Finance and Economics Discussion Series
Divisions of Research & Statistics and Monetary Affairs
Federal Reserve Board, Washington, D.C.

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2015-045

Please cite this paper as:
Damjan Pfajfar and Blaž Žakelj (2015). "Inflation Expectations and Monetary Policy Design: Evidence from the Laboratory," Finance and Economics Discussion Series 2015-045. Washington: Board of Governors of the Federal Reserve System, http://dx.doi.org/10.17016/FEDS.2015.045.

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

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June 11, 2015

Abstract

Using laboratory experiments within a New Keynesian 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 when expectations formation is not perfectly rational. Instrumental rules that use actual rather than forecasted inflation produce lower inflation variability and reduce expectational cycles. A forward-looking Taylor rule where a reaction coefficient equals 4 produces lower inflation variability than rules with reaction coefficients of 1.5 and 1.35. Inflation variability produced with the latter two rules is not significantly different. Moreover, the forecasting rules chosen by subjects appear to vary systematically with the policy regime, with destabilizing mechanisms chosen more often when inflation control is weaker.

JEL: C91, C92, E37, E52

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

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*The views expressed in this paper are those of the authors and do not necessarily reflect those of the Federal Reserve Board.

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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 economic policies and expectations is crucial for promoting economic stability. Friedman argues in favor of simple rules because they are easier to learn and because they facilitate the coordination of agents' beliefs. Several leading macroeconomists and policymakers, including Bernanke (2007), stress the importance of improving our understanding of the relationship between economic policies—especially 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 expectations and monetary policy. Laboratory experiments provide an opportunity to explore 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 non-rational. We study this question by employing several simple monetary policy rules in different treatments and examining the relationship between the design of monetary policy and inflation forecasts. Based on prior reasoning we would expect that, under rational expectations (RE), a policy rule that reacts to contemporaneous data would result in lower inflation variability than under a forward-looking rule. We would also expect that the higher the reaction coefficient attached to deviations of the inflation expectations from the target level, the lower should be the variability in inflation. Using simple nonparametric analysis of treatment differences, we find that the variability of inflation is significantly affected by the aggressiveness of monetary policy. Indeed, we find that the higher the reaction coefficient attached to deviations of the inflation expectations from the target level, the lower the variability in inflation. Our results confirm our prior that responding to contemporaneous inflation perform better than rules responding to inflation expectations.

As pointed out by Marimon and Sunder (1995), the actual dynamics of an economy are the product of a complex interaction between the underlying stability properties of the model and agents' behavior. Both inflation expectations and monetary policy influence the variability. To confirm the effects of the monetary policy mentioned above, we have to first determine how individuals form inflation expectations and then control for expectations formation. We find that subjects form expectations using different forecasting rules. The most often used by our subjects are trend extrapolation and a general model that, in some treatments, is of the form of Rational Expectations Equilibrium (REE) and includes all relevant information to forecast inflation in the next period. A significant share of the subjects also use adaptive expectations, adaptive learning, and sticky-information type models.[1] Furthermore, we have to be aware that under the trend extrapolation rule and adaptive expectations—rules that we characterize as potentially destabilizing—policy prescriptions are altered. Under these rules, a higher reaction coefficient attached to deviations of inflation expectations from the target level may result in a higher volatility of inflation. However, even when controlling for the expectation-formation mechanism, we are still able to identify significant effects of monetary policy: (i) when monetary policy attaches a higher weight to the deviation of expected inflation from the inflation target, we observe lower inflation variability and (ii) instrumental rules that respond to contemporaneous inflation (as opposed to inflation expectations) reduce inflation variability.

We also find that the interaction between monetary policy and inflation expectations is important. In particular, we find that the volatility of inflation is significantly higher when more subjects use trend extrapolation rules. At the same time, the design of monetary policy significantly affects the composition of forecasting rules used by subjects in the experiment—especially the proportion of subjects who use trend extrapolation rules, which are identified as the ones most dangerous to the stability of the main macroeconomic variables. The proportion of subjects using trend extrapolation rules increases in an environment characterized by excessive inflation variability and expectational cycles; this rule then further amplifies the cycles.

Our experiment relates to previous studies that investigate the expectation-formation process. Learning-to-forecast experiments have been conducted 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).[2] Marimon and Sunder (1995), and Bernasconi and Kirchkamp (2000) find that most subjects behave adaptively, although the latter provide evidence of a more complex form of adaptive expectations than argued by the former. Both papers also 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 explore 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 coordinate agent beliefs or help stabilize the economy. 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.[3]

[1] 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).

[2] See Duffy (2012) and Hommes (2011) for a survey of experimental macroeconomics.

[3] The effects of monetary policy design on expectations are also examined by Hazelett and Kernen

Adam (2007) conducts experiments in a sticky-price environment where inflation and output depend on expected inflation, and analyzes the resulting cyclical patterns of inflation around its steady state. These cycles exhibit significant persistence, and he argues that they closely resemble a Restricted Perception Equilibrium (RPE) where subjects make forecasts with simple underparametrized rules. In our experiment, we also detect cyclical behavior of inflation and the output gap in some treatments. However, we show that these phenomena are not only associated with the parameterization of the rule but also with the design of monetary policy and (the influence of monetary policy on) the way subjects form expectations. Recently, a setup similar to ours has been used by Assenza et al. (2013), who focus on the analysis of switching between different forecasting rules, and by Kryvtsov and Petersen (2013), who quantify the contribution of systematic monetary policy for macroeconomic stabilization.

This paper is organized as follows: Section 2 describes the underlying experimental economy and its properties under different expectation-formation processes. Section 3 outlines the experimental design. In Section 4 we study the relationship between the monetary policy design and expectation formation; Section 5 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.[4] 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, because subjects do not explicitly provide forecasts. We therefore choose learning-to-forecast design, where incentives are set in order to induce forecasts that are as accurate as possible.[5] In this framework, we do not assign the subjects a

(2002), who search for hyperinflationary paths in the laboratory.

[4] This small-scale NK model successfully reproduces several stylized facts about major economies and is also widely used for policy analysis. In an experimental setup, however, 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.

[5] The argument is similar to that of Marimon and Sunder (1993, 1994). Bao et al. (2013) 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.

particular role in the economy; rather they act as "professional" forecasters.[6]

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 $E_t\left(\pi_{t+1}|\mathcal{I}_{t-1}\right)$, or simply $E_t\pi_{t+1}$. In our case, E_t might not be restricted to just RE. The IS curve is specified as follows:

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

where the interest rate is i_t, π_t denotes inflation, y_t is the output gap, and g_t is an exogenous shock.[7] The parameter φ is the intertemporal elasticity of substitution in demand. We set φ to 0.164.[8] 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.[9] 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 Phillips curve:

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

λ is a parameter that is, among other things, related to price stickiness. McCallum and Nelson (1999) suggest the value 0.3. The parameter β is the subjective discount rate and is set to 0.99. The shocks g_t and u_t are unobservable to subjects and follow the following process:

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

where $0 < |\kappa| < 1$ and $0 < |\nu| < 1$. $\widetilde{g}_t$ and $\widetilde{u}_t$ are independent white noises, $\widetilde{g}_t \backsim N\left(0, \sigma_g^2\right)$ and $\widetilde{u}_t \backsim N\left(0, \sigma_u^2\right)$. g_t could be seen as a government spending shock or a taste shock, and the standard interpretation of u_t is a mark-up (or a cost-push) shock. In particular, κ and ν are set to 0.6, while their standard deviations are 0.08.[10] 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; otherwise all

[6] 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.

[7] Detailed derivations can be found in, e.g., Walsh (2003) or Woodford (2003).

[8] We implement McCallum and Nelson's (1999) calibration.

[9] 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.

[10] Parameterization of these shocks is quite important. Increasing κ and v would increase the variability of inflation and of the output gap. Values of κ and v higher than 0.6 (and closer to empirical estimates) were avoided as the frequency of the cycles drops and the possibility of having only one big recession (expansion) over the whole experimental time span increases.

agents can quickly coordinate on forecasts identical to the inflation target.[11]

To close the model, we use two alternative forms of Taylor-type interest rate rules in different treatments that are explained in Section 3. The *forward-looking* interest rate rule is specified as:

$$i_t = \gamma \left(E_t \pi_{t+1} - \overline{\pi} \right) + \overline{\pi}, \tag{3}$$

where the central bank responds to deviations in subjects' inflation expectations from the target, $\overline{\pi}$.[12] To ensure positive inflation for most of the periods, we set the inflation target to $\overline{\pi} = 3$. We vary γ in different treatments. The second specification is the *contemporaneous rule*, where the monetary authority responds to deviations in current inflation from the inflation target:[13]

$$i_t = \gamma \left(\pi_t - \overline{\pi} \right) + \overline{\pi}. \tag{4}$$

2.1 Rational Expectations

In this section, we derive the properties the model "should" have under REE. 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. For a comparison, we solve the model first as if the agents observe the shocks. Note that π_{t-1} does not enter the REE solution. The corresponding expectations (PLM) of the REE form (representation 1) are:

$$E_t \pi_{t+1} = \left(b_\pi + b_{\pi y} b_y \right) + b_{\pi y} b_{yy} y_{t-1} + \left(b_{\pi y} c_{yy} + c_{\pi y} \kappa \right) g_{t-1} + \left(b_{\pi y} c_{y \pi} + c_{\pi \pi} \nu \right) u_{t-1}. \tag{5}$$

Parameters b and c represent the REE solution (see Appendix A for details). Note that for the forward-looking rule there exists an alternative representation of the MSV-REE (representation 2), which is more useful in our case where subjects do not directly observe

[11] Besides that it is more realistic to have AR(1) shocks, without them, this would represent the dominant strategy, as we initialize the model in a REE; at the start of the experiment, we provide 10 data points to the subjects that are generated under RE.

[12] We assume that the central bank is responding to subjects' inflation expectations and not to their own inflation expectations.

[13] We note that this rule is characterized as non-operational, as at the time of interest rate decision the central bank does not know the realization of π_t. However, theoretical research has to a large extend focused on these type of instrumental rules.

the shocks:[14]

$$E_t\pi_{t+1} = (a_\pi + b_{\pi y}a_y) - \overline{\pi}\left(\frac{\gamma-1}{\gamma}\right)(\varphi\,(b_{\pi y}c_{yy} + c_{\pi y}\kappa) + \beta\,(b_{\pi y}c_{y\pi} + c_{\pi\pi}\nu)) \tag{6}$$
$$+ (b_{\pi y}c_{y\pi} + c_{\pi\pi}\nu)\,\pi_{t-1} + (b_{\pi y}b_{yy} + (b_{\pi y}c_{yy} + c_{\pi y}\kappa) - \lambda\,(b_{\pi y}c_{y\pi} + c_{\pi\pi}\nu))\,y_{t-1}$$
$$- (b_{\pi y}c_{yy} + c_{\pi y}\kappa)\,y_{t-2} + \left((b_{\pi y}c_{yy} + c_{\pi y}\kappa)\,\varphi\left(\frac{\gamma-1}{\gamma}\right) + \frac{1}{\gamma}\beta\,(b_{\pi y}c_{y\pi} + c_{\pi\pi}\nu)\right) i_{t-1.}$$

In this representation, REE also depends on π_{t-1}, i_{t-1}, and y_{t-2}. If we used a similar procedure in the contemporaneous rule treatment we would find that the REE is dependent on the initial values of the shocks and the whole history of π and y.

In Table A3, we present the detailed E-stability and determinacy properties of the model, while the summary is in Table 2. 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. Our models produce a determinate and E-stable outcome under RE when $\gamma > 1$ (for both representations). When $\gamma \leq 1$, the equilibria are E-unstable and indeterminate. Note that the models we analyze retain these stability properties although we replace the expectations of the output gap by the lagged output gap in the IS equation.

2.2 Restricted Perceptions

In this section, we outline ten models of expectation formation that have found support in the empirical literature. As we discuss later on, we will use these rules to describe the behavior of the subjects in our experiment. To be clear, our subjects are not introduced to these forecasting rules; they are asked simply to report their forecast for inflation given the observed data. Based on their observed behavior, we then assign a specific rule to each subject. This section solves the model assuming agents use expectation-formation mechanisms that are summarized in Table 1. Shocks were not directly observable, so these models do not include them.

In model M1, inflation expectations follow a simple AR(1) model, while model M2 represents a weighted-average model similar in formulation to the sticky information model of Carroll (2003).[15] We estimate this model stated in terms of observable variables with restrictions on the coefficients, where $\eta_0 = b_\pi + b_{\pi y}b_y$ and $\eta_1 = b_{\pi y}b_{yy}$ are REE coefficients.

We consider two versions of adaptive expectations, where agents revise their expectations according to the last observed error: first, a constant gain learning (CGL) model

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

[15] As in Carroll (2003), the model is a convex combination between the rational forecast and the forecast made in the previous period.

Model (Eq.)	Specification
AR(1) process (M1)	$\pi^k_{t+1\|t} = \alpha_0 + \alpha_1 \pi^k_{t\|t-1}$
Sticky information type (M2)	$\pi^k_{t+1\|t} = \lambda_1 \eta_0 + \lambda_1 \eta_1 y_{t-1} + (1-\lambda_1)\,\pi^k_{t\|t-1}$
Adaptive expectations CGL (M3)	$\pi^k_{t+1\|t} = \pi^k_{t-1\|t-2} + \vartheta(\pi_{t-1} - \pi^k_{t-1\|t-2})$
Adaptive expectations DGL (M4)	$\pi^k_{t+1\|t} = \pi^k_{t-1\|t-2} + \frac{\iota}{t}(\pi_{t-1} - \pi^k_{t-1\|t-2})$
Trend extrapolation (M5)	$\pi^k_{t+1\|t} = \tau_0 + \pi_{t-1} + \tau_1\,(\pi_{t-1} - \pi_{t-2})\,;\ \tau_1 \geq 0$
General model (M6)	$\pi^k_{t+1\|t} = \alpha_0 + \alpha_1 \pi_{t-1} + \alpha_2 y_{t-1} + \alpha_3 y_{t-2} + \alpha_4 i_{t-1}$
Recursive - lagged inflation (M7)	$\pi^k_{t+1\|t} = \phi_{0,t-1} + \phi_{1,t-1}\pi_{t-1}$
Recursive - lagged output gap (M8)	$\pi^k_{t+1\|t} = \phi_{0,t-1} + \phi_{1,t-1} y_{t-1}$
Recursive - trend extrapolation (M9)	$\pi^k_{t+1\|t} = \phi_{0,t-1} + \pi_{t-1} + \phi_{1,t-1}\,(\pi_{t-1} - \pi_{t-2})$
Recursive - AR(1) process (M10)	$\pi^k_{t+1\|t} = \phi_{0,t-1} + \phi_{1,t-1}\pi^k_{t\|t-1}$

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

(M3), where ϑ is the constant gain parameter, and second, a decreasing gain learning (DGL), where ι 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 the forward-looking rule.[16]

We also consider forecasting procedures that 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 $\widehat{\phi}_{t-1}$ be the vectors of variables and coefficients, respectively, specific to each rule; for example, for model M7, $\mathbf{X}_t = \begin{pmatrix} 1 & \pi_t \end{pmatrix}$ and $\widehat{\phi}_{t-1} = \begin{pmatrix} \phi_{0,t-1} & \phi_{1,t-1} \end{pmatrix}'$. In this version of CGL, agents update the coefficients according to the following stochastic gradient learning rule:

$$\widehat{\phi}_t = \widehat{\phi}_{t-2} + \xi \mathbf{X}'_{t-2}\left(\pi_t - \mathbf{X}_{t-2}\widehat{\phi}_{t-2}\right). \tag{7}$$

As a backdrop for our empirical part, we examine the stability properties of these rules in Appendix A.[17] In Table 2, we summarize the properties of the REE and different RPEs

[16] 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.

[17] Stability properties are presented for the specific parameterizations of monetary policy rules used across different treatments in this experiment. For a detailed description of treatments, see Section 3.

Treatment		M6, rep. 2	M2, M8,	M1, M7, M10	M6; $\alpha_4 = 0$	M5, M9
	Determinacy	yes	yes	yes (unit root)	no	no
1	$\mathbf{B}_1$ E-Stability	yes	yes	yes	yes (c.e.)	no (c.e.)
	$\mathbf{B}_2$ E-Stability	-	-	-	no	no (c.e.)
	Determinacy	yes	yes	yes (unit root)	no	no
2	$\mathbf{B}_1$ E-Stability	yes	yes	yes	yes (c.e.)	no (c.e.)
	$\mathbf{B}_2$ E-Stability	-	-	-	no (c.e.)	no (c.e.)
	Determinacy	yes	yes	yes (unit root)	no	yes
3	$\mathbf{B}_1$ E-Stability	yes	yes	yes	yes (c.e.)	-
	$\mathbf{B}_2$ E-Stability	-	-	-	no (c.e.)	no (c.e.)
	Determinacy	-	yes	yes	no	no
4	$\mathbf{B}_1$ E-Stability	-	yes	yes	yes (c.e.)	no (c.e.)
	$\mathbf{B}_2$ E-Stability	-	-	-	no (c.e.)	no (c.e.)

Table 2: Properties of solutions in the equilibrium under different expectation formation mechanisms. Notes: (c.e.) stands for complex eigenvalues. For a detailed version of this table with specific values of their respective ALM, determinacy, and E-stability conditions, see Table A3.

under both policy rules. Results are also reported in Figure 1. When all agents have RE, a higher γ leads to less variability in inflation. The general model (M6) produces less variability for higher γ. It also produces less variability than the REE. This is a somewhat surprising result because restricted perceptions usually generate more volatility (Evans and Honkapohja, 2001). Trend extrapolation (M5), however, leads to more volatility than the REE. The relationship with γ is also nonmonotonic for M5: the minimum is at $\gamma = 1.98$. After this threshold, volatility increases with higher γ.[18]

A comparison between the forward-looking rule and the contemporaneous rule at $\gamma = 1.5$ suggests that the REE for the contemporaneous rule produces about 25% less variability (0.52) than the forward-looking rule.[19] As discussed in the Appendix, this result is consistent with a comparison of the eigenvalues of the determinacy condition but not by the eigenvalues of the E-stability condition (see Table A3). A similar difference is seen for other expectation-formation mechanisms, except for M5, where the difference is considerably larger: inflation variance that is only 5% of a variance produced by the same expectation-formation mechanism under the contemporaneous rule. In Table 2 we can observe an explanation for this result: under the forward-looking rule only, this equi-

[18] We perform an additional simulation in which 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 γ between 1 and 2 (see Figure A9). When all the agents employ a sticky information type model, a higher γ 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 γ. 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 γ could result in less inflation variability.

[19] Figure 1 is reproduced for the contemporaneous rule in Figure A10 in Appendix A.

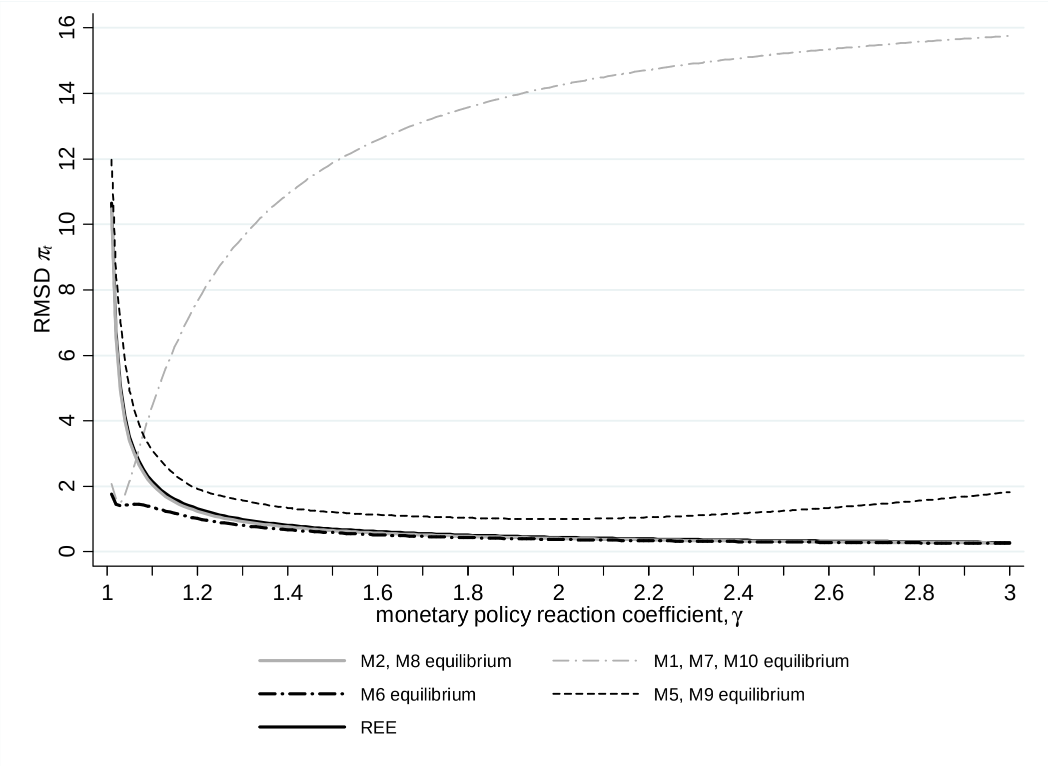

Figure 1: Equilibrium dynamics of inflation under different expectation formation rules for the forward-looking rule. Notes: RMSD π_t is root mean squared deviation of inflation from its target. Figure is based on a simulation over 1000 periods. Simulation is performed for the equilibrium values of the coefficients of the respective rules, see Appendix A.

librium exhibits a unit root. In contrast, under the contemporaneous rule, the variability of M6 is only 3% higher than under the forward-looking rule.

Generally, we can conclude that the properties of the system depend crucially on the expectation-formation mechanism. Under RE, a higher value of γ will result in lower variability of inflation, while under some expectation rules, e.g., trend extrapolation rules (M5), a higher value of γ leads to 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) (see Appendix). Therefore, the relationship between the variability of inflation and different forecasting rules is nontrivial.

3 Experimental Design

The experimental subjects participate in a simulated economy with 9 agents.[20] Each participant is an agent who makes forecasting decisions, and each simulated economy

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

is an independent group. All the participants were undergraduate students recruited 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 (6 groups per treatment), 216 subjects in total. Each subject was randomly assigned to one group; each group is exposed to only one treatment. The experimental economy lasts 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.[21] We gathered 15120 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 RE. The subjects' task is to provide inflation forecasts for period $t+1$. Figure 2 provides the timeline of decisions in the experiment. 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 effect on the realized output, inflation, and interest rate at time t. The parameters of the model are not revealed to subjects. This is the predominant strategy in learning-to-forecast experiments (see Duffy, 2012, and Hommes, 2011).[22] All the treatments have exactly the same shocks.

In every period t, there are two decision variables: *i)* a prediction of the $t+1$ period inflation; and *ii)* the 95% confidence interval of their inflation prediction. In this paper,

[21]The experimental interface was designed in z-Tree (Fischbacher, 2007). The experimental instructions can be found in the Online Supplementary material of the companion paper, Pfajfar and Žakelj (2014).

[22]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 proven by Marcet and Sargent (1989) and further formalized in a series of papers by Evans and Honkapohja (see 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. (2013) 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 (2012) 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).

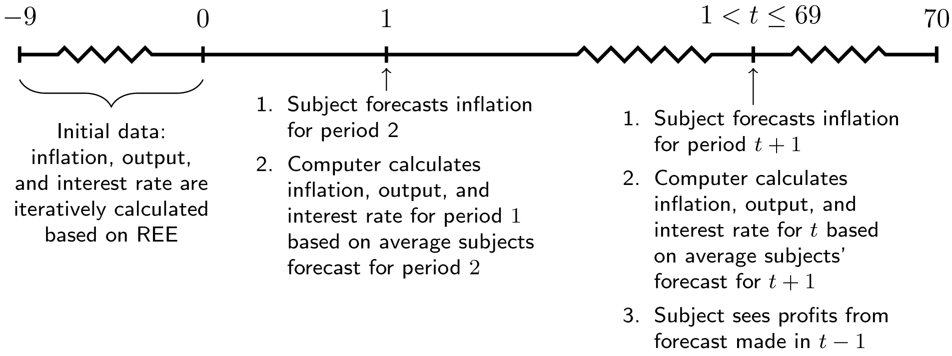

Figure 2: Timeline

we focus on inflation expectations, while our companion paper Pfajfar and Žakelj (2011) studies the behavior of confidence intervals. 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 $\frac{1}{K}\sum^k \pi^k_{t+1|t}$, where $\pi^k_{t+1|t}$ 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:

$$W = W_1 + W_2,\ W_1 = \max\left\{\frac{100}{1+f} - 20,\ 0\right\},\ f = \left|\pi_t - \pi^k_{t+1|t}\right|.$$

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.[23] The second component, W_2, represents an independent incentive that refers to their confidence intervals and is not the focus of this paper (see 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.

The different treatments are summarized in Table 3: The first three treatments, which are shown in Table 3, deal with the parameterization of the forward-looking rule given in

[23] Compared to more standard quadratic payoff functions, ours gives a greater reward for more accurate predictions and provides an incentive also to think 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 incentive scheme is used in Adam (2007) and Assenza et al. (2013).

Treatment	Parameter
Forward-looking rule (1)	$\gamma = 1.5$
Forward-looking rule (2)	$\gamma = 1.35$
Forward-looking rule (3)	$\gamma = 4$
Contemporaneous rule (4)	$\gamma = 1.5$

Table 3: Treatments

Eq. (3). In this setup, the coefficient γ determines the central bank's aggressiveness in response to deviations of expected inflation from its target. We are particularly interested 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 parameterization with a high stabilizing effect. Initially, we planned to perform a treatment with $\gamma < 1$. The findings from the pilot treatment, however, convinced us that such a low γ is not a suitable choice, as subjects quickly reached extremely high levels of inflation, leading to explosive behavior of the system.[24]

As we pointed out above, under RE, higher γ results in lower variability. Thus, among the first three treatments, the variability in inflation should be the lowest in treatment 3, where $\gamma = 4$. Comparing treatments 1 and 4, under RE the contemporaneous rule stabilizes inflation better than the forward-looking rule does. These two statements represent testable hypotheses in our experiment.

4 Results

Summary statistics of 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 standard deviations of inflation (expectations) vary considerably across the independent groups. The largest standard deviation of inflation expectations is 6.32 and the smallest 0.23, while the largest standard deviation of inflation is 5.87 and the smallest is 0.24. The differences across treatments are analyzed in the following subsections.

Moreover, if we compare the means of the inflation forecasts in treatments 1 and 4, we find that the median value in the latter treatment is significantly higher than in the

[24] 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 non-rational expectations, the Taylor principle is still required in order to generate stability. Assenza et al. (2013) 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.

	Treatment 1							Treatment 2							Treatment 3							Treatment 4						
	Inflation forecast targeting, γ=1.5							Inflation forecast targeting, γ=1.35							Inflation forecast targeting, γ=4.0							Inflation targeting, γ=1.5						
	1	2	3	4	5	6	All	7	8	9	10	11	12	All	13	14	15	16	17	18	All	19	20	21	22	23	24	All
	Inflation Expectations																											
Mean	2.94	3.00	3.04	3.01	3.12	3.14	3.04	3.11	3.09	3.12	3.18	2.72	3.04	3.04	3.02	3.03	3.01	3.00	3.00	3.00	3.01	3.12	3.29	3.07	3.05	3.10	3.15	3.13
StdDev	6.32	3.31	2.03	0.73	1.12	0.94	2.41	0.74	1.88	0.49	5.78	3.77	0.86	2.25	0.57	1.06	0.26	0.29	0.30	0.23	0.45	0.37	0.86	0.48	0.36	0.54	1.42	0.67
Min	-13.9	-6.1	-2.5	0.4	0.3	0.5	-13.9	1.0	-0.7	0.2	-12.0	-8.8	0.5	-12.0	1.7	0.0	2.0	1.2	2.1	2.4	0.0	2.3	1.0	1.6	2.3	0.5	0.0	0.0
Max	24.0	52.0	7.5	4.0	5.4	5.2	52.0	4.5	9.5	4.2	16.1	10.5	4.5	16.1	4.8	6.9	3.8	4.5	4.0	3.7	6.9	4.2	5.2	4.0	3.9	4.4	7.0	7.0
	Inflation																											
Mean	2.85	2.88	2.92	3.00	3.13	3.12	2.98	3.12	3.09	3.13	3.02	2.52	3.03	2.98	3.01	3.02	2.99	3.00	2.99	3.01	3.00	3.09	3.23	3.05	3.05	3.09	3.11	3.10
StdDev	5.87	2.91	1.97	0.76	1.10	0.90	2.25	0.76	1.82	0.51	5.53	3.58	0.88	2.18	0.52	0.94	0.24	0.26	0.31	0.24	0.42	0.39	0.81	0.48	0.38	0.52	1.29	0.65
Min	-9.5	-5.3	-0.8	0.7	0.8	1.2	-9.5	1.3	0.1	1.8	-9.0	-6.7	0.8	-9.0	2.0	1.0	2.5	2.4	2.5	2.5	1.0	2.4	1.8	1.9	2.5	1.8	0.7	0.7
Max	16.7	10.5	6.5	3.9	5.0	4.8	16.7	4.4	7.4	4.0	12.6	8.2	4.1	12.6	3.8	5.3	3.4	3.5	3.7	3.6	5.3	3.8	4.5	3.6	3.7	4.0	5.5	5.5

Table 4: Preliminary statistics by independent groups

former treatment (at 10% significance with the Kruskal-Wallis rank test, see Conover, 1999). Similar results are obtained when comparing treatments 2 and 3: the mean inflation is lower in the latter treatment. 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.

4.1 Inflation Variability and Monetary Policy

Woodford (2003) points out that within a standard NK model, monetary policy should minimize the variability in inflation and the output gap around its targets, as this behavior corresponds 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 3.

Does monetary policy have an influence on the inflation variability? Theory says that it should: As we demonstrated in Figure 1, simulations under RE show that a forward-looking rule produces a lower standard deviation of inflation with increasing γ. The first column of Table 5 summarizes these results. Specifically, when $\gamma = 1.35$ the standard deviation is 0.46, and when $\gamma = 4$ it reduces to 0.15. Table 5 also shows that when $\gamma = 1.5$, the contemporaneous rule produces a slightly lower standard deviation of inflation than the forward-looking rule. Turning to our experimental results, the standard deviation of inflation is higher than that simulated under RE. 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 $\gamma = 4$ (0.42) and the highest when $\gamma = 1.5$ (2.25). In the treatment with the contemporaneous rule, the average standard deviation is 0.65.

Treatment	Groups	Standard deviation under RE	Mean standard deviation	Median standard deviation	Comparison with treat. 1 (p-value)
1: Fwd-l. rule $\gamma = 1.5$	$1 - 6$	0.37	2.25	1.52	–
2: Fwd-l. rule $\gamma = 1.35$	$7 - 12$	0.46	2.18	1.35	0.6310
3: Fwd-l. rule $\gamma = 4$	$13 - 18$	0.15	0.42	0.29	0.0104
4: Cont. rule $\gamma = 1.5$	$19 - 24$	0.33	0.65	0.50	0.0250

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

When we test for 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 the 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).[25] According to these pairwise comparisons, 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 3, the frequency of cycles (in terms of number of changes from above to below the inflation target) is higher in treatment 3, where the monetary authority responds more strongly to deviations of inflation expectations from the inflation target. Our results suggest that the median (and mean) standard deviation is lower in treatment 2 compared to treatment 1, although not significantly different. We can also jointly compare the three inflation forecasting treatments and investigate the behavior in the standard deviation of inflation when changing γ. Using the Jonckheere-Terpstra test, we find that there is a descending standard deviation of inflation when we increase γ. Thus, we can argue that the size of the policy reaction (γ) is important. Regarding the form of the policy rule, the contemporaneous rule (treatment 4) produces a significantly lower standard deviation of inflation (and inflation forecasts) than the forward-looking rule with the same reaction coefficient (treatment 1); see Table 5.

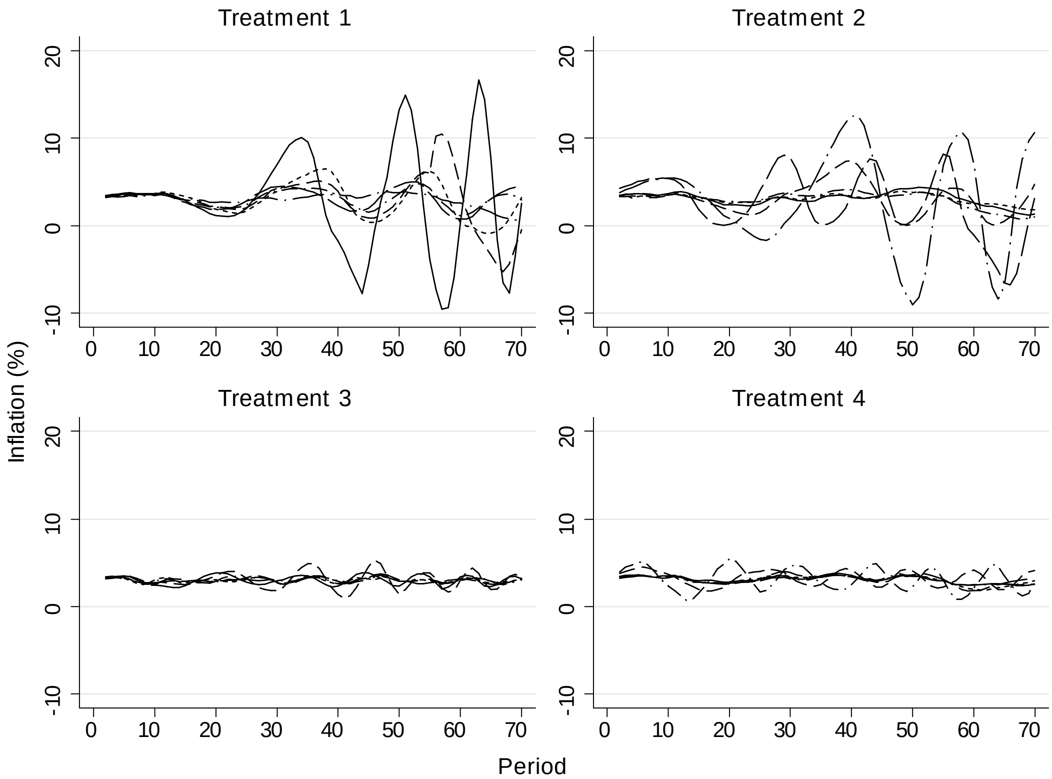

Figure 3: Group comparison of inflation realized by treatment. Notes: Each line represents one of the 24 independent groups. Treatment 1 has forward-looking rule (FWR) with $\gamma = 1.5$. Treatment 2 has FWR with $\gamma = 1.35$. Treatment 3 has FWR with $\gamma = 4$. Treatment 4 has contemporaneous rule 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 origins of these differences. There are two

[25] Results are identical if we consider only the last 40 periods of our sample.

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.

4.2 Formation of Individual Expectations

In this subsection, we choose among the ten models introduced in Table 1 to find the one that "best fits" the actual expectations of each individual. 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 ϑ 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 rationality under the assumption of homogeneous expectations for each of 216 subjects.[26] In addition, models M4 and M10 describe none of the participants. A detailed discussion on heterogeneity of expectation-formation mechanisms in this experiment can be found in Pfajfar and Žakelj (2014).

Model (Eq.)\ Treatments	1	2	3	4	All
AR(1) process (M1)	0.0	0.0	0.0	1.9	0.5
Sticky information type (M2)	5.6	7.4	11.1	1.9	6.5
Adaptive expectations CGL (M3)	11.1	1.9	7.4	14.8	8.8
Adaptive expectations DGL (M4)	0.0	0.0	0.0	0.0	0.0
Trend extrapolation (M5)	33.3	29.6	13.0	29.6	26.4
General model (M6)	33.3	29.6	55.6	29.6	37.0
Recursive - lagged inflation (M7)	3.7	13.0	3.7	13.0	7.8
Recursive - lagged output gap (M8)	0.0	1.9	1.9	1.9	1.4
Recursive - trend extrapolation (M9)	13.0	16.7	7.4	9.3	11.6
Recursive - AR(1) process (M10)	0.0	0.0	0.0	0.0	0.0

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. 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

[26] However, in experiments it is possible to go one step further, as we are able to control the subjects' information sets. For a detailed assessment of rationality, see Pfajfar and Žakelj (2014).

general model. Treatment 3 has the lowest proportion of trend extrapolating subjects and the highest proportion of subjects using the general model (M6).

4.3 Inflation Variability and Expectations

In the exercise in Section 2, 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. In particular, we focus on establish the relationship between the observed expectation-formation mechanisms and inflation variability, and the effect of monetary policy design on inflation variability.

The results from Section 4.1 demonstrate that the inflation volatility in every group in our experiment is significantly higher than that simulated on the basis of Rational Expectations Equilibrium (REE) and Restricted Perceptions Equilibria (RPEs) considered in Section 2.2, possibly with the exception of equilibrium dynamics under M6 in treatments with the forward-looking rule. Possible reasons for this discrepancy are (*i*) misspecification of the Perceived Law of Motion (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 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 inflation dynamics.

We first focus on (*i*), the role of the specification of the PLM. It has already been 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:[27]

$$sd_{s,t} = \eta_0 sd_{s,t-1} + \eta_1 \mathbf{p}_{js,t} + \eta_2 \mathbf{T} + \varepsilon_{s,t}, \tag{8}$$

[27] 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 based on her information set in that period. Note that this is different from calculations for Table 6. For details, see Pfajfar and Žakelj (2014). 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.

where $sd_{s,t}$ is the standard deviation of inflation in group s up to time t, $\mathbf{p}_{js,t}$ 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 $\mathbf{T}$ is a vector of treatment dummies. We limit ourselves to models M2–M7 and M9 since other rules were selected seldomly or not at all in this exercise. The results are reported in Table 7.

$sd_{s,t}$:	(a)	(b)	(c)	(d)
$sd_{s,t-1}$	1.0065***	1.0056***	1.0065***	1.0033***
	(0.0065)	(0.0073)	(0.0072)	(0.0054)
$p_{js,t}$ (j = M2)	-0.0007	-0.0013	-0.0019*	-0.0016
	(0.0014)	(0.0019)	(0.0011)	(0.0012)
$p_{js,t}$ (j = M3)		-0.0008	-0.0015**	
		(0.0009)	(0.0007)	
$p_{js,t}$ (j = M4)	-0.0015	-0.0017	-0.0027***	-0.0021**
	(0.0009)	(0.0011)	(0.0010)	(0.0009)
$p_{js,t}$ (j = M5)	0.0037***	0.0033**	0.0026**	0.0033***
	(0.0013)	(0.0015)	(0.0011)	(0.0013)
$p_{js,t}$ (j = M6)	0.0016**	0.0011		
	(0.0008)	(0.0011)		
$p_{js,t}$ (j = M7)		-0.0011		-0.0017
		(0.0014)		(0.0012)
$p_{js,t}$ (j = M9)			-0.0011	
			(0.0011)	
$T2$	0.0350	0.0330	0.0363	0.0368
	(0.0327)	(0.0339)	(0.0326)	(0.0351)
$T3$	-0.1191**	-0.1172**	-0.1273**	-0.1104**
	(0.0517)	(0.0500)	(0.0498)	(0.0490)
$T4$	-0.0916**	-0.0887**	-0.0989**	-0.0807*
	(0.0464)	(0.0440)	(0.0464)	(0.0465)
$cons$	-0.0208	0.0301	0.0984***	0.0638*
	(0.0607)	(0.1007)	(0.0218)	(0.0381)
N	1560	1560	1560	1560
χ^2	107822.0	216120.0	143881.7	97425.5

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.

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.[28] In contrast, having more agents that behave according to the

[28] 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.

adaptive expectations models (M3 and M4) (and potentially M2) decreases the standard deviation of inflation and thus has a stabilizing effect on the experimental economy. From the treatment dummies, we learn that treatments 3 and 4 both produce effects that are significant even when controlling for 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.

The second reason (*ii*) for the increased volatility in inflation is non-optimal parameter estimates of certain rules. In the Appendix we present simulations that demonstrate this point (Figures A1 and A2). Higher updating coefficients are related to higher inflation variability, especially for trend extrapolation and adaptive expectations. Hommes et al. (2005) show that coefficients in the trend extrapolation rules that are above 1 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_1) 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 have the highest average λ_1 (0.37), while those in treatment 2 have the lowest (0.11). Therefore, these expectation rules produce a less destabilizing effect in treatment 3 than in treatment 2. Similar evidence is also found for the adaptive expectation rule (M3), where rules with a coefficient (τ_1 or ϑ) larger than 1 represent another threat to stability. As can be seen in Figure A7, updating coefficients of the trend-extrapolation rule that are higher than 0.6 could induce severe instability.[29]

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 A1). 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 regression explains the most variability of the standard deviation of inflation. In all of these regressions, the treatment dummies have a significant effect, emphasizing the importance of the monetary policy (see Table A3).

The third issue (*iii*) we investigate 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 than does decreasing gain learning. Marcet and Nicolini (2003) show that this relationship could explain the evolution of inflation

[29] Results in this paragraph are based on estimations of all models in Table 2 for each individual. For further details see Figures A3 – A8, where we plot these results for different expectation formation mechanisms.

in Latin America. Furthermore, the variability increases with the level of the (constant) gain parameter. If this mechanism 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 result suggests that constant gain learning cannot explain the differences in volatility across the treatments.

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, at least partly, influences the choice of the expectation-formation mechanism. 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.[30] In a positive expectation system, e.g., an asset pricing model, they observe a cyclical behavior of prices similar to our behavior of inflation, and they note that when there is stronger positive feedback more agents resort to trend following rules. This result is also evident in Assenza et al. (2013). 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). The expectational feedback 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, π_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 forward-looking rule is $\beta + \lambda\varphi(1-\gamma)$, while for the contemporaneous rule it is $\frac{\beta+\lambda\varphi}{\lambda\gamma\varphi+1}$. We see that this derivative is decreasing in γ for both rules. Comparing treatments 1 and 4, we see that the derivative is higher for the contemporaneous rule than for the forward-looking rule.

By changing the monetary policy, we augment the degree of positive feedback from inflation expectations to current inflation. In an environment with higher expectational feedback, inflation expectations have a higher importance relative to 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: Inflation variability increases, and it becomes optimal for others to use the two lags of inflation as well (to have the PLM of the same form as the ALM), 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

[30] Fehr and Tyran (2008) also compare the two environments, although in a different context.

variability. Alternatively, if the number of subjects using these rules is the same, the coefficients must be higher to achieve the same effect. Therefore, the design of monetary policy is important for the expectation-formation mechanism and vice versa. We found that both the percentage of 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.

5 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 inflation expectations or current 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 the contemporaneous rule to result in a lower variability in inflation than under the forward-looking rule. We also expect lower variability in inflation when the reaction coefficient attached to deviations of the inflation expectations from the target level (γ) is higher. However, these policy prescriptions are altered under certain potentially destabilizing expectations formation mechanisms, especially trend extrapolation and adaptive expectations. Under these mechanisms, a higher γ 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 inflation variability across the alternative designs under scrutiny. 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. We find that instrumental rules that are less aggressive are more vulnerable to the emergence of potentially destabilizing forecasting mechanisms.

We also explore the contemporaneous rule, an instrumental rule that reacts to inflation rather than inflation expectations. The results show that the inflation variance under the contemporaneous rule is significantly lower than under the forward-looking rule at the same level of sensitivity of the interest rate to the deviation of the inflation (expectations) from the target. Bernanke and Woodford (1997) also suggest that forward-looking rules may entail undesirable properties. It is noteworthy that the lower inflation variance is not accompanied by a significantly smaller proportion of subjects using potentially destabilizing expectation-formation mechanisms. Under the contemporaneous rule, both the variability of interest rates and the expectational feedback are lower, resulting in lower inflation variability. Our analysis suggests that both the design of the monetary policy and the expectation-formation mechanisms are important for the dynamic stability of the model. Therefore, it is imperative to understand the interplay between the two.

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A Properties of the Model under Different 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.[31] 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.

A.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. If agents would observe the shocks there would exist a unique evolutionary stable REE with the following form:

$$\begin{bmatrix} y_t \\ \pi_t \end{bmatrix} = \mathbf{B} \begin{bmatrix} 1 \\ y_{t-1} \end{bmatrix} + \mathbf{C} \begin{bmatrix} g_{t-1} \\ u_{t-1} \end{bmatrix} + \mathbf{D} \begin{bmatrix} \widetilde{g}_t \\ \widetilde{u}_t \end{bmatrix}, \ \mathbf{B} = \begin{bmatrix} b_y & b_{yy} \\ b_\pi & b_{\pi y} \end{bmatrix}, \mathbf{C} = \begin{bmatrix} c_{yy} & c_{y\pi} \\ c_{\pi y} & c_{\pi\pi} \end{bmatrix}.$$

$\mathbf{B}$ is the matrix of coefficients specific to each treatment. It is presented in the first column of Table 2 below along with the other properties of possible equilibria in this framework. $\mathbf{C}$ and $\mathbf{D}$ are matrices of coefficient values for the exogenous variables. $\mathbf{D}$ is specific to the form of the Taylor rule employed. Note that π_{t-1} does not enter the REE solution. To solve this model for RE we use the method of undetermined coefficients. The corresponding expectations (PLM) of the REE form (representation 1) are:

$$\begin{aligned} E_t\pi_t &= b_\pi + b_{\pi y} y_{t-1} + c_{\pi y} g_{t-1} + c_{\pi\pi} u_{t-1}, \\ E_t\pi_{t+1} &= b_\pi + b_{\pi y} E_t y_t + c_{\pi y} E_t g_t + c_{\pi\pi} E_t u_t, \\ &= (b_\pi + b_{\pi y} b_y) + b_{\pi y} b_{yy} y_{t-1} + (b_{\pi y} c_{yy} + c_{\pi y}\kappa)\, g_{t-1} + (b_{\pi y} c_{y\pi} + c_{\pi\pi}\nu)\, u_{t-1}. \end{aligned} \tag{9}$$

We insert (10) 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 ($\mathbf{B}$ and $\mathbf{C}$) can be found in Table A3 in the Appendix. Note that for the forward-looking rule treatments there exists 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:

$$\begin{aligned} E_t\pi_{t+1} = {} & (a_\pi + b_{\pi y} a_y) - \overline{\pi} \left(\frac{\gamma-1}{\gamma}\right) (\varphi\,(b_{\pi y} c_{yy} + c_{\pi y}\kappa) + \beta\,(b_{\pi y} c_{y\pi} + c_{\pi\pi}\nu)) \\ & + (b_{\pi y} c_{y\pi} + c_{\pi\pi}\nu)\, \pi_{t-1} + (b_{\pi y} b_{yy} + (b_{\pi y} c_{yy} + c_{\pi y}\kappa) - \lambda\,(b_{\pi y} c_{y\pi} + c_{\pi\pi}\nu))\, y_{t-1} \\ & - (b_{\pi y} c_{yy} + c_{\pi y}\kappa)\, y_{t-2} + \left((b_{\pi y} c_{yy} + c_{\pi y}\kappa)\, \varphi \left(\frac{\gamma-1}{\gamma}\right) + \frac{1}{\gamma}\beta\,(b_{\pi y} c_{y\pi} + c_{\pi\pi}\nu)\right) i_{t-1}. \end{aligned} \tag{10}$$

[31] Support 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.

In this representation REE also depends on π_{t-1}, i_{t-1}, and y_{t-2}. If we used a similar procedure in the contemporaneous rule treatment we would find that the REE is dependent on the initial values of the shocks and the whole history of π and y.

A.2 Other models

A.2.1 Stability Properties of Restricted Perceptions

It is important to analyze the stability properties of the equilibria in all four underlying models under different expectation-formation mechanisms.[32]

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 ϑ and ι. Therefore, only temporary equilibria exist.[33] In the case of the sticky information type model (M2), this technique shows that the optimal coefficient is $\lambda_1 = 1$, and is studied in the second column of Table 2. Also, the AR(1) process model (M1) in equilibrium has a coefficient $\alpha_1 = 0$ and thus reduces to forecasting the steady state. 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 $\pi^k_{t+1|t} = \phi \mathbf{X}_t$, where $\mathbf{X}_t = \begin{bmatrix} 1 & y_t & \pi_{t-1} & \pi_{t-2} & \pi^k_{t|t-1} \end{bmatrix}'$. But first we define the RPE, which exists for all models except M3 and M4:[34]

Definition 1 *Restricted Perception Equilibria in Models M^* ($M^* \in \{M1, M2, M5, ..., M10\}$) 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^* $\left(\pi^k_{t+1|t} = \phi \mathbf{X}_t\right)$ with parameters ϕ^*_M to forecast inflation at time t for time $t+1$ where ϕ^*_M is the orthogonal projection of π_t on $\mathbf{X}_t$.*

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

1. *Iff $M^* \in \{M2, M8\}$, ϕ^*_M is the orthogonal projection of π_t on $\begin{bmatrix} 1 & y_{t-1} \end{bmatrix}$, the dynamics are characterized as a Underparameterized Perception Equilibrium level 1 (UPE1).*[35]

2. *Iff $M^* \in \{M1, M7, M10\}$, ϕ^*_M is the orthogonal projection of π_t on $\begin{bmatrix} 1 \end{bmatrix}$, the dynamics are characterized as a Underparameterized Perception Equilibrium level 2 (UPE2).*

3. *Iff $M^* = M6$ and $\alpha_3 = 0$, ϕ^*_M is the orthogonal projection of π_t on $\begin{bmatrix} 1 & y_{t-1} & \pi_{t-1} \end{bmatrix}$, the dynamics are characterized as a Misspecified Perception Equilibrium level 1 (MPE1).*

[32] Stability analysis of the economy with a single forecasting rule is, of course, not directly applicable to the environment of heterogeneous agents as observed in our experiment (see Berardi (2007) for analysis of such an environment). Given the number of rules considered in our case, too many combinations are possible to make an informed conclusion. Thus, separate analysis of each rule is more indicative of the possible outcomes.

[33] Strictly speaking, there might exist an equilibrium with a different (nonfundamental) representation using alternative methods to the undetermined coefficients, e.g., common factor representation.

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

[35] M2 is misspecified, but the inclusion of past forecasts does not alter the properties of the equilibrium.

4. *Iff $M^* \in \{M5, M9\}$, ϕ^*_M is the orthogonal projection of π_t on $\begin{bmatrix} 1 & \pi_{t-1} & \pi_{t-2} \end{bmatrix}$, the dynamics are characterized as a Misspecified Perception Equilibrium level 2 (MPE2).*[36]

In Table 2 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, $\mathbf{B}$, under each expectation-formation mechanism, the corresponding eigenvalues of the determinacy condition, and the values of the eigenvalues of the T-map, see Table A3 in the Appendix.[37]

The second column in the table presents a UPE1, which has the same form as the REE (9) except that we omit shocks from the representation because they were not directly observable by the subjects in our experiment. UPE1's determinacy and E-stability properties are the same as those of the RE. The third column of Table 2 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 2 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 π_{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 inclusion causes the eigenvalues of the T-map to be complex in all treatments, and only the $\mathbf{B}_1$ 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 τ_1, so only solution $\mathbf{B}_1$ is sensible in treatments 1, 2, and 4, while no evolutionary stable solution with positive τ_1 exists in treatment 3 (they exist only for $\gamma < 2.99$).

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 γ will result in lower eigenvalues of both the determinacy and E-stability conditions.[38] On the contrary, under some expectation rules, e.g., trend extrapolation rules (M5), a higher value of γ 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

[36] This equilibria is similar to the Behavioral Learning Equilibria of Hommes and Zhu (2014).

[37] 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 $\mathbf{C}$ and $\mathbf{D}$ are omitted as well) and not to the expectation formation rules for the cases under scrutiny.

[38] Increasing γ 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 γ is higher, while in the other cases, most notably for the lagged inflation model, the relationship is not monotonic.

solution, i.e., 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 γ).

B Additional Tables and Figures

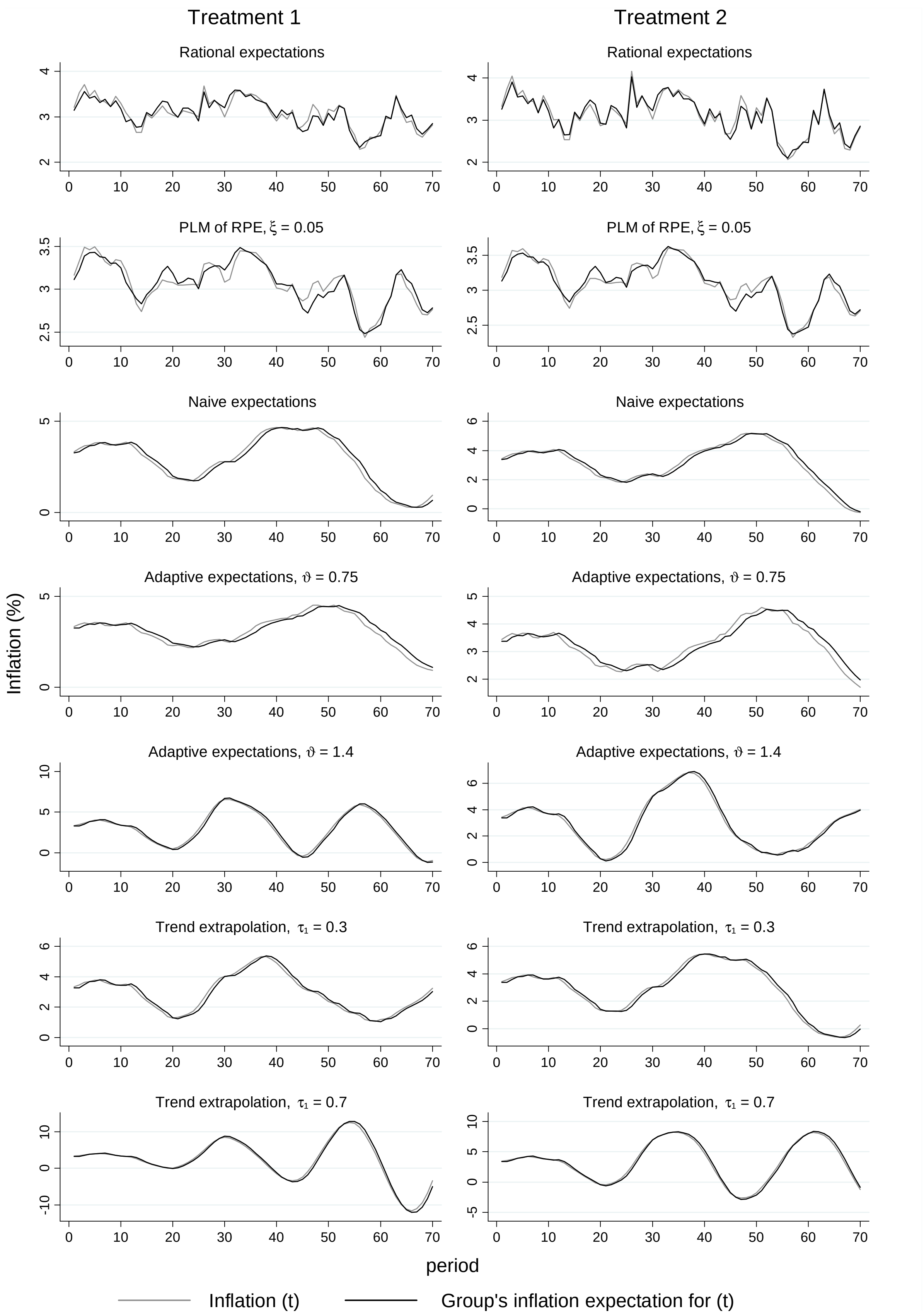

Figure A1: Simulation of inflation under alternative expectation formation rules (treatments 1 and 2).

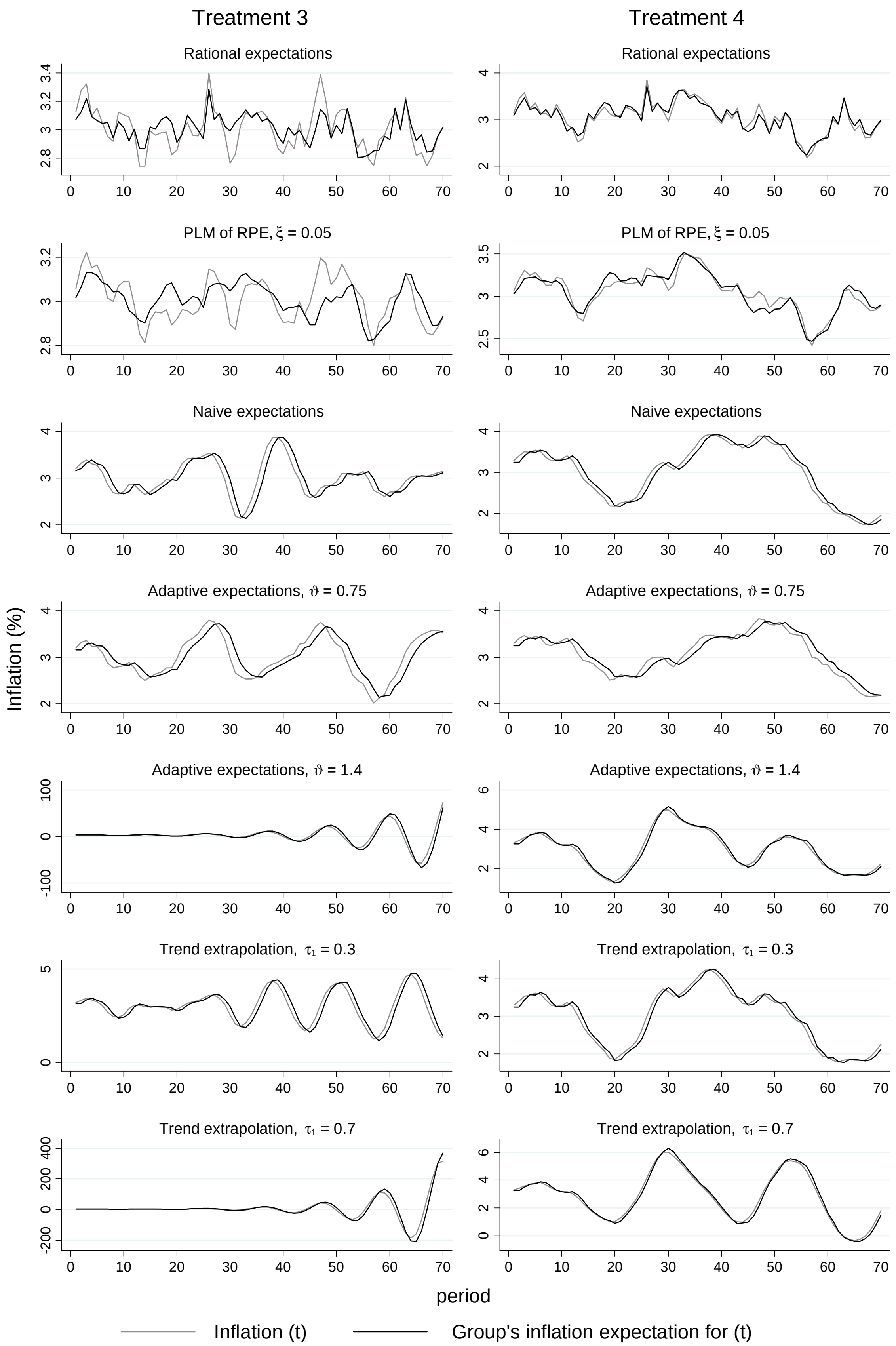

Figure A2: Simulation of inflation under alternative expectation formation rules (treatments 3 and 4).

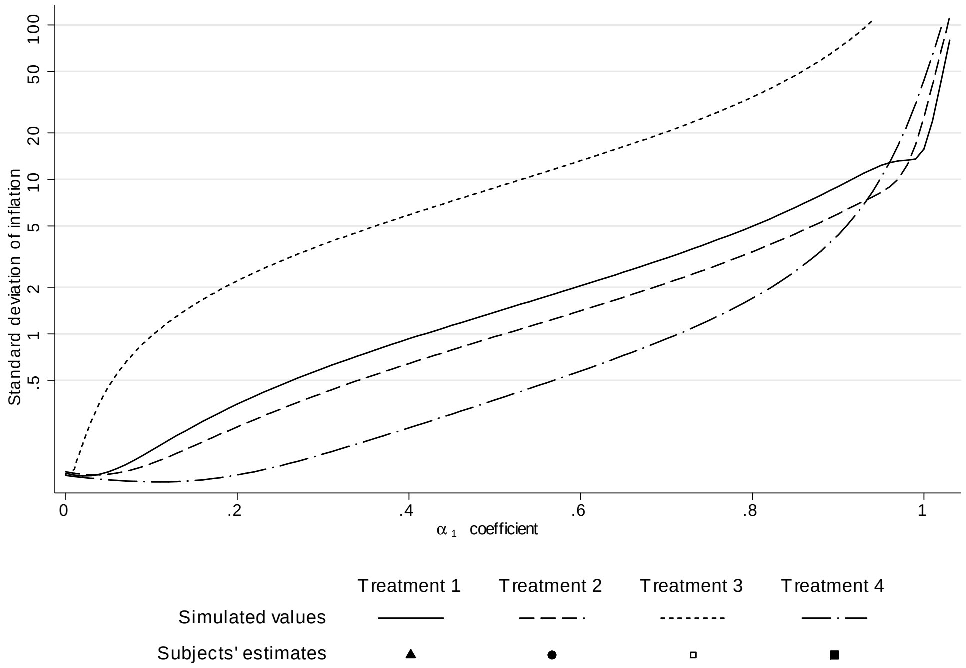

Figure A3: Standard deviation of inflation, subjects estimates of the **AR(1) process (M1),** and simulated values across the values of α_1 parameter.

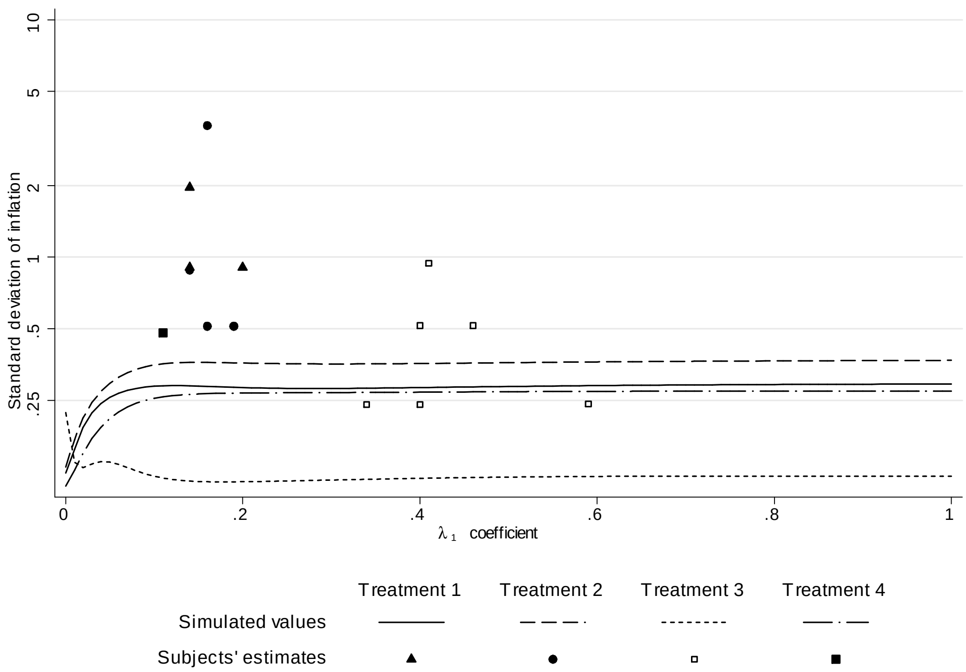

Figure A4: Standard deviation of inflation, subjects estimates of the **Sticky information process (M2),** and simulated values across the values of λ_1 parameter.

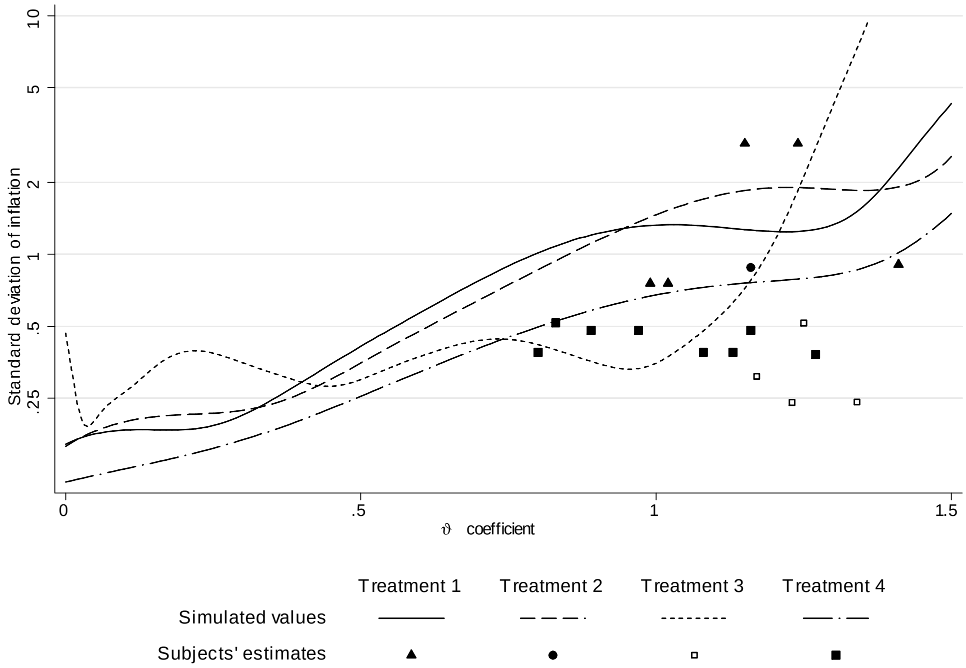

Figure A5: Standard deviation of inflation, subjects estimates of the **Adaptive expectations CGL (M3),** and simulated values across the values of ϑ parameter.

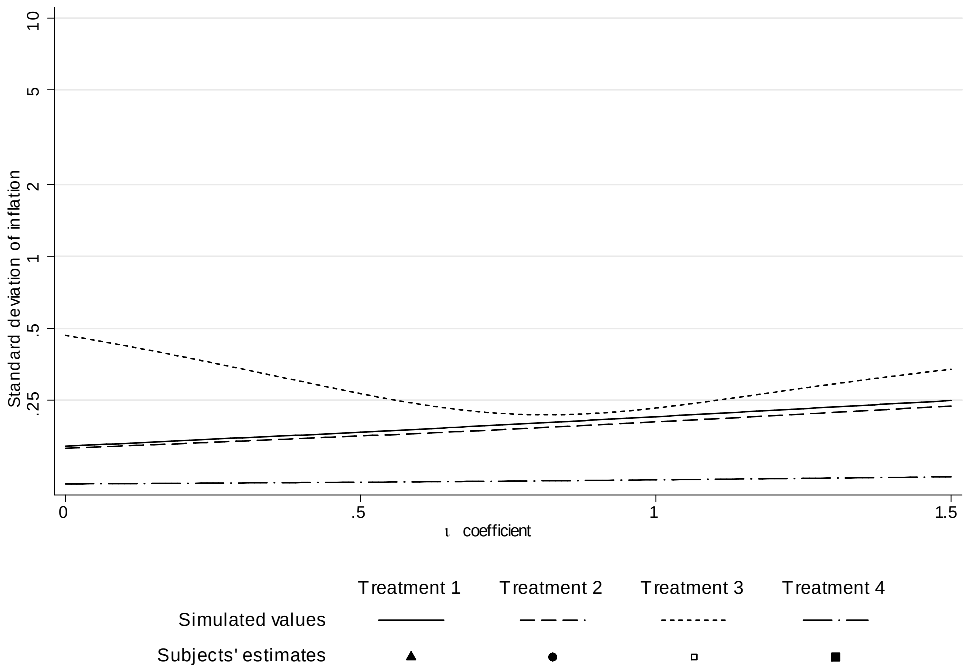

Figure A6: Standard deviation of inflation, subjects estimates of the **Adaptive expectations DGL (M4),** and simulated values across the values of ι parameter.

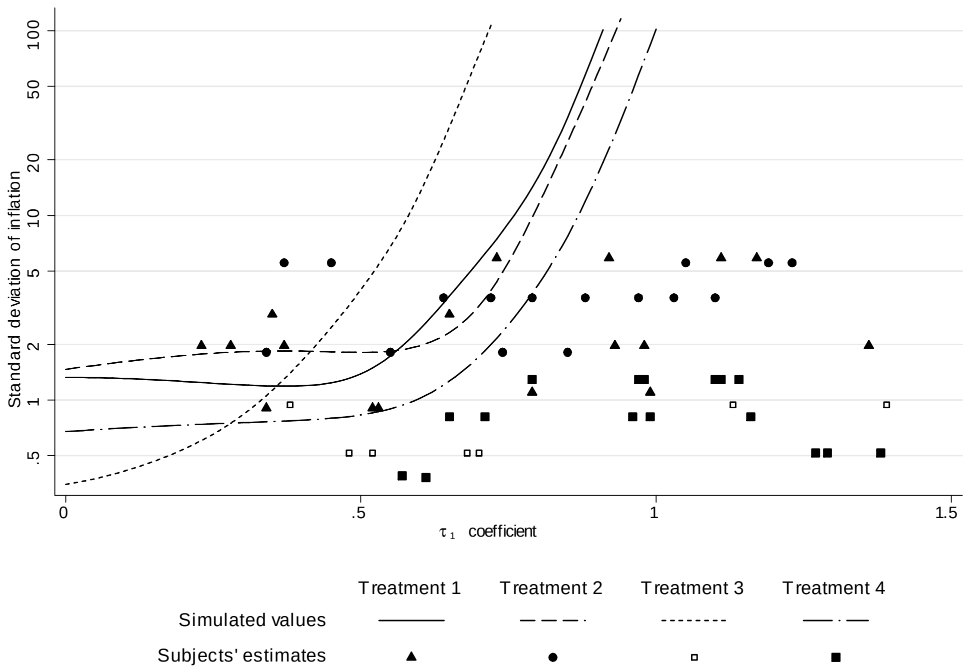

Figure A7: Standard deviation of inflation, subjects estimates of the **Trend extrapolation (M5),** and simulated values across the values of τ_1 parameter.

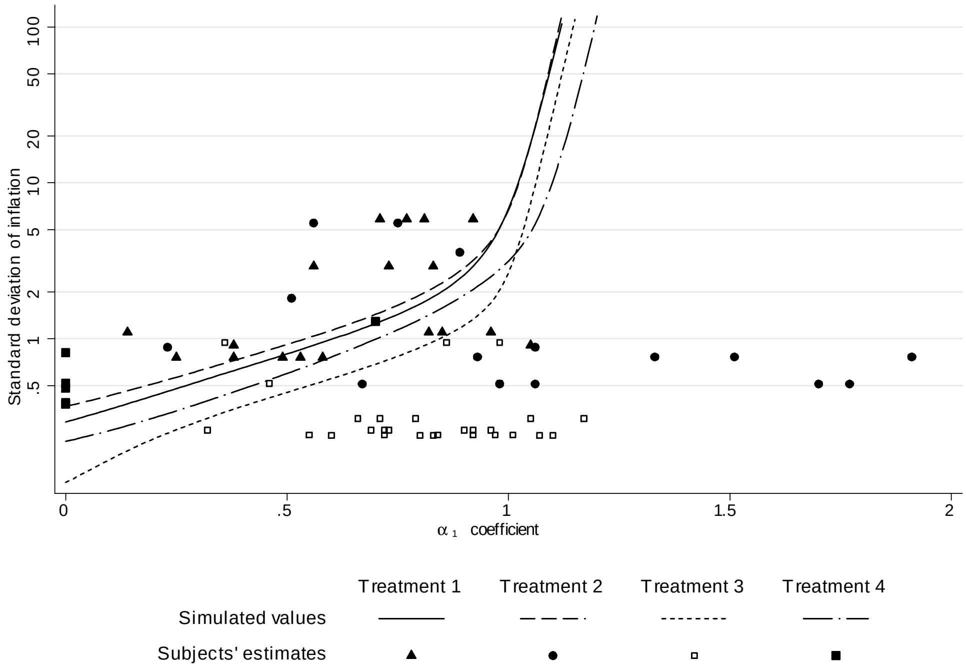

Figure A8: Standard deviation of inflation, subjects estimates of the **General model (M6),** and simulated values across the values of α_1 parameter.

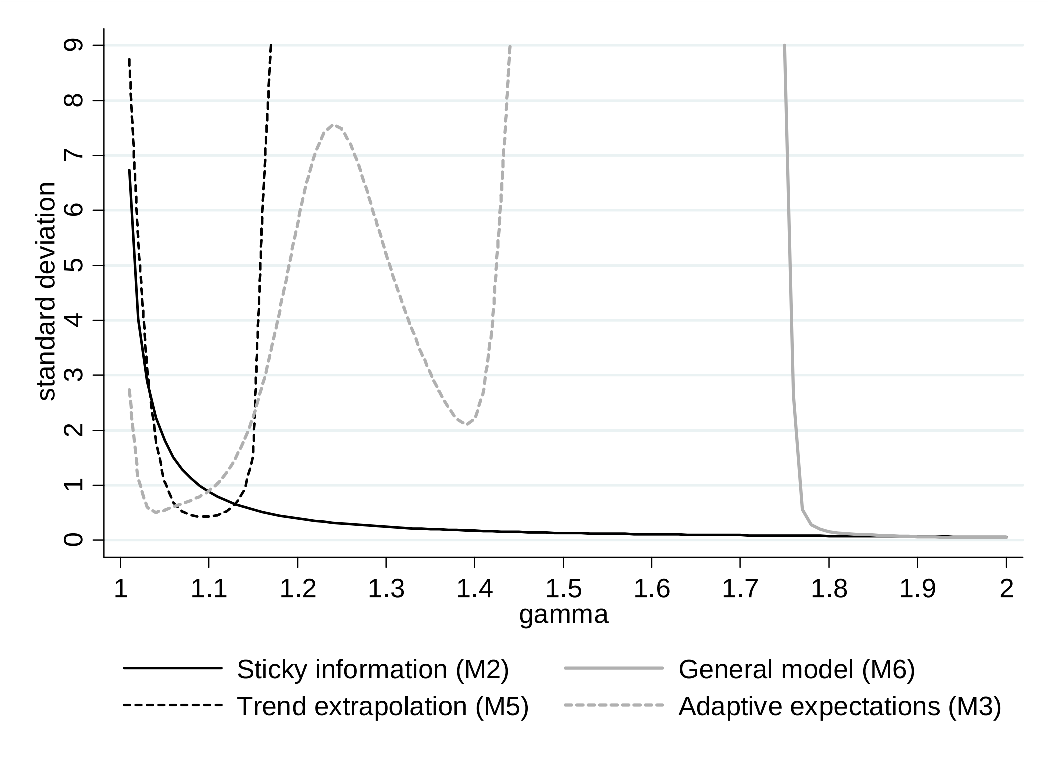

Figure A9: Variability of inflation and alternative expectation formation rules (forward-looking rule). Notes: Figure is based on real-time OLS estimations of a particular rule for 1000 periods.

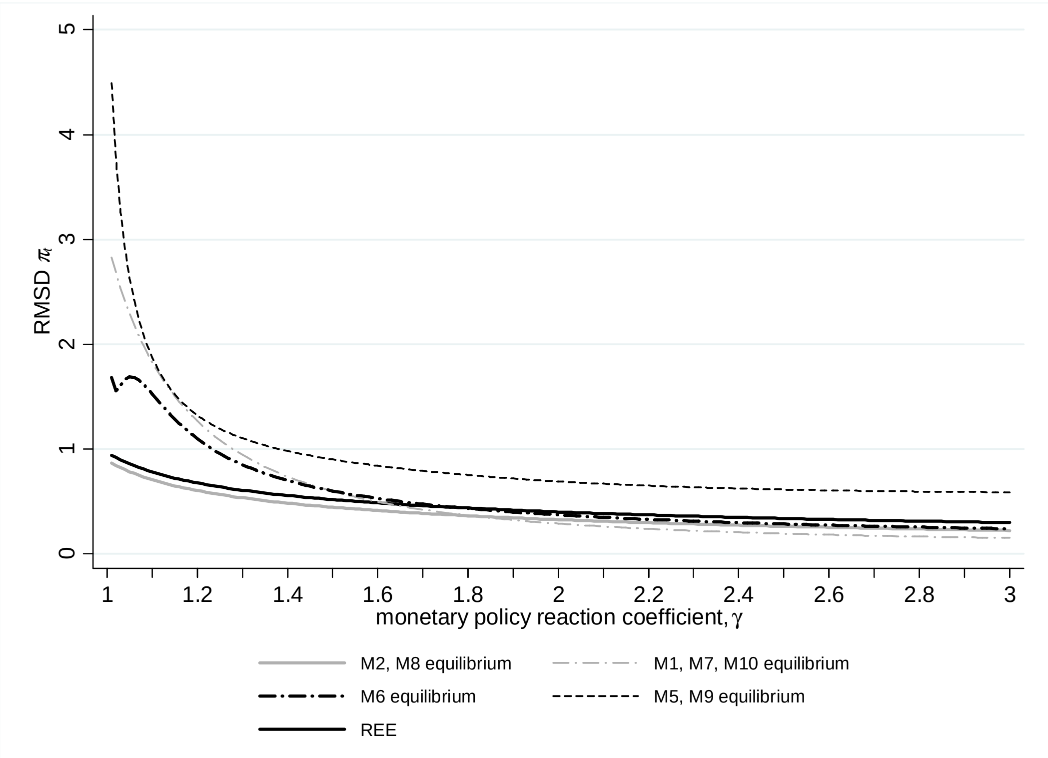

Figure A10: Equilibrium dynamics of inflation under different expectation formation rules for the contemporaneous rule. Notes: RMSD π_t is root mean squared deviation of inflation from its target. Figure is based on a simulation over 1000 periods.

sd_s :	AR(1) process (M1)		Sticky info. (M2)		Adaptive exp. (M3)		Trend extrap. (M5)		General model (M6)		Recursive lag inf. (M7)		Recursive RPE (M8)		Recursive trend (M9)	
	cluster	robust	cluster	robust	cluster	robust	cluster	robust	cluster	robust	cluster	robust	cluster	robust	cluster	robust
p_{js}	-0.5820	0.1439	-0.4882	-0.4535	-0.3334	-0.2545	0.3881**	0.3395 ***	-0.2529	-0.1308	-0.3633	-0.5153 **	-1.0107*	-0.8591	0.1348	-0.0590
	(0.506)	(0.203)	(0.280)	(0.356)	(0.253)	(0.201)	(0.103)	(0.101)	(0.145)	(0.154)	(0.167)	(0.229)	(0.418)	(0.577)	(0.261)	(0.281)
$T2$		0.5900		0.6353		0.2719		0.3524		0.6129		0.3195		0.7618		0.6254
		(1.156)		(1.099)		(1.201)		(0.894)		(1.119)		(1.053)		(1.149)		(1.121)
$T3$		-1.4204*		-1.1937 *		-1.5689 **		-0.9678		-1.1097		-1.8284 **		-1.2773 *		-1.4401*
		(0.680)		(0.611)		(0.695)		(0.568)		(0.927)		(0.751)		(0.693)		(0.740)
$T4$		-1.1720		-1.2793 *		-1.1559		-1.245 *		-1.0941		-1.4137 *		-0.9714		-1.1432
		(0.700)		(0.728)		(0.673)		(0.673)		(0.740)		(0.757)		(0.701)		(0.687)
$cons$	1.3896*	1.8357**	1.6501*	2.0624 **	1.6432**	2.1538 ***	0.4435	0.9871 **	2.2084*	2.1791 ***	1.6226*	2.4154 ***	1.4917*	1.8357 **	1.2248	1.8947**
	(0.506)	(0.670)	(0.646)	(0.759)	(0.510)	(0.746)	(0.234)	(0.513)	(0.759)	(0.628)	(0.632)	(0.805)	(0.523)	(0.670)	(0.680)	(0.867)
N	24	24	24	24	24	24	24	24	24	24	24	24	24	24	24	24
R^2	0.01	0.27	0.06	0.31	0.04	0.29	0.32	0.49	0.10	0.29	0.07	0.40	0.05	0.30	0.01	0.27

Table A1: Relation of standard deviation of inflation to certain behavioral types as denoted in Table 1. 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.

sd_s :	Trend extrapolation (M5) cluster	robust	cluster	robust
$\overline{\tau}_{1,s}$	1.6490	1.8727**		
	(1.016)	(0.730)		
$\overline{\tau}_{1,s}p_s$			0.4539*	0.4565***
			(0.186)	(0.137)
$T2$		0.6676		0.2027
		(0.849)		(0.817)
$T3$		-0.9487*		-1.0316*
		(0.541)		(0.519)
$T4$		-1.6194*		-1.6396**
		(0.799)		(0.748)
$cons$	0.5515*	0.8765*	0.4929*	1.0452**
	(0.1810)	(0.461)	(0.203)	(0.461)
N	24	24	24	24
R^2	0.21	0.49	0.33	0.56

Table A2: Relation of standard deviation of inflation to the average coefficient τ_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.

Treatment		M6	M2, M8	M1, M7, M10	M6; $\alpha_4 = 0$	M5, M9
		Rational Expectations equilibrium (rep. 2)	Underparameterized Perception equilibrium (level 1)	Underparameterized Perception equilibrium (level 2)	Misspecified Perception equilibrium (level 1)	Misspecified Perception equilibrium (level 2)
	Determinacy (Eigenv.)	yes $(0.77, 0.24)$	yes $(0.87, 0)$	yes $(1, 0)$	no $(0.98, 0; 0.98, 0)$	no $(0.32, 0.96, 0.96; 0.12.0.98, 0.98)$
	Solution $\mathbf{B}_1$	$\begin{bmatrix}0.031 & 0.39 & 0.37 & -0.030 & 0\\ -2.46 & 7.43 & -4.41 & 0.35 & 0\end{bmatrix}$	$\begin{bmatrix}0.013 & 0.87 & 0 & 0 & 0\\ 2.81 & 1.85 & 0 & 0 & 0\end{bmatrix}$	$\begin{bmatrix}0.07 & 1 & 0 & 0 & 0\\ 2.13 & 0.3 & 0 & 0 & 0\end{bmatrix}$	$\begin{bmatrix}0.03 & 0.98 & 0 & 0 & 0\\ 2.61 & 0.52 & 0 & 0 & 0\end{bmatrix}$	$\begin{bmatrix}0.26 & 1 & 0 & -0.10 & 0.02\\ -0.07 & 0.3 & 0 & 1.21 & -0.29\end{bmatrix}$
	Solution $\mathbf{B}_2$	-	-	-	$\begin{bmatrix}-0.06 & 0.98 & 0 & 0 & 0\\ 3.63 & -0.52 & 0 & 0 & 0\end{bmatrix}$	$\begin{bmatrix}0.26 & 1 & 0 & -0.07 & -0.01\\ -0.10 & 0.3 & 0 & 0.83 & 0.11\end{bmatrix}$
1	Eigenv. $\mathbf{B}_1$ (a)	$[0 \quad 0.69]$	$[0 \quad 0.81]$	$[0 \quad 0.94]$	$[0 \quad 0.92 + 0.02i]$	$[0 \quad 0 \quad 1.81]$
	Eigenv. $\mathbf{B}_1$ (b)	$[0 \quad \dots \quad 0 \quad -0.27 \quad -0.30 \quad 0.46]$	$[0 \quad 0 \quad -0.15 \quad 0.69]$	$[0 \quad 0 \quad -0.02 \quad 0.94]$	$[0 \quad 0 \quad -0.04 + 0.02i \quad 0.91 + 0.03i]$	$[0 \quad \dots \quad 0 \quad 1.17 \quad 1.76 \pm 0.17i]$
	Eigenv. $\mathbf{B}_2$ (a)	-	-	-	$[0 \quad 1.01 - 0.02i]$	$[0 \quad 0 \quad 1.85]$
	Eigenv. $\mathbf{B}_2$ (b)	-	-	-	$[0 \quad 0 \quad -0.04 - 0.02i \quad 0.99 - 0.00i]$	$[0 \quad \dots \quad 0 \quad 0.77 \quad 1.83 \pm 0.14i]$
	Determinacy (Eigenv.)	yes $(0.76, 0.01)$	yes $(0.89, 0)$	yes $(1, 0)$	no $(0.99, 0; 0.99, 0)$	no $(0.27, 0.97.0.97; 0.11, 0.99, 0.99)$
	Solution $\mathbf{B}_1$	$\begin{bmatrix}0.041 & 0.40 & 0.37 & -0.021 & 0\\ -2.18 & 10.5 & -6.23 & 0.35 & 0\end{bmatrix}$	$\begin{bmatrix}0.011 & 0.89 & 0 & 0 & 0\\ 2.78 & 2.20 & 0 & 0 & 0\end{bmatrix}$	$\begin{bmatrix}0.06 & 1 & 0 & 0 & 0\\ 1.90 & 0.3 & 0 & 0 & 0\end{bmatrix}$	$\begin{bmatrix}0.03 & 0.99 & 0 & 0 & 0\\ 2.48 & 0.51 & 0 & 0 & 0\end{bmatrix}$	$\begin{bmatrix}0.18 & 1 & 0 & -0.10 & 0.02\\ -0.05 & 0.3 & 0 & 1.18 & -0.25\end{bmatrix}$
	Solution $\mathbf{B}_2$	-	-	-	$\begin{bmatrix}-0.03 & 0.99 & 0 & 0 & 0\\ 3.41 & -0.51 & 0 & 0 & 0\end{bmatrix}$	$\begin{bmatrix}0.18 & 1 & 0 & -0.07 & -0.01\\ -0.06 & 0.3 & 0 & 0.83 & 0.11\end{bmatrix}$
2	Eigenv. $\mathbf{B}_1$ (a)	$[0 \quad 0.71]$	$[0 \quad 0.85]$	$[0 \quad 0.96]$	$[0 \quad 0.94 + 0.01i]$	$[0 \quad 0 \quad 1.86]$
	Eigenv. $\mathbf{B}_1$ (b)	$[0 \quad \dots \quad 0 \quad -0.26 \quad -0.28 \quad 0.48]$	$[0 \quad 0 \quad -0.13 \quad 0.74]$	$[0 \quad 0 \quad -0.02 \quad 0.96]$	$[0 \quad 0 \quad -0.03 + 0.01i \quad 0.93 + 0.02i]$	$[0 \quad \dots \quad 0 \quad 1.15 \quad 1.82 \pm 0.14i]$
	Eigenv. $\mathbf{B}_2$ (a)	-	-	-	$[0 \quad 1.002 - 0.01i]$	$[0 \quad 0 \quad 1.89]$
	Eigenv. $\mathbf{B}_2$ (b)	-	-	-	$[0 \quad 0 \quad 0.03 - 0.01i \quad 0.99 + 0.00i]$	$[0 \quad \dots \quad 0 \quad 0.80 \quad 1.87 \pm 0.12i]$
	Determinacy (Eigenv.)	yes $(0.79, 0.15)$	yes $(0.73, 0)$	yes $(1, 0)$	no $(0.83, 0; 0.83, 0)$	yes $(0.16, 0.96, 0.96)$
	Solution $\mathbf{B}_1$	$\begin{bmatrix}-1.22 & 0.34 & 0.48 & -0.18 & 0\\ -4.18 & 1.43 & -0.82 & 0.30 & 0\end{bmatrix}$	$\begin{bmatrix}0.027 & 0.73 & 0 & 0 & 0\\ 2.92 & 0.77 & 0 & 0 & 0\end{bmatrix}$	$\begin{bmatrix}0.09 & 1 & 0 & 0 & 0\\ 2.81 & 0.3 & 0 & 0 & 0\end{bmatrix}$	$\begin{bmatrix}0.03 & 0.83 & 0 & 0 & 0\\ 2.91 & 0.59 & 0 & 0 & 0\end{bmatrix}$	-
	Solution $\mathbf{B}_2$	-	-		$\begin{bmatrix}-0.10 & 0.83 & 0 & 0 & 0\\ 3.15 & -0.59 & 0 & 0 & 0\end{bmatrix}$	$\begin{bmatrix}2.40 & 1 & 0 & -0.38 & -0.07\\ -1.13 & 0.3 & 0 & 0.65 & 0.12\end{bmatrix}$
3	Eigenv. $\mathbf{B}_1$ (a)	$[0 \quad 0.39]$	$[0 \quad 0.46]$	$[0 \quad 0.69]$	$[0 \quad 0.55]$	-
	Eigenv. $\mathbf{B}_1$ (b)	$[0 \quad \dots \quad 0 \quad 0.218 \quad -0.45 \quad -0.58]$	$[0 \quad 0 \quad 0.23 \quad -0.38]$	$[0 \quad 0 \quad -0.15 \quad 0.69]$	$[0 \quad 0 \quad -0.30 + 0.03i \quad 0.41 + 0.06i]$	-
	Eigenv. $\mathbf{B}_2$ (a)	-	-	-	$[0 \quad 1.13]$	$[0 \quad 0 \quad 1.37]$
	Eigenv. $\mathbf{B}_2$ (b)	-	-	-	$[0 \quad 0 \quad 0.29 - 0.03i \quad 0.99 - 0.00i]$	$[0 \quad \dots \quad 0 \quad 0.39 \quad 1.29 \pm 0.28i]$
	Determinacy (Eigenv.)	-	yes $(0.84, 0)$	yes $(0.93, 0)$	no $(0.91, 0; 0.91, 0)$	no $(0.31, 0.93, 0.93; 0.12, 0.95, 0.95)$
	Solution $\mathbf{B}_1$	-	$\begin{bmatrix}0.016 & 0.84 & 0 & 0 & 0\\ 2.85 & 1.49 & 0 & 0 & 0\end{bmatrix}$	$\begin{bmatrix}0.07 & 0.93 & 0 & 0 & 0\\ 2.13 & 0.28 & 0 & 0 & 0\end{bmatrix}$	$\begin{bmatrix}0.03 & 0.91 & 0 & 0 & 0\\ 2.65 & 0.52 & 0 & 0 & 0\end{bmatrix}$	$\begin{bmatrix}0.24 & 0.93 & 0 & -0.09 & 0.02\\ -0.06 & 0.28 & 0 & 1.20 & -0.28\end{bmatrix}$
	Solution $\mathbf{B}_2$	-	-	-	$\begin{bmatrix}-0.09 & 0.91 & 0 & 0 & 0\\ 4.22 & -0.52 & 0 & 0 & 0\end{bmatrix}$	$\begin{bmatrix}0.24 & 0.93 & 0 & -0.06 & -0.01\\ -0.09 & 0.28 & 0 & 0.83 & 0.11\end{bmatrix}$
4	Eigenv. $\mathbf{B}_1$ (a)	-	$[0 \quad 0.86]$	$[0 \quad 0.95]$	$[0 \quad 0.93 + 0.01i]$	$[0 \pm 0.0i \quad 1.83]$
	Eigenv. $\mathbf{B}_1$ (b)	-	$[0 \quad 0 \quad -0.11 \quad 0.70]$	$[0 \quad 0 \quad -0.02 \quad 0.88]$	$[0 \quad 0 \quad -0.04 + 0.01i \quad 0.85 + 0.02i]$	$[0 \quad \dots \quad 0 \quad 1.16 \quad 1.74 \pm 0.16i]$
	Eigenv. $\mathbf{B}_2$ (a)	-	-	-	$[0 \quad 1.006 - 0.01i]$	$[0 \pm 0.0i \quad 1.87]$
	Eigenv. $\mathbf{B}_2$ (b)	-	-	-	$[0 \quad 0 \quad 0.04 - 0.01i \quad 0.92 + 0.00i]$	$[0 \quad \dots \quad 0 \quad 0.78 \quad 1.81 \pm 0.13i]$

Solution form: $X_t = \mathbf{B}W_{t-1} + \mathbf{C}Z_{t-1}$; where $X_t = \begin{bmatrix}y_{t-1}\\ \pi_{t-1}\end{bmatrix}$, $W_{t-1} = [1 \quad y_{t-1} \quad y_{t-2} \quad \pi_{t-1} \quad \pi_{t-2}]'$, $Z_{t-1} = \begin{bmatrix}g_{t-1}\\ u_{t-1}\end{bmatrix}$, $B = \begin{bmatrix}b_y & b_{yy} & b_{yy2} & b_{y\pi} & b_{y\pi 2}\\ b_\pi & b_{\pi y} & b_{\pi y2} & b_{\pi\pi} & b_{\pi\pi 2}\end{bmatrix}$, $C = \begin{bmatrix}c_{y\pi} & c_{yy}\\ c_{\pi\pi} & c_{\pi y}\end{bmatrix}$

Table A3: Properties of solutions under different expectation formation mechanisms. Notes: The second column represents also the REE under rep. 1 (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.