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EXPECTATIONALLY-DRIVEN MARKET VOLATILITY: AN EXPERIMENTAL STUDY

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Abstract

We study the existence and robustness of expectationally-driven price volatility in experimental overlapping generation economies. In the theoretical model under study there exist "pure sunspot" equilibria which can be "learned" if agents use some adaptive learning rules. Our data show the existence of expectationally-driven cycles, but only after subjects have been exposed to a sequence of real shocks and "learned" a real cycle. In this sense, we show evidence of *path-dependent* price volatility. C62, C92, E17, E32, E44.

1 Introduction

The existence of multiple equilibria in economic models has been a persistent embarrassment to theorists and a source of controversy in the formulation of macroeconomic policy. In models of dynamic economies, indeterminacies frequently manifest themselves as so-called "sunspot" equilibria. In these equilibria, the expectation that extrinsic random events matter becomes self-fulfilling, and causes extrinsic uncertainty to have real allocative effects.

While there is a large theoretical literature on when sunspots may matter (see, e.g., [20], [1], [3], [22] and [2]), empirical evidence that expectationally-driven randomness is at work in real-world markets has been scarce. For example, econometric estimates of stock price volatility exceed the predictions of economic theory (see [23], [9] or [24]). However, marshaling econometric evidence to support or reject the hypothesis that stock price changes (or any other prices) are driven by extrinsic noise is difficult for two reasons. First, since equilibria are defined in terms of subjective expectations, inherent unobservability of expectations in natural settings makes it difficult to construct convincing tests of theory. For example, years after Shiller's first paper on the subject, a hot debate continues on the validity of the evidence on "excess" stock price volatility (see [12]). Second, even if the fact of excess volatility were indisputably established, demonstrating that it is caused by extrinsic uncertainty is yet another challenge. Indeed, from an econometric perspective, the problem of demonstrating a sunspot effect is enormous, since it requires identifying the extrinsic random variable driving the process and demonstrating that it is in fact the cause of the observed volatility.

If it is difficult for the econometrician to detect the sunspot variable used by agents to coordinate their beliefs, it should also be difficult for the agents themselves to independently choose to coordinate their beliefs on the same extrinsic signal. If there is no communication among agents, can they share a secret undetected by an outside observer? It seems unlikely, unless the secret comes from common experience. In this case, the econometrician, observing economic fluctuations caused by extrinsic uncertainty, resembles an anthropologist trying to make sense of an unfamiliar tribal dance. If common experience is the shared secret, then the independent formation and coordination of beliefs can be explained as the outcome of a learning process. Tradition is preserved in the tribe because the new generation learns the ritual dance from the old.

If an equilibrium must be achieved as a decentralized process of learning, then not all rational expectations equilibria (REE) might pass this stability test. In other words, learning might serve as a guide to choosing among equilibria. This selection of equilibria can be characterized by explicitly defining how agents learn. For example, Marcet and Sargent ([14], [15]) and Evans ([4], [5]) use adaptive least-squares learning in overlapping generations (OLG) models with multiple rational expectations equilibria (REE) and show how learning selects from the (uncountable) set of equilibria. Experimental work by Marimon and Sunder ([16], [17]), on the same type of OLG models, brings evidence which is consistent with adaptive learning. For example, the REE that can not be achieved as a decentralized process of adaptive learning are not observed in their experimental environment. Their economic series tend to cluster around the stationary equilibria selected by adaptive learning.

One might expect that single-parameter (or expected value) stationary equilibria are easier to learn, and therefore more likely to emerge, than cyclic equilibria involving multiple parameters. Woodford [25], however, shows this intuition to be false: in simple OLG models exhibiting both monetary steady-state equilibria and cyclic sunspot equilibria, a cyclic sunspot equilibrium emerges asymptotically if agents follow certain adaptive learning schemes. The study of the necessary and sufficient conditions for the convergence to equilibrium cycles when agents learn adaptively has been further explored by Grandmont and Laroque [10],Guesnerie and Woodford [11], and Evans and Honkapohja [7]. There are two basic components underlying these stability results. The first has to do with the stability properties of the underlying non-linear map, $\phi(\cdot)$, that determines current values (e.g., of prices) as a function of future expected values; that is, $p_t = \phi(p^e_{t+1})$. The second has to do with the specific learning schemes used by the agents.

The beauty of experimental design is that the experimenter defines the underlying economy and selects the stability properties of the underlying equilibrium map. For example, for our OLG economy we choose parameters that guarantee the stability of a two-period cycle under certain learning schemes. However, the learning rules that agents actually use are not prespecified or constrained. Sufficient conditions for convergence to sunspot equilibria usually require that agents use learning schemes that are "in tune" with the underlying cycle; and this underlying cycle is stable. This is analogous to the way in which a radio receiver must be adjusted to the correct frequency for capturing and reproducing a clear sound signal. Some recent theoretical results illustrate this fact. For example, Guesnerie and Woodford [11] show that in a model (similar to the one we implement) both the monetary steady-state as well as the cyclic equilibrium can be the limit for the temporary equilibrium dynamics of the model, depending on the form of the adaptive forecasting schemes the agent use (see Section 2). Evans [6] has shown that, when the learning scheme is not restricted to any particular functional form a priori, any k-period cyclic sunspot equilibrium is unstable if an additional independent sunspot variable is introduced in the model (see also [19]). Similarly, Evans, Honkapohja and Sargent [8], extending Woodford's results, have shown that in a simple deterministic OLG model with equilibrium cycles if a sufficiently high fraction of agents believe that the past fluctuations in prices arise from some steady-state distribution, then equilibrium cycles of period $k \geq 2$ disappear. This multiplicity of outcomes, driven by alternative learning schemes, is the object of our study.

These theoretical results hinge on the difficulties of coordinating agents' beliefs and learning schemes. Common past experience provides a natural coordinating force. For example, if an extrinsic signal has been correlated in the past with an intrinsic shock, and agents continue to coordinate their beliefs on the extrinsic signal after the real shock disappears, then the signal ends up having a real effect. We also study this form of conditional price volatility. By studying *path dependent sunspots*, we also produce evidence on the more general phenomena of *path dependent equilibrium selection.* In models with multiple equilibria, historical factors might have been decisive in selecting a particular one (e.g., by being the only stable equilibrium in that particular episode.) This equilibrium may persist even after the circumstances that caused it to be selected disappear because the expectations linger on. Some macroeconomists have borrowed the term *hysteresis* from physics to describe these phenomena.

In our experiments we find that excess market volatility can be sustained by expectations alone, although subjects must be conditioned to expect cyclic movements in prices before they will consistently forecast such movements. Before these cyclic movements can be supported solely by extrinsic signals (or sunspots) subjects must be exposed to intrinsic events that are correlated with the extrinsic variables. In particular, we find no evidence, either in the current set of experiments or in a preliminary set (not reported here),to support the idea that cyclic equilibria can arise spontaneously. Nevertheless, if subjects experience cyclic price movements (induced by fluctuations in some factor having direct real effect), these fluctuations can be sustained by expectations alone, even after the real shock disappears (an event that our subjects can not detect). We interpret these results to be consistent with the hypothesis that if economic agents believe that some random events matter in the determination of market prices, such beliefs can be self-fulfilling even if these events are extrinsic to the economy. We cannot reject the null-hypothesis that only real shocks can sustain fluctuations in the long-run. However, the learning process can be slow to adapt to changes that are not clearly perceived by agents, causing persistency of equilibria. We discuss the experimental results in Section 4.

The theoretical model is described in Section 2. We analyze a version of the OLG model studied by Woodford [25] which exhibits a monetary steady-state equilibrium, 2-period cyclic equilibria and 2-state Markovian sunspot equilibria. Furthermore, for the chosen parameters there is a continuum of rational expectations (perfect foresight) equilibria with a common long-run steady state. In this set of experiments, we focus on deterministic equilibria; these are simpler to study in laboratory and cyclic equilibria represent extreme cases of Markovian sunspot equilibria (in the sense that the probability of state transition is taken to its limit of one).

The experimental environment imposes some restrictions on the design of the experiment that cause it to depart from the theoretical model. These differences must be taken into account. Our experimental design follows the one used by Lim, Prescott and Sunder [13] and Marimon and Sunder ([16],[17]), although our subjects are assisted by an "expert system" that computes their respective optimal competitive supply once subjects make their price forecasts. In summary, we place several "model restrictions" on our experimental subjects. They submit a point-forecast and the theoretical model takes care of the rest. Even with these restrictions in place, the problem of indeterminacy does not disappear, and we can focus our attention on study of learning behavior and how this affects the final outcomes.

By restricting subjects' forecasts to be *point*-forecasts we preclude taking explicit account of learning processes based on the *distribution* of prices (such as Bayesian learning). While the underlying model is deterministic, market uncertainty arises naturally in our experimental environment where beliefs are not perfectly coordinated at the outset. There is also a source of uncertainty because subjects can not observe if a real shock is taking place. Subjects may want to take this into account and use their forecast price distribution to compute their optimal supplies. If our subjects were risk averse, the supplies computed from their point-forecasts would underestimate the optimal supplies since they ignore the precautionary motive for holding cash balances (see [16]). Nevertheless, our theoretical model gives the same qualitative predictions (existence of a two-period cycle, etc.) when uncertainty is taken into account and randomness is small. More details of our experimental environment are given in Section 3.

2 The model

The theoretical model underlying each economy had identical, two-period-lived overlapping generations of agents trading a single completely perishable consumption good (called chips) and fiat money. Agents were allowed to trade in current period spot markets in each period of life but had to hold money in order to transfer value from one period to the next.

2.1 Agents' characteristics

Each agent's preferences for the consumption good are given by a modified CRR utility function

$$U(c_1, c_2) = \max\{0, 2[2(c_1/5)^{1/2} - 0.5(c_2/5)^{-2}] + 4\} \tag{1}$$

where c_1 denotes consumption in the first (young) period of life, and c_2 denotes consumption in the second (old) period of life. The max operator ensured that forecasting errors did not cause an unbounded negative payoff because such a payoff would be difficult to settle in the laboratory. The fixed payoff of 4 was included to avoid negative payoffs that may occur in the cyclic equilibria. The parameters were chosen to ensure that the non-negativity constraint would not be binding in any of the predicted equilibria.

Each agent was endowed with $\omega^1 = 10$ units of chips when young and $\omega^2 = 0$ units of chips when old. Each of the initial (Period 1) old agents was endowed with a fixed amount of money $\bar{m} = 25$ francs which he/she could trade for c_2 chips, receiving utility

$$V(c_2) = 0.5(c_2/5)^{-2}. \tag{2}$$

Agents were permitted to trade chips for money in a single period spot market. Young agents supplied chips to the old agents in exchange for money (labeled francs in the lab) which was carried forward to the next period when it was exchanged for chips. Letting p_t denote the price of chips in terms of money, agents faced the following budget constraints.

$$\begin{aligned} p_t \cdot c_1 + m_1 &= p_t \cdot \omega^1 \text{ (when young)} \\ p_{t+1} \cdot c_2 &= m_1 \text{ (when old).} \end{aligned}$$

Here m_1 denotes a young agent's demand for money. Letting p^e_{t+1} denote the young agent's forecast of the price at $t+1$, the first-order conditions for the optimal money demand in the model are

$$\frac{25(p^e_{t+1})^2}{m_1^3} - \frac{1}{p_t}(5[10 - \frac{m_1}{p_t}])^{1/2} = 0. \quad (3)$$

When this equation is solved for m_1, it yields the optimal money demand as a function of the current price p_t and the expected future price p^e_{t+1}.

2.2 Equilibria

The parameters of the model are such that it can exhibit several distinct *stationary rational expectations equilibria*. For the *non-stochastic model* considered in these experiments, there can exist simple steady-state equilibria together with cyclic equilibria of period 2. Perfect foresight equilibria in the model can be analyzed by substituting the fixed per-capita money supply of 25 francs into the first order conditions. Upon simplifying, this yields the equilibrium equation $p_t = \phi(p^e_{t+1})$ given implicitly by,

$$p_t(p^e_{t+1})^4(2p_t - 5) = 5^6. \quad (4)$$

It can be seen from this equation that in every economy there was a unique monetary steady-state equilibrium at price $p^* = 5$, where p^* solves the equation $p^* = \phi(p^*)$, i.e.,

$$(p)^5(2p - 5) = 5^6. \quad (5)$$

In addition, the preferences are such that there also exist two cyclic equilibria of period 2. Let $\bar{p}$ and $\underline{p}$ denote the cyclic equilibrium prices. The two cycles correspond to $\bar{p} = \phi(\underline{p})$ and $\underline{p} = \phi(\bar{p})$; these are $\underline{p} = 2.56$ and $\bar{p} = 14.75$ and are obtained analytically as solutions to the equation $\varphi(\bar{p}, \underline{p}) = (\phi(\underline{p}), \phi(\bar{p}))$, given by

$$(q,p) = ((\frac{5^6}{p(2p-5)})^{1/4}, (\frac{5^6}{q(2q-5)})^{1/4}). \quad (6)$$

Whether or not either of these equilibria are obtained depends on the ways in which agents form their forecasts, and on the stability properties of the equilibrium under these schemes.

2.3 REE equilibrium paths and price dynamics with adaptive learning

Is a stationary k-cycle $\bar{p} = (\bar{p}^1, \ldots, \bar{p}^k)$ locally stable in the sense that if prices are sufficiently close to $\bar{p}$ then the series of k-prices will converge to $\bar{p}$? The first stability requirement is given by the local stability properties of the map $\varphi(\cdot)$ at $\bar{p}$, defined by:

$$\varphi(\bar{p}^1, \ldots, \bar{p}^k) = (\phi(\bar{p}^2), \ldots, \phi(\bar{p}^k), \phi(\bar{p}^1))$$

where $p_t = \phi(p^e_{t+1})$. The second requirement is that agents' behaviors must reinforce the stability properties of the $\varphi(\cdot)$ map[1]. To achieve this, it is usually assumed that agents use k-order adaptive learning rules of the form

$$p^e_{t+k} = p^e_t + \alpha(p_t - p^e_t)$$

if t mod $k = j$ and where $0 < \alpha < 1$[2]. In a k-cycle, $p_t = \phi^k(p^e_{t+k})$, and if, in addition, it is assumed that $p^e_{t+k} = p^e_t$, then price expectations evolve

[1]In particular, if the second requirement on learning rules is satisfied, a necessary and sufficient condition for local stability of φ is the local asymptotic stability of differential equation $\dot{p} = \varphi(p_\tau) - p_\tau$ at $\bar{p}$, provided that some regularity conditions of ϕ are also satisfied (see [7]).

[2]In general, prices can be random variables, e.g.,$p_t = \phi(p^e_{t+1}) + \epsilon_t$, and then instead of a constant α, it is postulated a α^j_t which must satisfy assumptions of the form $\alpha^j_t \searrow 0$ and $\sum_t \alpha^j_t = +\infty$. These assumptions are satisfied when agents use adaptive least squares learning on $p_t, p_{t-k}, \ldots, p_{t-n\times k}, \ldots$ to forecast p_{t+k}.

according to the k-order adaptive rule,

$$p^e_{t+k} = p^e_t + \alpha(\phi^k(p^e_t) - p^e_t).$$

That is, in a two-period cycle, only past price information of even periods is relevant for forecasting the price of an even period. Furthermore, within the 2-period cycle, this forecasting rule is self-confirmed. In particular, for the above model, the map $\phi(\cdot)$ is locally unstable at the steady state $p^* = 5$; when it is considered as a backward map, $p_{n+1} = \phi^{-1}(p_n)$. This also means that as a perfect foresight (forward) map $p_t = \phi(p^e_{t+1})$, (4) describes a continuum of rational expectations equilibria with a long-run steady state p^*. One of these equilibrium paths is represented in Figure 1.1.

[Figure 1 about here]

In contrast, map $\varphi : R^2 \mapsto R^2$ is locally asymptotically stable at $(\underline{p}, \bar{p})(or(\bar{p}, \underline{p}))$, when considered as a map, $(p^1_{n+1}, p^2_{n+1}) = \varphi(p^1_n, p^2_n)$. The possibility of obtaining a cyclic fulfilled expectations equilibrium arises if agents use a second-order adaptive learning rule. Figure 1.4 plots a price series when agents have homogeneous second-order beliefs. However, if agents use first-order adaptive learning rules (i.e., they are not "tuned" with the cycle), then the resulting temporary equilibrium dynamics will converge to the monetary steady-state if they put sufficient weight on their own previous forecasts. Since (1-α) is the weight on previous forecasts, this condition requires the value of the parameter $\alpha \leq 0.88$ in our model with homogeneous learning rules[3]. Figure 1.2 illustrates a price path when agents use homogeneous first-order forecasting rules with low α's.

[3]For higher values of α the price process converges to a two-period cycle whose magnitude depends on α; as $\alpha \rightarrow 1$, the cycle converges to the cycles of $\varphi(\cdot, \cdot)$. In these cycles, however, prices differ in an obvious and systematic way from the expected prices. See Figure 1.3

We will use a variation of the first-order (linear) adaptive rule, by postulating forecasting schemes of the form

$$p_{t+1}^e = p_t^e + \alpha(p_{t-1} - p_t^e).$$

We use the specification in terms of p_{t-1} because subjects were required to make point (rather than functional) forecasts at the beginning of time t, when p_t was not in their information set. While this specification does affect the temporary equilibrium price trajectory, it does not affect the overall convergence properties of the model.

These observations on the convergence properties of the dynamics associated with various hypothesis about how agents forecast future prices allow us to pose some experimentally testable hypotheses. If agents have perfect foresight, the economy should converge to the monetary steady-state. On the other hand, if agents forecast adaptively, then the convergence properties will depend on the dynamics of their forecasts (see [25], [11] or [7] for detailed discussions of these issues). If forecasts extrapolate simple steady-states, we should see convergence to the monetary steady-state; if forecasts extrapolate cyclic patterns, we can expect to see cyclic equilibria.

To complete our discussion of the various types of equilibria, we deal briefly with the equilibria which result during the periods in which expectations are being conditioned. As noted in the Introduction and shown in Section 4, cyclic patterns did not arise spontaneously. In order to study conditional price fluctuations we exposed our subjects in several economies to a real shock by varying the size of the generations. This real shock induces cyclic movements in the temporary equilibrium prices. Table I reports the parameters and equilibria for the various experimental sessions in which this technique of inducing expectations was used. For the periods in which generation size varied, the reported equilibria were calculated numerically. Since numerical methods tend to mimic the (backward) dynamics of the $\phi(\cdot)$ map, only the cyclic equilibrium values were obtained, although theoretically, for small shocks, there is a steady-state equilibrium. As we have said in the Introduction, a source of uncertainty may be induced in our experimental environment by having different stages with and without real shocks. Suppose agents were to condition their forecasts on the presence of these shocks (and not on the perfectly correlated signal). Since the subjects do not observe whether the shocks are taking place, they should have some beliefs about the likelihood of occurrence of a real shock. We describe the deterministic equilibria as *benchmarks* or approximation to the stochastic equilibria when uncertainty is small.

[Table I about here]

3 The OLG experimental environment

In the experimental sessions, we forced subjects to act as competitive price takers by soliciting forecasts from each agent, and numerically constructing the optimal money demands for each young agent as functions of p_t given each agent's forecast of p_{t+1}. This was done by calculating the optimal m_1 (given the forecast) over a grid of 60 possible values of p_t, and interpolating linearly between these values.

The temporary equilibria in the market were computed by aggregating the money demands of young agents and numerically solving for the money market clearing price, given a fixed supply of fiat money. In the experiment, the fixed money supply was determined by the number of agents assigned to the old generation in Period 1. Once this assignment was made, the money supply remained constant throughout the economy. Once the competitive temporary equilibrium price was determined, chips were transferred from young agents to the old in exchange for money in the amounts specified by the young agents' money demands (evaluated at the market-clearing price), and according to the amount of money held by the old of that period. We report the behavior of five overlapping generations economies, numbered 1 through 5, each operated for many (27-67) periods. (For reasons explained later in this section, we do not report the results of eight other laboratory economies we conducted in this series. All data are available from the authors.) The key design features and the equilibrium predictions of the models discussed in the previous section about the performance of these economies are summarized in Table I.

3.1 Experimental environment

Overlapping generations were created in the laboratory by recruiting $N > 3n + 1$ subjects, where n was the number of agents in each generation. Each subject was seated at a networked personal computer and shielded from viewing the computer screens of others. In every period of the economy, n subjects entered the market as a new generation of young agents. The n subjects who entered the market in the preceding period constituted the old generation, and the remaining ($\geq n + 1$) subjects, called outsiders, were inactive. In the following period, n of the outsiders were randomly picked to constitute the young generation of that period, before the subjects who had just finished serving as the old were added to the pool of outsiders. This procedure ensured that every subject sat out of the economy for at least one period before re-entering the market, and that the number of periods for which the subject had to sit out was random.

At the beginning of each period, subjects saw a blinking square on their computer screens. Color of this square cycled between red and yellow in alternate periods. Colored squares for the prior periods remained on the screen but they did not blink (see Figure 2). For a certain number of consecutive periods in each economy (see Table 1), the economy was imparted a real shock by cyclically variying the number of subjects in each generation between a high and a low number in phase with the color of the blinking square on subjects' computer screens. Subjects remained unaware of the existence or absence of generation size shocks.

[Figure 2 about here]

Once the new generation of agents was assigned, all subjects were prompted to predict prices for the current and the following periods. Price predictions were used by the computer to form the utility-maximizing money demand functions for the newly entering young agents, and in a direct competition for the most accurate prediction of the current period price. The winner(s) of the competition received a fixed payoff of 5 "utils" above and beyond any earnings from the market activity. The competition generated incentives for accurate predictions and was used in terminating the economy (see below).

Once all subjects had entered their price predictions, the future price prediction of each young agent was used to compute a utility-maximizing money demand schedule (as a function of the current price) given the forecast of the future price by solving (3). The central computer aggregated money demand functions across the young agents and computed the market clearing temporary equilibrium price. Chips were transferred from the young to the old at the market-clearing price. The market-clearing price and other data were then displayed on the subjects' screens. Price and gross inflation were displayed in the color of the blinking square (red or yellow) for the period (see Figure 2).

After market-clearing, old agents were informed of their payoff based on total chip consumption in both periods of market participation according to (1). Each young agent was informed of the number of chips he or she consumed in the current period and the amount of money carried forward to the next period. Old agents then joined the pool of outsiders and young agents turned old. Results of the price prediction competition were announced and the winner(s) received the prediction prize. This completed one period of market activity, and the process was repeated for the next period.

The experimenter terminated each economy by selecting the termination option after all subjects had entered price predictions for the final period. Subjects were informed that the economy was over and the terminal old were allocated chips in exchange for money at the average of the terminal price predictions entered by the outsiders in the final period.

The subjects were undergraduate students in Spear's Intermediate Microeconomics class; they participated in the experiment as part of a class project. They were given some initial instruction on the structure of OLG models, the utility functions that would be used in the experiment, and the role of forecasts in determining the temporary equilibria of the model. Prior to the experimental sessions, however, there was no classroom discussion of the nature and types of equilibria that could occur. Subjects received points toward course credit in proportion to their total earnings of "utils" in the experiment. A summary of procedures and instructions is given in Appendix I. A full set of instructions is available from the authors.

4 Experimental results

Like our subjects, we also learned through the experiment. We briefly describe our early attempts at studying expectationally driven market volatility in an experimental environment, before reporting the results of five experimental economies.

4.1 Experimental priors

During a series of eight prior economies conducted in the spring of 1990, we discovered several things which led us to modify the setup used in the economies reported on here. First, in the trial sessions, subjects were required to solve the optimization problem themselves and to submit seven-point chip supply (equivalently, money demand) schedules to the central computer. These schedules were then aggregated to construct the market demand schedule and find the temporary equilibrium price. Data from these economies revealed that, given the time constraints and their lack of familiarity with the optimization problem, subjects generally made large errors in finding the optimal chip supply schedule. To control the noise this problem introduces into data, we eliminated the need for subjects to solve the optimization problem by having the computer calculate money demand functions given subjects' forecasts of the future price. This has the effect of controlling for Walrasian behavior and focuses the experimental results on the question of expectations alone.

The second issue concerns the generation of extrinsic uncertainty in the lab. During the trial sessions and the sessions reported here, extrinsic uncertainty was generated by changing the color of a blinking square on the computer screen according to the realization of the sunspot variable. In addition, the history of prices displayed on subjects' screens was color-coded to correspond to the realization of the sunspot variable. In the course of the trial economies, it became apparent that subjects will not use sunspot variable in their forecasts in the absence of any observed initial correlation of the movements of prices and the sunspot variable. Most price paths converged toward the steady-state monetary equilibrium in economies with purely exogenous signals (flashing light on the screen, etc.); this phenomena is illustrated in the first stage of Economy 5 (discussed below).

Our first attempt to induce subjects to consider the sunspot realizations followed a suggestion from Woodford [1990] paper: subjects were given an additional utility payoff depending on the realization of the sunspot. This had no discernible effect on the observed equilibrium prices. We then ran several sessions in which we initially "trained" expectations by varying the chip endowment according to the realization of the sunspot variable. After the training period, the endowment shocks were turned off and endowments remained constant for the remainder of the session. The first such economy generated what can be interpreted as excess volatility of prices during the period in which endowments were constant, but this effect was not replicated during any of the subsequent economies. We conjecture that this occurred because subjects became aware that a regime change was being made (since young agents in the market see the endowment realization), and this information was communicated to the market.

This experience led us to train expectations during the current round of economies by varying the generation size instead of varying endowments. This procedure ensured that subjects were not directly aware of the regime change when it occurred and could only make inferences about the state of the economy by observing prices. As with the trial economies, once the training period was past, generation size was held constant for the remainder of each session.

4.2 Session descriptions

We present data for five economies run during the week of November 5, 1990. Data on market-clearing temporary equilibrium prices, the number and identity of subjects entering as young agents, and each subject's prediction of current and future prices were recorded for each period.

We present a brief description of each experimental economy and a plot of the time-series of observed prices and generation size, before discussing the results.

Economy 1 This economy involved 14 subjects and a prediction prize of 5. Generation size alternated between 3 and 4 (with 4 initial old agents and hence an aggregate money supply of 100) for the first 17 periods, after which generation size remained constant at 4. The economy was terminated after period 46.

Economies 2 and 3 This session had 10 subjects and consisted of two economies. The first crashed after 27 periods (Economy 2) and the second after 29 periods (Economy 3). Prediction prize was 5. In Economy 2, generation size alternated between 2 and 3 (with 3 initial old and hence an aggregate money supply of 75) for the first 17 periods. In Economy 3, generation size alternated between 2 and 3 (with 3 initial old agents) for the first 11 periods. Generation size in both runs was constant at 3 after the shocks were terminated.

Economy 4 This economy consisted of a single run with 13 subjects. Prediction prize was 5. Generation size alternated between 3 and 4 (with

4 initial old agents and an aggregate money supply of 100) for the first 20 periods. It was terminated after 50 periods.

Economy 5 This economy consisted of a single run with 15 subjects. Prediction prize was 5. In this economy, generation size remained constant at 4 for the first 14 periods (with 4 initial old agents, aggregate money supply of 100). Thereafter, generation size alternated between 4 and 5 for 22 periods (periods 15-36) at which point generation size became constant at 4. The economy was terminated after period 67.

4.3 Temporary equilibrium price patterns

Five panels of Figures 3 plot the time-series of market-clearing prices for the five economies, together with the steady-state and the range of the two 2-cycle equilibria. Periods in which generation-size shocks were present are also indicated. We would like to draw attention to four features of the experimental data.

[Figure 3 about here]

- First, extrinsic shocks (pure sunspots) are not enough to generate cyclic patterns. For example, in Economy 5, subjects experienced generation-size shocks during Periods 15 through 36. Without prior exposure to such shocks, this economy exhibits approximate convergence toward the steady-state price of 5 in Periods 1 through 14. Behavior of the same economy during Periods 37-67, when generation-size shocks were absent, is different. We infer that the exposure to shocks during Periods 15-36 accounts for the difference. Further experiments with longer economies in which generation size remains fixed would be of interest.

- Second, the amplitude of price fluctuations is greater during the periods in which generation size is varied cyclically compared to periods when generation size is fixed. This feature is in accord with predictions from the model for the cyclic stationary equilibria when generation size fluctuates cyclically (see Table I).

- The third feature common to the data is a tendency for price fluctuations to persist after generation size is fixed. This occurs in all economies except in Economy 2. We interpret this persistence as evidence for the kind of expectationally-driven price volatility predicted by the sunspot equilibrium models. The persistence of fluctuations is clearest in Economies 1 and 5, and we will focus on these two economies in the following sections.

- Finally, the fourth common feature concerns the fixed-generation-size periods in which the observed price deviates significantly from the predicted cyclic equilibrium. All economies in which cyclic fluctuations persist after the termination of generation-size shocks exhibit periods in which the temporary equilibrium price is closer to the predicted steady-state price of 5 than to the cyclic price. It is interesting to note, however, that even after prices in the vicinity of steady-state equilibrium are observed, the pattern of cyclic fluctuations reestablishes itself in all economies except in Economy 2. In Economy 2, the price pattern seems to converge to the steady-state. Reestablishment of cyclic fluctuations is in accord with the stability predictions of the theoretical model when agents' forecasts are adapted to the cyclic equilibrium.

We turn next to a more detailed examination of the data from Economies 1 and 5.

4.4 A closer look at Economy 1

Economy 1 provides evidence of sustained, expectationally-driven cyclic movements in prices, so we focused our analysis more closely on the data from this session. Figure 4 shows the time-series of market-clearing prices for the periods after the fluctuations in generation size were terminated (periods 17-46). On the same graph, we also plot the steady-state equilibrium price, and prices corresponding to one of the two stationary REE cycles of period 2 predicted by the model. Price corresponding to the second cycle of period 2 simply lag behind the prices shown by π; these prices are not shown in the figure to preserve its clarity.

[Figure 4 about here]

Two empirical regularities should be noted in this data. First, the observed prices are consistently within the range of predicted high and the low prices (except for period 40). It appears as if the amplitude of the observed cycle has been attenuated. Uncertainty with respect to whether real shocks are present, might have a dampening effect on cycles.

The second regularity is the punctuation of the persistent cycle by occasional prices in the vicinity of 5, the predicted steady-state equilibrium price. Since price forecasts were the only input from subjects, this feature of the data is also attributable to regularities in forecasts. Hence, we turned to the data on individual subject's forecasts to search for an explanation of these regularities. We consider two hypotheses about the source of the observed deviations from the cyclic pattern. First, subjects might commit errors in entering their forecasts into the computer. We observed several instances in the lab when shifting the decimal point would have brought an individual forecast in line with previous cyclic predictions. On occasion, subjects also seem to deliberately enter outlandish forecasts, either because of boredom or by way of exploring the limits of software. In an economy where each young agent makes up a third to a quarter of the market, the effects of "dinging" the system in this way can be significant. While we observed both of these types of behavior, we do not feel it occurred regularly enough across all five economies to explain the observed deviations from the cyclic pattern.

The second hypothesis we entertained is that some subjects deviated systematically from second-order forecasting behavior. This could occur for many reasons, ranging from failure to perceive the cyclic pattern in the market clearing prices during the first 17 periods, to more sophisticated strategic attempts to manipulate forecasts. Given the cyclic color coding of price history on subjects' computer screens, it seems unlikely that the subjects could have missed the relationship entirely.

To test this second hypothesis, we used the individual price forecasts to crudely infer and classify subjects' forecast rules[4]. We estimated an ordinary least squares regression of p^e_{t+1} on p^e_t, p^e_{t-1}, p_{t-1}, and an intercept to identify which variables have significant coefficients at 5 percent level. Forecast p^e_{t+1} was regressed again on the subset of variables which had significant coefficients in the first regression. Coefficients of the second regression (along with their estimated standard errors) are shown Table II.

[Table II about here]

If the estimated forecasting equation for an individual fit the second-order scheme, he or she was classified as a second-order adaptive forecaster. Using this criterion, we classified ten subjects (all except for Subjects 3, 11,

[4]Data and time series charts of these and other individual forecasts discussed in the paper are available from the authors on request.

12, and 13) as second-order forecasters. We then examined the relationship between the number of second-order forecasters in each young generation and the deviation of prices from the predicted cyclic values. This analysis indicates that the degree of forecasting homogeneity does matter: the presence of non-second-order forecasters led to temporary equilibrium prices which deviated significantly from the cyclic equilibrium prices predicted with homogeneous second-order forecasters. This conclusion was also borne out in simple simulations of heterogeneous adaptive forecasting behavior in the model.

Why the amplitude of observed prices is less than the amplitude of the predicted cycle remains an open question. One possibility is that subjects systematically hedge their forecasts, based on their previous experience with deviations from the cyclic pattern. This could be consistent with explicitly modeling the uncertainty over the real nature of shock supporting the cycle. While it should be possible to study this kind of effect using richer adaptive forecasting rules, we have not yet undertaken any systematic study of this effect.

4.5 A closer look at Economy 5

Economy 5 was perhaps the most interesting of the five experimental economies. It differed from the others in that the 22 periods of alternating generation size (4-3) were preceded as well as followed by periods of fixed generation size (4). We analyze the results of the first 14 and the last 31 fixed-generation-size periods of this economy separately.

4.5.1 Periods 1-14

We began this economy without changes in generation size to test the hypothesis that subjects would spontaneously fix upon on the sunspot (i.e. the blinking colored light on their computer screens and the price history coded in corresponding colors) as being relevant to their forecasting problem. Figure 5.1 plots the price series for the first 14 periods of Economy 5, along with the steady-state equilibrium price of 5 in solid horizontal line. For comparison, Figure 5.2 plots the price series together with the predicted 2-cycle equilibrium prices for periods 37-67 of this economy. We interpret the observed pattern during the first 14 periods as one of convergence to the steady-state equilibrium, although 14 periods is not a long series.

[Figure 5 about here]

The damped oscillations apparent in the data for periods 1-14 also support the hypothesis that forecasts were of first-order. Figure 6 displays the forecast series P^e_{t+1} for each of the 15 subjects in the economy (superimposed on the realized value of the market clearing price P_{t+1} in broken line). Analysis of the individual forecasts for these periods also reveals the forecasts to be of first order. As in Economy 1, we regressed individual forecasts using mixed first and second order forecasting equations (a constant, p_{t-1}, p^e_{t-1} and p^e_t as explanatory variables) for each subject and found p^e_{t-1} to be significant only for Subjects 2 and 12 (the coefficient being negative for Subject 12).

[Figure 6 about here]

We again estimated a regression of p^e_{t+1} on p^e_t and p_{t-1} (see upper panel of Table III). While the first-order scheme does seem appropriate, especially considering the limitations of the small sample size, the estimated weights differ considerably across subjects. These coefficient estimates were used to define first-order forecasting automaton versions of the fifteen individual subjects. We simulated the first 14 periods of Economy 5 by replacing the human subjects by their automaton representations. The resulting price series, shown in a broken line in Figure 5.1, is almost indistinguishable from the series generated by human subjects.

We simulated this economy for a second time by using homogenous first-order forecasting automatons as agents. While a value of $\alpha = 0.25$ generates a reasonable approximation of the damped oscillations observed in Figure 5.1, the simulated economy with homogenous automatons generates oscillations that are too regular compared to the data from Economy 5. By contrast, in the first simulated economy, consisting of automatons that used the forecast functions estimated from the Economy 5 data, price series exhibits greater similarity to the Economy 5 data, both in lack of regularity and in dampened oscillations.

[Table III about here]

4.5.2 Periods 37-67

Figure 5.2 plots the price series for periods 37-67, together with the steady-state equilibrium price and the prices corresponding to one of the two cycles of period 2 predicted by the model. Again, we plot only one of the two cycles for the sake of clarity. Expectations were trained using cyclic variation in generation size during periods 15-36 (see Figure 3.5), after which generation size became constant, as in the previous four economies. The generation size remained unobservable to the subjects.

As in the previous economies, we again observe cyclic variations in the prices, together with deviations from the cyclic prices to prices in the proximity of the steady-state equilibrium. Also, as in previous economies, the steady-state equilibrium is not stable; deviations toward the steady-state are followed by reversion to the cyclic equilibrium. Unlike previous economies, however, in this economy the cycle reestablishes itself with the phase of the cycle reversed! Indeed, phase reversals occur three times in this economy.

One possible explanation is that these phase reversals occurred because subjects extrapolated trends they saw in the high and low prices. This was particularly easy to do in the lab because the color coding of the even and odd period prices had the effect of highlighting trends in these prices. (Several of the participants in this economy also reported that they began to expect periodic phase reversals to occur after experiencing the first two. This may explain the rapidity with which the final reversal occurred.)

Finally, in Figure 7 we also show the individual forecast series for these periods superimposed on the realized prices. The lower panel of Table III shows the estimates of the second-order forecasting scheme for each individual. As with Economy 1, the second-order forecasting scheme again fits the data reasonably well. However, unlike Economy 1, the coefficient estimates for Economy 5 suggest that subjects were placing much more weight on observed lagged prices than on their own previous forecasts. In Economy 5, only 7 out of 15 subjects have statistically significant coefficients for p^e_{t-1}, while p_{t-1} is significant for all but Subject 6. Furthermore, 9 of 15 subjects put weight of 0.85 or more on p_{t-1}. By contrast, only one subject (Subject 14) of Economy 1 put as much weight on the lagged price in the estimated forecasting equation.

[Figure 7 about here]

These differences in forecasting behavior between Economy 1 and Economy 5 may explain the presence of phase reversals in Economy 5. With high coefficients in on p_{t-1} in the second-order forecasting equations (and 4 subjects had weights greater than 1!) it is possible to have trend extrapolations on expected prices, damped by the temporary equilibrium dynamics. When the forecasting schemes are of second order, with high coefficients on realized prices, the price series for odd and for even periods can follow specific, separate, trends which may produce phase reversals.

5 Concluding remark

To our knowledge, we have provided the first experimental data that has some bearing on the existence of expectationally driven cycles and we have found that *if agents expect sunspots to matter, they can matter* (although we can not assess how persistent they can be). The question is, and has probably always been, *why should agents expect sunspots to matter?* Without a real cycling shock we have seen no evidence for the emergence of such beliefs. However, such beliefs can be induced after subjects have been exposed to real cycling phenomena. Our experimental environment might seem too special in that we have a simple deterministic real shock inducing a two period cycle (i.e., odd vs. even periods) and a well defined signal (color coded prices) and subjects cannot observe when the real shock effect disappears. Certainly, historical economies are more complex, but, at the same time, economic agents have greater communication possibilities than our experimental subjects had. Political events, decisions by important companies or banks, or simply economic policies that in their own right would have little impact, may be signals that, with the possible help from the press, can trigger and coordinate people's expectations. Our experiment suggests that this phenomenon is more likely to occur if the conditioning events are known to have been associated in the past with market movements. As with any starting work, more experimental work will need to be done to enhance our understanding of the role of the formation of expectations in determining equilibrium patterns.

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Table I

Parameters and Equilibria for Experimental Economies*

Economy	No. of Subjects (N) (experience)	Period	Generation Size (n)	Total Money Supply	Equilibrium Prices		
					Steady State	Cyclic	
						p	q
1	14	1–16	4–3**	100	N.A.	2.50	35.18
	(1 Trial Economy)	17–46	4	100	5.00	2.56	14.75
2	10	1–16	3–2**	75	N.A.	2.50	49.62
	(None)	17–27	3	75	5.00	2.56	14.75
3	10	1–10	3–2**	75	N.A.	2.50	49.62
	(Econ. 2)	11–30	3	75	5.00	2.56	14.75
4	13	1–20	4–3**	100	N.A.	2.50	35.18
	(None)	21–50	4	100	5.00	2.56	14.75
5	15	1–14	4	100	5.00	2.56	14.75
	(None)	15–36	5–4**	100	N.A.	2.50	29.13
		37–67	4	100	5.00	2.56	14.75

*The following parameters remained unchanged through all five economies:

Money endowment of the old in period 1 = 25 per capita
Chip endowment of the young (ω^1) = 10
Chip endowment of the old (ω^2) = 0
Prize for the best price prediction each period = 5
Probability of transition for sunspot variable =1

**Generation size alternated in consecutive periods.

Table II
Estimated Forecast equations for Individual Subjects*
Economy 1, Post-Generation Shock Periods (17-46)

Subject No.	$P^e_{t+1} = \alpha_0$ +	$\alpha_1\ P_{t-1}$ +	$\alpha_2\ P^e_{t-1}$ +	$\alpha_3\ P^e_t$	N	R^2
1		0.36 (0.18)	0.58 (0.15)		30	0.65
2		0.60 (0.09)	0.29 (0.08)		30	0.59
3	12.15 (2.16)			-0.35 (0.16)	30	0.15
4		0.59 (0.09)	0.40 (0.08)		30	0.79
5		0.31 (0.11)	0.64 (0.07)		30	0.82
6		0.48 (0.13)	0.46 (0.13)		30	0.65
7		0.45 (0.13)	0.54 (0.11)		30	0.77
8		0.30 (0.14)	0.42 (0.14)		30	0.05
9		0.66 (0.10)	0.32 (0.08)		30	0.79
10		0.30 (0.16)	0.53 (0.16)		30	0.29
11	17.15 (2.70)			-0.55 (0.21)	29	0.21
12			0.76 (0.09)		30	0.43
13	3.66 (1.26)		0.50 (0.11)		30	0.42
14		0.96 (0.06)			29	0.67

*(Standard errors of estimates are given in parentheses).

Table III

Estimated Forecast Equations for Individual Subjects*
Economy 5 (See Figures 6 and 7 for Forecast Data)

Subject No.	$P^e_{t+1} = \alpha_0$ +	$\alpha_1 P_{t-1}$ +	$\alpha_2 P^e_{t-1}$ +	$\alpha_3 P^e_t$	N	R^2
	Pre-Generation-Shock Periods (1-14)					
1		0.87 (0.37)		0.43 (0.25)	13	0.62
2		-0.38 (0.89)		1.44 (0.83)	13	0.16
3		0.05 (0.01)		0.98 (0.00)	13	1.00
4		-1.62 (1.48)		2.56 (1.46)	13	0.44
5		-5.76 (3.74)		6.77 (3.75)	13	0.96
6	No significant variables				13	
7		-0.04 (0.16)		1.02 (0.17)	13	0.96
8		-0.37 (0.55)		1.42 (0.51)	13	0.86
9		-2.41 (0.35)		3.33 (0.32)	13	0.87
10		1.14 (0.06)		-0.01 (0.01)	13	0.62
11		1.07 (0.03)		-0.03 (0.01)	13	0.92
12		0.62 (0.31)		0.47 (0.25)	13	0.68
13		0.03 (0.23)		1.04 (0.20)	13	0.69
14		-0.71 (0.26)		1.75 (0.24)	13	0.85
15		-0.13 (0.13)		1.02 (0.11)	13	0.06
	Post-Generation-Shock Periods (37-67)					
1		0.94 (0.23)	0.24 (0.20)		31	0.60
2		0.77 (0.05)	0.23 (0.05)		31	0.93
3		1.10 (0.07)	0.09 (0.03)		31	0.42
4		0.86 (0.19)	0.22 (0.17)		31	0.57
5		1.07 (0.06)	-0.05 (0.06)		31	0.86
6			-0.08 (0.02)	0.41 (0.02)	31	0.85
7		0.92 (0.16)	0.16 (0.09)		31	0.17
8		0.97 (0.13)	-0.01 (0.12)		31	0.74
9		0.59 (0.06)	0.35 (0.08)		31	0.85
10		0.62 (0.09)	0.40 (0.08)		31	0.85
11		0.73 (0.08)	0.28 (0.08)		31	0.85
12		0.56 (0.09)	0.41 (0.09)		31	0.72
13		0.87 (0.13)	0.14 (0.11)		31	0.58
14		1.09 (0.16)	0.01 (0.15)		31	0.71
15		1.05 (0.07)	-0.05 (0.09)		31	0.85

*(Standard errors of estimates are given in parentheses).

Figure 1
Rational Expectations and Adaptive Price Dynamics

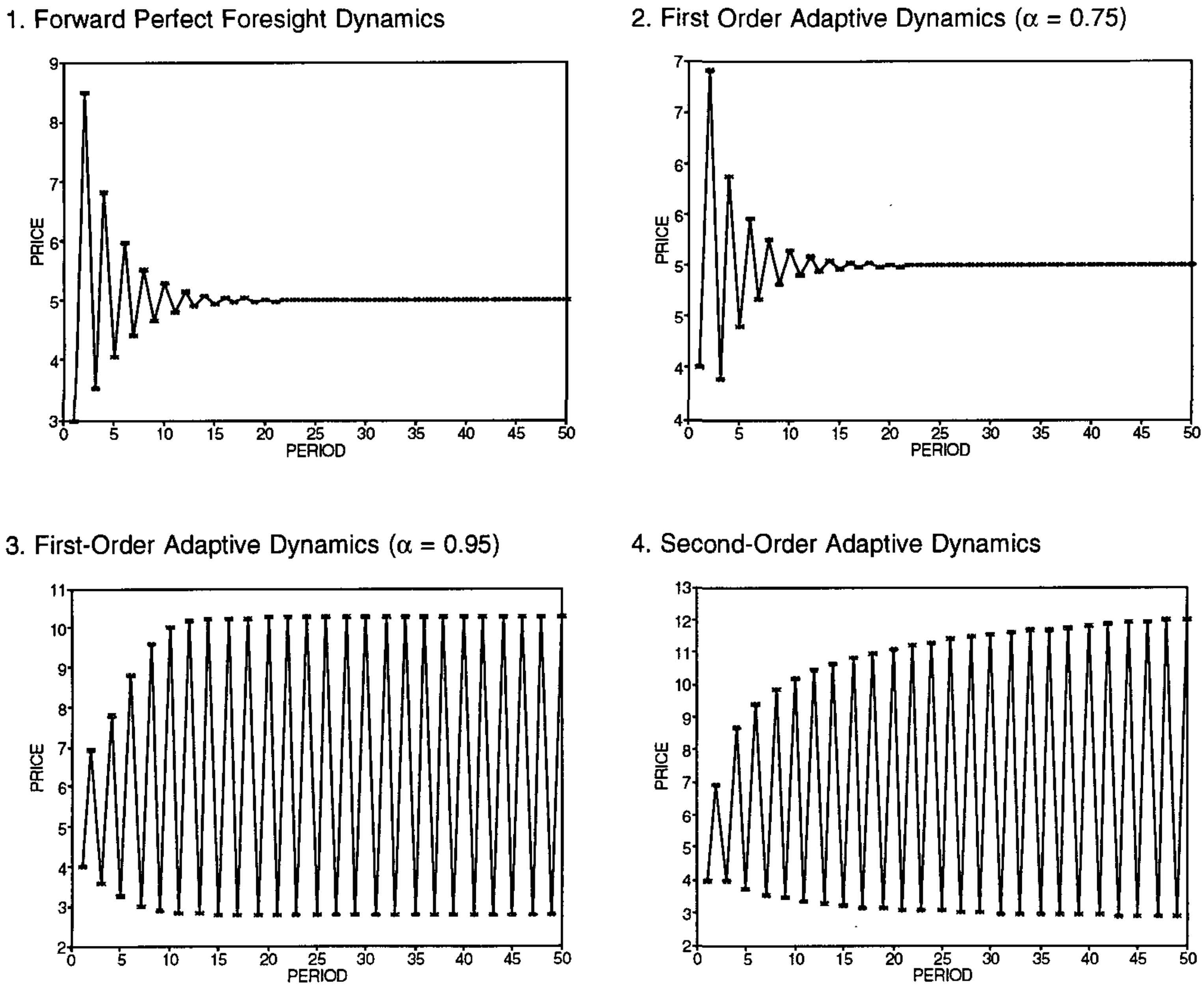


Figure 2

Main Subject Screen

Period# : 5
Player# : 7

	VALUES
Chip entry	10
Chip exit	0
Init. Money	25.000
Exchange	1.000
Pred. Prize	1.000

ENTRY

Please enter prediction for period 5:
Please enter prediction for period 6:

Are Predicted Prices OK (Y or N):
Sent information, please wait for results

Current Profit ($)	Cumulative Profit ($)
2.29	13.41

<== space for messages from experimenter==>

Period	Price	Money	Inflation	Money Growth	Best FE	Winner	MeanF
1	2.74	100	-	1.00	0.01	9	3.31
2	24.62	100	8.99	1.00	1.42	13	22.63
3	2.60	100	0.11	1.00	0.04	3	3.34
4	38.28	100	14.72	1.00	0.28	9	19.97
5	4.21	100	0.11	1.00	0.36	12	2.94

F1-Selling Offer Screen   F2-Prediction Screen   F3-Main Screen

Legend: Dark gray square or background = red on computer screen
Light gray square or background = yellow on computer screen
= Blinking square on computer screen

Best FE = Error in the winning price forecast
Mean F = Mean price forecast

Figure 3

Actual and Equilibrium Prices and Generation-Size Shocks

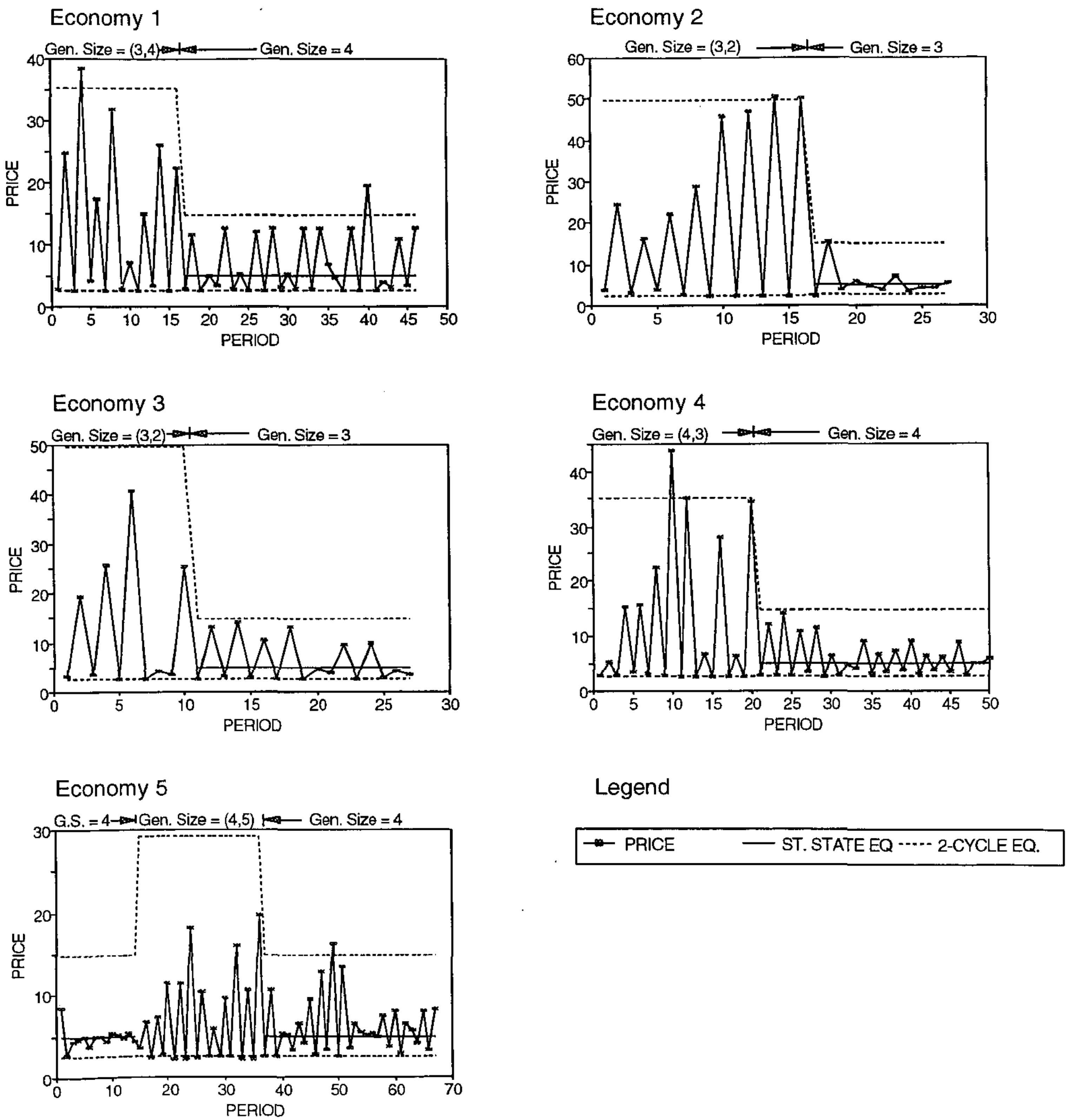


Figure 4

Actual, 2-Cycle, and Steady State Equilibrium Prices
Economy 1 (Post Generation-Shock Periods 17-46)

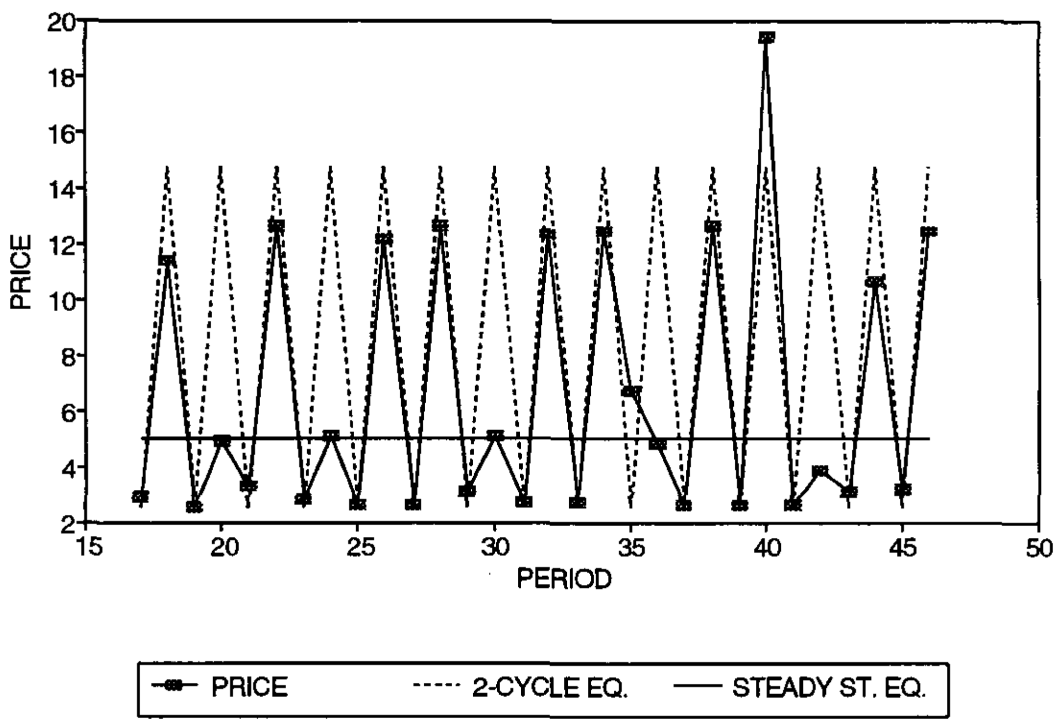
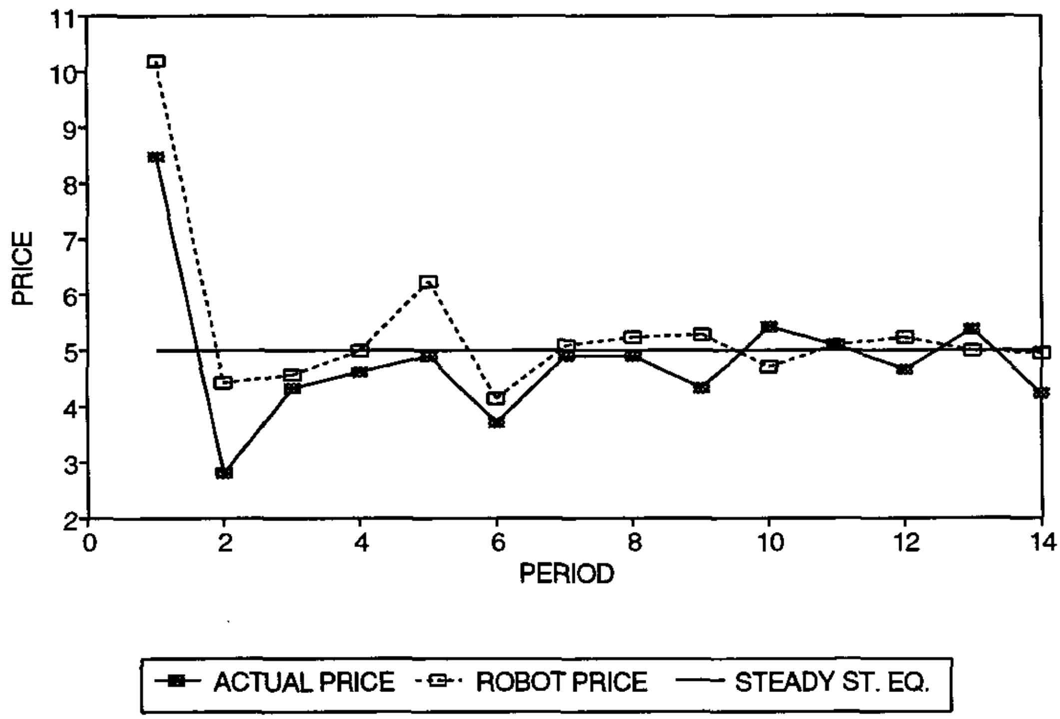


Figure 5

Economy 5 Time Series without Generation-Size Shock

1. Periods 1-14 (Actual and Robot Economy Prices and Steady State Equilibrium)



2. Periods 37-67 (Actual Prices and 2-Cycle and Steady State Equilibrium)

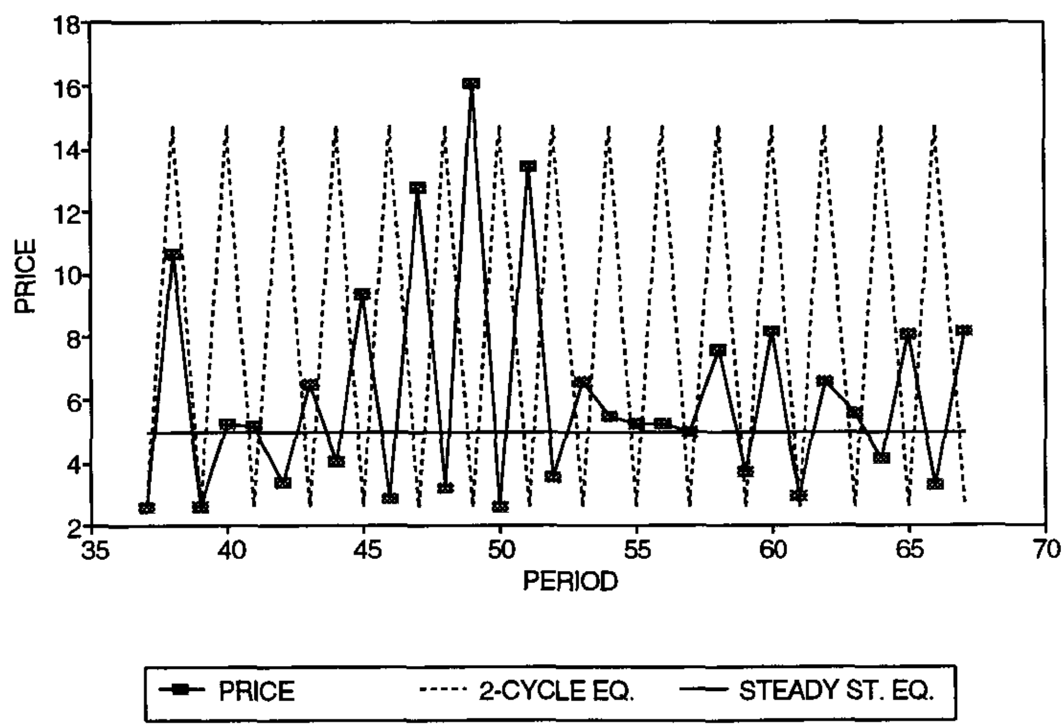
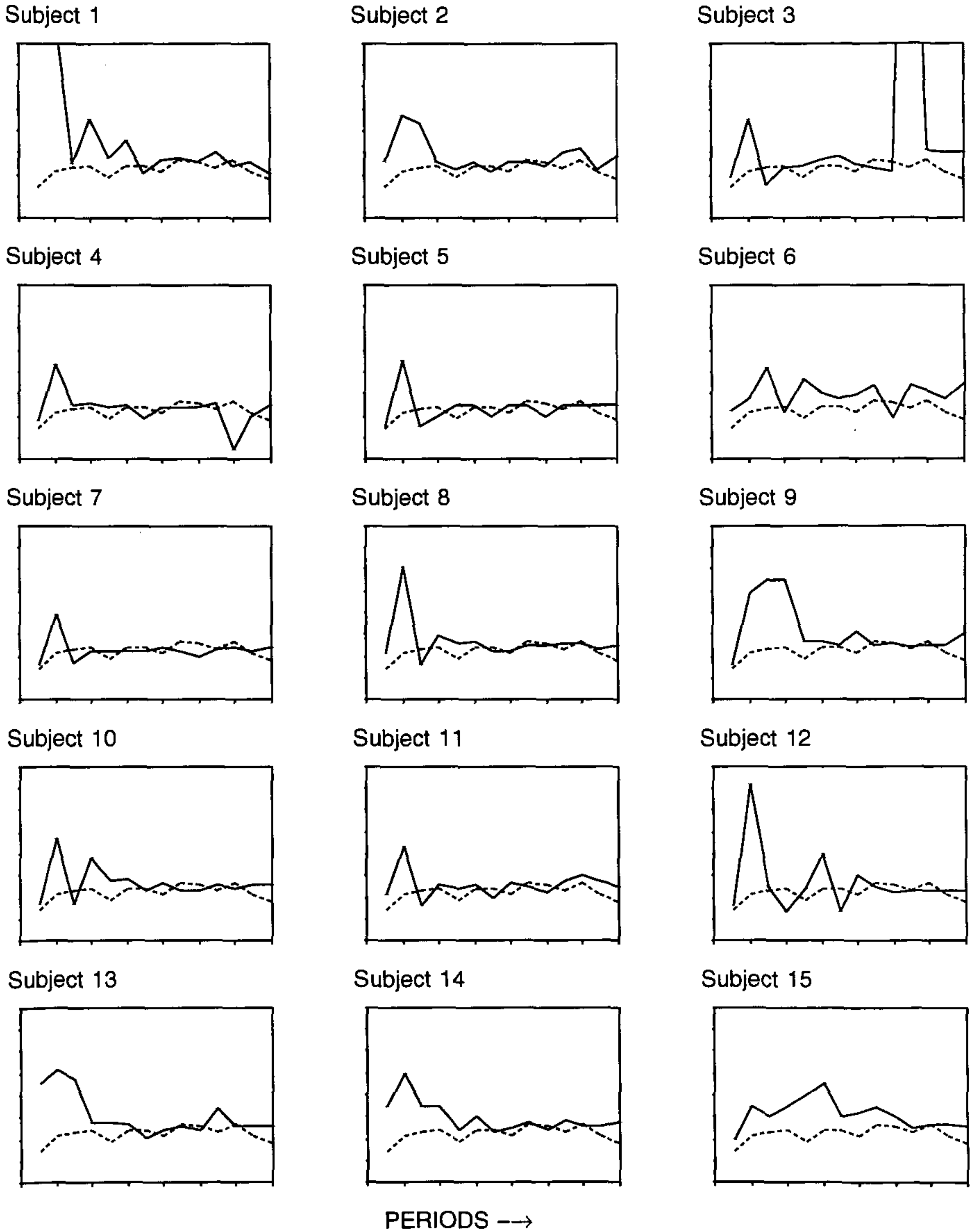


Figure 6

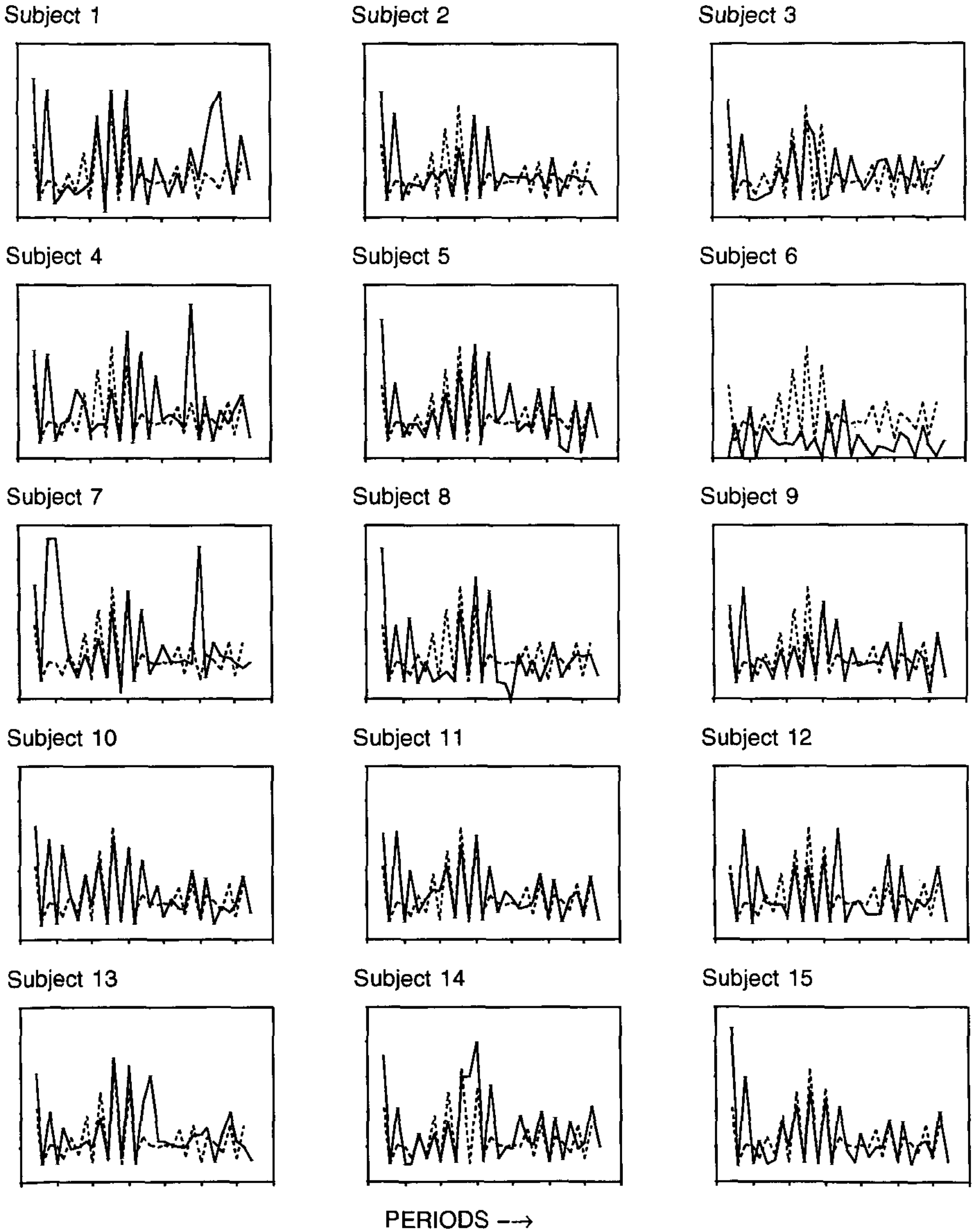
Individual Subjects' Price Forecasts Before Generation-Size Shocks
Economy 5 (Periods 1-14)



Legend: PRICE FORECAST (P^e_{t+1}) in solid line, ACTUAL PRICE (P_{t+1}) in dotted line.

Figure 7

Individual Subjects' Price Forecasts After Generation-Size Shocks
Economy 5 (Periods 37-67)



Legend: PRICE FORECAST (P^e_{t+1}) in solid line, ACTUAL PRICE (P_{t+1}) in dotted line.

Appendix

Summaries of our experimental procedure and of the instructions given to the subjects are given below. Full details are available from the authors.

Summary of Experimental Procedures

1. The central computer randomly chooses the initial period to be either "red" or "yellow," and displays a blinking square of the chosen color on subject screens. In subsequent periods, the color of the square cycles between red and yellow.
2. The computer selects n subjects from the pool of outsiders to enter the economy *in period t before the subjects who served as old in period t-1 are added to the* pool of outsiders. The number n remains fixed in periods without generation-size shock; it cycles in phase with the color of the blinking square between two numbers during the periods when generation-size shocks are in force (see Table 1).
3. Subjects are asked to submit their forecast of the market-clearing price of chips in period t. In addition, they are asked to enter their forecasts for period t+1.
4. From the forecasts of each member of the "young" generation, the computer constructs a money demand function using Equation (3), and aggregates the individual demands into money demand for the generation.
5. The central computer computes the point of intersection of money demand with the (constant) supply of money (25n for all economies reported here). Market clearing price is announced and individual subjects are informed of their allocations. Price is displayed on computer screens in red or yellow color as appropriate.

6. The old are informed of the number of dollars they earned on the basis of the chips they consumed in their young and the old period. Members of the old generation then join the pool of outsiders.

8. The young are informed of the units they consume in period t, and the number of units of fiat money they carry into period t+1.

9. The results of the price prediction competition are announced and the winner receives the prediction prize.

10. Cycle resumes at step 1.

Summary of Subjects' Instructions for Economy 1

This is an experiment in decision-making. The instructions are simple; if you follow them carefully and make good decisions, you might earn a considerable number of points.

We shall operate a market in which you may buy and sell chips in a sequence of periods. The type of currency used in this market is francs. The only use of this currency is to buy and sell chips. The points you take home with you are called dollars. The procedures for determining the number of dollars you take home with you is explained in these instructions.

You will participate in the market for two consecutive periods at a time: your entry period and your exit period. Different individuals may have different entry and exit periods. You may be asked to enter and exit more than once depending on the number of periods for which the market is operated.

You will see a flashing square on your computer screen in either red or yellow color. The color of the square alternates between red and yellow over periods.

Your dollar earnings are determined on the basis of your sale and purchase of chips. At the beginning of your entry period, you will be given ω^1 chips. You may keep them or sell some of them to others in exchange for francs. You cannot buy chips in this period. The number of chips you sell in your entry period (t) depends on your (and other entrants') price forecast for the following period (t+1). The central computer uses your forecast to construct your optimal money demand function that maximizes your earnings. The money demand functions of all entrants are aggregated to obtain the money demand function for the generation. The central computer calculates the point of intersections of this demand function and the money supply function (from the old) to arrive at the market-clearing price. All transactions take place at this price. The number of chips you "consume" (c_1) at the end of the entry period is ω^1 minus the number you sell. The francs you receive from selling any of your chips are carried over into your exit period.

In your exit period, you are given no chips ($\omega^2 = 0$). You can use the francs carried over from your entry period to buy chips from others. The number of chips you buy in your exit period is determined by the prevailing market price of chips in that period and the number of francs that you obtain by selling chips in your entry period. Francs have no use for you after you exit. Your computer has been programmed to automatically use up all your francs to purchase as many chips as possible at the market price. You cannot sell chips in your exit period. Thus the number of chips you "consume" in your exit period (c_2) is the number of chips your francs can buy. The number of points you earn at the end of your exit period is:

$$\text{Earnings} = \text{maximum } \{0,\ 4 + ((8c_1/\omega^1)^{0.5} - 0.5 \times (\omega^1/2c_2)^2)\}$$

where ω^1 = the number of chips you are given in entry period, i.e., 10,

c_1 = the number of chips you "consume" (ω^1 - what you sell) in your entry period, and

c_2 = the number of chips you "consume" (what you buy) in your exit period.

Your computer calculates and tells you this dollar amount. Note that your earnings cannot be negative. All chips are forfeited at the end of each period. The enclosed table (not included here) shows some calculations of your dollar payoff for several levels of chips "consumption" in entry and exit periods. The enclosed figure (not included here) shows various combinations of chip consumptions needed to earn a given dollar amount.

For some of you the first period itself is an exit period. In this case, you will receive 25 francs, in addition to the exit period endowment of 0 chip at the beginning of this period. Your computer automatically uses all your francs to purchase chips. Your dollar earnings for this period are determined by the following formula:

$$\text{Maximum } \{\ 0,\ (8c_2/\omega^1)^{0.5}\ \}.$$

The second source of your earnings is a prediction game. At the beginning of each period, all subjects are asked to predict the market price for that period and the following period. The winner (smallest error in predicting the current period price) receives $5.00. If there is a tie, the prize is split equally among the winners.

After the outside participants have entered their price forecasts for a period, the experimenter may terminate the economy. In this case, the francs being held by the exit participants are transformed into chips using the "average predicted price" provided by the outside participants.

Thus the specific rules are:

(1) All entry-period players are sellers and all exit-period players are buyers of chips.

(2) Computers are programmed so all franc holdings of every exit-period player will be used up to buy chips from the entry-period players at the market price of chips for the period.

(3) On the basis of the price prediction you (the entry subject) provide for the next period (t+1), the computer figures out the number of chips you should sell at various prices in order to maximize your points. It does the same for all entry players, and figures out the number of chips all entry players would like to sell at various prices.

(4) After considering the amount of francs in the hands of the exit-period players and the number of chips entry-period players would like to sell, the computer calculates and informs you about the market clearing price, your transactions and balances.

(5) The francs received by the entry-period players in the entry period are used to buy chips in the exit period which follows immediately.

(6) At the end of each period, the computer informs you about the average predicted market price for the current period and the winner(s) of the prediction game. Winner(s) receive a $5.00 prize.

(7) At the end of the experiment, francs held by all entry-period players are converted into chips using the average of predicted current period market prices by outside-market players.

(8) At the end of the experiment, the computer screen shows your cumulative profit. This is the number of points you have earned from the game.

List of Symbols

c_1: c subscript 1.

c_2: c subscript 2.

k: roman lower case k.

$\bar{m}$: m bar.

m_1: m subscript 1.

N: (roman) upper case N.

n: (roman) lower case n.

p_t^e: (roman) lower case p superscript e subscript t.

p_{t+k}^e: (roman) lower case p superscript e subscript t+k.

P_{t+1}^e: (roman) upper case P superscript e subscript t+1.

P_{t+1}: upper case (roman) P subcript t+1.

p^*: lower case (roman) p superscript asterisk.

$\bar{p}$: p bar.

$\underline{p}$: p underscore.

p_t: lower case roman p subscript t.

p_{t-k}: lower case roman p subscript t-k.

$\ldots$: Ellipsis.

$p_{t-n\times k}$: lower case roman p subscript (t-n times k).

p_{t+1}^e: lower case (roman) p supercript e subscript t+1.

$\bar{p}^1, \ldots, \bar{p}^k$: p bar superscript 1, p bar superscript k, etc.

$\dot{p}$: p dot.

p_τ: p of (greek) tau.

p_{n+1}: lower case roman p subscript n+1.

$V(c_2)$: (roman) V of c subscript 2.

$U(c_1, c_2)$: (roman) upper case U of (roman c subscript 1, roman c subscript 2).

$\alpha(p_t - p_t^e)$: (greek) alpha times (expression).

α_t^j: (greek) alpha superscript j subscript t.

$\alpha_t^j \searrow 0$: (greek) alpha superscript j subscript t converges to zero from above.

$\alpha \to 1$: (greek) alpha converges to 1.

$\sum_t \alpha_t^j$: (greek) alpha superscript j subscript t, summed over t.

$\phi(p_{t+1}^e)$: (greek) phi of lower case (roman) p supercript e subscript t+1.

$\phi(\cdot)$: function of (greek) phi.

$\phi^k(p_{t+k}^e)$: phi to the power k of (p supercript e subscript t+k).

$\phi^{-1}(p_n)$: phi inverse of (p subscript n).
$\phi(\cdot)$: function phi.
$\varphi(\cdot,\cdot)$: function script phi.
π: (greek) pi.
ω_1: (greek) lower case omega subscript 1.
ω_1: (greek) lower case omega subscript 2.
∞: infinity.