

Are Long-Horizon Expectations (De-)Stabilizing? Theory and Experiments*

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Abstract

We investigate the impact of finite forecasting horizons on price dynamics in a standard infinite-horizon asset-pricing model. Our theoretical results link forecasting horizon inversely to *expectational feedback*, and predict a positive relationship between expectational feedback and various measures of asset price volatility. A laboratory experiment is designed to test these predictions. In line with our theoretical results, short-horizon markets are prone to substantial and prolonged deviations from rational expectations; whereas markets populated by even a modest share of long-horizon forecasters exhibit convergence towards the fundamental price. This difference is consistent with distinct forecasting behaviors across horizons. Longer-horizon forecasts display more heterogeneity but also prevent coordination on incorrect anchors – a pattern that leads to mispricing in short-horizon markets.

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1 Introduction

Most macroeconomic and finance models involve long-lived agents making dynamic decisions in the presence of uncertainty. The benchmark modeling paradigm is the rational expectations (RE) hypothesis, which, in a stationary environment, can be captured by a one-step-ahead formulation of the model dynamics together with boundary conditions;¹ the impact of future plans at all horizons are fully summarized by one-step-ahead forecasts. Thus, under RE the issue of the decision horizon is hidden. When agents are more plausibly modeled as boundedly rational, one-step-ahead forecasts may be inadequate, and thus a stand must be taken on the decision and forecasting horizon employed. In this paper, using a simple asset-pricing model, we study the importance of the forecasting horizon length, both theoretically and in a lab experiment.

Under bounded rationality, theoretical and applied aspects of the decision horizon in general equilibrium settings have been considered by a variety of authors. At the short-horizon extreme, the commonly used one-step-ahead “Euler equation” learning is extensively discussed in Evans & Honkapohja (2001). At the other extreme, an infinite-horizon approach, developed by Preston (2005), has been utilized in several settings, e.g. Eusepi & Preston (2011). The work most closely related to this paper is Branch et al. (2012), in which general finite decision-horizon approaches were developed, including the one used in the current paper; see also Woodford (2018) for a related approach. Details, as well as the adaptation of this approach to our experimental framework, are discussed in Section 2.

The role of the forecast horizon is more than a theoretical question, as it may be relevant to many macroeconomic or financial issues: for example, forward guidance, fiscal policy or trading strategies. In fact, whether households or firms, when planning investment and savings, think only about the next period or instead think ahead several or many periods, and also how accurately they can forecast over those horizons, affects their economic and financial decisions and their reaction to policies. For example, how agents react to news about the future is critical to monetary policy, particularly now that publicly disclosing projections of future interest rates and forecasts of future macroeconomic variables has become a major part of central banking. The effects of fiscal transfers also depend on the ability of agents to evaluate the dynamic consequences of a given policy on future taxes and expenditures.

¹These boundary conditions include initial conditions on the state, as well as no-Ponzi scheme and transversality conditions. Typically, a non-explosiveness condition ensures these latter two.

Financial markets provide motivation for the specific focus of our experiment. In these markets it has long been thought that whether participants seek long-term returns or short-term profit opportunities is likely to affect their trade pattern and hence the volume of transactions as well as the level and volatility of asset prices. In our experimental set-up agents form forecasts over different horizons, and these forecasts may deviate from RE. Using a simple asset-pricing model we then investigate the impact of forecast horizons on asset prices. If agents have long horizons, does this lead to greater or smaller price volatility than if agents use shorter horizons? The answer is not obvious. There is a widespread view that short-horizon agents are likely to induce greater instability because of a tendency of these agents to chase short-term gains. On the other hand, in a standard RBC model that is known to be very stable under short-horizon adaptive learning, Evans, Guesnerie & McGough (2019) find that long-horizon decision-making instead leads to greater instability.

The primary goal of this paper is to design an asset pricing model populated by boundedly rational agents with finite forecasting horizons that can be analyzed for different configurations of horizons, and implemented in the laboratory. By tuning the horizon of the expectations, our lab experiment allows us to test how forecasting horizons affect price dynamics.

We choose the framework of a consumption-based asset pricing model *à la* Lucas (1978). In this model, heterogeneous expectations about future prices constitute a motive for trade between otherwise identical agents. To implement boundedly rational decision-making in our model, we impose that agents use “ T -step optimal learning” for a given planning horizon T , one of the approaches developed in Branch et al. (2012). Expectations about future asset prices constitute a central element of the price determination and impart positive feedback into the price dynamics: higher price forecasts translate into higher prices.

We show that our implementation of bounded rationality in the Lucas setting leads to a particularly simple connection between individual decisions and expectations about future asset prices: an individual agent’s conditional demand schedule reduces to a linear function of their endowment, the market clearing price and the agent’s expectation of the *average* asset price over any given horizon. This latter feature facilitates elicitation of forecasts from the human subjects in the lab.

Our contribution stands at the crossroad between two strands of the literature: the learning literature, as implemented, e.g. in dynamic general equilibrium models (Evans & Honkapohja 2001), and the experimental literature concerned with behavioral finance;

see, e.g., Palan (2013), Noussair & Tucker (2013) and references therein. While our focus lies in the former, we borrow from the latter the laboratory implementation that allows us to design a group experiment whose main features remain as close as possible to the theoretical learning setup (see Section 3).

Our experiment belongs to the class of “learning-to-forecast” experiments (LtFEs),² which focuses on the study of expectation-driven dynamics. An LtFE isolates the effects of expectations in a controlled environment. In these experiments, participants’ beliefs are elicited and the implied boundedly optimal economic decisions, conditional on beliefs, are computerized. The model’s expectational feedback permits expectation-driven fluctuations and (nearly) self-fulfilling price dynamics. What is novel in our LtFE, among other important features, is that we study the role of the forecasting horizon and use the experimental data to test different theories of learning and how these fit with short-horizon and long horizon forecasting.

It is useful to stress the external validity and fundamental importance of our lab experiment for behavior in macro-financial systems. In the real world agents try to optimize and make decisions over time, based on their current state and on their expectations of key future variables, and then the price is determined through some coordinating market mechanism. An important dimension of interest is the decision horizon of agents, and a question of considerable importance is how the behavior of asset prices depends on the decision horizon of agents and on how they form expectations over this horizon. Our goal is to examine this issue experimentally. However, as in all experiments, we have to design an environment that is simple enough to implement in a lab and that holds other relevant factors fixed.

To do so, our experimental design first specifies how markets clear. We use a mechanism that may appear artificial in the sense that it does not match most actual markets, but our specification is in line with how economic theory typically models market clearing. We then specify how agents make decisions, based on expectations, using boundedly rational decision-making over a finite planning horizon. We do so in a way such that if expectations of all agents were fully rational, they would make optimal decisions. Within the context of this design, we look at how expectations and prices behave in the lab. It is important to stress that our specification does not predetermine our results. Our experimental findings

²See the earlier contribution of Marimon et al. (1993). More recent experimental studies within macro-finance models include Adam (2007), Assenza et al. (2019), Kryvtsov & Petersen (2020). This literature is surveyed in Duffy (2016) and Arifovic & Duffy (2018).

need not have agreed with our theoretical predictions. In particular, if subjects had held fully rational expectations, the results across the four treatments would have been identical. Instead, the price behaviors across treatments differ greatly, which is reflected in distinct forecasting behaviors across horizons, even in treatments involving mixed horizons.

The asset-pricing model underlying our lab experiment is easily summarized: there is a fixed quantity of a single durable asset, yielding a constant, perishable dividend that comprises the model's single consumption good. The initial allocation of assets is uniform across agents (referred to, in the experiment, as participants). Each period, each agent forms forecasts of future asset prices and, based on these forecasts and their current asset holdings, forms their asset demand schedules. These schedules are then coordinated by a competitive market-clearing mechanism, yielding equilibrium price and trades. Participants' payoffs reflect both forecast accuracy and utility maximization. To accommodate the laboratory setting, the usual infinite-lifetime assumption is modified: at the end of each period, with a constant, known probability, the asset becomes worthless and the entire economy ends. This device emulates an infinite-horizon setting within an experimental economy with a fixed time frame and also yields a constant effective discount rate induced by the probability of termination. This economy has a unique perfect-foresight equilibrium price – the “fundamental price” – which is determined by the dividend and the discount factor.

We consider four experimental treatments, based on horizon length, T : one with a short horizon ($T = 1$), one with a long horizon ($T = 10$), and two treatments with mixtures of short and long horizons. We have two main questions in mind: (i) Does the horizon of expectations matter for the aggregate behavior of the market? (ii) If so, how do the horizon and the heterogeneity of those horizons affect this behavior? In particular, are long-horizon expectations (de)stabilizing?

We find that markets populated only by short-horizon forecasters are prone to significant and frequently prolonged deviations from the fundamental price. By contrast, if all traders are long-horizon forecasters, the price path is consistent with convergence to the fundamental price. A detailed analysis of individual forecasts reveals that the failure of convergence in short-horizon markets reflects the coordination of participants' forecasts on patterns derived from price histories, e.g. “trend-chasing” behavior. By contrast, the coordination of subjects' forecasts appears more challenging in longer horizon treatments: long-horizon forecasters display more disagreement. The resulting heterogeneity of long-horizon expectations impedes coordination on trend-chasing behavior and favors instead

adaptive learning of the fundamental price. From those two polar cases, a natural follow-up question is what share of long-horizon forecasters would be large enough to stabilize the market price. Our findings suggest that even a modest share of them is enough.

A relatively large body of the literature has investigated financial markets in a laboratory setting. To the best of our knowledge, all the existing LtFEs involve environments where only one-step-ahead expectations matter for the resulting price dynamics. Several experimental studies, including Haruvy et al. (2007), have been concerned with belief elicitation at longer horizons; however, in these studies, players' forecasts do not affect price dynamics. Hirota & Sunder (2007) and Hirota et al. (2015) studied the influence of trading horizons on prices in an experimental asset market where investors may either trade till maturity and collect dividends or exit earlier and earn capital gains. Their setup and payoff, among other important features, greatly differ from our study and their experiments are not LtFEs. Duffy et al. (2019), among others, study the impact of horizon uncertainty in the sense of uncertainty about the duration of the trade on prices in experimental asset markets, which again differs greatly from the focus of our experiment.

The rest of the paper is organized as follows. Section 2 gives a general theoretical framework. Section 3 details the experimental design and our hypotheses based on predictions from the learning model. Section 4 provides the results of the experiment and Section 5 concludes.

2 Theoretical framework: an asset-pricing model

The underlying framework of our experiment is a consumption-based asset-pricing model *à la* Lucas (1978). This model can be interpreted as a pure exchange economy with a single type of productive asset; at time t , each unit of the asset costlessly produces y_t units of consumption. The textbook model refers to this asset as a “tree” that produces “fruit.” In the experiment, we use the framing of a “chicken” producing “eggs.” This terminology reduces the likelihood that participants with a background in economics or finance would recognize the textbook asset-pricing model, and it also facilitates the implementation of an infinite-horizon environment in the lab by suggesting an asset with a finite life.

2.1 The infinite-horizon model

There are many identical agents, each initially endowed with $q > 0$ chickens, where each chicken lays $y > 0$ non-storable eggs per period. In each period, there is a market for chickens. Each agent collects the eggs from her chickens, consumes some, and sells the balance for additional chickens. Alternatively, the agent can sell chickens to increase current egg consumption. This decision depends on both the current price of chickens, and forecasts of future chicken prices.

To formalize the model, we consider the representative agent's problem:

$$\max E \sum_{t \geq 0} \beta^t u(c_t), \text{ s.t. } c_t + p_t q_t = (p_t + y)q_{t-1}, \text{ with } q_{-1} = q \text{ given,}$$

where $u' > 0$ and $u'' < 0$, q_{t-1} is the quantity of chickens held at the beginning of period t , c_t is the quantity of eggs consumed, and p_t is the goods-price of a chicken. Finally, E denotes the subjective expectation of the agent.

Under RE, which, in our non-stochastic setting reduces to perfect foresight (PF), the Euler equation is

$$u'(c_t) = p_t^{-1} (p_{t+1} + y) u'(c_{t+1}).$$

There is no trade in equilibrium, i.e. $c_t = q_t y$. Thus the perfect foresight steady state is given by $c = qy$ and $p = (1 - \beta)^{-1} \beta y$. We refer to $p = (1 - \beta)^{-1} \beta y$ as the fundamental price (value) of the asset, and often refer to the PF equilibrium as the RE equilibrium, or REE. Note that in REE, the representative agent holds wealth constant and consumes her dividend each period; this same behavior obtains even if agents are endowed with different initial wealth levels.

2.2 The model with finite-horizon agents

We relax the assumption of perfect foresight over an infinite horizon and consider the behavior of a boundedly rational agent with a finite planning horizon $T \geq 1$. This relaxation introduces the need to specify a terminal condition for the agent's decision-problem, in the form of an expected wealth target. Thus, in the non-stochastic case, in each period t , taking as given wealth q_{t-1} , prices p_t , terminal wealth expectations q_{t+T}^e , and price expectations p_{t+k}^e for $k = 1, \dots, T$, the agent chooses current and future planned consumption

and savings, c_{t+k} for $k = 0, \dots, T$ and q_{t+k} for $k = 0, \dots, T - 1$, to solve

$$\max \sum_{k=0}^T \beta^k u(c_{t+k}) \text{ s.t. } c_{t+k} + p_{t+k}^e q_{t+k} = (p_{t+k}^e + y) q_{t+k-1}, \quad (1)$$

where $p_t^e = p_t$ and $q_{t+T} = q_{t+T}^e$. The infinite-horizon version presented of Section 2.1 can be viewed as a limit in which $T \rightarrow \infty$.

It is convenient to work with first-order approximations of agent behavior. Letting dx be the deviation of a variable x from its steady-state value, the following proposition provides the first-order approximation to the time t asset demand dq_t in terms of current and expected future variables:

Proposition 1. *Let $\sigma = -cu''(c)/u'(c)$. Then*

$$dq_t = g(T)dq_{t-1} - \phi g(T)dp_t + T^{-1}h(T)dq_{t+T}^e + \phi h(T) \left(\frac{1}{T} \sum_{k=1}^T dp_{t+k}^e \right), \quad (2)$$

where

$$\phi = \frac{(1-\beta)q}{p\sigma}, \quad g(T) = \frac{1-\beta^T}{1-\beta^{T+1}}, \quad \text{and } h(T) = \frac{(1-\beta)T\beta^T}{1-\beta^{T+1}}.$$

All proofs are in the On-line Appendix. Hence, the individual demand schedule of an agent depends negatively on the market price dp_t , positively on her past and expected future wealth dq_{t-1} and dq_{t+T}^e , and, perhaps unexpectedly, on her forecast of the *average price* $\frac{1}{T} \sum_{k=1}^T dp_{t+k}^e$ over her planning horizon. These last two dependencies merit further discussion.

The model's decision-making problem is often written using the more common language of returns, $R_k = p_{k-1}^{-1}(p_k + y)$, and it can be shown that the agent's decision rules depend on the present value of expected future returns. To link this dependence with the proposition, and assuming perfect foresight for convenience, note that to first order, $dR_k = (\beta p)^{-1}(\beta dp_k - dp_{k-1})$. It follows that $\partial/\partial dp_m \sum_{k=1}^{\infty} \beta^k dR_k = 0$. Thus, in the infinite horizon case we have $\partial c_t/\partial p_{t+m} = 0$ and $\partial q_t/\partial p_{t+m} = 0$; further, in the finite horizon case, it can be shown that $\partial c_t/\partial p_{t+m}$ and $\partial q_t/\partial p_{t+m}$ are independent of m for $1 \leq m \leq T$. We conclude that the average price path is a sufficient statistic for dc_t and dq_t , exactly in line with Proposition 1. Details on the computations underlying this discussion are provided in Appendix A.1.

2.3 Price dynamics with heterogeneous agents

Thus far we have focused attention on the homogeneous model. We now consider a market populated by heterogeneous agents, indexed by i , possibly forecasting over heterogeneous horizons. We adopt equation (2) as the behavioral primitive characterizing agents' time t savings decisions. Formally, let α_i be the proportion of agents of type i , for $i = 1, \dots, I$, and let $\alpha = \{\alpha_1, \dots, \alpha_I\}$ and $\mathcal{T} = \{T_1, \dots, T_I\}$. Since we allow agents of different types to have planning horizons of the same length, we may assume agents of the same type hold the same forecasts. The demand schedule for an agent of type i is given by

$$dq_{it} = g(T_i) dq_{it-1} - \phi g(T_i) dp_t + T_i^{-1} h(T_i) dq_{i,t+T}^e + \phi h(T_i) \left(\frac{1}{T_i} \sum_{k=1}^{T_i} dp_{i,t+k}^e \right). \quad (3)$$

Thus, in this framework, heterogeneous wealth and expectations lead to heterogeneous demand schedules, providing a motive for trade and inducing price dynamics.

It remains to specify agents' beliefs about wealth at the horizon T_i , dq_{it+T}^e . To make this specification we adopt the follow principle: if, at a given time t , current price and expected future prices coincide with the PF steady state, then the agent's decision rule should reproduce fully optimal behavior.³ We can use this principle to derive the most parsimonious wealth forecasting model. The REE prices corresponds to $dp_{t+s} = 0$ for all s , so that by equation (3), we have

$$dq_{it} = g(T_i) dq_{it-1} + T_i^{-1} h(T_i) dq_{i,t+T}^e. \quad (4)$$

Because our environment is stationary, the optimal wealth path, given $dp_{t+s} = 0$, is constant: $dq_{it} = dq_{it-1}$. Inserting this into (4) gives $dq_{i,t+T}^e = dq_{it-1}$.⁴

We adopt the parsimonious forecast rule just derived as a behavioral primitive, which implies that the demand schedule of an agent of type i reduces to

$$dq_{it} = dq_{it-1} - \phi g(T_i) dp_t + \phi h(T_i) d\bar{p}_{it}^e(T_i), \quad (5)$$

where $d\bar{p}_{it}^e(T_i)$ denotes the expected average price of an agent of type i with planning hori-

³This can be viewed as a bounded optimality extension of the principle for forecast rules introduced by Grandmont & Laroque (1986), which in particular required that forecast rules be able to reproduce steady states.

⁴Some details of the dynamic implications of our behavioral assumptions are discussed in Appendix A.2.1.

zon T_i .

Market clearing in each period implies $\sum_i \alpha_i dq_{it} = \sum_i \alpha_i dq_{it-1} = 0$, $\forall t$, which uniquely determines the price p_t :

$$dp_t = \sum_i \xi(\alpha, \mathcal{T}, i) d\bar{p}_{it}^e(T_i), \text{ where } \xi(\alpha, \mathcal{T}, i) \equiv \frac{\alpha_i h(T_i)}{\sum_j \alpha_j g(T_j)}. \quad (6)$$

Thus the time t price only depends on the agents' forecasts of the *average* price of chickens over their planning horizon, i.e. $\{d\bar{p}_{it}^e(T_i)\}_{i=1}^I$. The asset-pricing model with heterogeneous agents is therefore an *expectational feedback* system, in which the perfect foresight steady-state price is exactly self-fulfilling and is unique.

Two special cases are of interest. If expectations are homogeneous across planning horizons, i.e. $d\bar{p}_{it}^e(T_i) = dp_t^e$, $\forall i$, then the following holds:

$$dp_t = \xi(\alpha, \mathcal{T}) dp_t^e, \text{ where } \xi(\alpha, \mathcal{T}) \equiv \sum_i \xi(\alpha, \mathcal{T}, i) = \frac{\sum_i \alpha_i h(T_i)}{\sum_j \alpha_j g(T_j)}. \quad (7)$$

If, in addition, all agents have the same planning horizon T , i.e. $\mathcal{T} = \{T\}$, we have

$$dp_t = \xi(T) dp_t^e, \text{ where } \xi(T) \equiv \frac{(1-\beta)T\beta^T}{1-\beta^T}. \quad (8)$$

The following proposition characterizes the expectational feedback parameter $\xi(\alpha, T)$ when expectations are homogeneous.

Proposition 2. *Let $I \geq 1$, $\alpha_i \geq 0$, $\sum \alpha_i = 1$, $T_i \geq 1$. Then:*

1. $0 < \xi(\alpha, \mathcal{T}) < 1$.
2. *If planning horizons are homogeneous then $1 \leq T < T' \implies \xi(T) > \xi(T')$.*
3. *If $\mathcal{T} = \{T_1, T_2\}$ and if $T_1 < T_2$ then $\frac{\partial}{\partial \alpha_1} \xi(\alpha, \mathcal{T}) > 0$.*

Proposition 2 says that the expectational feedback in this system is always positive but less than one. When there is a single planning horizon increasing its length reduces the expectational feedback. The strongest feedback occurs when $T = 1$, where $\xi(1) = \beta$. Finally, for two agent types, increasing the proportion of agents using the shorter horizon increases the expectational feedback.

Next we consider whether agents using simple learning rules would eventually coordinate their forecasts on the REE. Put differently, is the REE stable under adaptive learning?

In section 4.4, where we analyze subject-level forecasts from the experiment, we consider several types of forecast rules; here, for theoretical considerations, we focus on one prominent class of adaptive learning rules which has each of the N agents updating beliefs via

$$d\bar{p}_{it}^e(T_i) = d\bar{p}_{it-1}^e(T_i) + \gamma_t(dp_{t-1} - d\bar{p}_{it-1}^e(T_i)). \quad (9)$$

Here, $0 < \gamma_t \leq 1$ is called the “gain” sequence, which is assumed to satisfy $\sum_t \gamma_t = \infty$. There are two prominent cases in the literature: the “decreasing gain” case with $\gamma_t = t^{-1}$, which provides equal weight to all data; and the “constant gain” case with $\gamma_t = \gamma \leq 1$, which discounts past data.

Corollary 1. *For either decreasing or constant gain we have that $d\bar{p}_{it}^e(T_i) \rightarrow 0$ and $dp_t \rightarrow 0$, as $t \rightarrow \infty$. Furthermore, asymptotically, agents make fully optimal savings decisions.*

Corollary 1 shows that under adaptive learning of the form (9), the price dynamics converge to the REE, i.e. to the fundamental value. This result is independent of the number of agent-types and the lengths of their horizons, and can be extended to include heterogeneous gains.

The empirical macro literature employing adaptive learning is almost exclusively based on constant gain algorithms, and the analysis of our experimental results will be similarly focused. Under constant gain learning, the rate of convergence, i.e. $1 - \zeta$ where $\zeta = dp_t/dp_{t-1}$, is time invariant: see Appendix. We note that in the homogeneous horizon case $1 - \zeta = \gamma(1 - \xi)$, which emphasizes that the rate of convergence is inversely related to the magnitude of ξ .

The following result identifies the dependence of $1 - \zeta$ on the planning horizon.

Corollary 2. *Under constant gain learning, the rate at which market price converges to its fundamental value is increasing in individual planning horizons T_i .*

Numerical investigations indicate that this result can be extended to allow for heterogeneous (constant) gains that are held fixed as planning horizons are varied.

Stochastic models of the form (7) have been studied in closely related setups under constant gain learning, and it is also known that the extent and speed of convergence depend on the size of the expectational feedback parameter, which corresponds here to $\xi(\alpha, T)$.⁵ In short-horizon settings a number of authors have noted the possibility that when the expectational feedback parameter is near one, near-random-walk behavior of asset prices is

⁵See, e.g. Evans & Honkapohja (2001, Ch. 3.2, 3.3 and 7.5).

almost self-fulfilling, in that the associated forecast errors can be small, while, at the same time, it can lead to significant departures from REE and excess volatility.⁶ In our model this phenomenon arises most forcefully when $T = 1$ and β is near one so that ξ is near one.

Values of ξ near one also have implications for forecast accuracy. In particular, for some simple salient forecast rules, including those based on possibly-weighted sample averages (γ small) or near random walks (γ large), as well as higher-order trend-chasing models, expectations are nearly self-fulfilling. Thus in this case, even if price level is far from the REE, the agents' forecast errors can be small. We will come back to this point later when interpreting our experimental results.

The results and discussion above point to the following implications for this model under learning, which we would expect to be reflected experimentally:

Implication 1: Prices and individual forecasts converge over time towards the REE.

Implication 2: The extent and speed of convergence toward the REE will be greater the smaller is the expectational feedback parameter $\xi(\alpha, \mathcal{T})$.

Implication 3: Deviations of forecasts from REE will be smaller for smaller $\xi(\alpha, \mathcal{T})$.

Implication 4: The level of price volatility will be lower the smaller is $\xi(\alpha, \mathcal{T})$.

These implications are reflected in the hypotheses we develop and test below.

3 The experimental design

The experiment is couched in terms of a metaphorical asset market in which assets are chickens (and thus finite-lived), and dividends are eggs (and thus perishable), comprising the experiment's unique consumption good. Participants are traders who make saving decisions based on forecasts of future chicken prices. In the experiment, participants submit price forecasts that are then coupled with the decision rules derived in Section 2 to determine their demand-for-saving schedules. Equilibrium prices and saving decisions are determined each period via market clearing.

3.1 Environment and procedures

Each group in the experiment is composed of $J = 10$ participants. At the opening of a market, each forecaster/trader is endowed with a given number of chickens. This number is the

⁶See, e.g., Blanchard & Watson (1982), Branch & Evans (2011) and Adam et al. (2016)

same across all forecasters/traders, but participants can only observe their own endowment and do not know the total number of chickens in the market.

Upon entering the lab, each participant is assigned the single task of forecasting the average market price of a chicken in terms of eggs over a given horizon, and this horizon remains the same throughout the experiment. Trading is computerized: based on participants' forecasts, market clearing determines the actual amount of trade of each participant, given by Equation (5), together with the current market price as specified by Equation (6). The timing of the events within one experimental period is illustrated in Figure 1.

The dividend is common knowledge, and participants operate under no-short-selling and no-debt constraints. Each period, they must consume at least one egg. Eggs are both the consumption good and the medium of exchange, but only chickens are transferable between periods (see Crockett et al. (2019) for a similar setup).

Transposing this type of model to a laboratory environment requires resolving a number of issues, as discussed for instance in Asparouhova et al. (2016). Two major concerns are the emulation of stationarity and infinitely lived agents. Stationarity is an essential feature as it rules out rational motives to deviate from fundamentals, hence allowing us to get cleaner data on potential behavioral biases. An infinite-lifetime setting, together with exponential discounting and the dividend process, determines the fundamental value of the asset. This may play an important role in the belief formation process of the participants.

We use the standard random termination method originally proposed by Roth & Murnighan (1978) to deal with infinite lifetime in the laboratory. If each experimental market has a constant and common-knowledge probability of ending in each period, the probability of continuation is known to theoretically coincide with the discount factor. In the instructions of our experiment, the metaphor of the chickens allows us to tell the participants the story of an avian flu outbreak that may occur with a 5% probability in each period (corresponding to a discount factor $\beta = 0.95$). If this is the case, the market terminates: all chickens die and become worthless.

As for the stationarity issue, we choose a constant dividend process. The fundamental value associated with this dividend value and discount factor was not given to the participants. However, we think it likely that the experimental environment, including in particular the constant dividend process, is concrete enough to induce the idea of a fundamental value for a chicken in terms of eggs to the participants.

As discussed in Asparouhova et al. (2016), a major difficulty lies in the constant termination probability (discount factor). Participants should perceive the probability of a

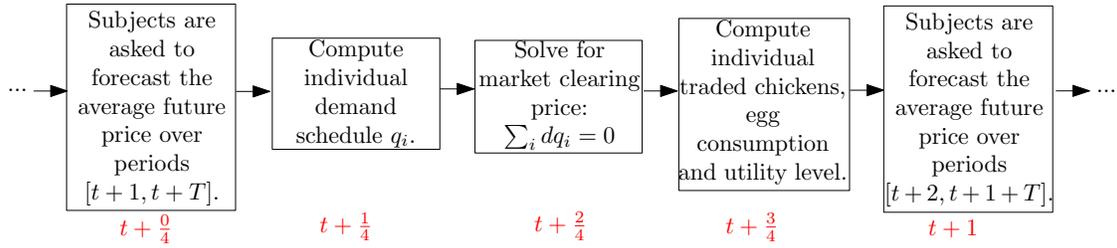


Figure 1: Timing of events within one period of an experimental market

market to end to be the same at the beginning of the experimental session as towards the end of the time span for which they have been recruited. We therefore use the “repetition” design of Asparouhova et al. (2016): we recruited the participants for a given time and ran as many markets as possible within this time frame. Furthermore, we recruited them for 2 hours and 30 minutes but completed most of the sessions within 2 hours so as to keep the participants’ perception of the session’s end in the distant future throughout the experiment (see also Charness & Genicot (2009) for such an implementation). We did so by starting a new market only if not more than 1 hour and 50 minutes had elapsed since the participants entered the lab. In case a market was still running after this time constraint, the experimenter would announce that the current 20-period block (see below) was the last one.

Finally, our framework involves two additional difficulties. Most importantly, participants have to form forecasts over a given horizon, say over the next 10 periods, but the market may terminate before period 10. In this case, the average price corresponding to their elicited predictions is not realized, and participants’ tasks cannot be evaluated (see below how the payoffs are determined). In order to circumvent this issue, we use the “block” design proposed by Fréchette & Yuksel (2017): each market is repeated in blocks of a given number of periods, and the termination or continuation of the market is observed only at the end of each block. This design allows the experiment to continue at least for the number of periods specified in the block, without altering the emulation of the stationary and infinite living environment from a theoretical viewpoint.

In our experiment, the length of a block is taken to be 20 periods, which corresponds to the expected lifetime of a chicken with a 5% probability of termination. The random draws in each period are “silent,” and participants observe only every 20 periods whether the chickens have died during the previous 20 periods. If this occurred, the market terminates and they enter a new market from period 1 on. If this did not occur, the market continues

	<i>Markets</i>				
	Market 1	Market 2	Market 3	Market 4	Market 5
Dividend y	2	4	1	5	3
Fundamental price p	38	76	19	95	57
Endowment q	4100	2100	8200	1700	2700

Table 1: Calibration of the markets, all groups, all treatments

for another 20-period block. In period 40, participants observe whether a termination draw has occurred between periods 20 and 40. If this is the case, the market terminates and a new one starts; if not, participants play another 20-period block till period 60, etc. Only periods during which the chickens have been alive count towards the earnings of the participants.

To prevent knowledge of the fundamental being carried over across markets we vary the dividend y , and thus the equilibrium price, between markets. We also vary the initial endowment of chickens to match the symmetric equilibrium distribution and keep liquidity and utility levels constant across markets: see Table 1.⁷ On entering each new market, participants receive the corresponding values through a pop-up message, and those values remain on the screen throughout the market (see On-line Appendix, Figure 8). To avoid perfect predictions, we add a small noise term v to the price, with $v \sim \mathcal{N}(0, 0.25)$.

3.2 Payoffs

We elicit price forecasts from participants, but those forecasts translate into trade decisions, and the predictions of our theoretical model partly rely on the properties of the utility function and the incentive to smooth consumption over time. For this reason, the payoff of the participants consists of two parts: at the end of each market, all participants receive experimental points based *either* on forecast accuracy *or* on their egg consumption with equal probability. This design avoids “hedging” and maintain equal incentives towards the two objectives (forecasting and consuming) throughout each market. Payoff tables are reported in Appendix D.

The consumption payoff is $u(c) = 120 \cdot \ln(c)$ ($c \geq 1$). Specifying a concave utility function provides tight control on subjects’ preferences and induces the consumption smoothing

⁷We remark that only integer values of chickens and eggs are allowed to be traded/consumed. The large number of chickens renders this imposition inconsequential.

behavior that underlies the predictions from the theoretical model (see also Crockett et al. (2019)). Participants are paid only for periods during which chickens continue to be alive. The payoff based on utility is simply the sum of their utility realized in each of those periods.

Payoffs based on predictions are made as follows. First, as usual in LtFEs, the forecasting payoff is a decreasing function of the squared forecast errors:

$$\max (1100 - 1100/49(\text{error})^2, 0).$$

If the error is higher than 7, the payoff is zero. Second, we must take account of the fact that there are necessarily periods before the death of the chickens for which forecast errors are not available. Consequently, the number of realized average prices over T periods, and the associated forecasting payments, is lower than the number of utility payments that take place in every period. To circumvent this discrepancy, the last rewarded forecast is paid $T + 1$ times to the participants. This also incentivizes them to submit accurate forecasts for every period, as they are uncertain about which one will be the last and, hence, the most rewarded. If the chickens die in the first block before $T + 1$ periods, participants were paid on utility. At the end of all the markets, the total number of points earned by each participant was converted into euros at a pre-announced exchange rate, and paid privately.

3.3 Instructions and information

Participants were given instructions that they could read privately at their own pace (see Appendix D). The instructions contain a general description of the markets for chickens, explanations about the forecasting task and how it translates into computerized trading decisions, information about the payoffs, and payoff tables, as well as an example. The instructions convey a qualitative statement of the expectations feedback mechanism that characterizes the underlying asset pricing model.

At the end of the instructions, participants had to answer a quiz on paper. Two experimenters were in charge of checking the accuracy of their answers, discussing their potential mistakes and answering privately any question. The first market opens only after all participants had answered accurately all questions of the quiz. This procedure allows us to be confident that all participants start with a reasonable understanding of the experimental environment and their task. Of the participants, 90% (218) reported that the instructions were understandable, clear or very clear.

3.4 Hypotheses and treatments

In the experiment, participants are either short-horizon forecasters ($T = 1$), i.e. they forecast the next period's price, or long-horizon forecasters ($T = 10$), i.e. they forecast the average price over the next ten periods. We design four treatments to test the implications of the model discussed in Section 2.3 based on the proportion α of short-horizon forecasters. These treatments, labeled L, M50, M70 and S respectively, are summarized in Table 2. This two-type setup leads to a special case of the pricing equation (6). From the implications established in Section 2.3, we obtain the first three main hypotheses to be tested through the experimental treatments.

First, based on Corollary 1, one might expect convergence in all treatments since the feedback parameter is always lower than one. However, the implications at the end of Section 2.3 suggest that convergence to the REE can be tenuous if ξ is close to one. Item 3 of Proposition 2 shows that the feedback parameter $\xi \in (0, 1)$ increases with the share of short-horizon forecasters α . Figure 2 illustrates the effect of α on ξ for calibration of the model implemented in the laboratory. As is clear from Figure 2a, the impact on ξ is nonlinear, magnifying the stabilization power of even a small share of long-horizon agents. Figure 2b illustrates the same phenomenon by plotting the expectational feedback equation (7) for the four different treatments. Note that the convergence challenge posed by a near-unity feedback parameter is particularly acute in Tr. S since in that case $\xi = \beta$. These considerations, Implications 1 - 4, and Proposition 2 suggest the following hypotheses:

Hypothesis 1a (Price convergence). *Under each treatment, participants' average forecasts and the resulting price level converge towards the REE.*

Hypothesis 1b (Price deviation). *The higher the share of short-horizon forecasters, the more likely participants' average forecasts and the resulting price level will fail to converge towards the REE.*

Hypothesis 2 (Price volatility). *Increasing the share of short-horizon planners increases the level of price volatility.*

Our theoretical results suggest coordination of agents' expectations will increase over time as agents learn the REE. Since heterogeneous expectations provide a motive for trade in our experiment, we test the following in all treatments:

Hypothesis 3 (Eventual coordination). *Price predictions of participants become more homogeneous over time. As a consequence, trade decreases over time.*

	<i>Treatments</i>			
	Tr. L	Tr. M50	Tr. M70	Tr. S
Share α (and number of forecasters) with horizon $T = 1$	0 (0 subject)	0.5 (5 subjects)	0.7 (7 subjects)	1 (10 subjects)
Share $1 - \alpha$ (and number of forecasters) with horizon $T = 10$	1 (10 subjects)	0.5 (5 subjects)	0.3 (3 subjects)	0 (0 subject)

Table 2: Summary of the four experimental treatments

Besides providing an empirical test of the theoretical implications of the model, one further advantage of learning-to-forecast experiments is that they make it possible to collect “clean” data on individual expectations because the information, underlying fundamentals, and incentives are under the full control of the experimenter. We can then use this rich dataset to test additional hypotheses regarding participants’ forecasting behavior. In the current context, it is of interest to compare the forecasts of short-horizon and long-horizon participants. A variety of factors suggest that long-horizon forecasting is more challenging than short-horizon forecasting. Long-horizon forecasting involves accounting for a sequence of endogenous outcomes, whereas short-horizon forecasting involves contemplation of only a single data point, and hence a lighter cognitive load.

This discussion suggests that there may be more variation of price forecasts for long-horizon forecasters than for short-horizon forecasters. To measure this we use *cross-sectional dispersion*, defined in terms of the relative standard deviation of subjects’ forecasts within each period. We have the following two hypotheses:

Hypothesis 4 (Coordination and forecast horizons). *Long-horizon forecasters exhibit more heterogeneity, i.e. greater cross-sectional dispersion of price forecasts, than do short-horizon forecasters.*

Hypothesis 5 (Trade volume and forecast horizons). *The higher the share of long-horizon forecasters in a market, the greater the cross-sectional dispersion of price forecasts and, hence, the higher the trade volume.*

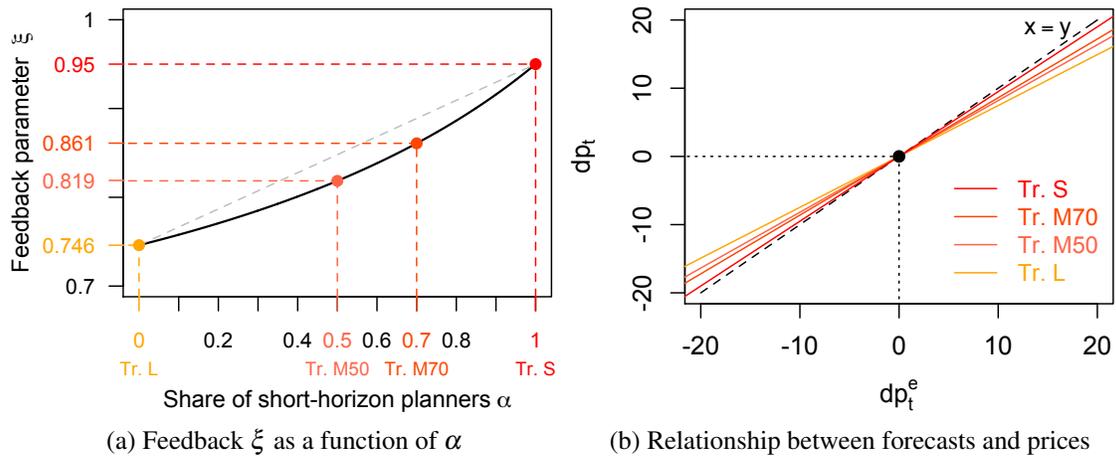


Figure 2: Price equation in the four experimental treatments

3.5 Implementation

The experiment was programmed using the Java-based PET software.⁸ The experimental sessions were run in the CREED lab at the University of Amsterdam between October 14 and December 16, 2016. Most subjects (124 out of 240) had participated in experiments on economic decision making in the past, but no person participated more than once in this experiment. With the four treatments, each involving six groups of ten subjects, we recruited a total of 240 subjects, who participated in a total of 63 markets, ranging from 20 to 60 periods. The average earnings per participant amount to 22.9 euros (ranging from 10.8 to 36.6 euros).

4 The experimental results

In Section 4.1, we provide a graphical overview of the price data from the experimental markets. In Section 4.2 we examine our hypotheses using cross-treatment statistical comparisons. Section 4.3 conducts an empirical assessment of convergence to REE using price data. Finally, Section 4.4 connects the cross-treatment differences in terms of aggregate behavior to distinct forecasting behaviors across horizons by analyzing individual data.⁹

⁸The PET software was developed by AITIA, Budapest under the FP7 EU project CRISIS, Grant Agreement No. 288501.

⁹We adopt a 5% confidence threshold to assess statistical significance. When carrying out econometric analysis, we use OLS estimates, autocorrelation in error terms is detected by Breusch-Godfrey tests, and heteroskedasticity using Breusch-Pagan tests. When needed, we use the consistent estimators described in

4.1 A first look at the data

Figure 3 displays an overview of the realized prices in the experimental markets for each of the four treatments. Each line represents a market, with the reported levels corresponding to the deviations from the market’s fundamental value, expressed in percentage points.¹⁰ Plots with individual forecast data for each single market are given in Appendix B: see figures 9 to 11. In those figures, blue corresponds to long-horizon ($T = 10$) forecasts, red to short-horizon ($T = 1$) forecasts, dots to rewarded forecasts and crosses to non-rewarded forecasts. Finally, the solid line is the realized price and the dashed horizontal line is the fundamental price.

A first visual inspection of the market price data in Figure 3 leads us to identify three different emerging patterns: (i) *convergence* to the fundamental price (see, for instance, in Figure 3d, Tr. L, Gp. 2 in purple or Gp. 6 in orange); (ii) *mispricing*, that we characterize by mild or dampening oscillations around a price value that is different from the fundamental value; either above the fundamental price, i.e. *overpricing*, or below the fundamental price, i.e. *underpricing* (see, for an example of each type of mispricing, the two markets played by Gp. 1 in Tr. M70 on Figure 3b, red lines); and (iii) *bubbles and crashes*, described by large and amplifying oscillations (where the top of the “bubble” reached several times the fundamental value); see, for instance, the markets of the first group in Tr. S (Figure 3a, red lines).

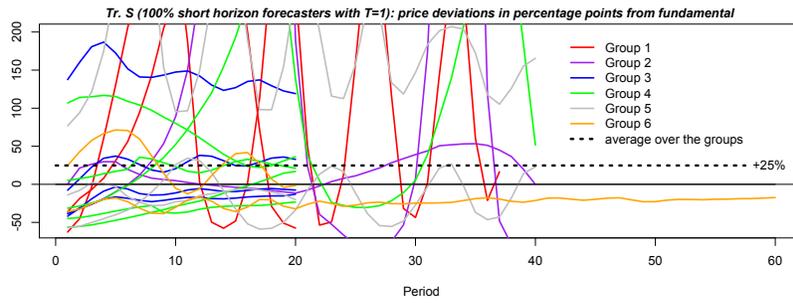
This first glance at the data already leads us to question Hypothesis 1a, as it is clear that not every market exhibits price convergence towards the fundamental value. On the other hand, we see patterns in the data that are in line with Hypothesis 1b: while large deviations from fundamentals are observed in the short-horizon treatments (Tr. S and Tr. M70), they are absent from the long-horizon treatments (Tr. M50 and Tr. L), where the price appears to evolve closer to the REE. Moreover, the problem of mispricing seems particularly acute in the short-horizon markets.

Interestingly, though, the observed bubbles break endogenously, which is *not* usual in LtFEs.¹¹ Several features of our setting may be behind this phenomenon: (i) the framing

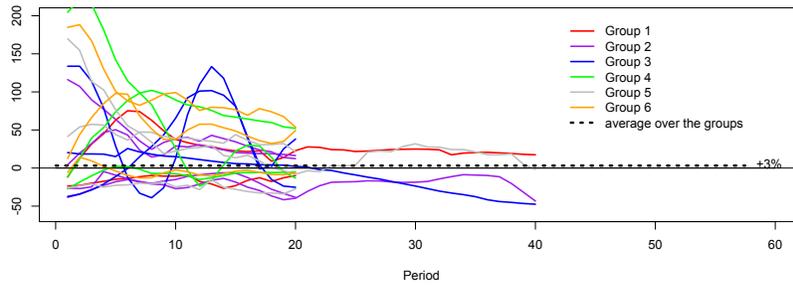
Newey & West (1994). Significant differences between distributions are established using K-S tests and Wilcoxon rank sum tests to address non-normality issues.

¹⁰The apparent asymmetry around zero in the proportional deviations from fundamental values reflects that the price cannot be negative, while there is no upper bound except for the artificial one of 1000 that is unknown to the subjects until they hit it.

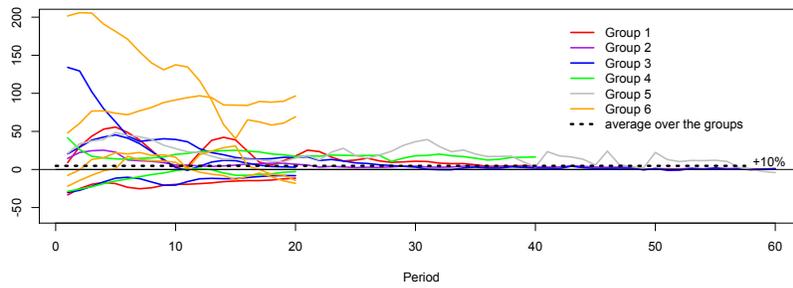
¹¹The only exception is Market 2 of Group 2, in Tr. S, where one participant hits the upper-bound of 1000 and receives the message that his predictions have to be lower than this number. Note that this bound has been implemented for technical reasons, and none of the participants were aware of this bound, unless



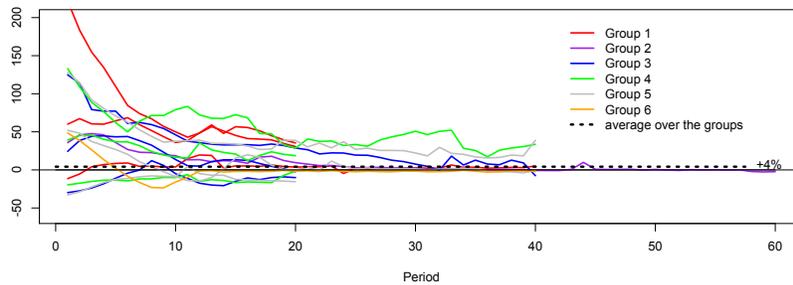
(a) Treatment S: 100% of short-horizon forecasters



(b) Treatment M70: 70% of short-horizon forecasters, 30% of long-horizon forecasters



(c) Treatment M50: 50% of short-horizon forecasters, 50% of long-horizon forecasters



(d) Treatment L: 100% of long-horizon forecasters

Figure 3: Overview of the realized price levels in all experimental markets: the plots report deviations in percentage points from the fundamental value

in terms of chickens and eggs, or (ii) incentives related to the payoff-relevant utility: in the end-of-experiment questionnaire some participants reported attempting to lower the price because they experienced low payoff along a bubble.¹²

In the rest of this section, we explore the differences between treatments and confront these with our theoretical implications and experimental hypotheses. We now formulate five main results in the context of our five hypotheses.

4.2 Cross-treatment comparison

Table 3 reports cross-treatment comparisons of aggregate data. The first rows show significant cross-treatment differences regarding the price deviation (from fundamental), price volatility and, to a lesser extent, forecast dispersion: see Table 3 for definitions of these terms. These differences confirm the visual impression that the horizon of the forecasters matters for price dynamics and convergence towards the REE. The discrepancy between the realized price and the fundamental is strikingly lower in Tr. L than in Tr. S. Moreover, while the discrepancy from the REE is not statistically different between Tr. L and Tr. M50, prices are significantly closer to the fundamental price in those two treatments than in Tr. M70. These difference lead us to reject Hypothesis 1a in favor of Hypothesis 1b:

Finding 1 (Price convergence). *Increasing the share of long-horizon forecasters from zero percent to 30% and also from 30% to 50% significantly reduces price deviation from the REE.*

Turning to Hypothesis 2, we find long-horizon forecasters have a stabilizing influence on prices. The price in Tr. S is significantly more volatile than in all other treatments, while price volatility is not significantly different between Tr. M50 and Tr. L. Those observations yield the following finding, consistent with Hypothesis 2:

Finding 2 (Price volatility). *Increasing the share of long-horizon forecasters from zero percent to 30% and also from 30% to 50% significantly reduces price volatility.*

Our results suggest a *threshold effect* in the share of short-horizon forecasters on price convergence and volatility. A large share of short-horizon forecasters (more than half of the market) is necessary to hinder stabilization and convergence.

they reach it. This bound was reached 25 times out of the 18,170 forecasts elicited across all markets and subjects (which is about 0.1% of all forecasts).

¹²We also note that a high price provides incentives to sell – and therefore to submit a lower prediction than the average of the group – a strategy that was also reported a few times.

	<i>Diff-diff treatments</i>					
	<i>L-S</i>	<i>L-M70</i>	<i>L-M50</i>	<i>M70-S</i>	<i>M50-S</i>	<i>M50-M70</i>
Price deviation^a (p-value)	-0.564 (0.000)	-0.111 (0.000)	0.012 (0.205)	-0.453 (0.000)	-0.576 (0.000)	-0.123 (0.000)
Price volatility^b (p-value)	-2.12 (0.000)	-0.111 (0.000)	-0.029 (0.315)	-2.013 (0.000)	-2.094 (0.000)	-0.082 (0.000)
Trade volume^c (p-value)	0.088 (0.000)	0.061 (0.000)	0.14 (0.000)	0.027 (0.000)	-0.052 (0.000)	-0.079 (0.000)
Forecast dispersion^d (p-value)	0.161 (0.015)	0.08 (0.53)	0.115 (0.047)	0.081 (0.005)	0.046 (0.532)	-0.035 (0.025)
EER (forecasts)^e (p-value)	-0.071 (0.231)	-0.026 (0.924)	-0.083 (0.452)	-0.045 (0.304)	0.012 (0.5)	0.057 (0.622)
EER (utility)^e (p-value)	0.01 (0.984)	-0.003 (0.492)	0.002 (0.614)	0.013 (0.663)	0.008 (0.754)	-0.01 (0.414)

Note: The table reports the differences between treatments, and the associated p-values of the one-sided Wilcoxon rank sum tests. In bold are the significant differences between treatments. K-S tests give the same predictions, except between treatments M70 and S regarding the volatility of the price, in which case the pair-difference becomes insignificant.

^a Average of the absolute price deviation from its fundamental value p_m , over all periods $t \geq 1$ of each market m , computed as $(p_m)^{-1} | p_{m,t} - p_m |$.

^b Relative price standard deviation computed over all periods t of each market m as $\frac{\sqrt{\text{Var}(p_{m,t})}}{\text{mean}(p_{m,t})}$.

^c Sum over all periods t and all markets m of exchanged assets among subjects in proportion of the steady-state endowment q_m , i.e. $\sum_{j=1}^{10} | \frac{q_{j,t} - q_{j,t-1}}{q_m} |$.

^d Relative standard deviation between subjects' forecasts $\frac{\sqrt{\text{Var}(p_{j,t}^e)_{j \in J}}}{\text{mean}(p_{j,t}^e)_{j \in J}}$, $t \geq 1$, averaged over all periods of each market.

^e Earnings Efficiency Ratio (EER) computed over all periods of each market, averaged over the 10 subjects as follows: (i) for the forecasting task, it is the average number of forecasting points earned in each market over the total amount of points possible in the market (1100 per period in case of perfect prediction); (ii) for the consumption task, it is the average number of utility points earned in each market over the total utility points earned at equilibrium (1081 per period).

Table 3: Cross-treatment statistical comparisons

To consider the issue of coordination between participants, we first look at the overall dynamics of the markets over time.¹³ The trade volume significantly decreases in all treat-

¹³A regression per treatment of the trade volume on the period leads to the coefficients -0.433, -0.348, -0.699 and 0.021 for, respectively, Tr. L, M50, M70 and S, with the associated p-values $< 2e - 13$ except for Tr. S with 0.493. Similarly, with the forecast dispersion as a dependent variable, the same estimated coefficients are -0.004, -0.004, -0.005 and 6.185e-05 with the associated p-values of 0.020, 5.4e-06, 0.002 and 0.935.

ments except Tr. S, and similar dynamics are observed for the within-participants forecast dispersion over time. Therefore, in the context of Hypothesis 3, we obtain the following result:

Finding 3 (Eventual coordination). *Participants' forecasts become more homogeneous over time, thus the trade volume decreases over time, except in Tr. S.*

Regarding the differences of participants' degree of coordination between treatments, Table 3 shows that there is some evidence that forecasts are more homogeneous in treatments with short-horizon forecasters than in treatments with long-horizon forecasters. The forecast dispersion is higher in Tr. L than in Tr. S, and higher in Tr. M70 than in Tr. S. Within-horizon coordination can also be compared in the mixed treatments, especially in Tr. M50, where the groups of short-horizon and long-horizon forecasters are of the same size. For instance, in this treatment, looking at the first market of Gp. 4, or at all markets in Gp. 5 and 6, it is clear that short-horizon forecasts are closer to each other than the long-horizon ones (see Figure 10 in Appendix B). This is confirmed by statistical analysis: in this treatment, the average dispersion between short-horizon forecasters is 0.057, versus 0.163 among the long-horizon forecasters, and the difference is significant (p-value $< 2.2e - 16$). Therefore, in line with hypotheses 4 and 5, we find the following:

Finding 4 (Coordination and forecast horizons). *Long-horizon forecasters exhibit greater cross-sectional forecast dispersion than do short-horizon forecasters.*

Also, from the trade-volume and forecast-dispersion rows in Table 3:

Finding 5 (Trade volume and forecast horizons). *The higher the share of long-horizon forecasters in a market, the greater the cross-sectional dispersion of price forecasts and the higher the trade volume.*

These findings align with the survey-data analysis of (Bundick & Hakkio 2015), as well as the experimental work of Haruvy et al. (2007), which is done in non-self-referential environments.

There are two additional considerations of interest that are less directly connected to our hypotheses: first, we consider possible learning effects resulting from repetition; and second, we discuss the implications of performance metrics based on received utility versus forecast accuracy.

The repetition design of our experiment allows us to look for the presence of a *learning effect* in sequential markets with the same group of subjects. Replications of the seminal

Smith et al. (1988) bubble experiment have shown that large deviations from fundamentals disappear if the market is repeated several times with the same participants (Dufwenberg et al. 2005).

Results from our experiment convey the impression that price fluctuations do not decrease with participants' experience: see figures in Appendix B. On the contrary, a bubble can take several markets to arise, and price deviations from fundamental tend to amplify with market repetitions. This is especially the case in Groups 1, 2 and 4 of Tr. S. Deviations from fundamental tend also to increase with market repetition in Gp. 5 of Tr. L.¹⁴ Not only are learning effects absent, in fact our results suggest that volatility in the form of bubbles and crashes persists across markets.

Turning now to the role of performance metrics, we take a final look at Table 3 and consider the earnings of the participants in the experiment in the different treatments. While not directly connected to our hypotheses, incentives are an essential ingredient of theory testing using laboratory experiments. The data from the last two rows of Table 3 reveal that there is no noticeable difference in participants' earnings across treatments, whether based on utility or forecasting. Discussion of this absence of differences across treatments is provided in Evans, Hommes, McGough & Salle (2019).

4.3 Assessing convergence to the REE

We now test formally whether convergence to the fundamental value occurs in the experimental markets. We follow the method presented in Noussair et al. (1995) which consists in estimating the value to which the price would converge asymptotically if a market were extrapolated into the infinite future. As the lengths of our markets differ and most are short due to the stochastic termination rule, this approach appears particularly suited to our experiment.

We estimate the following equation for each of the four treatments separately:

$$\frac{p_{g,m,t} - p_{g,m}}{p_{g,m}} = \frac{1}{t} \sum_{g=1}^6 \sum_{m \in \Omega_{M_g}} D_{g,m} b_{1,g,m} + \frac{t-1}{t} \sum_{g=1}^6 \sum_{m \in \Omega_{M_g}} D_{g,m} b_{2,g,m}, \quad (10)$$

with $p_{g,m,t}$ the realized market price in period t in Group $g \in \{1, \dots, 6\}$ and market m ; Ω_{M_g}

¹⁴Linear regressions of the absolute deviations of prices and forecasts from the REE on the order of the market confirms the absence of convergence along sequential markets. However, we remark that by design, repeated markets had different fundamental prices, which makes it difficult to carry over knowledge from one market to the next.

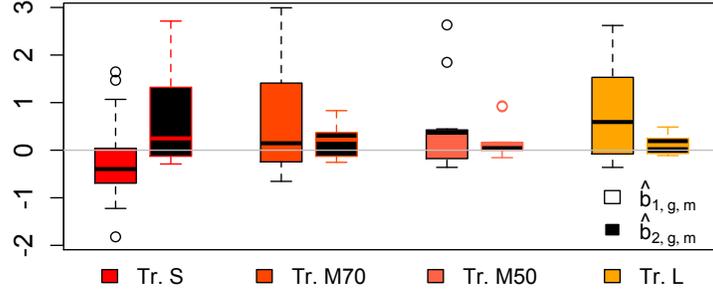


Figure 4: Distribution of estimated initial ($\hat{b}_{1,g,m}$) and final ($\hat{b}_{2,g,m}$) price values in relative deviation from fundamental per treatment

	<i>Market level</i>	
	weak conv: $ \hat{b}_{1,g,m} > \hat{b}_{2,g,m} $	strong conv: $ \hat{b}_{2,g,m} = 0$
Tr. S	7/18 \simeq 39%	3/18 \simeq 17%
Tr. M70	11/18 \simeq 61%	2/18 \simeq 11%
Tr. M50	10/13 \simeq 77%	3/13 \simeq 23%
Tr. L	13/14 \simeq 93%	4/14 \simeq 29%

Note: Number of markets exhibiting weak and strong convergence, as defined in the main text, over the total number of markets in each treatment, and corresponding fractions of converging markets.

Table 4: Fractions of markets exhibiting significant convergence

the number of markets played by Group g ; $D_{g,m}$ a dummy taking the value one if the price comes from Group g and market m and zero otherwise; and $p_{g,m}$ is the fundamental value of the price in Group g and market m .

The estimated coefficients of these regressions provide the fitted initial ($\hat{b}_{1,g,m}$) and asymptotic ($\hat{b}_{2,g,m}$) prices. If $\hat{b}_{2,g,m}$ is not significantly different from zero, we cannot reject the hypothesis of *strong convergence* towards the fundamental, i.e. $b_{2,g,m} = 0$. If $|\hat{b}_{1,g,m}| > |\hat{b}_{2,g,m}|$ holds significantly, the evidence supports *weak convergence* towards the fundamental, i.e. $|b_{1,g,m}| > |b_{2,g,m}|$. The results are collected in Table 4. Figure 4 further reports the distributions of the estimated coefficients per treatment, while the details of the estimations are deferred to Appendix C.

Figure 4 reveals a net decrease in the estimated distances of the price to fundamental

in Tr. M70, M50 and L (compare the paired box plots per treatment).¹⁵ However, such a decrease is not observed in Tr. S. The estimated final distances are particularly concentrated around zero in Tr. L, and even more strikingly in Tr. M50. Econometric analysis shows that weak convergence is obtained in all but one market in Tr. L, and the vast majority of them in Tr. M50. By contrast, fewer than two-thirds of the markets in Tr. M70 exhibit weak convergence, and fewer than one-half of the markets in Tr. S. Results on strong convergence show a similar pattern.

As a complement to Finding 1, we draw from this exercise the following insight:

Finding 6 (Statistical convergence). *Convergence to the REE is more frequently observed when the share of long-horizon forecasters is increased.*

This finding conforms with Hypothesis 1b and Table 4 rejects Hypothesis 1a.

We now examine factors that contribute to the convergence failures observed in Tr. M70 and Tr. S. Initial conditions in a given market may be correlated with terminal conditions in the previous market: see figures in On-line Appendix B. Price patterns, such as systematic mispricing and oscillatory behaviors, sometimes appear to carry over from one market to another even though the information from previous markets is not displayed to participants.

We compute the correlation between the estimated initial price values $\{\hat{b}_{1,g,m}\}$ and the price levels prevailing in the preceding market. This correlation is 0.6644 (p-value 0.0000) when the previous prevailing prices is measured as the average price over the last 10 periods of the previous market, and is 0.3444 (p-value: 0.0057) when measured as simply the last observed price in the preceding market.¹⁶

Equation (10) can also be used to assess the role of the previously observed price levels in convergence failures, by conducting an analysis of the variance of the estimated asymptotic coefficients $\{\hat{b}_{2,g,m}\}$ in terms of three factors: the fundamental value; the price in period one; and the last price in the previous market.¹⁷ Results, reported in Figure 5, reveal

¹⁵A box plot illustrates a distribution by reporting the four quartiles, with the thick line being the median, and the two whiskers being respectively Q1 and Q4 within the lower limit of $Q1 - 1.5(Q3 - Q1)$ and the upper limit of $Q3 + 1.5(Q3 - Q1)$. Outside that range, data points, if any, are outliers and represented by the dots. In the figure, each pair of box plots represents a treatment. The first box plot of each pair gives the distribution of the estimated initial values $\hat{b}_{1,g,m}$, the second one the estimated asymptotic values $\hat{b}_{2,g,m}$ in (10). The zero line represents convergence to fundamental.

¹⁶For the first markets, we took 50 as the previous value because it corresponds to the middle point of the empty price plot that the participants observe before entering their first forecast; see the screen shots, On-line Appendix, Figure 8. Removing the first markets results in fewer data points, but the correlation pattern persists.

¹⁷The variance decomposition was done using the Fourier amplitude sensitivity test.

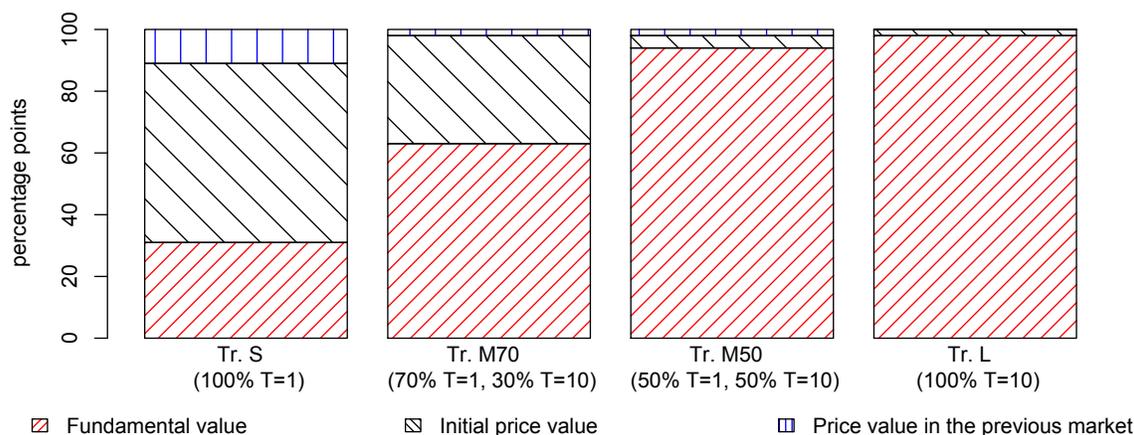


Figure 5: Contribution to the variance of the estimated final values $\hat{b}_{2,g,m}$

a striking feature of the experiment: the asymptotic price values are almost entirely driven by the fundamental values in Tr. L and M50, while initial price levels and previously realized prices explain a considerable amount of the asymptotic price values in Tr. M70, and an even larger amount in Tr. S. This analysis confirms the dynamics reported in Table 4, and sheds further light on Hypotheses 1a and 1b: coordination of subjects' forecasts on an incorrect anchor, namely past observed prices, is responsible for the lack of convergence observed in Tr. M70 and Tr. S and, hence, the rejection of Hypothesis 1a.

Finding 7 (Fundamental and non-fundamental factors).

- (i) *When the share of long-horizon forecasters is large enough, the asymptotic market price is driven by fundamentals only.*
- (ii) *If short-horizon forecasters dominate, the asymptotic market price is partly driven by non-fundamental factors, in particular past observed price levels.*

To shed some light on the causal mechanisms behind those results, we now seek to understand how the participants formed their price forecasts and how those individual behaviors connect to the observed market prices in the experiment.

4.4 Participants' forecasts and aggregate outcomes

At the end of the experiment, participants were asked to describe in a few words their strategies. Analysis of the answers makes clear that the vast majority of participants, aside

from strategic deviations for trading purposes, made use of past prices. The observation that expectations about future market prices depend on past trends has also found wide support in the experimental literature – see the early evidence reported in Smith et al. (1988) and Andreassen & Kraus (1990), and more recent evidence found in Haruvy et al. (2007); see also the empirical literature, starting from early contributions such as Shiller (1990).

To estimate the dependence of participants’ forecasts on past data, we begin with the following class of simple, yet flexible, agent-specific forecasting models:

$$p_{j,t}^e = \beta_0 + \beta_1 p_{t-1} + \beta_2 p_{t-2} + \delta_1 p_{j,t-1}^e. \quad (11)$$

This class extends the constant gain implementation of equation (9) to include models conditioning on p_{t-2} . Clearly, participants could have paid attention to even more lags of the observable variables – a few reported to have done so – but most referred to at most the last two of prices in their strategy. Of course, including lagged expectations is an indirect way of accounting for the influence of additional lags of prices.¹⁸

We focus on the following three special cases of the forecasting model (11):

Naive expectations:	$\beta_0 = \beta_2 = \delta_1 = 0$ and $\beta_1 = 1$
Adaptive expectations:	$\beta_0 = \beta_2 = 0$, $\beta_1 \in (0, 1)$, and $\beta_1 + \delta_1 = 1$
Trend-chasing expectations:	$\beta_0 = \delta_1 = 0$, $\beta_1 > 1$, and $\beta_1 + \beta_2 = 1$

Under naive expectations, $p_{j,t}^e = p_{t-1}$. Although we label this “naive,” these are the optimal forecasts if the price process follows a random walk, and naive expectations are therefore “nearly rational” when prices follow a near-unit root process. We note that naive expectations corresponds to constant-gain adaptive learning with $\gamma = 1$: see Section 2.3. Under adaptive expectations, agents forecast as

$$p_{j,t}^e = p_{j,t-1}^e + \beta_1 (p_{t-1} - p_{j,t-1}^e). \quad (12)$$

This rule, which corresponds to the constant-gain adaptive learning rule of Section 2.3 with $0 < \gamma < 1$, is known to be optimal if the price process is the sum of a random walk component and a white noise component, i.e. a mixture of permanent and transitory shocks: see Muth (1961).

¹⁸In principle, this forecasting model could generate negative price forecasts, in which case it would be natural for agents to impose a non-negativity condition.

Under trend-chasing expectations, agents forecast as

$$p_{j,t}^e = p_{t-1} + \phi (p_{t-1} - p_{t-2}), \text{ where } \phi = \beta_1 - 1 > 0. \quad (13)$$

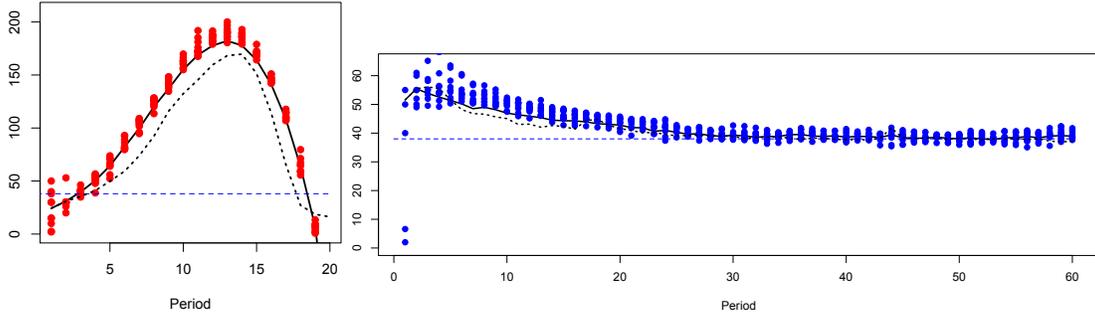
This rule performs well in bubble-like environments in which price changes are persistent. In fact, this forecasting rule is optimal if the first difference in prices follows a stationary AR(1) process. Intuitively, agents are forecasting based on the assumption that the proportion ϕ of last period's price change will continue into the future. Finally, we note that (13) can lead to stable cyclical price dynamics.

We focus on the class of simple rules (11) for parsimony and because they nest the special cases that are salient in the literature. However, it is important to note that adaptive learning is much more general, both in terms of included regressors and in allowing parameters to evolve over time as new data become available.

Figure 6 illustrates the potential for these simple forecasting rules to explain the price data in five different experimental markets: see graphs (a) to (e). The dashed horizontal line is the fundamental price and the dotted line is the realized price in the experimental market. Dots correspond to simulated price forecasts and the solid line gives the implied, simulated market prices. To construct the simulated price forecasts, a parametric specification of a particular forecasting model is chosen, and, for each agent, is initialized using their forecasts in the first two periods of the experiment. In each subsequent period, agents' forecasts are determined using the forecasting model and previously determined simulated prices, to which a small, idiosyncratic white noise shock is added. Note that the lines identifying the simulated and experimental price time series are close to each other. Figure 6 also highlights the systematic differences between treatments and horizons in belief formation and links them to the observed price patterns.

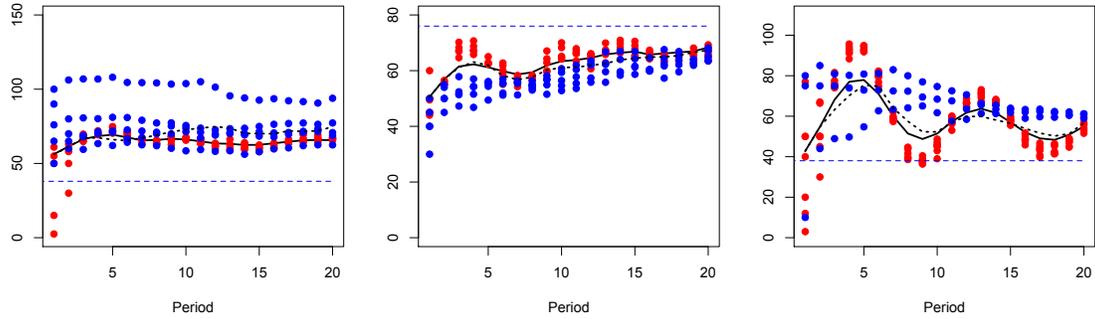
Graph (a) provides an example of trend-chasing behavior that emerged from treatment S. The simulated data are based on setting $\phi = \beta_1 - 1 = 0.3$. This market strikingly illustrates the possibility of a bubble and crash being generated by trend-chasing forecast rules. Graph (b) gives an example of adaptive expectations associated to treatment L, with parameterization is $\beta_1 = 0.7$ and $\delta_1 = 0.3$, illustrating apparent convergence to the fundamental price.

Graphs (c) and (d) correspond to results from treatment M50, in which the short-horizon forecasters are naive and trend-following, respectively, and the long-horizon forecasters form expectations adaptively. The simulated price paths depend on the individual-



(a) Bubble and crash with trend-chasing forecasting

(b) Convergence with adaptive learners



(c) Overpricing with myopic and adaptive learners

(d) Underpricing with trend-chasing and adaptive learners

(e) Overpricing with oscillations with trend-chasing and adaptive learners

Note: The blue dashed line is the fundamental price, the dotted lines represent the prices in the experimental markets, the dots and the solid lines are the simulated forecasts and prices. The forecasts in the first two periods are taken from the experiment. An idiosyncratic shock distributed as $\mathcal{N}(0, 2)$ is added then in each subsequent period to the forecasts. Fig. (a): Tr. S, Gp. 1, Market 1, trend-chasing forecasting model with $\beta_1 = 1.3$ (see Eq. (11) below); Fig. (b): Tr. L, Gp. 2, Market 1, convergence with adaptive learning, $\delta_1 = 0.3$; Fig. (c): Tr. M50, Gp. 6, Market 1, overpricing with static short-horizon forecasters ($\beta_1 = 1$) and adaptive long-horizon forecasters ($\delta_1 = 0.1$); Fig. (d): Tr. M50, Gp. 1, Market 2, trend-chasing short-horizon forecasters ($\beta_1 = 1.3$) and adaptive long-horizon forecasters ($\delta_1 = 0.1$); Fig. (e): Tr. M70, Gp. 6, Market 1, trend-chasing short-horizon forecasters ($\beta_1 = 1.75$), adaptive long-horizon forecasters ($\delta_1 = 0.1$).

Figure 6: Simulated versus experimental time series for selected price patterns

specific initial forecasts in each market, which is a significant factor in the different dynamics exhibited. Graph (c) exhibits persistent departures from fundamentals, while in graph (d) the short-horizon trend-chasers generate cyclic dynamics as well as apparent convergence. Finally, graph (e) corresponds to M70 with short-horizon trend-chasing forecasters and with long-horizon forecasters forming expectations adaptively. Here the cyclicality arising from the trend-followers is even more pronounced, while the presence of only 30% long-horizon types appears insufficient to impart convergence.

Using step-by-step elimination, we examined individual participant-level forecast data, pooled across markets, and looked for simplifications of the model (11) in an attempt to determine if, and to what extent, participants used one of the three simple rules listed above, and whether there exist systematic differences in forecasting behaviors across horizons. We found, considering all 240 participant forecast series,¹⁹ that more than half the short-horizon participants had forecasts consistent with trend-chasing rules, and more than a third of the long-horizon participants had forecasts consistent with adaptive expectations.²⁰

The estimated coefficients $\hat{\beta}_0, \hat{\beta}_1, \hat{\beta}_2$ and $\hat{\delta}_1$ from (11) for each participant are illustrated in Figure 7: smaller, solid triangles identify long-horizon forecasters and larger triangles identify short-horizon forecasters.²¹ Panel 7a shows a scatterplot of the components $\hat{\beta}_1$ and $\hat{\beta}_2$ for each participant. Under the restrictions $\hat{\beta}_0 = \hat{\delta}_1 = 0$ and $\hat{\beta}_1 > 1$, the trend-chasing model aligns with the constellation of points on the part of the downward-sloping dashed line that lies within the shaded region. Clearly, there are striking differences in the behaviors of participants tasked with short-horizon versus long-horizon forecasting.

A substantial number of the short-horizon points in panel 7a lie on, or close to, the trend-chasing constellation. The trend-chasing restrictions cannot be rejected for 56% of the short-horizon forecasters. Panel 7b shows the corresponding scatterplot of the components $\hat{\beta}_1$ and $\hat{\delta}_1$. Under the assumptions that $\hat{\beta}_0 = \hat{\beta}_2 = 0$ and $0 < \hat{\beta}_1 < 1$, the adaptive-expectations model aligns with the constellation of points on the part of the downward-sloping dashed line that lies within the shaded region in panel 7b.²² In contrast with the behavior exhibited by short-horizon forecasters, a substantial number of the long-horizon points in panel 7b lie on, or close to, the adaptive-expectations constellation. The adaptive-expectations restrictions cannot be rejected for more than one-third of the participants in long-horizon treatments. We summarize these findings as follows:

Finding 8 (Individual forecast behaviors). *Short-horizon and long-horizon forecasters display different forecasting behaviors:*

(i) *More than one-half of the short-horizon forecasters form forecasts consistent with*

¹⁹The experiments included 18 treatment S, 14 treatment L, 18 treatment M70, and 13 treatment M50 markets, with 10 participants in each market, giving 630 market-participant forecast series.

²⁰For 212 of 240 participants, the step-by-step elimination process leads to a forecasting model in which at least one variable other than the intercept is significant. Also, the average R^2 is high for each treatment (ranging from an average of 0.884 in Tr. L to 0.962 in Tr. M50), which confirms the ability of the simple class of rules (11) to capture the main features of participants' behavior.

²¹A few of the participants' estimated coefficients lie outside the ranges chosen for Figure 7.

²²We note that naive expectations corresponds to limiting cases (i.e. $\hat{\beta}_1 \rightarrow 1$) of both trend-chasing and adaptive-expectations forecasting models.

trend-chasing behavior.

(ii) *More than one-third of the long-horizon forecasters form forecasts consistent with adaptive expectations.*

These results align with Hypothesis 1b, in the sense that distinct forecasting behaviors across horizons imply differences in price patterns. Trend-chasing behavior tends to preclude, and adaptive expectations tend to impart convergence to REE. Finding 8 also suggests greater forecast-model heterogeneity in long-horizon treatments, which provides some support to Hypothesis 4.

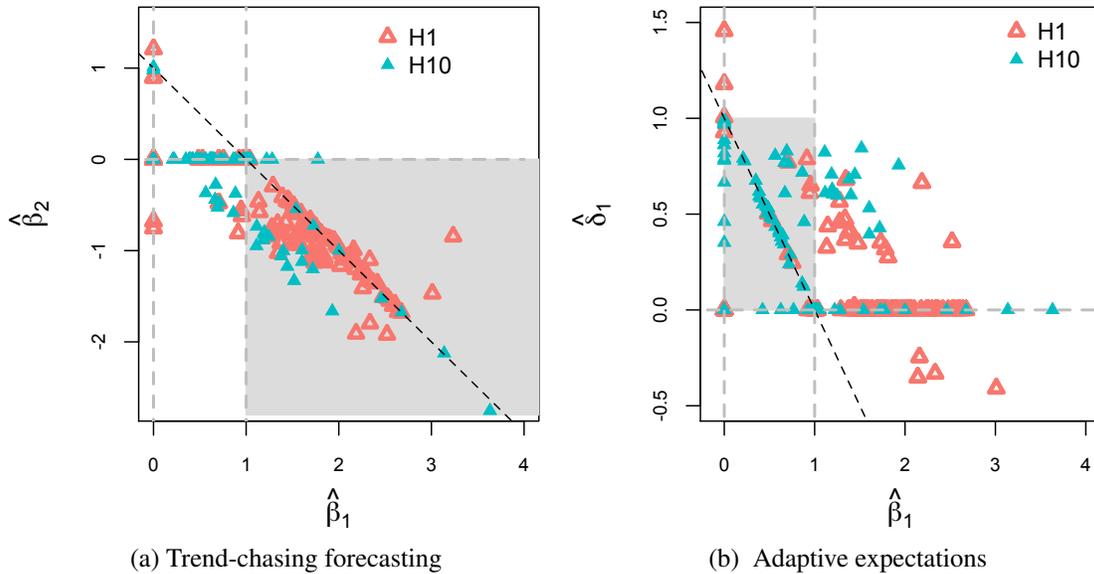


Figure 7: Distribution of the estimated coefficients of Equation (11) for the 240 subjects

The plots in Figure 7 include estimates that do not appear, even after accounting for statistical significance, to align with any of the special cases identified above. There are several possible explanations. First, it is possible that some subjects use less parsimonious forecasting rules than are captured by the class (11). Second, given that most subjects participated in multiple markets, it is quite possible that some of these participants used different rules in different markets. Our pooling estimation strategy does not account for this. Third, in general, under the adaptive learning approach, in addition to the intercept, the other coefficients in the subjects' forecasting rules may evolve over time to reflect recent patterns of the data. Finally, we note that if ξ is near one, then *any* collective forecast of

the deviation of price from fundamentals is nearly self-fulfilling; this point is particularly relevant for treatment S .

Finding 8 sheds further light on the reasons behind the observed treatment differences. Admittedly, our data cannot formally disentangle the impact of the feedback parameter ξ from the role of distinct expectation formation mechanisms on price dynamics. Yet, even in treatments with mixed horizons, it is clear that subjects systematically used distinct rules to forecast over short and long horizons. Hence, behavioral differences across horizons do contribute to the observed treatments differences.

In summary, longer forecast horizons induce lower expectation feedback and long-horizon treatments are empirically associated with adaptive expectations; both of these features induce price stability and more frequent convergence to the fundamental price. By contrast, shorter forecast horizons result in higher expectation feedback and short-horizon treatments are empirically associated with trend-chasing behavior; both of these features lead to persistent departures from the fundamental price.

5 Conclusions

We have investigated the impact of forecast horizons on price dynamics in a self-referential asset market. To do this, we developed a model with boundedly rational agents and heterogeneous planning horizons, and derived theoretical predictions for the effects of the planning horizon on the dynamic and asymptotic behavior of market price. We then tested our predictions by implementing our asset market in a lab experiment, eliciting price forecasts at different horizons from human subjects and trading accordingly.

The central finding of this paper is that price dynamics in our model are governed by the forecast horizons of agents. This finding was first demonstrated analytically in a simple asset-pricing model, and then tested in a laboratory experiment. Our experimental design, which holds everything fixed except for the proportions of long-horizon and short-horizon subjects, finds dramatically different pricing patterns in the different treatments.

Markets populated by only short-horizon forecasters fail to converge to the REE, and typically exhibit systematic mispricing, i.e. large and prolonged deviations from fundamentals. These price patterns stand in contradiction to rational expectations. By contrast, in line with our theoretical predictions, we find that even a relatively modest share of long-horizon forecasters is sufficient to induce convergence toward the REE.

We emphasize that, in our design, payoffs are determined in part by discounted consumption utility, as reflected in our forecast-based trading mechanism. By design, this eliminates incentives to obtain capital gains arising from speculation about future crowd behavior, which is the focus of models like (De Long et al. 1990). Also, because dividends are (and are known to be) constant, our design rules out the possibility that heterogeneous beliefs about future dividends cause price deviations from fundamentals. Nor do fluctuations arise from confusion about how the market works, as the vast majority of participants reported to understand their experimental task. Finally, we can exclude the role of liquidity in mispricing, as this is kept constant across all treatments and markets.

Instead, our central experimental finding that even a modest proportion of long-horizon subjects tends to guide the economy to the REE can be related both to the magnitude of the model's expectational feedback and to the systematic different forecasting behaviors identified over short and long horizons. Trend-chasing behavior is widely observed among short-horizon forecasters while adaptive expectations better describes long-run predictions. Hence, long-horizon forecasts induce greater stability of the REE; whereas coordination of forecasts on trend-following beliefs, and anchoring of individual expectations on non-fundamental factors, are largely responsible for mispricing in short-horizon markets. Instability of this type has been noted in the adaptive learning literature. Our experiment shows that this theoretical outcome constitutes an empirical concern as well.

We emphasize that while several previous experimental studies eliciting only one-step-ahead forecasts have reported similar coordination failures, our experimental design eliminated several dimensions present in these previous studies that may have contributed to their findings: our study employs a framing that does not use the vocabulary of speculative asset markets; we emulate a stationary and infinite environment that induces discounting with a stochastic ending after which the value of the asset drops to zero; and our payoff scheme incentivizes participants to smooth consumption. Despite these features, we obtain systematic mispricing when only short-horizon subjects are present, which implies an expectational feedback parameter close to one. Most importantly, we identify systematic variations in the behaviors of short-horizon and long-horizon forecasters that are consistent with the distinct price patterns across horizons.

The convergence in long-horizon markets occurs despite the higher cognitive load associated with long-horizon forecasts. This finding is not obvious, because long-horizon forecasting is more challenging than short-horizon forecasting: participants have to average over a given number of future periods; further, the observability of the forecast errors

and the resulting feedback from the experimental environment is delayed to the end of the forecast horizon, when the average price is realized. Long-horizon forecasters also display more disagreements among each other due a greater uncertainty. Despite these obstacles, their presence stabilizes the market.

An interesting insight from our findings is that heterogeneity in behavior need not be detrimental to market stabilization. In our setup, when short-horizon agents are present, introducing long-horizon agents contributes to breaking the coordination of participants' beliefs on non-fundamental factors.

A second interesting insight from our study is that the type of forecast rule used by a given subject depends on the planning horizon exogenously imposed on them. This suggests that boundedly rational agents should not be viewed as characterized by invariant behavioral types.

Finally, we note that our study conveys implications for macro-finance models with heterogeneous, boundedly rational agents. Our findings that agents' decision horizons play a central role in the determination of asset prices clearly suggest that the forecasting horizon of agents must be taken into account when assessing economic models and designing policy.

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On-line Appendix

A Finite-horizon learning in the Lucas model

Section A of this appendix provides further details on the technical results found in Section 2, and includes the proofs of the propositions and corollaries.

A.1 Technical details of Section 2.2

In this section we begin by establishing Proposition 1, and then we turn to developing further the corresponding intuition that was summarized in the main text.

Proof of Proposition 1. Without loss of generality, let $t = 0$. Let $Q_k = p_k q_k$, and $R_k = p_{k-1}^{-1}(p_k + y_k)$, so that $c_k + Q_k = R_k Q_{k-1}$. The associated first-order condition (FOC) is $u'(c_k) = \beta R_{k+1} u'(c_{k+1})$. Linearizing the FOC and iterating gives

$$\begin{aligned} dc_k &= dc_{k-1} + \frac{(1-\beta)Q}{\sigma} dR_k, \text{ or} \\ dc_k &= dc_0 + \frac{(1-\beta)Q}{\sigma} \sum_{m=1}^k dR_m. \end{aligned} \quad (14)$$

Linearizing $c_k + Q_k = R_k Q_{k-1}$ and iterating gives

$$\begin{aligned} dc_k &= RdQ_{k-1} - dQ_k + QdR_k, \text{ or} \\ \sum_{k=0}^T \beta^k dc_k &= RdQ_{-1} - \beta^T dQ_T + Q \sum_{k=0}^T \beta^k dR_k, \end{aligned} \quad (15)$$

where $R = \beta^{-1}$. Combining (14) and (15), we get

$$\sum_{k=0}^T \beta^k \left(dc_0 + \frac{(1-\beta)Q}{\sigma} \sum_{m=1}^k dR_m \right) = RdQ_{-1} - \beta^T dQ_T + Q \sum_{k=0}^T \beta^k dR_k,$$

or

$$\left(\frac{1-\beta^{T+1}}{1-\beta} \right) dc_0 = RdQ_{-1} - \beta^T dQ_T + Q \sum_{k=0}^T \beta^k dR_k - \frac{(1-\beta)Q}{\sigma} \sum_{k=0}^T \beta^k \sum_{m=1}^k dR_m.$$

Now notice

$$\sum_{k=0}^T \beta^k \sum_{m=1}^k dR_m = \sum_{k=1}^T \left(\frac{\beta^k - \beta^{T+1}}{1 - \beta} \right) dR_k.$$

It follows that

$$dc_0 = \frac{1 - \beta}{1 - \beta^{T+1}} \left(RdQ_{-1} - \beta^T dQ_T + QdR_0 + \frac{Q}{\sigma} \sum_{k=1}^T \psi(k, T) dR_k \right), \quad (16)$$

where $\psi(k, T) = \beta^k(\sigma - 1) + \beta^{T+1}$.

The linearized flow constraint provides

$$dQ_0 = RdQ_{-1} + QdR_0 - dc_0.$$

Combine with 16 to get

$$\begin{aligned} dQ_0 &= R \left(\frac{\beta(1 - \beta^T)}{1 - \beta^{T+1}} \right) dQ_{-1} + Q \left(\frac{\beta(1 - \beta^T)}{1 - \beta^{T+1}} \right) dR_0 \\ &\quad + \left(\frac{\beta^T(1 - \beta)}{1 - \beta^{T+1}} \right) dQ_T - \left(\frac{1 - \beta}{1 - \beta^{T+1}} \right) \left(\frac{Q}{\sigma} \right) \sum_{k=1}^T \psi(k, T) dR_k, \end{aligned}$$

or

$$dQ_0 = \phi_0(T) dQ_{-1} + \phi_1(T) dR_0 + \phi_2(T) dQ_T + \phi_3(T) \sum_{k=1}^T \psi(k, T) dR_k.$$

Next, linearize the relationship between prices, dividends and returns:

$$dR_k = \frac{1}{p} (dp_k + dy_k - Rdp_{k-1}).$$

Since $\beta R = 1$, we may compute

$$\begin{aligned} \sum_{k=1}^T \beta^k (dp_k - Rdp_{k-1}) &= \beta^T dp_T - dp_0 \\ \sum_{k=1}^T (dp_k - Rdp_{k-1}) &= dp_T - Rdp_0 - R(1 - \beta) \sum_{k=1}^{T-1} dp_k. \end{aligned}$$

It follows that $\sum_{k=1}^T \psi(k, T) dR_k$

$$\begin{aligned}
&= \frac{1}{p} \sum_{k=1}^T \psi(k, T) dy_k + \frac{\sigma-1}{p} \sum_{k=1}^T \beta^k (dp_k - R dp_{k-1}) + \frac{\beta^{T+1}}{p} \sum_{k=1}^T (dp_k - R dp_{k-1}) \\
&= \frac{1}{p} \sum_{k=1}^T \psi(k, T) dy_k + \frac{\sigma-1}{p} (\beta^T dp_T - dp_0) + \frac{\beta^{T+1}}{p} \left(dp_T - R dp_0 - R(1-\beta) \sum_{k=1}^{T-1} dp_k \right) \\
&= \frac{1}{p} \sum_{k=1}^T \psi(k, T) dy_k + \frac{\beta^T}{p} (\sigma-1+\beta) dp_T - \frac{1}{p} (\sigma-1+\beta^T) dp_0 - \frac{\beta^T(1-\beta)}{p} \sum_{k=1}^{T-1} dp_k.
\end{aligned}$$

Finally, assuming dividends are constant, and using these computations, together with $dQ_k = pdq_k + qdp_k$, we may write the demand for trees as

$$dq_0 = \theta_0(T) dq_{-1} + \theta_*(T) dp_{-1} + \theta_1(T) dp_0 + \theta_2(T) dq_T + \theta_3(T) \sum_{k=1}^{T-1} dp_k + \theta_4(T) dp_T,$$

where

$$\begin{aligned}
\theta_0(T) &= \phi_0(T) &= R \left(\frac{\beta(1-\beta^T)}{1-\beta^{T+1}} \right) \\
\theta_*(T) &= \frac{\phi_0(T)q}{p} - \frac{\phi_1(T)}{\beta p^2} &= 0 \\
\theta_1(T) &= -\frac{q}{p} + \frac{\phi_1(T)}{p^2} - \frac{\phi_3(T)}{p^2} (\sigma-1+\beta^T) &= -\frac{(1-\beta)q}{(1-\beta^{T+1})p\sigma} (1-\beta^T) \\
\theta_2(T) &= \phi_2(T) &= \frac{(1-\beta)\beta^T}{1-\beta^{T+1}} \\
\theta_3(T) &= -\frac{(1-\beta)\beta^T}{p^2} \phi_3(T) &= \frac{(1-\beta)^2\beta^T}{1-\beta^{T+1}} \frac{q}{p\sigma} \\
\theta_4(T) &= \phi_2(T) \frac{q}{p} + \frac{\phi_3(T)}{p^2} ((\sigma-1)\beta^T + \beta^{T+1}) &= \theta_3(T)
\end{aligned}$$

The result follows. ■

Intuition for Proposition 1. We begin with a distinct short proof that when $dp_0 = 0$, time zero consumption demand, dc_0 , depends only on the sum of future prices. To this end, set

$dq_{-1} = dp_0 = 0$, and let dq_t be given. The linearized budget constraints yield

$$\begin{aligned}
dc_0 + pdq_0 + qdp_0 &= (p+y)dq_{-1} + qdp_0, & \text{or } dc_0 &= -pdq_0 \\
dc_1 + pdq_1 + qdp_1 &= (p+y)dq_0 + qdp_1, & \text{or } \beta dc_1 &= pdq_0 - \beta pdq_1 \\
dc_2 + pdq_2 + qdp_2 &= (p+y)dq_1 + qdp_2, & \text{or } \beta^2 dc_2 &= pdq_1 - \beta^2 pdq_2 \\
&\vdots & & \vdots \\
dc_t + pdq_t + qdp_t &= (p+y)dq_{t-1} + qdp_t, & \text{or } \beta^t dc_t &= pdq_{t-1} - \beta^t pdq_t.
\end{aligned}$$

Summing, we obtain

$$\sum_{n=0}^t \beta^n dc_n = -\beta^t pdq_t. \quad (17)$$

The agent's FOC may be written $p_n u'(c_n) = \beta(p_{n+1} + y)u'(c_{n+1})$, which linearizes as

$$dc_{n+1} = dc_n + \psi(\beta dp_{n+1} - dp_n) \equiv dc_n + \psi \Delta p_{n+1},$$

where $\psi = (\sigma\beta)^{-1}q(1-\beta)$ and $\Delta p_{n+1} \equiv \beta dp_{n+1} - dp_n$. Backward iteration yields $dc_n = dc_0 + \psi \sum_{m=1}^n \Delta p_m$, which may be imposed into (17) to obtain

$$\sum_{n=0}^t \beta^n dc_0 + \psi \sum_{n=1}^t \beta^n \sum_{m=1}^n \Delta p_m = -\beta^t pdq_t. \quad (18)$$

Now a simple claim:

Claim. $\sum_{n=1}^t \beta^n \sum_{m=1}^n \Delta p_m = \beta^{t+1} \sum_{n=1}^t dp_n$.

The argument is by induction. For $t = 1$, use $dp_0 = 0$ to get the equality. Now assume it holds for $t - 1$. Then

$$\begin{aligned}
\sum_{n=1}^t \beta^n \sum_{m=1}^n \Delta p_m &= \sum_{n=1}^{t-1} \beta^n \sum_{m=1}^n \Delta p_m + \beta^t \sum_{m=1}^t \Delta p_m \\
&= \beta^t \sum_{n=1}^{t-1} dp_n + \beta^t \sum_{m=1}^t \Delta p_m \\
&= \beta^t \sum_{n=1}^{t-1} dp_n + \beta^t \sum_{m=1}^t \beta dp_m - \beta^t \sum_{m=1}^t dp_{m-1} = \beta^{t+1} \sum_{m=1}^t \beta dp_m,
\end{aligned}$$

where the second equality applies the induction hypothesis.

Combining this claim with equation (18) demonstrates that when $dp_0 = 0$, time zero con-

sumption demand, dc_0 , depends only on $\sum_{n=1}^t dp_n$, completing our short proof.

We turn now to intuition for Proposition 1 by establishing that $\partial dc_0 / \partial dp_m$ is independent of m for $1 \leq m \leq T$. First, as noted in the body, to first order we have $dR_k = (\beta p)^{-1}(\beta dp_k - dp_{k-1})$. It follows that

$$\frac{\partial dR_k}{\partial dp_m} = \begin{cases} p^{-1} dp_m & \text{if } k = m \\ -(\beta p)^{-1} dp_m & \text{if } k = m + 1 \\ 0 & \text{otherwise} \end{cases}$$

Thus for $m < T$ we have $\partial / \partial dp_m \sum_{k=0}^T \beta^k dR_k = 0$, and we note that this computation holds for $T = \infty$.

Next, recall it was assumed that $dq_{-1} = dp_{-1} = 0$. It follows that $R_0 Q_{-1}$ linearizes as $q dp_0$. Thus we may write equation (15) as

$$\sum_{k=0}^T \beta^k dc_k = q dp_0 - \beta^T p dq_T - \beta^T q dp_T + Q \sum_{k=0}^T \beta^k dR_k. \quad (19)$$

Next, we claim that

$$dc_0 = \frac{1-\beta}{1-\beta^{T+1}} \left(q dp_0 - \beta^T p dq_T - \beta^T q dp_T + \frac{Q(\sigma-1)}{\sigma} \sum_{k=1}^T \beta^k dR_k + \frac{Q}{\sigma} \beta^{T+1} \sum_{k=1}^T dR_k \right). \quad (20)$$

To see this, combine (14) and (19) to get

$$\sum_{k=0}^T \beta^k \left(dc_0 + \frac{(1-\beta)Q}{\sigma} \sum_{m=1}^k dR_m \right) = q_{-1} dp_0 - \beta^T dQ_T + Q \sum_{k=1}^T \beta^k dR_k,$$

or

$$\left(\frac{1-\beta^{T+1}}{1-\beta} \right) dc_0 = q dp_0 - \beta^T dQ_T + Q \sum_{k=1}^T \beta^k dR_k - \frac{(1-\beta)Q}{\sigma} \sum_{k=1}^T \beta^k \sum_{m=1}^k dR_m.$$

Now notice

$$\sum_{k=1}^T \beta^k \sum_{m=1}^k dR_m = \sum_{k=1}^T \left(\frac{\beta^k - \beta^{T+1}}{1-\beta} \right) dR_k,$$

from which equation (20) follows. Using (20), we find

$$\frac{\partial dc_0}{\partial dp_T} = -\beta^T q + \frac{Q(\sigma-1)}{\sigma p} \beta^T + \frac{Q}{\sigma p} \beta^{T+1} = \beta^T \frac{Q}{\sigma p} (\beta - 1). \quad (21)$$

For $1 \leq m < T$, and noting our above result that $\partial/\partial dp_m \sum_{k=1}^T \beta^k dR_k = 0$, we may use equation (20) to compute

$$\frac{\partial dc_0}{\partial dp_m} = \frac{\partial}{\partial dp_m} \frac{Q}{\sigma} \beta^{T+1} \sum_{k=1}^T dR_k = \beta^T \frac{Q}{\sigma p} (\beta - 1),$$

which is exactly the same value as was computed for $\partial dc_0/\partial dp_T$ in equation (21). It follows that $\partial dc_0/\partial dp_m$ is independent of m for $1 \leq m \leq T$, whence the average expected price path is a sufficient statistic for the determination of dc_0 , and hence for asset demand dq_0 .

A.2 Technical details of Section 2.3

In this section, we couple Proposition 1 with our assumption that each agent's expected wealth target depends on her current wealth, given by the parsimonious forecast rule $dq_{t+T}^e = dq_{t-1}$. We analyze the behavior of demand, planned consumption, chicken holdings and equilibrium prices under this additional assumption.

A.2.1 Individual demand schedule

Without loss of generality, assume homogeneous planning horizons and omit index i . Denote the expected average price over the next T periods by $d\bar{p}_t^e(T)$:

$$d\bar{p}_t^e(T) \equiv \frac{1}{T} \sum_{k=1}^T dp_{t+k}^e.$$

Then demand of the agent may be written

$$\begin{aligned} dq_t &= dq_{t-1} - \phi g(T) dp_t + \phi h(T) d\bar{p}_t^e(T) \\ dc_t &= ydq_{t-1} + p\phi g(T) dp_t - p\phi h(T) d\bar{p}_t^e(T), \end{aligned}$$

where

$$\phi = \frac{(1-\beta)q}{p\sigma}, \quad g(T) = \frac{1-\beta^T}{1-\beta^{T+1}}, \quad \text{and} \quad h(T) = \frac{(1-\beta)T\beta^T}{1-\beta^{T+1}}.$$

It follows that the agent's demand for chickens is decreasing in current price and increasing in expected average price.

We now consider the agent's time t plan for holding chickens over the planning period

t to $t + T$. Assuming that, at time t , the agent believes that her expected average price over the time period $t + k$ to $t + T$ will be $dp_t^e(T)$ for each $k \in \{1, \dots, T - 1\}$, we may compute the plans for chicken holdings as

$$dq_{t+k} = dq_{t+k-1} - \phi(g(T-k) - h(T-k))d\bar{p}_t^e(T).$$

Letting $\Delta_T(j) = g(T-j) - h(T-j)$, it follows that

$$dq_{t+k} = dq_{t-1} - \phi g(T)dp_t + \phi h(T)d\bar{p}_t^e(T) - \phi \left(\sum_{j=1}^k \Delta_T(j) \right) d\bar{p}_t^e(T) \quad (22)$$

$$\begin{aligned} dc_{t+k} &= ydq_{t-1} - y\phi g(T)dp_t + y\phi h(T)d\bar{p}_t^e(T) \\ &\quad - \phi y \left(\sum_{j=1}^{k-1} \Delta_T(j) \right) d\bar{p}_t^e(T) + p\phi \Delta_T(k)d\bar{p}_t^e(T). \end{aligned} \quad (23)$$

Written differently, we have

$$\Delta dq_t = -\phi(g(T)dp_t - h(T)d\bar{p}_t^e(T)) \quad (24)$$

$$\Delta dq_{t+k} = -\phi \Delta_T(k)d\bar{p}_t^e(T). \quad (25)$$

The formulae identifying the changes in consumption are less revealing.

Now observe that $\Delta_T(k) > 0$. Indeed, letting $n = T - k$, we have

$$\begin{aligned} \Delta_T(k) &= \frac{1 - \beta^n - (1 - \beta)n\beta^n}{1 - \beta^{n+1}} = (1 - \beta) \left(\frac{\frac{1 - \beta^n}{1 - \beta} - n\beta^n}{1 - \beta^{n+1}} \right) \\ &= (1 - \beta) \left(\frac{\sum_{i=0}^{n-1} \beta^i - n\beta^n}{1 - \beta^{n+1}} \right) = (1 - \beta) \left(\frac{\sum_{i=0}^{n-1} (\beta^i - \beta^n)}{1 - \beta^{n+1}} \right) > 0. \end{aligned}$$

We may now consider the following thought experiments. Here we assume all variables are at steady state (i.e. zero in differential form) unless otherwise stated. All references to periods $t + k$ concern “plans,” not realizations, and it is assumed that $k \in \{1, \dots, T - 1\}$.

1. **A rise in price.** If $dp_t > 0$, then by equations (24) and (25) chicken holdings are reduced in time t by $-\phi g(T)dp_t$ and the reduction is maintained throughout the period. Consumption rises in period t by $p\phi g(T)dp_t$ and is reduced in subsequent periods by $y\phi g(T)dp_t$. Intuitively, the rise in price today, together with change in expected future prices, lowers the return to holding chickens between today and to-

morrow, causing the agent to substitute toward consumption today. After one period, the new, lower steady-state levels of consumption and chicken holdings are reached and maintained through the planning period.

2. **A rise in expected price.** If $d\bar{p}_i^e(T) > 0$, then by Equations (24) and (25), current chicken holdings rise by $\phi h(T)d\bar{p}_i^e(T)$ and then decline over time. Consumption falls in time t , rises in time $t + 1$, and is otherwise more complicated. Notice that our assumption of random-walk expectations of future chicken holdings forces holdings back to the original steady state.

A.2.2 Proof of Proposition 2

First item 1. That $\xi(\alpha, T) > 0$ follows from construction. The argument is completed by observing

$$\begin{aligned} \xi(\alpha, T) &= \frac{(1-\beta)\sum_i \left(\frac{\alpha_i T_i \beta^{T_i}}{1-\beta^{T_i+1}} \right)}{\sum_j \left(\frac{\alpha_j (1-\beta^{T_j})}{1-\beta^{T_j+1}} \right)} = \frac{\sum_i \left(\frac{\alpha_i T_i \beta^{T_i}}{1-\beta^{T_i+1}} \right)}{\sum_j \left(\frac{\alpha_j \left(\frac{1-\beta^{T_j}}{1-\beta} \right)}{1-\beta^{T_j+1}} \right)} \\ &= \frac{\sum_i \left(\frac{\alpha_i T_i \beta^{T_i}}{1-\beta^{T_i+1}} \right)}{\sum_j \left(\frac{\alpha_j \left(\sum_{k=0}^{T_j-1} \beta^k \right)}{1-\beta^{T_j+1}} \right)} < \frac{\sum_i \left(\frac{\alpha_i T_i \beta^{T_i}}{1-\beta^{T_i+1}} \right)}{\sum_j \left(\frac{\alpha_j \left(\sum_{k=0}^{T_j-1} \beta^{T_j} \right)}{1-\beta^{T_j+1}} \right)} = 1. \end{aligned}$$

Next, item 2. For convenience, we allow T to take any positive real value. It suffices to show that

$$f(x) = \log \xi(x) - \log(1-\beta) = \log x + x \log \beta - \log(1-\beta^x)$$

is decreasing in x for $x > 0$. Notice that

$$f'(x) = \frac{1}{x} + \frac{\log \beta}{1-\beta^x},$$

hence for $x > 0$,

$$f'(x) \leq 0 \iff \frac{1}{\log \beta^{-1}} \leq \frac{x}{1-\beta^x} \equiv h(x).$$

Using L'Hopital's rule, we find that $h(0) = 1/\log \beta^{-1}$; thus it suffices to show that $h'(x) > 0$ for $x > 0$. Now compute

$$h'(x) = \frac{1 - \beta^x(1 + x \log \beta^{-1})}{(1 - \beta^x)^2}.$$

It follows that for $x > 0$,

$$h'(x) > 0 \iff h_1(x) \equiv \frac{1 - \beta^x}{\beta^x} > x \log \beta^{-1} \equiv h_2(x).$$

Since $h_1(0) = h_2(0)$ and

$$h_1'(x) = \beta^{-x} \log \beta^{-1} > \log \beta^{-1} = h_2'(x),$$

the result follows.

Finally, item 3. Let $g(T_i) = (1 - \beta^{T_i+1})^{-1}(1 - \beta^{T_i})$. Assume $T_1 < T_2$, and, abusing notation somewhat, write

$$\xi(\alpha, T) = \frac{\alpha \xi(T_1)g(T_1) + (1 - \alpha)\xi(T_2)g(T_2)}{\alpha g(T_1) + (1 - \alpha)g(T_2)},$$

where we recall that

$$\xi(T) = (1 - \beta) \frac{T \beta^T}{1 - \beta^{T+1}}.$$

It suffices to show $\xi_\alpha > 0$. But notice this holds if and only if

$$\begin{aligned} & (\alpha g(T_1) + (1 - \alpha)g(T_2))(\xi(T_1)g(T_1) - \xi(T_2)g(T_2)) \\ & > (\alpha \xi(T_1)g(T_1) + (1 - \alpha)\xi(T_2)g(T_2))(g(T_1) - g(T_2)) \\ & \iff \\ & \alpha(\xi(T_1) - \xi(T_2)) > (1 - \alpha)(\xi(T_2) - \xi(T_1)). \end{aligned}$$

The last inequality holds from item 3 of the lemma and the fact that $T_2 > T_1$. ■

A.2.3 Proof of Corollaries 1 and 2

Proof of Corollary 1. Here we provide the argument for the constant gain case. The decreasing gain case is somewhat more involved but ultimately turns on the same computations.

Stack agents' expectations into the vector $d\bar{p}_t^e$, and let

$$\hat{\xi} = \begin{pmatrix} \xi(\alpha, \mathcal{T}, 1) & \cdots & \xi(\alpha, \mathcal{T}, N) \\ \xi(\alpha, \mathcal{T}, 1) & \cdots & \xi(\alpha, \mathcal{T}, N) \\ \vdots & \ddots & \vdots \\ \xi(\alpha, \mathcal{T}, 1) & \cdots & \xi(\alpha, \mathcal{T}, N) \end{pmatrix}.$$

Observe that $\hat{\xi}$ has an eigenvalue of zero with multiplicity $N - 1$, and the remaining eigenvalue given by $\text{tr} \hat{\xi} = \sum_i \xi(\alpha, \mathcal{T}, i)$, which, by Proposition 2, is contained in $(0, 1)$.

The recursive algorithm characterizing the beliefs dynamics of agent i may be written,

$$d\bar{p}_t^e(i, T_i) = d\bar{p}_{t-1}^e(i, T_i) + \gamma \left(\sum_i \xi(\alpha, \mathcal{T}, i) d\bar{p}_{t-1}^e(i, T_i) - d\bar{p}_{t-1}^e(i, T_i) \right),$$

or, in stacked form,

$$d\bar{p}_t^e = \left((1 - \gamma)I_N + \gamma\hat{\xi} \right) d\bar{p}_{t-1}^e. \quad (26)$$

Stability requires that the eigenvalues of $(1 - \gamma)I_N + \gamma\hat{\xi}$ be strictly less than one in modulus, and this is immediately implied by our above observation about the eigenvalues of $\hat{\xi}$. Via Eq. (6), convergence of expected price deviations to zero implies convergence of the realized price deviation to zero. ■

Proof of Corollary 2. The matrix $(1 - \gamma)I_N + \gamma\hat{\xi}$ has, as eigenvalues, $N - 1$ copies of $1 - \gamma$ and

$$\zeta = 1 - \gamma + \gamma \sum_i \xi(\alpha, \mathcal{T}, i).$$

Denote by S the corresponding matrix of eigenvectors and change coordinates: $z_t = S^{-1} d\bar{p}_t^e$. The dynamics (26) becomes the decoupled system $z_t = \Lambda z_{t-1}$. Denote by z_t^ζ the component of z_t corresponding to the eigenvalue ζ . With the aid of a computer algebra system, it is straightforward to show that

$$z_t^\zeta = \left(\sum_i \xi(\alpha, \mathcal{T}, i) \right)^{-1} \sum_i \xi(\alpha, \mathcal{T}, i) d\bar{p}_t^e(i, T_i) = \xi(\alpha, \mathcal{T})^{-1} dp_t.$$

It follows that $dp_t/dp_{t-1} = z_t^\zeta/z_{t-1}^\zeta = \zeta$. The argument is completed by noting that ζ is decreasing in T_i . ■

B Additional figures

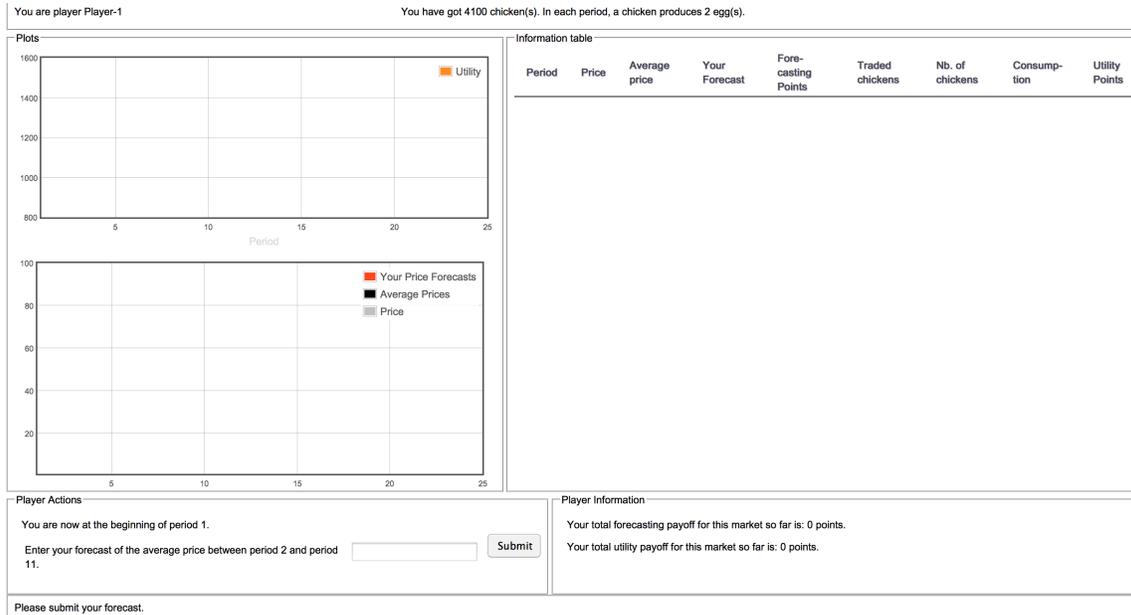


Figure 8: Screen shot of the experimental interface for a long-horizon participant

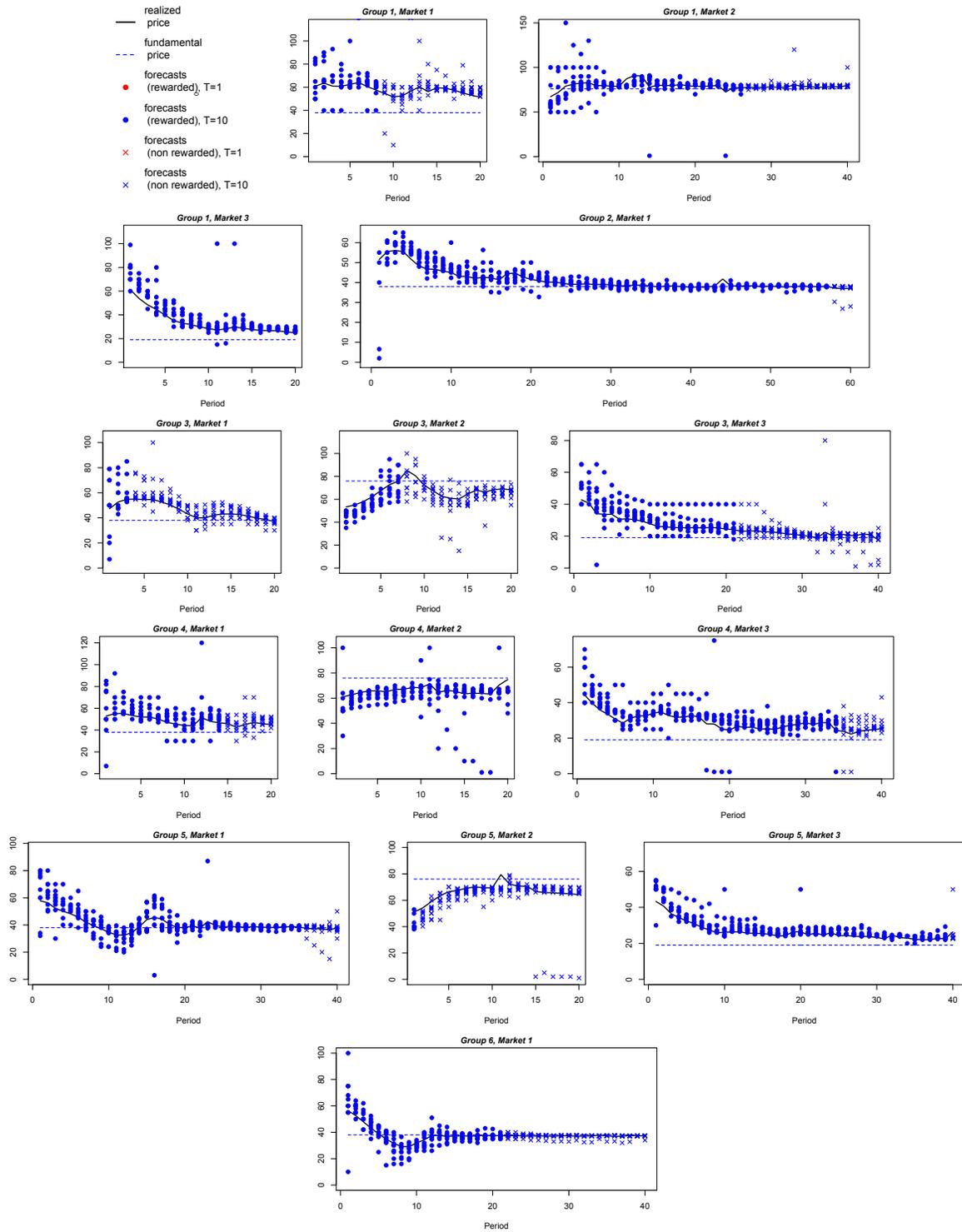


Figure 9: Prices and participants' forecasts in Treatment L: 100% $T = 10$ (6 groups)

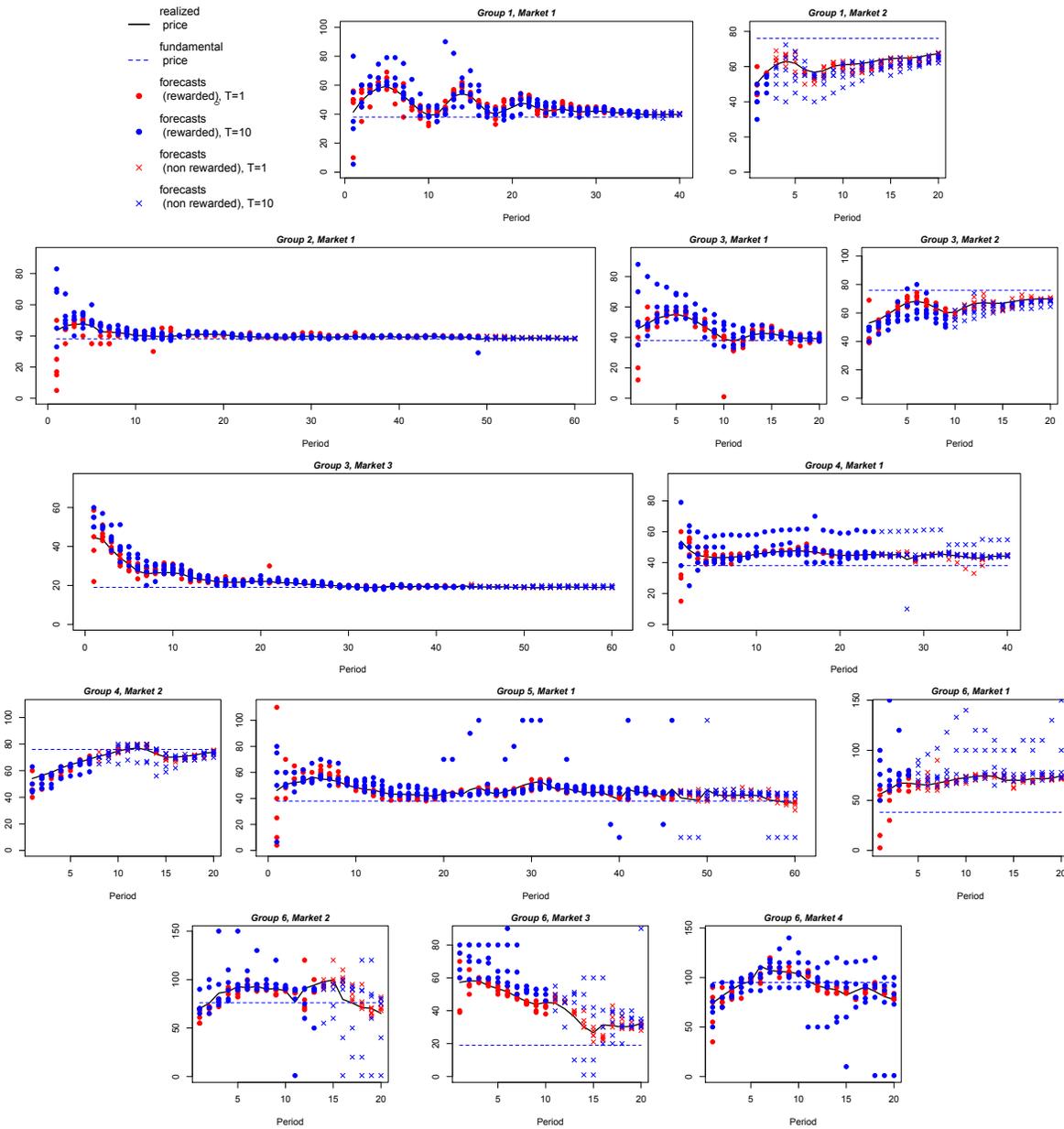


Figure 10: Prices and participants' forecasts in Treatment M50: 50% $T = 1$ /50% $T = 10$ (6 groups)

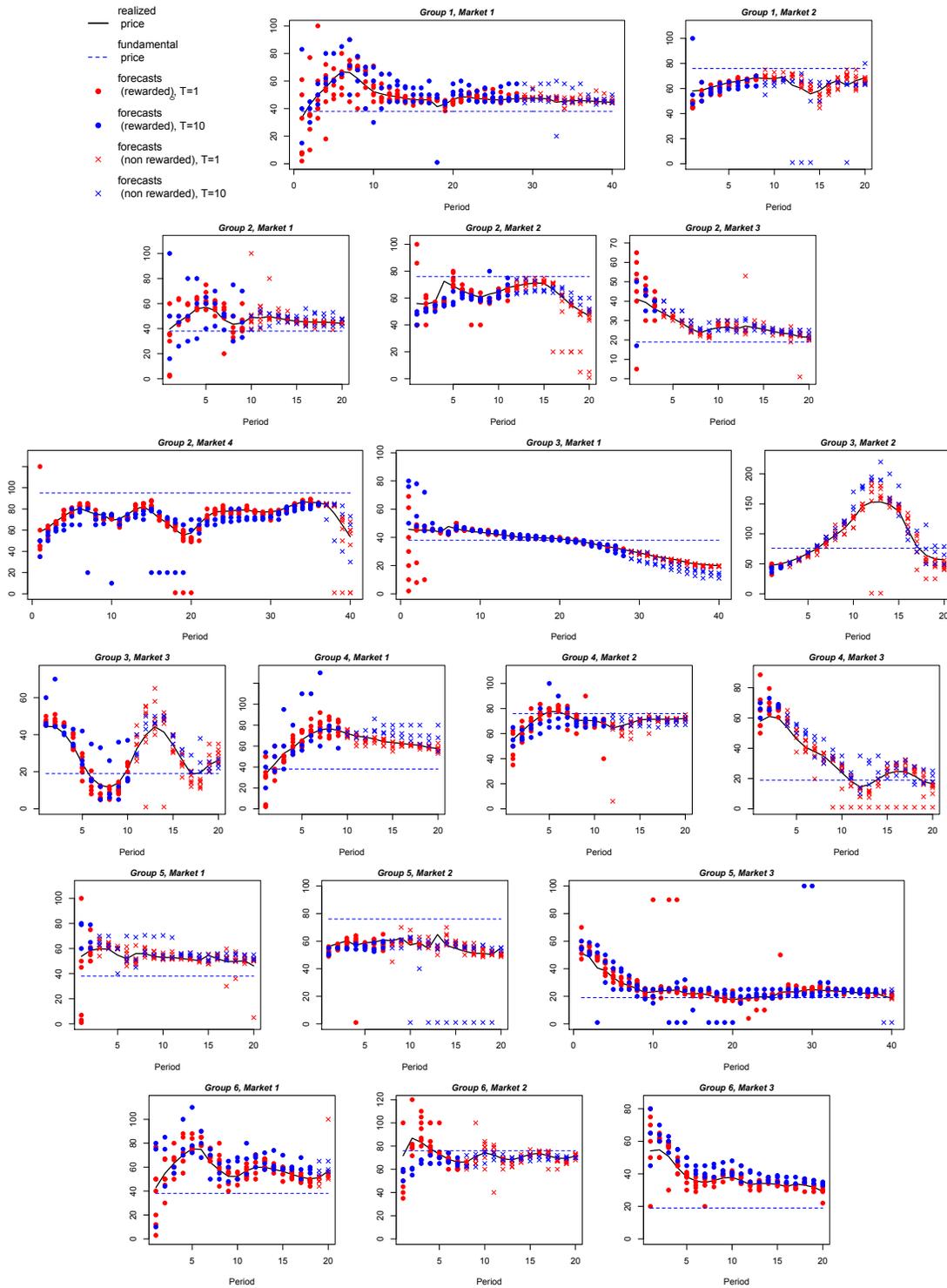


Figure 11: Prices and participants' forecasts in Treatment M70: 70% $T = 1$ /30% $T = 10$

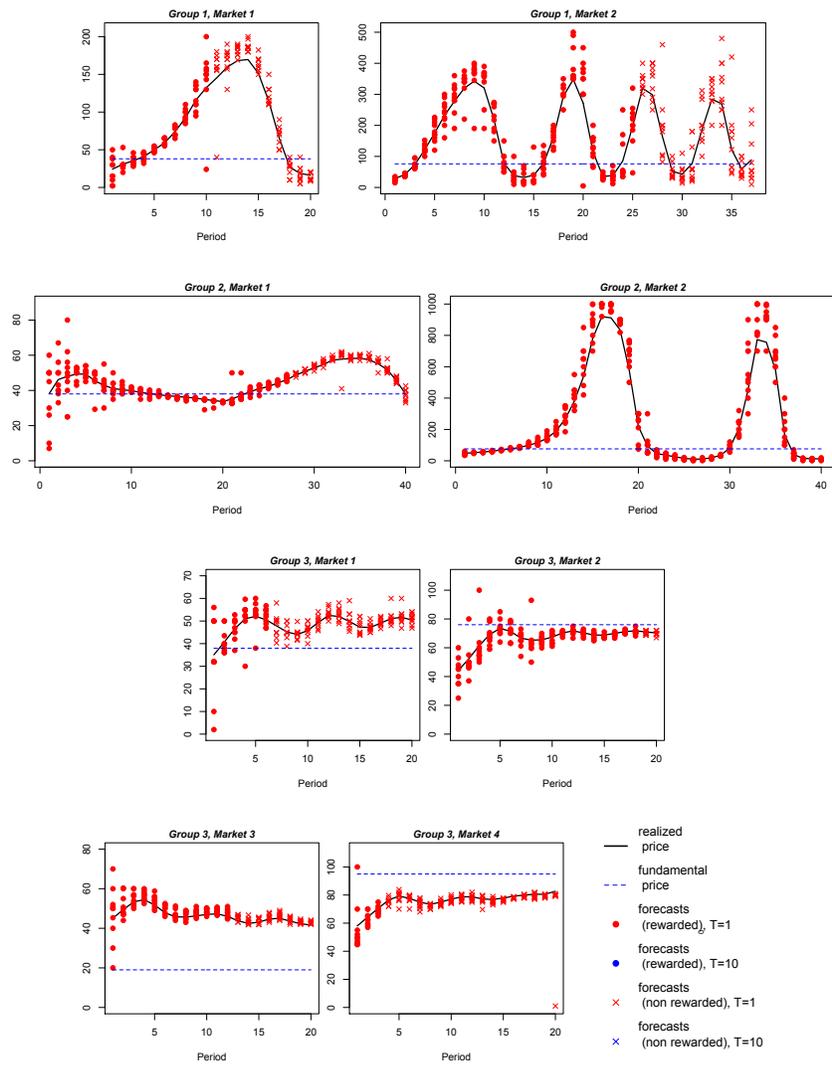


Figure 12: Prices and participants' forecasts in Treatment S: 100% $T = 1$ (groups 1 - 3)

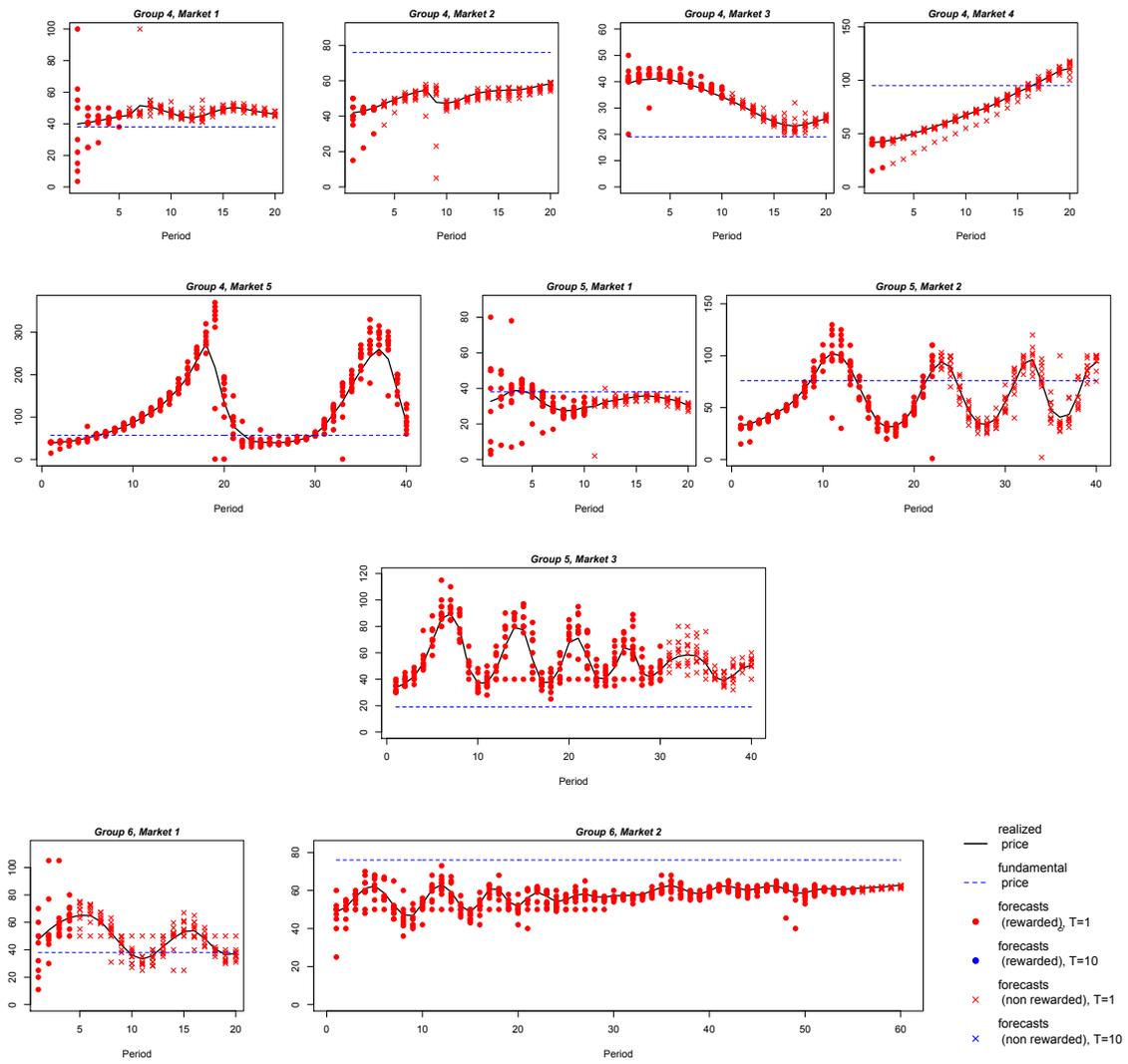


Figure 13: Prices and participants' forecasts in Treatment S: 100% $T = 1$ (groups 4 - 6)

C Test of the equilibration hypothesis: estimation outcomes of Equation (10)

For each treatment, we report below the estimated coefficients $\{\hat{b}_{1,m}, \hat{b}_{2,m}\}$ in Equation (10) for each market $m_{i,m}$ (subscript i corresponds to the group number and subscript m to the number of the market). Standard deviations are reported between brackets. We highlight in bold the markets that exhibit weak convergence, and denote with a star those exhibiting strong convergence.

$$\begin{aligned}
 \text{Tr. S} \quad & m_{1,1} : \left\{ \begin{array}{c} -1.012, 1.715 \\ (0.464) \quad (0.449) \end{array} \right\}; m_{1,2} : \left\{ \begin{array}{c} -0.565, 1.321 \\ (0.365) \quad (0.224) \end{array} \right\}; m_{2,1}^* : \left\{ \begin{array}{c} 0.040, 0.183 \\ (0.104) \quad (0.103) \end{array} \right\}; m_{2,2} : \\
 & \left\{ \begin{array}{c} -1.821, 2.714 \\ (0.958) \quad (0.903) \end{array} \right\}; m_{3,1} : \left\{ \begin{array}{c} -0.069, 0.335 \\ (0.015) \quad (0.011) \end{array} \right\}; \mathbf{m}_{3,2} : \left\{ \begin{array}{c} -0.433, -0.048 \\ (0.009) \quad (0.005) \end{array} \right\}; m_{3,3} : \left\{ \begin{array}{c} 1.646, 1.393 \\ (0.122) \quad (0.084) \end{array} \right\}; \\
 \mathbf{m}_{3,4} : \left\{ \begin{array}{c} -0.408, -0.155 \\ (0.007) \quad (0.006) \end{array} \right\}; m_{4,1} : \left\{ \begin{array}{c} -0.001, 0.265 \\ (0.018) \quad (0.011) \end{array} \right\}; \mathbf{m}_{4,2} : \left\{ \begin{array}{c} -0.500, -0.290 \\ (0.021) \quad (0.017) \end{array} \right\}; \mathbf{m}_{4,3} : \\
 & \left\{ \begin{array}{c} 1.469, 0.554 \\ (0.217) \quad (0.180) \end{array} \right\}; \mathbf{m}_{4,4}^* : \left\{ \begin{array}{c} -0.805, -0.121 \\ (0.130) \quad (0.111) \end{array} \right\}; m_{4,5} : \left\{ \begin{array}{c} -1.224, 1.220 \\ (0.506) \quad (0.354) \end{array} \right\}; m_{5,1} : \left\{ \begin{array}{c} -0.076, -0.143 \\ (0.028) \quad (0.019) \end{array} \right\}; \\
 \mathbf{m}_{5,2} : \left\{ \begin{array}{c} -0.693, -0.126 \\ (0.064) \quad (0.047) \end{array} \right\}; m_{5,3} : \left\{ \begin{array}{c} 1.068, 1.910 \\ (0.335) \quad (0.162) \end{array} \right\}; m_{6,1} : \left\{ \begin{array}{c} 0.527, 0.232 \\ (0.134) \quad (0.099) \end{array} \right\}; \mathbf{m}_{6,2} : \left\{ \begin{array}{c} -0.384, -0.223 \\ (0.026) \quad (0.014) \end{array} \right\}. \\
 \text{Observations: } & 518; \text{ Adj. } R^2 = 0.381; \text{ F Statistic: } 9.849 \text{ (df = 36; 482)}
 \end{aligned}$$

$$\begin{aligned}
 \text{Tr. M70} \quad & m_{1,1} : \left\{ \begin{array}{c} 0.137, 0.295 \\ (0.082) \quad (0.053) \end{array} \right\}; \mathbf{m}_{1,2} : \left\{ \begin{array}{c} -0.245, -0.142 \\ (0.003) \quad (0.002) \end{array} \right\}; m_{2,1} : \left\{ \begin{array}{c} 0.154, 0.272 \\ (0.027) \quad (0.021) \end{array} \right\}; \mathbf{m}_{2,2} : \\
 & \left\{ \begin{array}{c} -0.257, -0.156 \\ (0.016) \quad (0.013) \end{array} \right\}; \mathbf{m}_{2,3} : \left\{ \begin{array}{c} 1.410, 0.256 \\ (0.034) \quad (0.028) \end{array} \right\}; \mathbf{m}_{2,4} : \left\{ \begin{array}{c} -0.391, -0.202 \\ (0.007) \quad (0.004) \end{array} \right\}; m_{3,1}^* : \left\{ \begin{array}{c} 0.493, -0.127 \\ (0.141) \quad (0.093) \end{array} \right\}; \\
 \mathbf{m}_{3,2} : \left\{ \begin{array}{c} -0.655, 0.431 \\ (0.023) \quad (0.019) \end{array} \right\}; \mathbf{m}_{3,3} : \left\{ \begin{array}{c} 1.497, 0.286 \\ (0.030) \quad (0.024) \end{array} \right\}; m_{4,1} : \left\{ \begin{array}{c} -0.147, 0.831 \\ (0.040) \quad (0.033) \end{array} \right\}; \mathbf{m}_{4,2} : \left\{ \begin{array}{c} -0.248, -0.043 \\ (0.008) \quad (0.006) \end{array} \right\}; \\
 \mathbf{m}_{4,3}^* : \left\{ \begin{array}{c} 2.993, 0.184 \\ (0.142) \quad (0.115) \end{array} \right\}; \mathbf{m}_{5,1} : \left\{ \begin{array}{c} 0.542, 0.371 \\ (0.023) \quad (0.019) \end{array} \right\}; m_{5,2} : \left\{ \begin{array}{c} -0.227, -0.255 \\ (0.012) \quad (0.010) \end{array} \right\}; \mathbf{m}_{5,3} : \left\{ \begin{array}{c} 2.140, 0.088 \\ (0.030) \quad (0.018) \end{array} \right\}; \\
 m_{6,1} : \left\{ \begin{array}{c} 0.348, 0.569 \\ (0.054) \quad (0.043) \end{array} \right\}; m_{6,2} : \left\{ \begin{array}{c} 0.047, -0.069 \\ (0.006) \quad (0.005) \end{array} \right\}; \mathbf{m}_{6,3} : \left\{ \begin{array}{c} 2.210, 0.716 \\ (0.041) \quad (0.033) \end{array} \right\}. \\
 \text{Observations: } & 441; \text{ Adj. } R^2 = 0.783; \text{ F Statistic: } 45.21 \text{ (df = 36; 405)}
 \end{aligned}$$

$$\begin{aligned}
\text{Tr. M50 } m_{1,1} &: \left\{ \begin{array}{c} 0.373, 0.163 \\ (0.108) (0.055) \end{array} \right\}; \mathbf{m}_{1,2} : \left\{ \begin{array}{c} -0.341, -0.157 \\ (0.012) (0.012) \end{array} \right\}; \mathbf{m}_{2,1} : \left\{ \begin{array}{c} 0.295, 0.035 \\ (0.045) (0.012) \end{array} \right\}; \mathbf{m}_{3,1}^* : \\
&\left\{ \begin{array}{c} 0.391, 0.128 \\ (0.080) (0.075) \end{array} \right\}; \mathbf{m}_{3,2} : \left\{ \begin{array}{c} -0.337, -0.106 \\ (0.012) (0.010) \end{array} \right\}; \mathbf{m}_{3,3}^* : \left\{ \begin{array}{c} 1.846, 0.029 \\ (0.140) (0.043) \end{array} \right\}; \mathbf{m}_{4,1} : \left\{ \begin{array}{c} 0.368, 0.166 \\ (0.019) (0.010) \end{array} \right\}; \\
\mathbf{m}_{4,2} &: \left\{ \begin{array}{c} -0.361, -0.033 \\ (0.022) (0.013) \end{array} \right\}; \mathbf{m}_{5,1} : \left\{ \begin{array}{c} 0.447, 0.170 \\ (0.092) (0.035) \end{array} \right\}; m_{6,1} : \left\{ \begin{array}{c} 0.426, 0.911 \\ (0.019) (0.014) \end{array} \right\}; m_{6,2} : \left\{ \begin{array}{c} -0.026, 0.139 \\ (0.052) (0.046) \end{array} \right\}; \\
\mathbf{m}_{6,3} &: \left\{ \begin{array}{c} 2.633, 0.932 \\ (0.265) (0.200) \end{array} \right\}; \mathbf{m}_{6,4}^* : \left\{ \begin{array}{c} -0.176, -0.003 \\ (0.049) (0.044) \end{array} \right\}.
\end{aligned}$$

Observations: 421; Adj. $R^2 = 0.887$; F Statistic: 128.3 (df = 26; 395)

$$\begin{aligned}
\text{Tr. L } \mathbf{m}_{1,1} &: \left\{ \begin{array}{c} 0.697, 0.487 \\ (0.035) (0.024) \end{array} \right\}; m_{1,2} : \left\{ \begin{array}{c} -0.079, 0.057 \\ (0.026) (0.017) \end{array} \right\}; \mathbf{m}_{1,3} : \left\{ \begin{array}{c} 2.621, 0.381 \\ (0.128) (0.077) \end{array} \right\}; \mathbf{m}_{2,1}^* : \\
&\left\{ \begin{array}{c} 0.663, 0.034 \\ (0.097) (0.032) \end{array} \right\}; \mathbf{m}_{3,1}^* : \left\{ \begin{array}{c} 0.457, 0.155 \\ (0.090) (0.066) \end{array} \right\}; \mathbf{m}_{3,2} : \left\{ \begin{array}{c} -0.325, -0.074 \\ (0.020) (0.020) \end{array} \right\}; \mathbf{m}_{3,3}^* : \left\{ \begin{array}{c} 1.632, 0.179 \\ (0.138) (0.097) \end{array} \right\}; \\
\mathbf{m}_{4,1} &: \left\{ \begin{array}{c} 0.512, 0.223 \\ (0.040) (0.026) \end{array} \right\}; \mathbf{m}_{4,2} : \left\{ \begin{array}{c} -0.205, -0.113 \\ (0.005) (0.005) \end{array} \right\}; \mathbf{m}_{4,3} : \left\{ \begin{array}{c} 1.531, 0.412 \\ (0.091) (0.062) \end{array} \right\}; \mathbf{m}_{5,1}^* : \left\{ \begin{array}{c} 0.676, -0.007 \\ (0.040) (0.011) \end{array} \right\}; \\
\mathbf{m}_{5,2} &: \left\{ \begin{array}{c} -0.362, -0.077 \\ (0.015) (0.014) \end{array} \right\}; \mathbf{m}_{5,3} : \left\{ \begin{array}{c} 1.579, 0.249 \\ (0.086) (0.036) \end{array} \right\}; \mathbf{m}_{5,3} : \left\{ \begin{array}{c} 0.522, -0.068 \\ (0.041) (0.025) \end{array} \right\}.
\end{aligned}$$

Observations: 441; Adj. $R^2 = 0.910$; F Statistic: 160.8 (df = 28; 413)

D Supplementary material

Instructions (*N.B.: for short-horizon forecasters*)

Welcome to our experiment! The experiment is **anonymous**, the data from your choices will only be linked to your station ID, never to your name. You will be paid privately at the end, after all participants have finished the experiment. During the experiment, you are not allowed to communicate with other participants. If you have a question at any time, please raise your hand and we will come to your desk.

Please read these instructions carefully and **answer the quiz (five questions)**. Once we have made sure that all participants have answered correctly, we will start the experiment. **At the end of the experiment** and before the payment, you will be asked to **fill out a short questionnaire**.

Thank you for your participation!

Your role: price forecasting on a chicken market

You are a farmer in a chicken market and have to *submit price forecasts*. There are 10 farmers in the market, every farmer is a participant like you. The group of farmers will not change during the experiment. Every chicken produces the same number of eggs at the beginning of each period. Eggs are **either** traded for chickens in the market **or** consumed by the farmers. Eggs cannot be carried over between periods. You do not need to make trading decisions, a computerized trader will do it for you based on your forecasts.

Sequence of markets: You may play in several markets in a row

In each period after the first one, an outbreak of avian flu may occur with a constant and independent probability of 5%. If this happens, all chickens die and become worthless, and a new market starts. We will run **as many markets as possible** during the time for

which you have been recruited. You will play in every market for at least **20 periods** because **you will only find out after 20 periods whether and in which period the chickens have died** from avian flu.

If the chickens have died within the first 20 periods, the market stops in period 20, you receive new chickens and **enter a new market**. If the chickens have not died within the first 20 periods, **you play for 20 more periods**, till period 40, and then observe whether the chickens have died between period 21 and period 40. If this is the case, a new market starts. If not, you continue in the market for another 20 periods, etc., till the chickens die and the market ends. **All periods after the chickens died will not be counted towards your earnings**.

At the beginning of each market, the **number of eggs produced per chicken** and the **number of chickens that you have received** will be displayed on your computer interface, which is mainly self-explanatory. The number of eggs per chicken **remains fixed for the whole market**. You never observe the number of chickens of the other 9 farmers.

Your task: Forecasting the price in the next period

In each period, your task is to **forecast the price** of a chicken *in the next period*: in period 1, you have to forecast the price in period 2; in period 2, you have to forecast the price in period 3, etc. **Based on your forecasts, a computerized trader buys or sells chickens on your behalf**. Not all participants may have a computerized trader using forecasts for the next period, they may use a different time horizon.

The price of a chicken in terms of eggs is always adjusted so that the demand for chickens equals the supply (up to small random errors). The price depends on all participants' forecasts: if all participants forecast an **increase (resp. decrease) in the price**, the *current price* will tend to **increase (resp. decrease)**. **Once every participant has submitted**

a **forecast**, the computers trade, **the current price of a chicken is determined** and you observe how many chickens you have bought or sold and your egg consumption. Your egg consumption is your amount of eggs at the beginning of the period plus the eggs you received from selling chickens (or minus the eggs you used to buy chickens). Your trader ensures that you always consume at least one egg and always have at least one chicken in any period.

Whether your trader buys or sells chickens depends both on *your forecast and the forecasts of the other participants*. The higher your forecast compared to the forecasts of the other participants, the more chickens your trader buys, and the fewer eggs you consume now (but the more later on). The lower your forecasts compared to the ones of the other participants, the more chickens your trader sells, and the more eggs you consume now (but the fewer later on).

Your payoff: forecasting accuracy and egg consumption

You may earn points in **two ways**. **First**, you may earn points based on your **price forecast accuracy**. The closer your forecast to the **realized price**, the higher your payoff. **There is a forecasting payoff table on your desk** that indicates how many points you make that way. If your prediction is perfect (zero error), you earn a maximum of 1100 points. If your forecast error is larger than 7, you earn zero point.

You receive your **first forecasting payoff** once the first price that you had to forecast becomes observable, that is **at the end of period 2**. Your corresponding forecast error is the difference between your forecast of the price in period 2 that you made in period 1 and the realized price in period 2.

If the chickens die, some of your last forecasts will not be rewarded because **only the price of living chickens counts towards the computation of the average price** that you

had to forecast. For this reason, we pay **2 times your last rewarded forecast**, that is the one for which we can compute the price that you had to forecast. Your total forecasting payoff in each market is the sum of your realized forecasting payoff in that market.

Second, you may earn points with your **egg consumption**. **There is a consumption payoff table on your desk** that indicates how many points you earn that way. The more eggs you consume, the higher your consumption payoff. Notice that **consuming few eggs in one period** (e.g. 20) **and a lot in the next** (e.g. 980) **gives you less points** ($359 + 827 = 1186$, see your payoff table!) **than consuming an equal amount of eggs (500) in the two periods** ($746 \times 2 = 1492$). Your total consumption payoff in each market is the sum of your consumption payoff in every period for which the chickens are alive.

At the end of **each market**, you will be rewarded **either** with your total consumption **or** your total forecasting payoff **with equal probability**. This **does not depend** on how you have been rewarded in the previous markets. **If the chickens do not live for at least 2 periods, you will not have any forecasting score, so you will be rewarded with your consumption payoff**. All participants are paid in the same way.

Your total amount of points over all markets will be converted into euro and paid to you at the end of the experiment. One euro corresponds to 2000 points.

Quiz

1. Assume you are at the end of period 13. Here is the sequence of realized prices:

$$p_1 = 32, p_2 = 61, p_3 = 77, p_4 = 78, p_5 = 120, p_6 = 42, p_7 = 96, p_8 = 100, p_9 = 90, p_{10} = 70, p_{11} = 71, p_{12} = 46, p_{13} = 4.$$

(a) In period 12, what did you have to predict?

- i. The price in period 13.
- ii. The price in period 12.
- iii. The difference between the price in period 12 and in period 13.
- iv. None of the above.

(b) Assume that, in period 12, you predicted a price of 2.5.

- i. What is your forecast error?
 - ii. How many forecasting points do you earn?
- (USE YOUR PAYOFF TABLE ON YOUR DESK!)**

2. What is the probability for all the chickens to die if you are entering...

- (a) ... period 6?
- (b) ... period 45?

3. If the chickens die in period 23, when will you find out?

4. If you forecast a high price for the next period, ...

N.B.: Multiple answers may be possible.

- (a) Your forecast will not impact your demand for chickens.
- (b) Your trader is likely to buy chickens.
- (c) Your trader is likely to sell chickens.
- (d) You are likely to consume fewer eggs now but more later on.
- (e) You are likely to consume more eggs now but fewer later on.
- (f) This also depends on the other participants' forecasts.

5. If all participants tend to forecast an increase in the price in the future compared to past levels, what is the implication on the realized current market price?

N.B.: Multiple answers may be possible.

- (a) The realized market price is likely to increase.
- (b) The realized market price is likely to decrease.
- (c) The realized market price is likely to remain stable.
- (d) The realized market price will not be impacted by participants' forecasts.

Instructions (*N.B.: for long-horizon forecasters*)

Welcome to our experiment! The experiment is **anonymous**, the data from your choices will only be linked to your station ID, never to your name. You will be paid privately at the end, after all participants have finished the experiment. During the experiment, you are not allowed to communicate with other participants. If you have a question at any time, please raise your hand and we will come to your desk.

Please read these instructions carefully and **answer the quiz (five questions)**. Once we have made sure that all participants have answered correctly, we will start the experiment. **At the end of the experiment** and before the payment, you will be asked to **fill out a short questionnaire**.

Thank you for your participation!

Your role: price forecasting on a chicken market

You are a farmer in a chicken market and have to **submit price forecasts**. There are 10 farmers in the market, every farmer is a participant like you. The group of farmers will not change during the experiment. Every chicken produces the same number of eggs at the beginning of each period. Eggs are **either** traded for chickens in the market **or** consumed by the farmers. Eggs cannot be carried over between periods. You do not need to make trading decisions, a computerized trader will do it for you based on your forecasts.

Sequence of markets: You may play in several markets in a row

In each period after the first one, an outbreak of avian flu may occur with a constant and independent probability of 5%. If this happens, all chickens die and become worthless, and a new market starts. We will run **as many markets as possible** during the time for which you have been recruited. You will play in every market for at least **20 periods** because **you will only find out after 20 periods whether and in which period the chickens have died** from avian flu.

If the chickens have died within the first 20 periods, the market stops in period 20, you receive new chickens and **enter a new market**. If the chickens have not died within the first 20 periods, **you play for 20 more periods**, till period 40, and then observe whether the chickens have died between period 21 and period 40. If this is the case, a new market starts. If not, you continue in the market for another 20 periods, etc., till the chickens die and the market ends. **All periods after the chickens died will not be counted towards your earnings.**

At the beginning of each market, the **number of eggs produced per chicken** and the **number of chickens that you have received** will be displayed on your computer interface, which is mainly self-explanatory.

The number of eggs per chicken **remains fixed for the whole market**. You never observe the number of chickens of the other 9 farmers.

Your task: Forecasting the average price over the next 10 periods

In each period, your task is to **forecast the *average price*** of a chicken *over the next 10 periods*: in period 1, you have to forecast the average price over period 2 to period 11 (i.e. the **average price over the next 10 periods**); in period 2, you have to forecast the average price over period 3 to period 12, etc. **Based on your forecasts, a computerized trader buys or sells chickens on your behalf**. Not all participants may have a computerized trader using forecasts for the next 10 periods, they may use a different time horizon.

The price of a chicken in terms of eggs is always adjusted so that the demand for chickens equals the supply (up to small random errors). The price depends on all participants' forecasts: if all participants forecast an **increase (resp. decrease) in the average price over the next 10 periods**, the *current price* will tend to **increase (resp. decrease)**. **Once every participant has submitted a forecast**, the computers trade, **the current price of a chicken is determined** and you observe how many chickens you have bought or sold and your egg consumption. Your egg consumption is your amount of eggs at the beginning of the period plus the eggs you received from selling chickens (or minus the eggs you used to buy chickens). Your trader ensures that you always consume at least one egg and always have at least one chicken in any period.

Whether your trader buys or sells chickens depends both on your forecast and the forecasts of the other participants. The **higher your forecast compared to the forecasts of the other participants, the more chickens your trader buys, and the fewer eggs you consume now (but the more later on)**. The **lower your forecasts compared to the ones of the other participants, the more chickens your trader sells, and the more eggs you consume now (but the fewer later on)**.

Your payoff: forecasting accuracy and egg consumption

You may earn points in **two ways**. **First**, you may earn points based on your **price forecast accuracy**. The closer your forecast to the realized *average* price, the higher your payoff. **There is a forecasting payoff table on your desk** that indicates how many points you make that way. If your prediction is perfect (zero error), you earn a maximum of 1100 points. If your forecast error is larger than 7, you earn zero point.

You receive your **first forecasting payoff** once the first average price that you had to forecast becomes

observable, that is **in period 11**. Your corresponding forecast error is the difference between your forecast of the average price over the periods 2 – 11 that you made in period 1 and the realized average price over the periods 2 – 11.

If the chickens die, some of your last forecasts will not be rewarded because **only the price of living chickens counts towards the computation of the average price** that you had to forecast. For this reason, we pay **11 times your last rewarded forecast**, that is the one for which we can compute the average price that you had to forecast. Your total forecasting payoff in each market is the sum of your realized forecasting payoff in that market.

Second, you may earn points with your **egg consumption**. **There is a consumption payoff table on your desk** that indicates how many points you earn that way. The more eggs you consume, the higher your consumption payoff. Notice that **consuming few eggs in one period** (e.g. 20) **and a lot in the next** (e.g. 980) **gives you less points** ($359 + 827 = 1186$, see your payoff table!) **than consuming an equal amount of eggs (500) in the two periods** ($746 \times 2 = 1492$). Your total consumption payoff in each market is the sum of your consumption payoff in every period for which the chickens are alive.

At the end of **each market**, you will be rewarded **either** with your total consumption **or** your total forecasting payoff **with equal probability**. This **does not depend** on how you have been rewarded in the previous markets. **If the chickens do not live for at least 11 periods, you will not have any forecasting score, so you will be rewarded with your consumption payoff**. All participants are paid in the same way.

Your total amount of points over all markets will be converted into euro and paid to you at the end of the experiment. One euro corresponds to 2000 points.

Example

The box below provides an example of a sequence of events in a market where the chickens die in period 15, so you play until period 20.

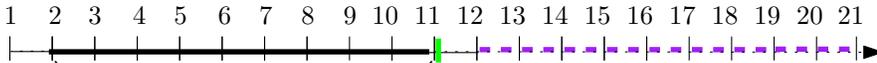
You enter **period 1**.
 Every player submits a forecast of the average price over periods 2 to 11:
 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20


You then observe P_1 (the price **in period 1**), the number of chickens you traded, your corresponding egg consumption and consumption points in period 1.

You enter **period 2**.
 Every player submits a forecast of the average price from period 3 to 12:
 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20


You then observe P_2 , the number of chickens you traded, your corresponding egg consumption and consumption points in period 2.

⋮

You enter **period 11**.
 Every player submits a forecast of the average price from period 12 to 21:
 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21


$$\tilde{P}_{2,11} = \frac{P_2 + P_3 + P_4 + P_5 + P_6 + P_7 + P_8 + P_9 + P_{10} + P_{11}}{10}$$

You observe P_{11} and the average price $\tilde{P}_{2,11}$ over period 2 to 11. You then see your forecast error and forecasting payoff for your forecast made in period 1.

You also observe the number of chickens you traded, your corresponding egg consumption and consumption points in period 11.

⋮

You enter **period 20**, submit a forecast for $\tilde{P}_{21,30}$ **and then** observe whether the chickens have died over the last 20 periods: the chickens died **in period 15**, this market ends.

1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20


$$\tilde{P}_{6,15} = \frac{P_6 + P_7 + P_8 + P_9 + P_{10} + P_{11} + P_{12} + P_{13} + P_{14} + P_{15}}{10}$$

Your last forecasting payoff is for your forecast in period 5 of the average price $\tilde{P}_{6,15}$ between periods 6 and 15 because the chickens have died in period 15, so we do not have prices afterwards. **This payoff is multiplied by 11.**
 Your other forecasting payoffs are in period 1 (for periods 2 to 11), period 2 (for periods 3 to 12), period 3 (for periods 4 to 13) and period 4 (for periods 5 to 14). **Your forecasts made from period 6 till 20 are not rewarded.**
 Your total consumption payoff is the sum of your consumption points from period 1 to 15. **Your egg consumption from period 16 till 20 is not rewarded.**

In this market, you earn **either** your consumption payoff **or** your forecasting payoff with equal probability. You then enter a new market.

Quiz

1. Assume you are entering period 14. Here is the sequence of realized prices:

$p_1 = 32, p_2 = 61, p_3 = 77, p_4 = 78, p_5 = 120, p_6 = 42, p_7 = 96, p_8 = 100, p_9 = 90, p_{10} = 70, p_{11} = 71, p_{12} = 46, p_{13} = 4.$

- (a) In period 2, what did you have to predict?
 - i. The price in period 3.
 - ii. The average price over periods 3 to 12.
 - iii. The average price over periods 2 to 11.
 - iv. The difference between the price in period 3 and in period 11.
 - v. The difference between the price in period 2 and in period 11.
 - vi. None of the above.
- (b) Compute the average price over period 3 to 12:
(USE THE CALCULATOR ON YOUR DESK!)
- (c) Assume that, in period 2, you predicted an average price over periods 3 to 12 of 82.5.
 - i. What is your forecast error?
 - ii. How many forecasting points do you earn?**(USE YOUR PAYOFF TABLE ON YOUR DESK!)**

2. What is the probability for all the chickens to die if you are entering...

- (a) ... period 6?
- (b) ... period 45?

3. If the chickens die in period 23, when will you find out?

4. If you forecast a high average price over the next 10 periods, ...

N.B.: Multiple answers may be possible.

- (a) Your forecast will not impact your demand for chickens.
- (b) Your trader is likely to buy chickens.
- (c) Your trader is likely to sell chickens.
- (d) You are likely to consume fewer eggs now but more later on.
- (e) You are likely to consume more eggs now but fewer later on.
- (f) This also depends on the other participants' forecasts.

5. If all participants tend to forecast an increase in the price over the next 10 periods compared to past levels, what is the implication on the realized current market price?

N.B.: Multiple answers may be possible.

- (a) The realized market price is likely to increase.
- (b) The realized market price is likely to decrease.
- (c) The realized market price is likely to remain stable.
- (d) The realized market price will not be impacted by participants' forecasts.

Forecasting payoff table

$$\text{Your payoff} : 1100 - \frac{1100}{49} (\text{Your forecast error})^2$$

2000 points = 1 euro

error	points	error	points	error	points	error	points
0	1100	1.85	1023	3.7	793	5.55	409
0.05	1100	1.9	1019	3.75	784	5.6	396
0.1	1100	1.95	1015	3.8	776	5.65	383
0.15	1099	2	1010	3.85	767	5.7	371
0.2	1099	2.05	1006	3.9	759	5.75	358
0.25	1099	2.1	1001	3.95	750	5.8	345
0.3	1098	2.15	996	4	741	5.85	332
0.35	1097	2.2	991	4.05	732	5.9	319
0.4	1096	2.25	986	4.1	723	5.95	305
0.45	1095	2.3	981	4.15	713	6	292
0.5	1094	2.35	976	4.2	704	6.05	278
0.55	1093	2.4	971	4.25	695	6.1	265
0.6	1092	2.45	965	4.3	685	6.15	251
0.65	1091	2.5	960	4.35	675	6.2	237
0.7	1089	2.55	954	4.4	665	6.25	223
0.75	1087	2.6	948	4.45	655	6.3	209
0.8	1086	2.65	942	4.5	645	6.35	195
0.85	1084	2.7	936	4.55	635	6.4	180
0.9	1082	2.75	930	4.6	625	6.45	166
0.95	1080	2.8	924	4.65	615	6.5	152
1	1078	2.85	918	4.7	604	6.55	137
1.05	1075	2.9	911	4.75	593	6.6	122
1.1	1073	2.95	905	4.8	583	6.65	107
1.15	1070	3	898	4.85	572	6.7	92
1.2	1068	3.05	891	4.9	561	6.75	77
1.25	1065	3.1	884	4.95	550	6.8	62
1.3	1062	3.15	877	5	539	6.85	47
1.35	1059	3.2	870	5.05	527	6.9	31
1.4	1056	3.25	863	5.1	516	6.95	16
1.45	1053	3.3	856	5.15	505	error ≥ 7	0
1.5	1049	3.35	848	5.2	493		
1.55	1046	3.4	840	5.25	481		
1.6	1043	3.45	833	5.3	469		
1.65	1039	3.5	825	5.35	457		
1.7	1035	3.55	817	5.4	445		
1.75	1031	3.6	809	5.45	433		
1.8	1027	3.65	801	5.5	421		

Consumption payoff table

Your payoff : $\log(\text{your egg consumption}) \times 120$

2000 points = 1 euro

eggs	points	eggs	points	eggs	points	eggs	points
1	0	420	725	1000	829	12000	1127
2	83	440	730	1250	856	14000	1146
3	132	460	736	1500	878	16000	1162
4	166	480	741	1750	896	18000	1176
5	193	500	746	2000	912	20000	1188
6	215	520	750	2250	926	22000	1200
7	234	540	755	2500	939	24000	1210
8	250	560	759	2750	950	26000	1220
9	264	580	764	3000	961	28000	1229
10	276	600	768	3250	970	30000	1237
20	359	620	772	3500	979	32000	1245
30	408	640	775	3750	988	34000	1252
40	443	660	779	4000	995	36000	1259
50	469	680	783	4250	1003	38000	1265
60	491	700	786	4500	1009	40000	1272
70	510	720	790	4750	1016	42000	1277
80	526	740	793	5000	1022	44000	1283
90	540	760	796	5250	1028	46000	1288
100	553	780	799	5500	1034	48000	1293
120	575	800	802	5750	1039	50000	1298
140	593	820	805	6000	1044	52000	1303
160	609	840	808	6250	1049	54000	1308
180	623	860	811	6500	1054	56000	1312
200	636	880	814	6750	1058	58000	1316
220	647	900	816	7000	1062	60000	1320
240	658	920	819	7250	1067	62000	1324
260	667	940	822	7500	1071	64000	1328
280	676	960	824	7750	1075	66000	1332
300	684	980	827	8000	1078	68000	1335
320	692	1000	829	8250	1082	70000	1339
340	699	1020	831	8500	1086	72000	1342
360	706	1040	834	8750	1089	74000	1345
380	713	1060	836	9000	1093	76000	1349
400	719	1080	838	10000	1096	80000	1352

Once you have finished the experiment, please fill out this questionnaire!

Table number (letter and number on the yellow card): _____

Gender

- male
 female
 other

Age: _____

Nationality: _____

Which of the following *comes closest* to your field of study?

- Economics, Business
 Psychology, Social Sciences, Law, Humanities
 Mathematics, Physics, IT
 Medicine, Biology, Chemistry,
 Other: _____
 no studies

How would you describe your command of English?

- Excellent
 Very good
 Good
 Satisfactory
 Poor

How clear were the instructions of the experiment?

- Very clear
 Clear
 Understandable
 Slightly confusing
 Confusing

Have you participated in a *similar* economic experiment before?

- yes
 no

Did you perceive the length of the markets to be:

- As announced in the instructions
 Longer than announced in the instructions
 Shorter than announced in the instructions

Could you, in few words, summarize your strategy(ies) in this experiment?

If you would like to leave any comments for us, please do so here:
