Feedback complexity, bounded rationality, and market dynamics

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ABSTRACT

In a set of experimental markets, we investigate how the dynamic structure of the market as well as its price-setting institutions affect market performance and stability. We compare the outcomes to two alternative hypotheses: The standard neoclassical assumption of optimality and rational expectations, and a behavioral hypothesis based on previous studies of humans in dynamic decision making tasks, where subjects frequently ignore critical elements of the feedback structure in which they operate. We consider the implications of such misperceptions for the process of market adjustment, as well as the ability of market forces and financial incentives to mitigate these effects.

We find that feedback structure has a strong effect on performance relative to optimal, as the markets showed large fluctuations in prices and quantities. The only condition where performance (but not the dynamics) are relatively unaffected is where computer-mediated automatic price-clearing eliminates cumulative imbalances. The observed behavior is consistent with individual misperceptions of feedback, thus demonstrating that markets moderate but do not eliminate the negative impact of misperceptions of feedback.

We analyze the decisions of individual subjects by fitting them to simple equations and then used the estimated equations in a dynamic simulation model of the complete market. The simulations reproduce the most salient features of the dynamic behavior, and variations between markets can be related to differences in certain parameter values of the decision functions that can be interpreted as reflecting the degree of misperceptions of feedback. In this manner, the analysis constitutes a link between observation of individual decision making behavior and the theory of aggregate market outcomes.

An examination of decision timing data and verbal protocols provide evidence that increasing complexity of the decision-making task leads subjects to simplify their task by ignoring certain aspects, particularly strategic interactions between firms, and revert to simpler, more reactive behavior. Moreover, subjects tend to attribute observed oscillations and other systematic behavior patterns to exogenous forces rather than their own interaction with the system. This latter phenomenon may have important implications for the ability of agents to learn over time to improve their behavior.
1. Introduction

The standard assumptions in neoclassical economics of rational, optimizing agents with unbiased expectations stand in sharp contrast to evidence from psychological studies of biases and errors in human decision making (Hogarth and Reder 1987). The contrast has become stronger over the years, as modern dynamic economic theories employ increasingly sophisticated methods of optimal filtering and control (Arrow 1987) while behavioral scientists continue to accumulate evidence of human shortcomings in such tasks. In particular, a number of recent studies show that decision making in complex dynamic environments is poor relative to normative standards, or even simple decision rules, especially when decisions have indirect, delayed, nonlinear, and multiple feedback effects (e.g., Brehmer 1992, Diehl 1992, Funke 1991, Kleinmuntz 1985, Smith et al. 1988, Sterman 1989a, b).

Since real markets involve human beings, it is important to examine how shortcomings at the individual level might affect overall market outcomes. The process of market adjustment through arbitrage, adaption, learning and, in the longer run, through competitive selection, must be examined explicitly to determine where neoclassical approaches might be sufficient and where other theories are called for. Moreover, such studies must be rooted in actual observations of human decision making.

Thus, although there are many dynamic decision making tasks in the real world for which no or only poorly functioning markets exist (e.g., real-time process control, organizational settings such as schools and bureaucracies, environmental dynamics, etc.), the ability of market forces to mitigate individual departures from rationality in dynamic tasks is a critical area of research for psychology and economics. Conversely, in cases where market forces do not eliminate misperceptions of feedback, one must search for alternatives to the neoclassical assumptions of perfect rationality and equilibrium in order to provide an explicit theory of disequilibrium market processes, based on assumptions about individual behavior that accord with observed human decision making.

Accordingly, the research questions addressed in the present study are: 1) To what extent can market mechanisms and financial incentives alleviate the problems observed in non-market dynamic decision making experiments? 2) What is the effect of feedback complexity on market behavior and performance? 3) Can one explain aggregate market behavior from the individual decision-making behavior?

We study these questions in a set of six experimental markets, varying both the feedback complexity and the market institution, as explain in the next section. In Section 3, we compare aggregate performance and stability to "optimal" across the conditions, and in Section 4, we demonstrate how salient features of the macro-level experimental outcomes can be explained by a set of simple decision heuristics on the micro-level of individual agents. In Section 5, we examine timing data and questionnaire responses to gain further insight into how subjects cope with varying task characteristics. Our
conclusions and comments are found in Section 6.

2. Experimental design and method

2.1. Experimental treatments

In most respects, the study follows standard procedures in experimental economics, such as performance-based rewards to the participants, single-individual agents (firms), discrete time periods, and no verbal communication between subjects. However, one important difference is the dynamic structure of the market. Most studies in experimental economics involve markets with relatively simple dynamic structure, where markets are reinitialized each period so that no inventories of unsold goods or backlogs of unfilled orders carry over to future periods, unlike most real-world situations. In this manner, markets are "reset" each period so that past decisions do not influence current or future options (Plott 1982, Smith 1982). Yet human performance can degrade significantly in dynamic decision-making tasks involving delays, accumulations (stocks and flows), non-linearities, and self-reinforcing feedback (Sterman 1989a, b). Thus, the experimental markets in this study involved two feedback complexity conditions:

- **A simple condition,** where production initiated at the beginning of each period becomes available for storage or delivery during that same period, and where industry demand is unaffected by the average level of activity in the market;

- **A complex condition,** where there is a lag between the time production is initiated and the time it becomes available for storage or delivery, and where industry demand is influenced by average market production, representing a multiplier effect from income to aggregate demand.

Experimental studies in economics, even without dynamic complexity, have shown that the institutional structure of the market influences the convergence to and nature of equilibrium (Plott 1986, Smith 1986). Double auctions typically converge rapidly and reliably to competitive equilibrium. Posted price systems, where agents announce buying or selling prices, converge more slowly and often do not reach competitive equilibrium. Our experiments thus involved three price-setting institutions:

- **Fixed prices:** All prices are completely fixed and equal. Fluctuations in demand are accommodated entirely by changes in inventories. (All firms receive an equal share of market demand.)

- **Posted seller prices:** Each firm sets its own price and production rate, and demand is fully accommodated by changes in inventories.

- **Clearing prices:** Prices move to equate demand to the given supply each period. In this condition, the need for inventories is eliminated. The market-clearing price vector, given the current period's output vector and demand function, is found by the computer.
We combined the two feedback complexity conditions and three price setting conditions into a between-subjects design with six experimental conditions. Each subject would play only once. The experiment involved four markets in each treatment condition, for a total of 24, and with a total of 97 subjects.

2.2. Market structure

The market consists of \( K \) firms (operated by experimental subjects) and a consumer sector (modeled by the computer). The market can be interpreted as a regional industry where the level of activity and employment may influence aggregate demand in the region. Following standard models of monopolistic competition, the products of the industry have some limited degree of differentiation (the firm demand elasticity is large but finite) but the market is otherwise close to the perfect-competition ideal.

Time is divided into discrete periods. At the beginning of each period \( t \), each firm \( i \) decides how much production \( y_{i,t} \) to initiate and, in the posted-price condition, what price \( p_{i,t} \) to charge for its product. Firms make these decisions \textit{ex ante}, i.e., before demand for the current period is revealed.

Each firm maintains an inventory \( n_{i,t} \) to accommodate fluctuations in demand. The inventory is decreased by current sales \( x_{i,t} \) and increased by production, the latter with a time lag \( \delta \) from the time production was initiated. Hence,

\[
(2.1) \quad n_{i,t+1} = n_{i,t} + y_{i,t-\delta} - x_{i,t}.
\]

Profits equal revenue less production cost and inventory holding costs. Production costs are proportional to output (constant returns to scale) and holding costs are proportional to the absolute value of inventory. (The inventory variable can be thought of as a net value of actual minus desired inventory, i.e. it can be negative. Alternatively, a negative inventory could represent a backlog of unfilled orders. In any case, demand is assumed to be unaffected by inventory, i.e., both buyer and seller costs are fully subsumed in the holding-cost term.) Thus, given constant unit production costs \( \omega \) and unit holding costs \( \gamma \), profits \( v_{i,t} \) are

\[
(2.2) \quad v_{i,t} = p_{i,t}x_{i,t} - \omega y_{i,t} - \gamma |n_{i,t}|.
\]

Buyer utility is assumed to be a CES function of goods bought from individual firms with elasticity of substitution \( \varepsilon \). Therefore, the utility of purchases of individual goods is a function of the "aggregate good"

\[
(2.3) \quad X_j = \left[ \frac{1}{K} \sum_{i=1}^{K} \left( \frac{x_{i,t}}{x_{j,t}} \right)^{\varepsilon} \right]^{\frac{1}{\varepsilon}}.
\]

Kampmann (1992) shows that one can define an aggregate price index
so that utility-maximizing consumer demand for firm i's product satisfies

(2.5)  \( x_{i,t} = X_t \left( \frac{p_{i,t}}{P_t} \right)^{-\varepsilon} \).

The aggregate demand \( X_t \) in turn depends on aggregate price \( P_t \). The elasticity of aggregate demand with respect to aggregate price is assumed to be a constant \( \mu \) around the competitive-equilibrium price, \( p^* \). Specifically,

(2.6)  \( X_t = X^*_t \cdot f \left( \frac{P_t}{p} \right); \ f(1) = 1; \ f'(1) = -\mu. \)

\( X^*_t \) is a "reference" aggregate demand that determines the location of the demand curve (see below). To ensure global robustness, aggregate demand becomes a linear function of price at points far from the competitive-equilibrium value, i.e., elasticity increases for rising prices and decreases for lower prices. As shown in Kampmann (1992), under perfect competition (large number of firms \( K \)), the competitive-equilibrium price depends only on \( \omega \) and \( \varepsilon \):

(2.7)  \( p^* = \frac{w \varepsilon \omega}{\varepsilon - 1} \).

The reference demand \( X^*_t \) depends on total production activity, introducing a multiplier effect which can be interpreted as a consumption multiplier where income (production) drives demand. Thus \( X^*_t \) consists of an autonomous demand component \( G \), assumed to be constant, and a variable "multiplier" component proportional to the overall average production in progress \( S_t \) and currently initiated production \( Y_t \). Thus,

(2.8)  \( X^*_t = (1 - \alpha)G + \frac{\alpha}{\delta + 1} (S_t + Y_t); \ 0 \leq \alpha < 1; \) where

(2.9)  \( Y_t = \frac{1}{K} \sum_{i=1}^{K} y_{i,t}, \)

(2.10)  \( S_t = \sum_{j=1}^{\delta} Y_{t-j}, \ \delta > 0; \ S_0 = 0, \ \delta = 0 \)

The demand multiplier \( \alpha \) and the production lag \( \delta \) are both experimental treatment variables, as discussed above. In the "simple" case, \( \alpha = \delta = 0 \); in the "complex" case, \( \alpha = 0.5, \ \delta = 3 \). A marginal propensity to consume of \( 0.5 \) corresponds approximately
to the marginal propensity to consume (MPC) out of pre-tax income in a typical national
economy. The after-tax MPC is much higher, over 0.9, and one could argue that if tax
revenue influences government spending, or if tax revenue is adjusted, the overall
coefficient would be higher than 0.5. The higher the value of $\alpha$, the less stable the
system becomes. A low value of $\alpha$ is thus an a fortiori assumption: any effects with $\alpha$
at this value are likely to be even larger for higher, possibly more realistic values.

The ratio of unit inventory cost to unit production cost, $\gamma / \omega$, balances the need for
positive profits while motivating subjects to control inventories. The chosen value of
0.5 was based on simulations and pilot experiments. Only 5 of 97 subjects suffered a
cumulative loss.

Finally, the firm elasticity $\varepsilon = 2.5$ and the industry elasticity $\mu = 0.75$. The industry
elasticity is high compared to many typical goods industries (Hauthakker and Taylor
1970). The lower the value of $\mu$, the less stable the system, so that our choice of $\mu$
again constitutes an a fortiori assumption that biases the system toward stability.

The unit production cost $\omega$ and autonomous demand $G$ are arbitrary scaling
parameters, which were varied from market to market to discourage cross-market
comparisons by subjects.

2.3. Experimental Protocol

In most respects, the experimental protocol followed the standard experimental
economics procedures, such as performance-based pay, written instructions, and no
verbal communication between subjects. Complete details of the protocol are provided

In an extension of the usual procedure, the market was implemented on networked
computers, which automatically administered and recorded subject decisions, as well as
the timing of choices and all keystrokes and mouse events, thus providing a very detailed
and rich record of the experiment. Each market consisted of an average of four firms
with one subject per firm.¹

After initial instruction, subjects played a short practice session, which both allowed
them to become familiar with mechanics of the game and provided a history from which
they could judge the parameters of the system. All markets were initialized with
production of $2/3$ of the competitive-equilibrium level and the initial price was set to clear
the market at the initial level of output.

¹ The experience in experimental economics is that four or five firms is usually enough to assure
competitive conditions (Plott 1982, 1986). A few markets had only three firms but were all in
the fixed-price condition, where the absence of strategic interactions minimize possible effects of
having relatively few firms.
The game was played for three hours or 50 time periods, whichever came first. The average length of each game was 44 time periods. While subjects were not informed of the 50-period maximum, they were told that the game would be stopped within a fixed time. Thus, as was pointed out to the subjects, there was some degree of time pressure in that taking longer to deliberate would decrease the number of periods they could play, reducing their cumulative profits.

Subjects received a money payment in proportion to their accumulated profits, with a minimum payment of $10, even if cumulative profits were negative. The average payout per subject was $35, which is typical of rewards in experimental economics. The participants were mostly graduate and undergraduate students in economics and management; almost all had some formal education in economics and/or quantitative fields such as statistics or operations research.

Figure 2.1 shows an example of the computer display, which, in comparison to most experiments, provides a rather extensive information interface. The display presented all the variables characterizing the firm and the average state of the market in "user-friendly" format, and, through pop-menus, gave access to historical data in time plots, scatter plots, or number tables, in any combination of the user's own design. (To minimize possible information display effects the same display was maintained across all experimental conditions, with only the smallest modifications necessary to accommodate the different conditions.)

3. Effects of experimental treatments

3.1. Hypotheses

The six-cell experimental design was motivated by simulations and formal analysis (see Kampmann 1992), which demonstrate that if firms act according to the traditional neoclassical assumptions of non-cooperation, optimizing behavior, and consistency of expectations, the differences between the six conditions would be very small: In all cases, the markets would settle smoothly and rapidly (after a short initial learning period) to the non-cooperative equilibrium, as illustrated in the simulation in Figure 3.1.

If firms engage in strategic behavior the question of market convergence becomes more complicated. If all firms were committed to full collusion from the outset and never defected from the coalition, the market would move quickly to the collusive equilibrium. Such a situation is unlikely; it is more plausible that continuous attempts at achieving or defecting from cooperation would occur. Neoclassical economic theory offers no a priori reason to expect such attempts to follow a systematic pattern. For lack of a better description, one would expect them to be essentially random, and the market should converge quickly to a stochastic stationary state.²

² It is conceivable that a game-theoretic analysis of the experimental market systems could reveal
On the other hand, if individuals suffer from misperceptions of feedback, i.e., if their decision making heuristics do not sufficiently account for the production lag or the multiplier effect, the simulations in Kampmann (1992) predict large systematic effects of the experimental treatments. In particular,

- **Complexity will decrease profits and stability in all three price regimes** because subjects' mental models do not account well for delays and feedbacks. Oscillations are expected under complexity.

- **The effects of complexity will be strongest under fixed prices, weaker under posted prices, and weakest under clearing prices.** Fixed prices imply that all imbalances accumulate in buffers, amplifying individual judgmental errors. Market-clearing prices eliminate inventory accumulation, automatically compensating for judgmental errors. Under posted prices subjects must adjust prices properly to clear out inventory imbalances, precisely the task non-market studies show to be problematic.

- **Complexity will slow learning in all three price regimes** because the excess variance makes inferences about causal structure and market dynamics more difficult.

- **Collusion will be most evident in the simple (posted and clearing price) conditions and least evident in the complex posted-price condition**, because the complex conditions are more demanding cognitively, reducing attention available for formulation of strategic behavior, and because excess variance complicates signaling and signal detection.

### 3.2. Results: profits

One compact measure of market behavior is the average profit earned by the participant firms. Profits are the most relevant measures of subject performance since profits determined subject compensation. In the analysis below the first 10 periods have been excluded to minimize variations caused by initial learning and experimentation, and profits are broken into two components: "gross profits" (profits before inventory costs), and "net profits" (after inventory costs).

Gross profits are primarily related to the price-output operating point of the market, i.e., a measure of the degree of collusion, whereas inventory costs are a function both of firm's production policy and the overall variation in prices and output, i.e., a measure of the degree of control. The relative importance of these two measures is inherently different in the three price regimes. Under fixed prices there is no possibility of collusion and inventory costs is the primary determinant of performance. Conversely, under clearing-
prices inventory costs are eliminated and performance depends only on reaching the best price-output point. The posted-price regimes involve elements of both.

Figure 3.2 compares the actual outcomes to the simulated profits of non-cooperating rational agents. The simulations assume a certain amount of random noise (5%) in the decisions of each agent and also compares the profits of non-cooperating and fully cooperating agents, respectively. Because the collusive profit level is slightly higher in the simple case than in the complex case, profits in the figure have been normalized to an index that is zero at the competitive-equilibrium profit level \( v_c \) and one at the collusive profit level \( v_m \), i.e., the index is

\[
\bar{v} = \frac{v - v_c}{v_m - v_c}.
\]

It is evident from the figure that, in contrast to the very small differences with rational non-cooperating agents, the experimental treatments do have strong effects. This is both due to higher inventory costs and to lower gross profits, as is seen in by comparing the top and bottom parts of Figure 3.2.

Table 3.1 reports analysis of variance of the normalized gross profits in the four price-varying conditions. While the price regime has no significant effect, the effect of complexity is significant: On average, gross profits relative to optimal in the complex conditions are 10-15% lower than in the corresponding simple conditions, in some cases even falling below the competitive equilibrium level.

Table 3.2 repeats the analysis for inventory costs alone, excluding the price-clearing condition where inventories are zero. (Costs were transformed with logarithms to minimize differences in within-cell variance.) The hypothesis of constant inventory costs in the non-clearing conditions is strongly rejected (p<0.1%). Complexity has a very large effect on inventory costs – on average, inventory costs are about 13 times larger in the complex conditions. But there is also a strong interaction: the effect of complexity on inventory costs is much smaller in the posted-price than in the fixed-price regime.

Thus, the data show effects that do not follow from the standard assumptions of non-cooperation and rationality. In fact, these effects agree with the predictions of the behavioral hypotheses: Profits relative to optimal are lowered by the introduction of complexity in all three price regimes, sometimes dramatically. Most of the drop stems from higher inventory costs (except of course in the price-clearing conditions), but profits before inventory costs are lower as well. As a result, the effect of complexity on net profit is very large in the fixed-price and posted-price regimes, and smaller in the clearing-price regime. Finally, there is much greater variance in profits in the complex posted and fixed-price cases than in the other four conditions (The Bartlett test for homogeneity of group variances in net profits shows significant differences at p<0.1%).
3.3. Effects on Market Dynamics and Convergence

Figure 3.1 showed examples of market adjustment when firms are "rational" in the following sense: They correctly estimate the structural parameters of the system from data accumulated during the initial learning period; they are predetermined to either cooperate or, in the case of Figure 3.1, to compete, and have correct expectations of the behavior of other firms; and they act to maximize their expected profits, except for a random uncorrelated error of 5% (see Kampmann 1992). In all six conditions, the markets converge to a stochastic stationary state after less than 10 time periods. The variation in market averages differs across conditions, but in all cases it is lower than the variance of any random errors in decision-making.

Figures 3.3-3.8 show the actual behavior of production and prices for each market for each of the experimental conditions. A quick glance reveals significant differences in the pattern of behavior across the conditions. The complex markets generally show larger and longer term variation in prices and quantities, and less tendency to converge to equilibrium, than the corresponding simple markets. There appear to be persistent cyclical movements in several of the complex markets.

In the simple condition with fixed prices (Figure 3.3) production settles quickly in the expected range. Apart from a few occasional departures from the equilibrium level, production is constant at its steady-state value. The task facing the decision maker here is a simple inventory control problem with a constant exogenous outflow. Previous experiments have shown, unsurprisingly, that humans perform quite well under such simple circumstances (Diehl 1992, MacKinnon and Wearing 1985).

The variation in production is dramatically larger in the fixed-price complex condition (Figure 3.4). All markets show substantial cycles of "boom and bust". The initial increase in demand leads to inventory depletion before additional output can go through the supply line. In the face of rising demand and falling inventories, firms raise their production, leading to still higher demand, which in turn causes firms to raise production further. Because of the production delay and the continuous accumulation of inventory imbalances, firms have great difficulty catching up with demand. The upward spiral continues until higher production restores normal inventory levels, at which point all firms cut their production, leading to a decrease in demand and excessive unintended inventory accumulation. The result is a "recession" where production falls below equilibrium. The cycle in some markets is exceedingly large; in Market 25, output peaks at around four times the equilibrium value. None of the markets show any sign of being in equilibrium at the end of the trial.

The markets with clearing prices also show marked differences between the simple and the complex condition. The markets in the simple clearing-price condition show no systematic pattern of behavior (Figure 3.5). Some appear to settle in a range close to, or slightly above, the competitive price equilibrium, but with a fair amount of short-term fluctuation. Others show some longer-term fluctuation.
In contrast, the complex clearing-price markets all display a distinct "boom and bust" pattern of an initial dramatic overshoot in production, followed by a gradual downward adjustment in output (Figure 3.6). Although the initial boom and bust is substantial, the cycle is not sustained as it is in the corresponding fixed-price condition. A key structural difference between the fixed and clearing price regimes is the lack of cumulative effects of market imbalances in the latter. The market-clearing system effectively "forgets" imbalances after they have gone through the pipeline delay, making it more forgiving of past errors.

The posted-price markets also show effects of complexity on behavior. In the simple condition (Figure 3.7), prices are relatively calm, and in three of the four markets, prices seem to be driven down toward the competitive level. In market #32, firms change their prices little throughout most of the game. In all markets, inventories are kept closely in check and never depart substantially from the desired level, as they can be controlled directly through adjustments in production.

The posted-price complex condition generally shows larger variance in prices and production compared to the simple case, although the variance differs from market to market (Figure 3.8). Market #16 exhibits dramatic, expanding oscillations in prices and output. In markets #18 and #38 both prices and inventories, and in #18 also production, show a moderate but quite regular cycle. Market #17 shows relatively little variance in output or prices, except for a one-time peak in prices.

Spectral analysis confirmed what is evident from inspection of the results (see Kampmann 1992). While the spectra produced by rational agents will, after an initial learning period, be either nearly white or concentrated in the high-frequency range, the spectra of the experimental markets in the all complex conditions show the variance is concentrated in the low frequencies corresponding to the 10-20 period cycles or longer term movements evident in the figures.

4. Individual heuristics and aggregate outcomes

It was argued above that the aggregate market outcomes show behavior that is consistent with the notion of "misperceptions of feedback". This section probes further into this idea by proposing simple decision rules which capture much of the individual decisions made by subjects in the experiments and, when embedded in a simulation of the complete market, reproduce the salient features of the aggregate behavior. The results of the analysis is reported below for two conditions, the complex fixed-price and posted-price condition, respectively, since the complex conditions show the most characteristic behavior patterns which need to be explained. In the last section, an examination of the verbal and timing data collected during the experiments show that feedback complexity affects the degree to which firms manage to collude and indicate that firms' decisions become more reactive and simplistic as the task complexity increases. Moreover, there is clear evidence that subjects attribute cyclical fluctuations in the market to exogenous factors, even though these dynamics were generated endogenously by their own actions.
Fixed prices, complex condition

In the fixed-price conditions, subjects make only one decision each period, namely how much production to initiate. In addition to this decision, subjects were asked to provide a forecast of future average demand. This forecast provides insight into subjects’ expectations, which must be a key component of their production planning.

The output decision is an example of what Sterman has called generic stock management tasks (1989a, b). Any reasonable decision rule, including the optimal rule, consists of three components. First, forecast expected demand \( x^e_t \) for the time period when initiated production will be finished. Second, look at current inventory \( n_t \) and compare it to its desired level \( n^d \), which is zero here; adjust production upward if there is a deficit, downward if there is excess inventory. Third, look at the current supply line \( s_t \) of initiated but not yet finished production and compare this to the desired level \( s^d \); adjust production upward if there is too little, downward if there is too much. This latter mechanism prevents cumulative over- or under-ordering because it recognizes the delay between ordering and finishing production. A simple equation, which also respects the non-negativity constraint on production, specifies the output decision as

\[
y_t = \max\left\{0, x^e_t - \alpha_n n_t + \alpha_s \left( s^d - s_t \right) \right\},
\]

where \( \alpha_n, \alpha_s, \) and \( s^d \) are constant parameters.

Table 4.1 shows the results of estimating equation (4.1), using the solicited forecasts for the expectation \( x^e_t \) and using nonlinear least-squares estimation. It is evident from the table that the fit is rather good; the \( R^2 \) varies between .86 and .99. The table shows that most subjects pay some attention to their inventory levels: The coefficient is positive and significant in all but two cases, though it is generally less than one, indicating some conservatism in inventory adjustment. In contrast, attention to supply lines is much lower or absent: The coefficient is only significantly positive in four cases. Moreover, it is smaller than the inventory coefficient in all cases.

These results are in full accord with Sterman's findings (1989a, b). The low attention paid to the supply line is a key indicator of misperceptions of feedback, in that the decision maker fails to take sufficient account of the cumulative delay in the system. A

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3 In the following, the firm subscript \( i \) has been dropped for notational convenience.

4 Equation (4.1) is in fact a Tobit model, for which consistent and asymptotically efficient maximum-likelihood methods exist (Amemiya 1973). However, the small-sample properties of this method are not well-known. Simulations performed by Kampmann (1992) suggest that the nonlinear least-squares method gives better estimates in the case at hand.

5 The chosen \( R^2 \) measures variations from zero and thus differs from the conventional measure of variations around the sample mean. Our measure takes credit for predicting the absolute level as well as variations around the mean, resulting in higher values.
simple metaphor would be a person with a headache who continues to take aspirins until it goes away, instead of taking two pills and wait for the effect.

A fully endogenous simulation of the market also requires modeling expectations. The solicited forecasts \( x_t^e \) were fitted to a simple adaptive-extrapolative equation using past values of the forecasted variable \( x_t \). Specifically,

\[
(4.2) \quad x_t^e = x_{t-1}^e + \beta_1 (x_t - x_{t-1}^e) + \beta_2 (x_{t-1} - x_{t-2}^e).
\]

The term with parameter \( \beta_1 \) is an exponential moving average while the term with parameter \( \beta_2 \) adds an extrapolation of recent movements in \( x_t \). Table 4.2 shows the results of estimating equation (4.2). The measure of fit varies between a low of 0.05 and a high of 0.75, with an average of 0.44.\(^6\) The adaptive parameter \( \beta_1 \) is significant and not greater than unity for all subjects. This indicates some conservatism in judgment, where subjects only adjust their forecasts gradually toward recent history. The extrapolative parameter \( \beta_2 \) is significant and positive in all cases. In fact, in over half the cases, it is greater than unity, indicating a belief that changes in demand will accelerate.

Extrapolative expectations are highly dysfunctional in this particular system because they amplify the self-reinforcing mechanism of the aggregate multiplier: If, for instance, inventories are below their desired level, firms raise output to replenish them; the increase in output adds to aggregate demand through the multiplier; if firms extrapolate this increase, they will want to increase output still more to accommodate future higher demand, thus increasing demand still further. (This process is seen most clearly in market #25 in Figure 3.4, which also has the highest extrapolative coefficients in Table 4.2.)

Figure 4.1 shows the results of a fully endogenous simulation of each market, where forecasts and output decisions are simulated with the estimated behavioral rules (4.1) and (4.2) for each agent. The figure presents both the deterministic case with the estimated rules used alone, and an ensemble of stochastic simulations where a random error is added to each decision. The errors are assumed to be normal and i.i.d., with a standard deviations equal to the standard-error-of-estimate in the regressions.

Inspection of Figure 4.1 reveals that the simulations recreate both the relative variability of the four markets and the periodicity of the fluctuations. The deterministic simulations show greater stability than the corresponding observations and stochastic simulations--a clear example of the "bootstrap effect" (Dawes 1979), where the "human factor" in fact reduces to random variance in the decision which decreases performance. When this

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\(^6\) The dependent variable in the regression is \( x_t^e - x_{t-1}^e \), and the \( R^2 \) is based on variations of this variable from zero. Hence, this measure does not take credit for predicting the absolute value of the forecast.
noise is added in the stochastic simulations, the envelope of outcomes is very similar to
the observed history, though performance is still slightly better than observed!

Kampmann (1992) supplements the visual inspection with more formal comparisons of
market performance and variability, all showing strong correlations between simulated
and actual results, with correlation coefficients of .95 or greater in all cases. In addition,
he finds strong correlations between performance and certain coefficients in the decision
rules. In particular, profits are strongly correlated with the degree of attention to supply
lines (the coefficient \( \alpha_s \) in (4.1)), providing further evidence that the observed
problematic behavior result from misperceptions of feedback.

**Posted-price, complex condition**

In the posted-price condition, firms decide both on the amount of output to initiate and
the price to charge for their product each period. Moreover, subjects were asked to
provide forecasts for future average sales and prices. Unlike the fixed-price condition, it
is now possible for firms to manipulate the amount they sell by changing their price.
Prices thus provide a way to bypass a long production lag in regulating inventories.
Indeed, the optimal policy is to maintain production at the long-term profit-maximizing
level, ignoring inventory costs and imbalances and instead use prices to control
inventories (Kampmann 1992, Appendix A).

The inventory-control component in price, combined with the long lags from initiation to
completion of production makes it much more difficult for firms to signal collusion or
punish defections. Variability in prices is costly, due to the resulting inventory
fluctuations. Moreover, the presence of the multiplier effect makes it more difficult for
firms to discern whether they are operating in the right price-output range: Sales, and
thus profits, are affect by the current amount of production in the pipeline, which may
vary substantially over time. Given these task characteristics, one would expect firms to
devote less attention to strategic interaction and more attention to controlling inventories
and judging trends. Output would be adjusted gradually to reflect long-term sales levels.
Indeed, these notions were reflected in questionnaire responses (see below).

These considerations led to the following output decision rule, as a function of last
period's sales \( x_{t-1} \) and current inventory \( n_t \),

\[
(4.3) \quad y_t = y_{t-1} + \gamma_1 (x_{t-1} - y_{t-1}) + \gamma_2 n_t.
\]

(There was no evidence that the supply line control entered decisions: In regressions
with a supply line term included, all coefficients for this term were insignificant.)

The price decision was modeled by the equation

\[
(4.4) \quad p_t = \phi_0 + \phi_1 (P^* - \phi_0) + \phi_2 n_t,
\]
where $P_t^e$ is the subject's observed price forecast. The rule represents the assumption that subjects anchor their price on a weighted average of a long-term target price level, the parameter $\phi_0$, and their expectations of the aggregate price level $P_t^e$. They then modify this anchor with the last term in (4.4) to adjust their inventory level toward zero (i.e., the parameter $\phi_2$ should be negative).

Tables 4.3 and 4.4 report the results of the regressions. The pricing equation fares better than the output equation--the average $R^2$ in Table 4.4 is .66, which is quite high for a regression with a constant term, and it is above .5 in all but two cases. The inventory coefficient $\phi_2$ is negative and significant in all cases except one. The coefficient $\phi_1$ is significant and close to unity in all but two cases, indicating that a large number of subjects are pure "followers" in that they anchor exclusively on the expected market average price.

The production equation has less explanatory power (the average $R^2$ is only .26). The coefficient is often significant and always between 0 and 1, indicating that subjects adjust their output gradually to past sales. The inventory coefficient is only significant in three cases, one of which with the wrong sign. Thus, it appears that subjects rarely use production to regulate inventories.

In modeling expectations, the simple adaptive-extrapolative rule was used as in the fixed-price case. Table 4.5 shows the results of estimating the forecasting rules (4.2) for average sales and

$$(4.5) \quad P_t^e = P_{t-1}^e + \theta_1(P_{t-1} - P_{t-1}^e) + \theta_2(P_{t-1} + P_{t-2})$$

for average price, respectively. Generally, the rules explain the forecasts quite well (the lowest $R^2$ is .07, the highest .81, and the average .45). Moreover the adaptive parameter is significant in all but two cases and always less than unity, for both demand and price forecasts. There is some tendency to extrapolate trends--13 out of the 30 coefficients were significant (and positive), though it less pronounced than in the fixed-price case above.

Figure 4.2 shows the result of incorporating the estimated decision- and forecasting rules into a complete endogenous simulation of each market, similar to the fixed-price case above. Comparing the simulated and observed prices in the figure, it is evident that the proposed simple decision rules do indeed capture a great deal of the pattern of behavior in each market: The relative variability as well as the period of fluctuation is the same.

---

7 The first three time periods incorporate actual decisions. Since the first three periods were part of the practice round, one would expect there to be a fair amount of random experimentation. Moreover, the initial decisions provide a shock to the system, moving it out of equilibrium so that the subsequent adjustment process is more clearly revealed than if one incorporated adaptive rules from the beginning of the simulation.
As in the fixed-price condition above, there is also a strong boot-strapping effect, resulting in higher stability of the deterministic simulations. When random noise is added in the stochastic simulations, the cyclical tendencies of the observed outcomes reappear.

The simulations also demonstrate how the observed tendency for some markets to cycle can arise from the interaction of prices and inventories. If firms respond to inventory imbalances by adjusting their prices downward and if they also anchor their decisions on last period's average price, then prices will continue to drift lower as long as there is an excess inventory. Eventually, the lower prices increase sales enough that inventories fall back toward their desired level, but by the time equilibrium has been reached, average price may now be close to its minimum, due to the cumulative drift, and sales may be substantially above production. The results would be that inventories continue to fall below their desired level. If production also responds to inventory imbalances and if firms do not account sufficiently for the supply line, the cycle is further amplified.

5. Effects of complexity on decision making

In addition to the actual decisions made by subjects, the experiments provided a wealth of other data, including subjects' verbal description of their decision making, answers to questions about causes of the observed outcomes, and the time taken to deliberate decisions. This data points to additional insights into the way subjects approached the task and the accompanying "mental images" with which they represented this task, as well as the cognitive effort asserted. Some of these results reflect appropriate adjustments of subject behavior to the task at hand, similar to the results obtained by, e.g., Payne, et al. (1988). Others, however, point to inherent limitations in subjects' understanding of the dynamic structure of the market, and thus give evidence of "misperceptions of feedback".

Exogenous vs. endogenous accounts of dynamics

A key prerequisite for understanding and thus improving the performance of any system is to attribute the correct causes to the behavior one observes. An important element of misperceptions of feedback that hampers this understanding is the human tendency to overlook the part of the problem that is generated internally by our own and our competitors interaction with the system, in favor of "blaming the environment" or "exogenous factors".

To gain a measure of this tendency, subjects were asked to sketch a time graph of their best guess of external factors that might have influenced overall demand in the market. While these sketches showed no distinct pattern in the simple conditions, the vast majority of subjects in the complex conditions plotted graphs that looked very similar to the observed market sales, even though there were in fact no exogenous influences on demand. For instance, in the fixed-price complex condition, 13 out of 14 subjects drew an oscillatory pattern, even though it was pointed out to them that there might not be any
exogenous influences at all. Moreover, 12 out of the 14 emphasized forecasting "the 
business cycle" or "trends" or "shifts" in demand, as seen in the following quotes from 
the post-game questionnaire responses:

"Once I had the general pattern of a complete business cycle, I was able to make estimates of the 
average increase or decrease per period. ... It became clear after a while that given the instability 
of sales and the constant prices, profit maximization became simply inventory minimization."

"The major problem was determining the timing of the peaks and troughs of the business cycle, 
and my guess is that it's mostly due to external factors and thus had to pinpoint exactly."

Only 2 out of the 14 subjects ever mentioned the multiplier effect--a key ingredient in the 
system's tendency to oscillate. These results are similar to the exogenous accounts of 
the cycle found in the "beer distribution game" (Sterman, 1989b).

If one believes that good performance primarily requires pinpointing a business cycle, or 
predicting trends in demand, not realizing that cycles or trends may be self-generated, 
there is little possibility of learning from history. In fact, if a majority of agents 
extrapolate current trends, the results can be devastating, as observed in Market #16 in 
Figure 3.4.

**Decision timing and mental effort**

A number of scholars in behavioral decision theory have posed the hypothesis that, 
given a certain psychological resistance to exerting cognitive effort, decision makers are 
likely to adapt their heuristics for the task at hand, trading off the mental effort involved 
with the expected quality of the decision (e.g., Payne, et al. 1988). More generally, a 
limited capacity to process information requires the individual to adopt simplified rules or 
heuristics (Simon, 1979).

One rough measure of mental effort is the amount of time taken to deliberate decisions. 
As mentioned previously, the experimental protocol did not involve overt time pressure 
but still gave incentives to act quickly. Subjects were free to take as much time as they 
wanted to make their decisions, although it was pointed out to them that taking longer 
could result in fewer rounds played and, hence, in lower cumulative profits.

Since both the information processing requirements and the "leniency" of the task, i.e., 
the "forgiveness" of the system to errors, differs across the experimental conditions, 
one would expect deliberation times to vary as well. A more lenient system would allow 
for faster decision making, while a more complex task would require more effort.

First, the mental effort required varies because the number of decisions was not the 
same: The fixed-price conditions involved one decision (output) and one forecast 
(sales); the clearing-price conditions also involved only one decisions but two forecasts 
(sales and price); and the posted-price conditions involved both price and output 
decisions and both a price and demand forecast.
Second, the "arithmetic" of inventory control may be simpler than the task of finding the optimal price-output pair. The inventory control task involves three steps: Form an expectation of future demand and anchor production on this figure. Then, look at current inventory and adjust production to account for a current excess or insufficient inventory. Finally, (in the complex condition only) look at the pipeline of unfinished production and adjust production if there is "too much" or "too little" in the pipeline. All these steps involve addition or at least simple linear operations. In contrast, the task of finding the optimal price-output position involves calculating marginal profits as a function of price, relative to market average price. None of these figures are readily available in the information display but must be calculated from tables or graphs. The posted-price condition is the most difficult because it involves both inventory control and price-output optimization.

Third, both the clearing-price and the posted-price regimes allow for possible collusion among firms. Here, firms must also consider whether to cooperate or defect and how to get other firms to cooperate. All of these three task characteristics speak for the following ranking of deliberation times in both the simple and complex conditions: Fixed < clearing < posted.

On the other hand, the leniency of the tasks does not follow the same ordering. In the clearing-price regime, profits are not very sensitive to deviations in the output decisions around the optimal price-output point. In the two other regimes, the cost of excess or insufficient inventory makes it more important to set production at the right level. Thus, even though the clearing-price regime involves one more forecast to make than the fixed-price regime, the overall deliberation time may be smaller, all other things equal, since the output decision is less crucial for performance. This would, all other things equal, call for the following ranking of deliberation times: Clearing < fixed < posted.

Finally, one would expect there to be a strong effect of complexity on decision times. In all three price regimes, the introduction of complexity makes the task more difficult, though the added difficulty varies in the three price regimes. One would therefore expect there to be some interaction effects on deliberation time between price regime and complexity.

In the fixed-price regimes, the difference between the simple and complex condition is probably the largest. The simple fixed-price condition amounts to only a trivial inventory control task in the face of constant demand. In the corresponding complex condition, the task is complicated by the time lag and the supply line correction, and by the possible large variations in demand caused by the multiplier effect.

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8 Of course, one might imagine that subjects use a search procedure rather than trying to calculate marginal profits. However, such a search is difficult because profits depend not only on the decision parameter (price or output) but on other variables as well (other prices, the multiplier effect, etc.).
In the clearing-price regime, the introduction of complexity is somewhat less important, since inventory accumulations are absent in this condition. Thus, by the time the started production is ready to sell, the system will have "forgotten" all its history. In contrast, inventory accumulations in the other two price regimes perpetuate past errors in the form of inventory imbalances. The main complicating effect of complexity here is that the multiplier effect on demand influences the price level in the complex condition whereas the average price in the simple condition only depends on average output. However, since profits are not particularly sensitive to deviations from the optimal output choice, the agent can get by quite well as long as the forecasted average price and output are not too far off. Thus, one would expect the clearing-price regime to show a smaller effect of complexity on deliberation time than the two other regimes.

The posted-price regime involves both the inventory-control element of the fixed-price regime and the price-output search and strategic considerations of the clearing-price regimes. Since each of these elements is compounded by the complexity treatment, one might expect the effect of complexity on deliberation time to be largest in the posted-price regime. On the other hand the treatment effects are unlikely to be additive in this fashion. The simple posted-price condition is "at least an order of magnitude" more complicated than the simple fixed-price condition since it involves both strategic behavior aspects, a variable demand, and a search for the best output-price position. Thus, whether the effect of complexity is larger in the fixed-price or the posted-price regime is ambiguous.

To summarize, the expected differences in deliberation times are based on the assumption that subjects on average will use more mental effort (measured by deliberation time) in the more difficult tasks (from an information-processing point of view), but that the effect will also depend on the leniency of the system, i.e. how important it is to be close to optimal. These considerations above leads to the following hypotheses about average deliberation times in the six experimental conditions:

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Ranking</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1 Fixed simple</td>
<td>&lt; Clearing simple</td>
</tr>
<tr>
<td>H2.1 Fixed complex</td>
<td>&lt; Clearing complex</td>
</tr>
<tr>
<td>H2.2 Clearing complex</td>
<td>&lt; Fixed complex</td>
</tr>
<tr>
<td>H3 0</td>
<td>&lt; Clearing complex - Clearing simple</td>
</tr>
<tr>
<td>H4 0</td>
<td>&lt; Clearing complex - Clearing simple</td>
</tr>
</tbody>
</table>

The hypotheses H2.1 and H2.2 are alternatives, depending on whether the task
complexity dominates (H2.1) or the leniency effect dominates (H2.2). (The fixed-price simple condition is so trivial that the leniency effect is unlikely to dominate the task complexity effect in the simple conditions. Hence, H2.2 only applies to the complex conditions.)

Figure 5.1 shows the average time taken to deliberate decisions, i.e. the time elapsed between the beginning of a new round and the moment the subjects executed their decisions, excluding the first 10 rounds. A glance at the figure reveals that there do appear to be significant differences in deliberation times across the six experimental conditions. The expected ranking based on task complexity does indeed occur for the simple condition (H1). In the complex condition, the clearing-price measure is lower than the corresponding fixed-price measure, concurring with the ranking where the leniency effect (H2.2) dominates the task complexity effect (H2.1).  

However, the effect of introducing complexity shows some surprising violations of the hypotheses: While the effect is strong in the fixed-price condition, it absent in the clearing-price condition and appears to be negative in the posted-price condition, or at least not positive. (Test for a negative effect showed moderate significance, p=.06.) This "rebound" effect is consistent with the findings of Diehl (1992), where complexities of the same type as here--delays and positive feedback--caused subjects to become cautious and "under-control."

What might account the reduced effort? There is no question that the decision task in the complex posted-price condition is extremely complicated, if one considers all aspects and consequences of the decisions. Hence, it is possible that the subjects in this condition simply give up trying to "figure out the system" in detail. Instead of worrying about optimizing, they may resort to "damage control." Subjects' pricing policy may revert to a simple heuristic along the following lines, ignoring any attempts at searching for the best price-output point or signaling collusion: 1) form expectation about average price, and anchor on this average, and 2) adjust the anchor up or down, depending on whether inventory is negative or positive. Indeed, these considerations led to the heuristic rule (4.4) above.

There is also evidence from the post-game questionnaires that subjects concentrated more on inventory control in their pricing policy in the complex posted-price condition and less on strategic interaction with other firms. Only 3 out of 15 subjects mentioned words like 'collusion', 'signal', 'cooperate', 'free rider', 'support prices', etc., in their responses. In the corresponding simple condition, 16 out of 20 subjects used such

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9 A two-way ANOVA with price regime and complexity as factors show highly significant effects (p<.02 or less) of both factors and their interaction (see Kampmann 1992). Although much of this significance might come from the fact that the simple fixed-price condition is so much lower than the others, a contrast test of equality of the other conditions was strongly rejected (p<.0005).
words. The difference is highly significant. Conversely, the responses in the complex posted-price condition contained frequent references to using prices to control inventory, as seen in the following quotes:

"The price decision generally attempted to clear out the planned production and inventory."

"I attempted to use my price-setting to manipulate what my sales in that period would be. If I wanted to dampen demand, I overcharged, if I wanted to boost sales, I undercharged."

"I set price above or below market price depending on how I needed to manipulate my inventory ... Price was my primary decision maker. Production stayed relatively constant."

"Optimal price seemed to be about 6.3, and demand could support 375 units at this price. I tried to hold things there, so I matched production to my anticipated sales. I occasionally used price to throttle demand to stabilize inventory but more commonly, I regulated production based on anticipated sales and inventories."

"I played it safe--mostly keeping my prices close the average market price, except when I was trying to unload inventory."

"I tried to make my prices follow the market to minimize my inventory. If I had positive inventory, I had to sell at lower prices to get rid of them."

9 out of the 15 subjects in this condition made such remarks while only 1 out of 20 did so in the simple posted-price condition--again a highly significant difference.

It is interesting to note that rational agents should indeed use prices as an inventory control measure in the complex posted-price condition but not in the corresponding simple condition (see Kampmann 1992, Appendix A). However, deriving this result analytically is exceedingly difficult, and a more reasonable interpretation of the outcome here is that subjects were forced into a reactive price-setting rule, as their inventories fluctuated.

A slightly different explanation may be offered for the absence of any complexity effect in the clearing-price regime. The lack of any effect is certainly surprising, since both communication and figuring out the best price-output level is much harder in the clearing-price regime. On the other hand, the fact that both the simple and the complex price-clearing conditions are quite forgiving of errors may induce subjects over time, as they discover this leniency, to worry less about making "the right" decisions and instead try to make more decisions.

In conclusion, the results do not indicate that the observed mental effort uniformly follows the objective properties of the task; although there is evidence for some of the effects one would expect based on this perspective, there does seem to be a threshold

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10 The Fisher-Irwin exact test of equal proportions is rejected at p<.0005.

11 The one-tailed Fisher-Irwin exact test rejects equal proportions at p=.001.
level of complexity beyond which mental effort is reduced, or at least not increased. Instead, subjects appear to resort to simplified heuristics. In particular, subjects appear to give up worrying about strategic interaction when the dynamic structure becomes sufficiently complex.

6. Conclusions

The experimental results demonstrate that misperceptions of feedback can have large effects on market behavior, although the consequences of these misperception depend strongly on the pricing mechanism employed. The effects are most dramatic in the fixed-price regime, where subjects generated sustained cycles, replicating previous non-market studies despite financial incentives for performance. In the clearing-price regime, automatic market clearing suppresses the accumulation of imbalances and thus makes the system much more forgiving of poor attention to delays and feedback. In the posted-price regime, the possibility of using prices to control inventories makes the system potentially easier to handle. However, in three out of the four markets, inventories and prices continue to oscillate throughout the trial: the cycle involving output and inventories in the fixed-price condition is replaced by one involving prices and inventories in the posted-price condition. While much of the decrease in profits is the result of excessive inventory fluctuations, the introduction of complexity also made it more difficult for firms to find the price-output level that would maximize profits before inventory costs.

Thus, markets seem to moderate, but do not eliminate, the effects of decision-makers' misperceptions of feedback structure. The mere existence of markets does not imply that individual misperceptions of feedback are automatically ameliorated. Misperceptions continue to occur, and their consequences are a function of the dynamic structure of the market setting. Therefore, models of economic dynamics must be grounded in empirical study of managerial decision making to capture the misperceptions of feedback which may produce systematically sub optimal dynamics even in the presence of well-functioning market institutions.

The study highlights the importance of linking studies of individual decisions to the resulting aggregate outcomes. It is not enough to look at isolated individual choices, one must also consider how a stream of such choices interact with the surrounding system to produce a dynamic pattern of behavior. In this realm, our study shows how statistical studies of individual decisions can be combined with simulations of the entire system to assess the overall outcomes. The analysis was able to explain many of the salient features of the observed market outcomes. Furthermore, it was possible to give psychological interpretation to the coefficients in the decision rules.

The study also shows how one might rely on a variety of data sources, such as verbal protocols and timing data, to gain further insight into the mental processes involved at the individual level. In particular, we showed how decision makers cope with increasing complexity by narrowing the scope of their decisions from broad considerations of
strategic interactions among firms to a more reactive concern with inventory control. Since the data are easy to collect, particularly when the experiment is computerized, we recommend that future studies in experimental economics make more use of such sources.

An important question that has only partially been addressed here is the scope for learning in changing behavior over time. Indeed, a frequent criticism of experimental studies is that they employ inexperience subjects and/or do not allow for sufficient learning.

The psychological literature on learning has shown that effective learning is possible only when there is immediate and unequivocal feedback from the environment. If feedback is delayed or distorted, or if simultaneous side effects complicate the outcomes, learning ability declines significantly (Brehmer 1980, Brehmer 1992). Thus, the potential for learning must clearly be strongly affected by the feedback structure of the system, again emphasizing the need for explicit considerations of this element in economic theory building.

Although we considered learning partly outside the scope of this work, the results cast some doubt on its potential. As we have seen in the verbal protocol data, there is a tendency for subjects to believe that observed fluctuations are caused by exogenous factors rather than by their own interaction with the system. This false attribution could become a strong impediment to learning. Indeed, Kampmann (1992) included an analysis of learning, defined as a change in the parameter values of decision functions and an improvement of forecasting consistency and accuracy. Apart from the very first part of the game, there was little evidence of learning. (In the analysis presented here, the first 10 periods were excluded to remove this initial learning effect.)

Nonetheless, it is fair to say that a lot of issues relating to learning, particularly in qualitative changes in decision heuristics, remains to be explored. The same could be said of competitive selection and endogenous market dominance by firms.

Another caveat relates to the external validity of the experiment. To what extent can laboratory settings with relatively young participants tell us about real-world decision making? This is a familiar issue in the debate between psychologists and economists (see e.g., Hogarth and Reder 1987) and will not be discussed in detail here, except to say that other dynamic decision-making experiments have explored the effect of experience, education, and expertise on performance and have not found any significant differences (e.g., Bakken 1992).

One step toward assessing the real-world validity of the results would be to try to classify industries according to their feedback structure (production and product-development delays, market institution, etc.) and relate their feedback properties to measures of market stability.
References


Bakken, B. E. 1992 Learning and transfer in simulated dynamic environments, " PhD. Dissertation, MIT Sloan School of Management., Cambridge, MA.


### Tables

**Table 3.1: Analysis of variance of gross profits**

Two-way analysis of variance of normalized average profits (equation (3.1)) before inventory costs in each market, excluding the first 10 time periods, using price condition ($P$) and complexity ($C$) as factors, excluding the fixed-price conditions, where profits before inventory costs do not vary in the long run under fixed prices. $N=16$; Multiple-$R^2=.401$.

<table>
<thead>
<tr>
<th>Source</th>
<th>Sum-of-squares</th>
<th>D.f.</th>
<th>Mean square</th>
<th>F-ratio</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>$C$</td>
<td>0.074</td>
<td>1</td>
<td>0.074</td>
<td>5.957</td>
<td>0.031</td>
</tr>
<tr>
<td>$P$</td>
<td>0.021</td>
<td>1</td>
<td>0.021</td>
<td>1.700</td>
<td>0.217</td>
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<tr>
<td>$C*P$</td>
<td>0.005</td>
<td>1</td>
<td>0.005</td>
<td>0.373</td>
<td>0.553</td>
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<tr>
<td>ERROR</td>
<td>0.149</td>
<td>12</td>
<td>0.012</td>
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<td></td>
</tr>
</tbody>
</table>

**Table 3.2: Analysis of variance of inventory costs**

Two-way analysis of variance of the logarithm of the average inventory costs in each market, excluding the first 10 time periods, using price condition ($P$) and complexity ($C$) as factors, excluding the clearing-price conditions, where inventories are identically zero. $N=16$; Multiple-$R^2=.798$.

<table>
<thead>
<tr>
<th>Source</th>
<th>Sum-of-squares</th>
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<th>Mean square</th>
<th>F-ratio</th>
<th>P</th>
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<tr>
<td>$C$</td>
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<td>81.308</td>
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<td>0.000</td>
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<tr>
<td>$P$</td>
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<td>1</td>
<td>13.070</td>
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<td>$C*P$</td>
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<td>12.477</td>
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Table 4.1: Estimates in the decision rule (4.1)

<table>
<thead>
<tr>
<th>Market no.</th>
<th>Firm</th>
<th>$\alpha_s$</th>
<th>Standard error*</th>
<th>$\alpha_n$</th>
<th>Standard error*</th>
<th>$s^d$</th>
<th>Standard error*</th>
<th>$R^2$ **</th>
</tr>
</thead>
<tbody>
<tr>
<td>25</td>
<td>1</td>
<td>.28        (0.21)</td>
<td></td>
<td>.23        (0.20)</td>
<td></td>
<td>1.44  (1.00)</td>
<td></td>
<td>.91++</td>
</tr>
<tr>
<td>25</td>
<td>2</td>
<td>1.00 †</td>
<td></td>
<td>.20        (0.03)</td>
<td>a</td>
<td>3.04  (0.77)</td>
<td>a</td>
<td>.86++</td>
</tr>
<tr>
<td>25</td>
<td>3</td>
<td>1.00 †</td>
<td></td>
<td>-.27       (0.03)</td>
<td>a</td>
<td>1.55  (0.88)</td>
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<td>.94</td>
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<tr>
<td>26</td>
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<td></td>
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<td>2.64  (0.96)</td>
<td>a</td>
<td>.97</td>
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<td>2</td>
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<td>c</td>
<td>.31        (0.21)</td>
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<td>3.00  (0.37)</td>
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<td>.97</td>
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<td>3</td>
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<td>c</td>
<td>.21        (0.17)</td>
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<td>2.73  (0.6)</td>
<td>a</td>
<td>.94</td>
</tr>
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<td>1</td>
<td>.24        (0.12)</td>
<td>b</td>
<td>.06        (0.09)</td>
<td></td>
<td>3.58  (1.84)</td>
<td>c</td>
<td>.95+</td>
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<tr>
<td>35</td>
<td>2</td>
<td>.41        (0.12)</td>
<td>a</td>
<td>.20        (0.09)</td>
<td>b</td>
<td>2.59  (0.56)</td>
<td>a</td>
<td>.88</td>
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<td>35</td>
<td>3</td>
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<td>b</td>
<td>.12        (0.10)</td>
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<td>a</td>
<td>.97++</td>
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<td>4</td>
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<td>a</td>
<td>.22        (0.10)</td>
<td>b</td>
<td>3.52  (0.5)</td>
<td>a</td>
<td>.95</td>
</tr>
<tr>
<td>36</td>
<td>1</td>
<td>.36        (0.17)</td>
<td>a</td>
<td>.16        (0.13)</td>
<td></td>
<td>2.53  (0.79)</td>
<td>a</td>
<td>.90+</td>
</tr>
<tr>
<td>36</td>
<td>2</td>
<td>.39        (0.12)</td>
<td>a</td>
<td>.12        (0.08)</td>
<td></td>
<td>3.34  (0.98)</td>
<td>a</td>
<td>.85++</td>
</tr>
<tr>
<td>36</td>
<td>3</td>
<td>.20        (0.19)</td>
<td></td>
<td>.07        (0.14)</td>
<td></td>
<td>2.83  (1.55)</td>
<td>c</td>
<td>.99++</td>
</tr>
<tr>
<td>36</td>
<td>4</td>
<td>.66        (0.24)</td>
<td>a</td>
<td>.27        (0.14)</td>
<td>b</td>
<td>3.33  (0.42)</td>
<td>a</td>
<td>.97+</td>
</tr>
</tbody>
</table>

† The estimated parameter was greater than 1. The equation was reestimated with the parameter constraint to the interval [0,1].

* The value shown is the computed asymptotic standard error of the estimate, based on the estimated Hessian (2nd derivative) matrix of the loss function (the sum of squared residuals). The small-sample properties of this estimate are not known, and the results should therefore be interpreted with caution. Assuming the estimate is normally distributed, the column also shows the result of testing for a non-zero parameter: a: p<.01, b: p<.05, c: p<.10.

** The residuals were tested for auto correlation (using simple OLS). + and ++ indicates positive serial correlation at the 5% and 1% level, respectively.

Table 4.1: Estimates in the decision rule (4.1)

<table>
<thead>
<tr>
<th>Market</th>
<th>Firm</th>
<th>$\beta_1$</th>
<th>Std. error*</th>
<th>$\beta_2$</th>
<th>Std. error*</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>25</td>
<td>1</td>
<td>.45 (.14)</td>
<td>a</td>
<td>1.47 (.42)</td>
<td>a</td>
<td>.23</td>
</tr>
<tr>
<td>25</td>
<td>2</td>
<td>.29 (.07)</td>
<td>a</td>
<td>1.58 (.15)</td>
<td>a</td>
<td>.75</td>
</tr>
<tr>
<td>25</td>
<td>3</td>
<td>.09 (.06)</td>
<td>a</td>
<td>1.31 (.15)</td>
<td>a</td>
<td>.72</td>
</tr>
<tr>
<td>26</td>
<td>1</td>
<td>.71 (.16)</td>
<td>a</td>
<td>1.47 (.33)</td>
<td>a</td>
<td>.43</td>
</tr>
<tr>
<td>26</td>
<td>2</td>
<td>.47 (.16)</td>
<td>a</td>
<td>0.50 (.25)</td>
<td>a</td>
<td>.30</td>
</tr>
<tr>
<td>26</td>
<td>3</td>
<td>.32 (.13)</td>
<td>a</td>
<td>0.59 (.21)</td>
<td>a</td>
<td>.35</td>
</tr>
<tr>
<td>35</td>
<td>1</td>
<td>.62 (.16)</td>
<td>a</td>
<td>1.45 (.27)</td>
<td>a</td>
<td>.41</td>
</tr>
<tr>
<td>35</td>
<td>2</td>
<td>.28 (.12)</td>
<td>a</td>
<td>0.75 (.24)</td>
<td>a</td>
<td>.25</td>
</tr>
<tr>
<td>35</td>
<td>3</td>
<td>.93 (.16)</td>
<td>a</td>
<td>2.51 (.35)</td>
<td>a</td>
<td>.56</td>
</tr>
<tr>
<td>35</td>
<td>4</td>
<td>.37 (.13)</td>
<td>a</td>
<td>0.94 (.20)</td>
<td>a</td>
<td>.41</td>
</tr>
<tr>
<td>36</td>
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<td>.22 (.11)</td>
<td>a</td>
<td>0.77 (.18)</td>
<td>a</td>
<td>.57</td>
</tr>
<tr>
<td>36</td>
<td>2</td>
<td>.36 (.10)</td>
<td>a</td>
<td>1.15 (.17)</td>
<td>a</td>
<td>.60</td>
</tr>
<tr>
<td>36</td>
<td>3</td>
<td>.58 (.15)</td>
<td>a</td>
<td>1.52 (.23)</td>
<td>a</td>
<td>.54</td>
</tr>
<tr>
<td>36</td>
<td>4</td>
<td>.21 (.15)</td>
<td>a</td>
<td>0.07 (.15)</td>
<td>a</td>
<td>.05</td>
</tr>
</tbody>
</table>

* Significance of t-test for zero parameter: a: p<.01, b: p<.05, c: p<.10.

Table 4.2: Estimates in the forecasting rule (4.2)
<table>
<thead>
<tr>
<th>Market</th>
<th>Firm</th>
<th>$\gamma_1$</th>
<th>Std. error*</th>
<th>$\gamma_2$</th>
<th>Std. error*</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>16</td>
<td>1</td>
<td>.24 (.10)b</td>
<td>- .04 (.06)</td>
<td>.13</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>.30 (.10)a</td>
<td>- .04 (.04)</td>
<td>.24</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>.33 (.15)b</td>
<td>- .19 (.18)</td>
<td>.13</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>.73 (.03)a</td>
<td>.01 (.02)</td>
<td>.93++</td>
<td></td>
<td></td>
</tr>
<tr>
<td>17</td>
<td>1</td>
<td>.33 (.08)a</td>
<td>- .01 (.04)</td>
<td>.35</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>.28 (.07)a</td>
<td>- .03 (.03)</td>
<td>.31</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>.03 (.04)</td>
<td>- .05 (.05)</td>
<td>.05</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>.04 (.05)</td>
<td>- .02 (.04)</td>
<td>.04</td>
<td></td>
<td></td>
</tr>
<tr>
<td>18</td>
<td>1</td>
<td>.44 (.13)a</td>
<td>- .08 (.05)</td>
<td>.25</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>.34 (.10)a</td>
<td>.34 (.12)a</td>
<td>.58+</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>.08 (.05)c</td>
<td>.00 (.03)</td>
<td>.09</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>.06 (.10)</td>
<td>- .12 (.09)</td>
<td>.05</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* Significance of t-test for zero parameter: a: p<.01, b: p<.05, c: p<.10.
++ Durbin-Watson test indicated significant positive auto correlation at the 1% level.
+ Durbin-Watson test indicated significant positive auto correlation at the 5% level.
- - Durbin-Watson test indicated significant negative auto correlation at the 1% level.

Table 4.3: Estimates in the output decision rule (4.3)

<table>
<thead>
<tr>
<th>Market</th>
<th>Firm</th>
<th>$\phi_0$</th>
<th>Std. error*</th>
<th>$\phi_1$</th>
<th>Std. error*</th>
<th>$\phi_2$</th>
<th>Std. error*</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
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<td>.19 (.19)</td>
<td>1.04 (.15)a</td>
<td>- .11 (.04)b</td>
<td>.70++</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>.68 (.13)a</td>
<td>.50 (.10)a</td>
<td>- .07 (.01)a</td>
<td>.77+</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>1.10 (.32)a</td>
<td>.57 (.28)b</td>
<td>- .60 (.15)a</td>
<td>.55</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>.20 (.14)</td>
<td>.83 (.12)a</td>
<td>- .05 (.01)a</td>
<td>.69+</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>17</td>
<td>1</td>
<td>.02 (.10)</td>
<td>1.05 (.07)a</td>
<td>- .11 (.05)c</td>
<td>.87</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>.35 (1.1)</td>
<td>.75 (.92)</td>
<td>- .16 (.09)c</td>
<td>.08+</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>.49 (.11)a</td>
<td>.80 (.09)a</td>
<td>- .16 (.16)a</td>
<td>.82</td>
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<tr>
<td></td>
<td>4</td>
<td>.47 (.07)a</td>
<td>.56 (.06)a</td>
<td>- .28 (.05)a</td>
<td>.83</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>18</td>
<td>1</td>
<td>- .05 (.14)</td>
<td>1.05 (.12)a</td>
<td>- .03 (.01)c</td>
<td>.74+</td>
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<tr>
<td></td>
<td>2</td>
<td>1.10 (.55)c</td>
<td>.15 (.45)</td>
<td>- .22 (.10)b</td>
<td>.13</td>
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<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>- .04 (.13)</td>
<td>1.05 (.11)a</td>
<td>- .06 (.06)</td>
<td>.83</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>38</td>
<td>1</td>
<td>.23 (.08)a</td>
<td>.78 (.07)a</td>
<td>- .26 (.04)a</td>
<td>.80</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>- .08 (.09)</td>
<td>1.08 (.07)a</td>
<td>- .23 (.03)a</td>
<td>.88</td>
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<td>3</td>
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<td>.80 (.17)a</td>
<td>- .24 (.08)a</td>
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<td></td>
<td>4</td>
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<td>.85 (.09)a</td>
<td>- .32 (.08)a</td>
<td>.74++</td>
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<td></td>
<td></td>
</tr>
</tbody>
</table>

* Significance of t-test for zero parameter: a: p<.01, b: p<.05, c: p<.10.
++ Durbin-Watson test indicated significant positive auto correlation at the 1% level.
+ Durbin-Watson test indicated significant positive auto correlation at the 5% level.

Table 4.4: Estimates in the pricing decision rule (4.4)
Table 4.5: Estimates in the forecast rules for demand (4.2) and price (4.5) in the posted-price complex condition

<table>
<thead>
<tr>
<th>Market &amp; Firm</th>
<th>$\beta_1$</th>
<th>Std. error*</th>
<th>$\beta_2$</th>
<th>Std. error*</th>
<th>$R^2$</th>
<th>$\theta_1$</th>
<th>Std. error*</th>
<th>$\theta_2$</th>
<th>Std. error*</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>16 1 1 2 3 4</td>
<td>0.23 0.21 0.19 0.21</td>
<td>0.09 b .10 b .09 b .09 b</td>
<td>-.10 (.16) .27 (.09) a -.05 (.08)</td>
<td>.43 0.49 .15</td>
<td>.44 (.13) a .33 (.12) b .51 (.12) a</td>
<td>.37 (.13) a .20 (.19) -.12 (.14)</td>
<td>.44 .22 .36</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>17 1 2 3 4</td>
<td>0.82 0.10 1.00 0.45</td>
<td>0.18 .16 .16 a .15 a</td>
<td>-.11 (.26) .70 (.25) a .66 (.19) a</td>
<td>.57 0.62 .40</td>
<td>.69 (.17) a .56 (.15) a .67 (.18) a</td>
<td>.49 (.15) a .48 (.21) b .51 (.18) a</td>
<td>.81 .49 .45</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>18 1 2 3</td>
<td>0.99 0.14 0.53</td>
<td>0.17 a .10 .13 a</td>
<td>-.17 (.37) .39 (.33) .00 (.18)</td>
<td>.51 0.07 .41</td>
<td>.54 (.14) a .16 (.10) .65 (.18) a</td>
<td>.26 (.16) .38 (.18) b .35 (.15) b</td>
<td>.51 .22 - .66</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>38 1 2 3 4</td>
<td>0.46 0.21 0.45 0.88</td>
<td>0.12 a .04 a .12 a .11 a</td>
<td>-.28 (.31) .03 (.15) .02 (.24) .47 (.19) b</td>
<td>.25 0.30 .67++</td>
<td>.72 (.14) a .50 (.12) a .82 (.17) a</td>
<td>.55 (.14) a .03 (.17) .32 (.16) b</td>
<td>.74 .77 .43 .79</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* Significance of t-test for zero parameter: a: p<.01, b: p<.05, c: p<.10.
++ Durbin-Watson test indicated significant positive auto correlation at the 1% level.
- - Durbin-Watson test indicated significant negative auto correlation at the 1% level.
Figure 2.1: Example of computer display

The figure shows the display in the posted-price complex condition. Displays in the other conditions were kept as similar as possible to this display to minimize the effect of displays on performance. The top portion represents the current state of inventory and the supply line of unfinished production. On the bottom left is a report for the previous period, with information on prices, forecasts, sales, profits, and production, in an "annual-report" format. The subject enters decisions on the bottom left, and the pop-up menus allow access to five number tables, three time graphs, and three x-y plots of historical data. The variables in the graphs and tables were initially selected but could be redefined by selecting any combination of historical variables.
Figure 3.1: Simulated behavior of rational agents

The figure shows examples of market average output and price (in a market with 4 firms) under the assumption that firms correctly estimate the structural parameters in the system and act to maximize their expected profits, given their expectation of non-cooperative rational-expectations equilibrium. A moderate amount of random error (standard deviation 5%) was introduced in the decision rules for both price and output.
Figure 3.2 Observed performance compared to simulated rational agents

The figure shows gross and net average market profits (excluding the first 10 periods) observed in the experiments (white bars), compared to simulations of rational non-cooperating agents (gray bars) who correctly estimate the structural parameters of the system, have rational expectations, and act in accordance with maximization of expected profits, except for a random error (with standard deviation 5%). The diamonds indicate individual markets for the observed values and standard deviations for the simulated values.
Figure 3.3:
Observed behavior of market averages: fixed-price simple condition
The figure shows market-average production and inventory for each of the four markets, relative to the equilibrium output level (horizontal line at 1). Inventory is shown on the right-hand scale.
Figure 3.4:

Observed behavior of market averages: fixed-price complex condition
The figure shows market-average production and inventory for each of the four markets, relative to the equilibrium output level (horizontal line at 1). Inventory is shown on the right-hand scale.
Figure 3.5:

Observed behavior of market averages: clearing-price simple condition

The figure shows market average production and price, relative to competitive equilibrium (horizontal line at 1). Also shown are the collusive-equilibrium price (top horizontal line) and output (bottom horizontal line).
Figure 3.6:

**Observed behavior of market averages: clearing-price complex condition**

The figure shows market average production and price, relative to competitive equilibrium (horizontal line at 1). Also shown are the collusive-equilibrium price (top horizontal line) and output (bottom horizontal line).
Figure 3.7:

**Observed behavior of market averages: posted-price simple condition**

The figure shows market average production, price, and inventory, relative to competitive equilibrium (horizontal line at 1). Also shown are the collusive-equilibrium price (top horizontal line) and output (bottom horizontal line).
Figure 3.8: Observed behavior of market averages: posted-price complex condition

The figure shows market average production, price, and inventory, relative to competitive equilibrium (horizontal line at 1). Also shown are the collusive-equilibrium price (top horizontal line) and output (bottom horizontal line).
Figure 4.1: Simulated inventory in the fixed-price complex condition
The figure shows endogenous simulations of each market with the decision rule (4.1) and forecast rule (4.2), using the estimated parameter values obtained from a statistical analysis of individual decisions. The figure compares the observed market average inventory to a deterministic simulation and to an ensemble of stochastic simulations with normal i.i.d. errors with a variance equal to the residual variance in the regressions.
Figure 4.2: Simulated prices in the posted-price complex condition

The figure compares the observed market-average price to endogenous simulations of each market with the decision rules (4.2), (4.3), (4.4), and (4.5), respectively, using the estimated parameter values obtained from a statistical analysis of individual decisions. The deterministic simulation employs the rules without noise while the stochastic simulation adds normal i.i.d. errors with a variance equal to the residual variance in the regressions, although the standard error was limited to a maximum of .1. The first three time periods incorporate actual decisions to reproduce any initial shock to the system from subjects' initial experimentation.
Figure 5.1: Average deliberation times across experimental conditions
The figure shows the average time between the beginning of a new round (time period) and the time the subject executed his or her decision. The first ten rounds have been excluded to eliminate initial variance due to learning the basics of the task. The graph depicts the averages for each condition ("Avg. per round") as well as for each market ("Individual mkts."). Also shown is the deliberation time divided by the total no. of decisions and forecasts required each round ("Per decision"). This is an attempt to correct for the fact that the fixed, clearing, and posted price regimes require a different number of forecasts and decisions.