportion of subjects using potentially destabilizing expectation formation mechanisms.

Our economy is represented by a simplified version of a commonly used model in macroeconomics, where this model is already a simplification of reality. We need to take this into account when making policy prescriptions. Our analysis suggests that both the design of the monetary policy and expectation formation mechanisms are important for the dynamic stability of the model. Therefore, it is imperative to understand the interplay between the two, as has already been argued by Friedman (1948 and 1960) and recently recognized by Bernanke (2007). Our paper attempts to shed light on the understanding of this relationship. The observed behavior of individuals and simulation results suggest that instrumental rules that are less aggressive could produce less variability in inflation at least under certain (stable) expectation formation mechanisms. However, they are more vulnerable to the emergence of potentially destabilizing rules. Therefore, one could argue that nonlinear Taylor-type rules would perform best in this environment: when inflation is stable around the target $\gamma$ should be relatively small, but if inflation cycles emerge (for any reason) the response should be sufficiently strong initially and then smoothed when the policy starts to bite.
References


Figure A1: Inflation and inflation expectations per group, Part 1.
Figure A2: Inflation and inflation expectations per group, Part 2.
Rational expectations

PLM of RPE, $\xi = 0.05$

Naive expectations

Adaptive expectations, $\vartheta = 0.75$

Adaptive expectations, $\vartheta = 1.4$

Trend extrapolation, $\tau_1 = 0.3$

Trend extrapolation, $\tau_1 = 0.7$

Figure A3: Simulation of inflation under alternative expectation formation rules (treatments 1 and 2).
Figure A4: Simulation of inflation under alternative expectation formation rules (treatments 3 and 4).
Figure A5: Standard deviation of inflation for the subjects that form expectations according to the \textbf{AR(1) process (M1)} and simulated values across the values of $\alpha_1$ parameter.

Figure A6: Standard deviation of inflation for the subjects that form expectations according to the \textbf{Sticky information process (M2)} and simulated values across the values of $\lambda_1$ parameter.
Figure A7: Standard deviation of inflation for the subjects that form expectations according to the Adaptive expectations CGL (M3) and simulated values across the values of $\vartheta$ parameter.

Figure A8: Standard deviation of inflation for the subjects that form expectations according to the Adaptive expectations DGL (M4) and simulated values across the values of $\iota$ parameter.
Figure A9: Standard deviation of inflation for the subjects that form expectations according to the Trend extrapolation (M5) and simulated values across the values of $\tau_1$ parameter.

Figure A10: Standard deviation of inflation for the subjects that form expectations according to the General model (M6) and simulated values across the values of $\alpha_1$ parameter.
Figure A11: Variability of inflation and alternative expectation formation rules (inflation forecast targeting). Notes: Figure is based on real-time OLS estimations of a particular rule for 1000 periods.

Figure A12: Equilibrium dynamics of inflation under different expectation formation rules in inflation targeting. Notes: RMSD $\pi_t$ is root mean squared deviation of inflation from its target. Figure is based on a simulation over 1000 periods.
Figure A12: Group comparison of inflation realized by treatment. Each line represents one of the 24 independent groups. Treatment 1 has inflation forecast targeting (IFT) with \( \gamma = 1.5 \). Treatment 2 has IFT with \( \gamma = 1.35 \). Treatment 3 has IFT with \( \gamma = 4 \). Treatment 4 has inflation targeting with \( \gamma = 1.5 \).
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<td>2.1538*** (0.746)</td>
<td>0.4435 (0.510)</td>
<td>2.2084* (0.759)</td>
<td>2.1791*** (0.628)</td>
<td>1.6226* (0.632)</td>
<td>1.8357** (0.670)</td>
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<td>2.0624** (0.759)</td>
<td>2.1538*** (0.746)</td>
<td>2.2084* (0.759)</td>
<td>0.4435 (0.510)</td>
<td>2.2084* (0.759)</td>
<td>2.1791*** (0.628)</td>
<td>1.6226* (0.632)</td>
<td>1.8357** (0.670)</td>
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<td></td>
<td>1.4917* (0.650)</td>
<td>1.6226* (0.632)</td>
<td>2.4154*** (0.805)</td>
<td>1.1491* (0.523)</td>
<td>1.8357** (0.670)</td>
<td>1.2248 (0.680)</td>
<td>1.8947*** (0.867)</td>
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<tr>
<td>R^2</td>
<td>0.01</td>
<td>0.27</td>
<td>0.04</td>
<td>0.29</td>
<td>0.40</td>
<td>0.07</td>
<td>0.30</td>
<td>0.01</td>
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Table A1: Relation of standard deviation of inflation to certain behavioral types as denoted in Table 2. Notes: OLS estimates. Standard errors in parentheses. */**/*** denotes significance at 10/5/1 percent level. Under column robust, robust standard errors are calculated. Under column cluster, standard errors allow for correlation within treatment.
<table>
<thead>
<tr>
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<th>cluster</th>
<th>robust</th>
<th>cluster</th>
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<tr>
<td>$\tau_{1,s}$</td>
<td>1.6490</td>
<td>1.8727 ***</td>
<td>(1.016)</td>
<td>(0.730)</td>
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<tr>
<td>$\tau_{1,s}p_s$</td>
<td>0.4539 *</td>
<td>0.4565 ***</td>
<td>(0.186)</td>
<td>(0.137)</td>
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<td>$T2$</td>
<td>0.6676</td>
<td>0.2027</td>
<td>(0.849)</td>
<td>(0.817)</td>
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<tr>
<td>$T3$</td>
<td>-0.9487 *</td>
<td>-1.0316 *</td>
<td>(0.541)</td>
<td>(0.519)</td>
</tr>
<tr>
<td>$T4$</td>
<td>-1.6194 *</td>
<td>-1.6396 **</td>
<td>(0.799)</td>
<td>(0.748)</td>
</tr>
<tr>
<td>$cons$</td>
<td>0.5515 *</td>
<td>0.8765 *</td>
<td>0.4929 *</td>
<td>1.0452 **</td>
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<tr>
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<td>(0.1810)</td>
<td>(0.461)</td>
<td>(0.203)</td>
<td>(0.461)</td>
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<tr>
<td>$N$</td>
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<tr>
<td>$R^2$</td>
<td>0.21</td>
<td>0.49</td>
<td>0.33</td>
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</table>

Table A2: Relation of standard deviation of inflation to the average coefficient $\tau_1$ from equation (M5) of subjects that use trend extrapolating rule. Notes: OLS estimates. Standard errors in parentheses. */**/*** denotes significance at 10/5/1 percent level. Under column robust, robust standard errors are calculated. Under column cluster, standard errors allow for correlation within treatment.
Table A3: Properties of solutions under different expectation formation mechanisms. Notes: The first column represents the REE (except for the shocks). Eigenvalues labelled with (a) are associated with the constant, while (b) are associated with other endogenous variables in the model as represented in matrix B.
Thank you for participating in this experiment, a project in economic investigation. Your earnings depend on your decisions and the decisions of the other participants. There is a show-up fee of 4 Euros assured. From now on until the end of the experiment you are not allowed to communicate with each other. If you have a question raise your hand and one of the instructors will answer the question in private. Please do not ask aloud.

The Experiment

All participants receive exactly the same instructions. You and 8 other subjects all participate as agents in the same fictitious economy. You will have to predict future values of given economic variables. The experiment consists of 70 periods. The rules are the same in all the periods. You will interact with the same 8 subjects during the whole experiment.

Imagine that you work in a firm where you have to predict inflation for the next period. Your profit depends on the accuracy of your inflation expectation.

Information in Each Period

The economy will be described with 3 variables in this experiment: the inflation rate, the output gap, and the interest rate.

- **Inflation** measures the general rise in prices in the economy. In each period it depends on the inflation expectations of the agents in the economy (you and the other 8 participants in this experiment), the output gap and small random shocks.

- The **output gap** measures by how much (in %) the actual Gross Domestic Product differs from the potential one. If the output gap is greater than 0, it means that the economy is producing more than the potential level; if negative, less than potential level. In each period it depends on the inflation expectations of the agents in the economy, the past output gap, the interest rate and small random shocks.

- The **interest rate** is (in this experiment) the price of borrowing the money (in %) for one period. The interest rate is set by the monetary authority. Their decision mostly depends on the inflation (expectations) of the agents in economy.

All the given variables might be relevant to your inflation forecast, but it is up to you to work out their relation and the possible benefit of knowing them. The evolution of the variables will partly depend on your and the other subjects’ inputs and also the various random shocks influencing the economy.

- You enter the economy in period 1. In this period you will be given computer-generated past values of inflation, the output gap and the interest rate for 10 periods back (Called: -9, -8, ... -1, 0)

- In period 2 you will be given all the past values as seen in period 1 plus the value from period 1 (Periods: -9, -8, ... 0, 1).

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46 The instructions used for the experiments at Universitat Pompeu Fabra are in Spanish. In the experimental sessions, they were accompanied with screenshots of the experimental interface and the profit table with earnings for various combinations of estimation error and confidence interval.
In period 3 you will see all the past values as in period 2 (Periods: -9, -8, \ldots, 1, 2) plus YOUR prediction about inflation in period 2 that you made in period 1.

In period $t$ you will see all the past values of actual inflation up to period $t - 1$ (Periods: -9, -8, \ldots, $t - 2$, $t - 1$) and your predictions up to period $t - 1$ (Periods: 2, 3, \ldots, $t - 2$, $t - 1$).

What Do You Have to Decide?

Your payoff will depend on the accuracy of your prediction of inflation in the future period. In each period your prediction will consist of two parts:

1. **Expected inflation**, (in \%) that you expect in the NEXT period ($\text{Exp:Inf.}$)

2. The **Confidence Interval** ($\text{Conf:Int.}$) around your prediction for which you think there is 95\% probability that the actual inflation will fall into. The interval is determined as the number of percentage points for which the actual inflation can be higher or lower.

**Example 3** Let's say you think that inflation in the next period will be 3.7\%. And you also think it is most likely (95\% probability) that the actual inflation will not differ from that value by more than 0.7 percentage points. Therefore, you expect that there is 95\% probability that actual inflation in the next period will be between 3.0\% and 4.4\% ($3.7\% \pm 0.7\%$). Your inputs in the experiment will be 3.7 under 1) and 0.7 under 2).

Your goal is to maximize your payoff, given with the equation:

$$W = \max \left\{ \frac{100}{1 + |\text{Inflation} - \text{Exp:Inf.}|} - 20, 0 \right\} + \max \left\{ \frac{100x}{1 + \text{Conf:Int.}} - 20, 0 \right\}$$

where $\text{Exp:Inf.}$ is your expectation about the inflation in the NEXT period, $\text{Conf:Int.}$ is the confidence interval you have chosen, Inflation is the actual inflation in the next period, and $x$ is a variable with value 1 if

$$\text{Exp:Inf.} - \text{Conf:Int.} \leq \text{Inflation} \leq \text{Exp:Inf.} + \text{Conf:Int.}$$

and 0 otherwise.

This expression tells you, that $x$ will be 1, if actual inflation falls between $\text{Exp:Inf.} - \text{Conf:Int.}$ (3.0\% in our example) and $\text{Exp:Inf.} + \text{Conf:Int.}$ (4.4\% in our example).

The first part of the payoff function states that you will receive some payoff if the actual value in the next period differs from your prediction in this period by less than 4 percentage points. The smaller this difference is, the higher the payoff you receive. With a zero forecast error ($|\text{Inflation} - \text{Exp:Inf.}| = 0$), you would receive 80 units. However, if your forecast is 1 percentage point higher or lower than the actual inflation rate, you will get only 30 units ($100/2 - 20$). If your forecast error is 4 percentage points or more, you will receive 0 units ($100/5 - 20$).

The second part of the payoff function simply states that you will get some extra payoff if the actual inflation is within your expected interval and if that interval is no larger than ±4 percentage points. The more certain of the actual value you are, the smaller interval you give, and the higher your payoff will be if the actual inflation is indeed in the given interval, but there will also be a greater chance that the actual value
falls outside your interval. In our example this interval is ±0.7 percentage points. If the actual inflation falls in this interval you receive 38.8 units \((100/(1+0.7) - 20)\) in addition to the payoff from the first part of the payoff function. If the actual values is outside your interval, your receive 0.

On the attached sheet you can find a table which shows various combinations of forecast error and confidence interval needed to earn a given number of points. See also the figure on the next page.

**Information After Each Period**

Your payoff depends on your predictions for the next periods and the actual realization in the next period. Because the actual inflation will only be known in the next period, you will also be informed about you current period \((t)\) prediction and earnings after the end of the NEXT period \((t+1)\). Therefore:

- After period 1 you will not receive any earnings, since you did not make any prediction for period 1.
- In any other period, you will receive information about the actual inflation rate in this period (and other macro variables) and your inflation and confidence interval prediction from the previous period. You will also be informed if the actual inflation value is in your expected interval and what your earnings for this period are.

The units in the experiment are fictitious. Your actual payoff will be the sum of profits from all the periods converted to euros in 1/500 conversion. If you have any questions please ask them now!

**Questionnaire**

1. If you believe that inflation in the next period will be _ _ 4.2% _ _, and you are quite sure that it will be higher than _ _ 3.5% _ _ and lower than _ _ 4.9% _ _, you will type:

   Under (1) _ _ _ _ _ _ _ _ _ _ for inflation, and

   Under (2) _ _ _ _ _ _ _ _ _ _ for confidence interval.

2. You are now in period _ _ _ _ _ _ _ _ _ _. You have information about past inflation, the output gap and the interest rate up to period _ _ _ _ _ _ _ _ _ _ and you have to predict the inflation for period _ _ _ _ _ _ _ _ _ _.

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47 Options (1) and (2) point to the different fields on the screenshot of the experimental interface.