When Does Learning in Games Generate Convergence to Nash Equilibria? The Role of Supermodularity in an Experimental Setting *

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When Does Learning in Games

Generate Convergence to Nash Equilibria?

The Role of Supermodularity in an Experimental Setting

Abstract

This study clarifies the conditions under which learning in games produces convergence to Nash equilibria in practice. Previous work has identified theoretical conditions under which various stylized learning processes achieve convergence. One technical condition is *supermodularity*, which is closely related to the more familiar concept of strategic complementarities. We experimentally investigate the role of supermodularity in achieving convergence through learning. Using a game from the literature on solutions to externalities, we systematically vary a free parameter below, close to, at and beyond the threshold of supermodularity to assess its effects on convergence. We find that supermodular and "near-supermodular" games converge significantly better than those far below the threshold. From a little below the threshold to the threshold, the improvement is statistically insignificant. Within the class of supermodular games, increasing the parameter far beyond the threshold does not significantly improve convergence. Simulation shows that while most experimental results persist in the long run, some become more pronounced.

Keywords: learning, supermodular games

JEL Classification: C90; D70

1 Introduction

When do players learn to play Nash equilibria? The answer to this important question will help us identify when the outcomes predicted by theory will be realized in competitive environments involving real people. This question has been examined both theoretically (see Fudenberg and Levine (1998) for a survey) and experimentally (see Camerer (2003) for a survey).

According to the theoretical literature, games with strategic complementarities (Milgrom and Roberts 1991, Milgrom and Shannon 1994) have robust dynamic stability properties: under numerous learning dynamics, they converge to the set of Nash equilibria that bound the serially-undominated set. The learning dynamics include Bayesian learning, fictitious play, adaptive learning, Cournot best reply and many others. These games include the supermodular games of Topkis (1979), Vives (1985, 1990), Cooper and John (1988), and Milgrom and Roberts (1990). In supermodular games, each player's marginal utility of increasing her strategy rises with increases in her rival's strategies, so that (roughly) the players' strategies are "strategic complements."

Existing literature recognizes that games with strategic complementarities encompass important economic applications of noncooperative game theory, for example, macroeconomics under imperfect competition (Cooper and John 1988), search (Diamond 1982), bank runs (Diamond and Dybvig 1983, Postlewaite and Vives 1987), network and adoption externalities (Dybvig and Spatt 1983), and mechanism design (Chen 2002).

Past experimental studies of learning and mechanism design suggest that, in addition to equilibrium efficiency, mechanism choice should depend on whether players learn to play the equilibrium and the nature of play on the path to equilibrium. In reviewing the experimental literature on incentive-compatible mechanisms for pure public goods, Chen (forthcoming) finds that mechanisms with strategic complementarities, such as the Groves-Ledyard mechanism under a high punishment parameter, converge robustly to the efficient equilibrium (Chen and Plott 1996, Chen and Tang 1998). Conversely, those far away from the threshold of strategic complementarities do not seem to converge (Smith 1979, Harstad and Marrese 1982). In previous experiments, parameters are set either far away from the threshold for strategic complementarities (e.g., Chen and Tang (1998)) or very close to the threshold (e.g., Falkinger, Fehr, Gächter and Winter-Ebmer (2000)).[1] However, these experiments do not systematically set the parameters below, close to, at and above the threshold to assess the effect of strategic complementarities on convergence. This is the first such systematic experimental study of games with strategic complementarities.[2] Consequently,

[1] Proofs of supermodularity of the Groves-Ledyard and the Falkinger mechanisms are presented in Chen (1997).

[2] By systematically varying the free parameter in the Groves-Ledyard mechanism, Arifovic and Ledyard (2001) study learning

this study answers three important questions that the theory on games with strategic complementarities does not address. First, as the parameters approach the threshold of strategic complementarities, will play converge to equilibrium gradually or abruptly? Second, is there a clear performance ranking among games with strategic complementarities? Third, how important is strategic complementarity compared to other factors? The answer to the first question can help us assess, *a priori*, whether a game "close" to being supermodular, such as the Falkinger mechanism (Falkinger 1996), might also have good convergence properties. The answer to the second question will help us choose the best parameters within the class of games with strategic complementarities. The answer to the third question will help us assess the importance of strategic complementarities in learning and convergence.

To address these questions, this study adopts an experimental game from the literature on solutions to externalities. Varian (1994) proposes a simple class of two-stage mechanisms, the compensation mechanisms, whose subgame-perfect equilibria implement efficient allocations. In a generalized version of Varian's mechanism (Cheng 1998), one can vary, without altering the equilibrium, a parameter which determines whether the condition for strategic complementarities is satisfied.

There have been two experimental studies of the compensation mechanisms, neither of which adopts a version with strategic complementarities. Andreoni and Varian (1999) study the mechanism in the context of the Prisoners' Dilemma. They find that adding a commitment stage to the standard Prisoners' Dilemma game nearly doubles the amount of cooperation to two-thirds. Hamaguchi, Mitani and Saijo (2003) investigate a version with a larger strategy space and find 20% Nash equilibrium play.

In this paper, we examine the compensation mechanism in an economic environment with a much larger strategy space. Furthermore, we choose various versions to study systematically the effect of strategic complementarities on convergence.

The rest of the paper is organized as follows. Section 2 introduces games with strategic complementarities and presents theoretical properties of the compensation mechanisms. Section 3 presents the experimental design. Section 4 introduces the set of hypotheses. Section 5 presents experimental results on the level and speed of convergence, as well as efficiency. Section 6 presents the calibration of three learning models, validation of the models on a hold-out sample, and simulation of performance in the long run using a calibrated learning model. Section 7 discusses our findings. Section 8 concludes.

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dynamics and mechanism convergence using genetic algorithms compared with experimental data.

2 Strategic Complementarity and the Compensation Mechanisms

Games with strategic complementarities (Milgrom and Shannon 1994) need an order structure on strategy spaces (e.g., subsets of the real line), a weak continuity requirement on payoffs, and satisfaction of the single-crossing property.[3] These games include supermodular games, first introduced by Topkis (1979), and further studied by Vives (1985, 1990), Cooper and John (1988), and Milgrom and Roberts (1990).

Supermodular games are games in which the incremental return to any player from increasing her strategy is a nondecreasing function of the strategy choices of other players (*increasing differences*). Furthermore, if a player's strategy space has more than one dimension, components of a player's strategy are complements (*supermodularity*). Membership in this class of games is easy to check. Indeed, for smooth functions in $\mathbb{R}^n$, letting P_i be the strategy space and π_i be the payoff function of player i, the following theorem characterizes increasing differences and supermodularity.

THEOREM 1 (Topkis (1978)) *Let π_i be twice continuously differentiable on P_i. Then π_i has increasing differences in (p_i, p_j) if and only if $\partial^2\pi_i/\partial p_{ih}\partial p_{jl} \geq 0$ for all $i \neq j$ and all $1 \leq h \leq k_i$ and all $1 \leq l \leq k_j$; and π_i is supermodular in p_i if and only if $\partial^2\pi_i/\partial p_{ih}\partial p_{il} \geq 0$ for all i and all $1 \leq h < l \leq k_i$;*

Increasing differences means that an increase in the strategy of player i's rivals raises her marginal utility of playing a high strategy. The supermodularity requirement ensures complementarity among components of a player's strategies and is automatically satisfied in a one-dimensional strategy space. Note that a supermodular game is a game with strategic complementarities, but the converse is not true.

Supermodular games have interesting theoretical properties. In particular, they are robustly stable. Milgrom and Roberts (1990) prove that, in these games, learning algorithms consistent with adaptive learning converge to the set bounded by the largest and the smallest Nash equilibrium strategy profiles. Intuitively, a sequence is consistent with adaptive learning if players "eventually abandon strategies that perform consistently badly in the sense that there exists some other strategy that performs strictly and uniformly better against every combination of what the competitors have played in the not too distant past" (Milgrom and Roberts 1990). This includes numerous learning dynamics, such as Bayesian learning, fictitious play, adaptive learning, Cournot best reply. While strategic complementarity is sufficient for convergence, it is not a necessary condition. Thus, while games with strategic complementarities ought to converge robustly to the Nash equilibrium, games without strategic complementarities may also converge under specific learning

[3] Let P be the strategy space and π_i be the payoff function of player i. For all $z, y \in P$ with $z \geq y$, the following single-crossing conditions hold: $[\pi_i(z_i, y_{-i}) \geq \pi_i(y_i, y_{-i})] \Rightarrow [\pi_i(z_i, z_{-i}) \geq \pi_i(y_i, z_{-i})]$ and $[\pi_i(z_i, y_{-i}) > \pi_i(y_i, y_{-i})] \Rightarrow [\pi_i(z_i, z_{-i}) > \pi_i(y_i, z_{-i})]$.

algorithms. Whether these specific learning algorithms are a realistic description of human learning is an empirical question.

While the theory on games with strategic complementarities predicts convergence to equilibrium, it does not address four practical issues. First, as the parameters of a game approach the threshold of strategic complementarities, does play converge gradually or abruptly? Second, is convergence faster further past the threshold? Third, how important is strategic complementarity compared to other features of a game which might also induce convergence to equilibrium? Last, for supermodular games with multiple Nash equilibria, will players learn to coordinate on a particular equilibrium? We choose a game which allows us to answer the first three questions. The fourth question has been addressed by van Huyck, Battalio and Beil (1990) and Cox and Walker (1998).[4]

Specifically, we use the compensation mechanism to study the role of strategic complementarities in learning and convergence to equilibrium play. In the mechanism, each of two players offers to compensate the other for the "costs" of the efficient choice. Assume that when player 1's production equals x, her net profit is $rx - c(x)$, where r is the market price and $c(\cdot)$ is a differentiable, positive, increasing and convex cost function. Production causes an externality on player 2, whose payoff is $-e(x)$, also assumed to be differentiable, positive, increasing and convex. The mechanism is a two-staged game where the unique subgame-perfect Nash equilibrium induces the Pareto efficient outcome of x such that $r = e'(x) + c'(x)$. In the first stage (the announcement stage), player 1 announces p_1, a per unit subsidy to be paid to player 2, while player 2 simultaneously announces p_2, a per unit tax to be paid by player 1. Announcements are revealed to both players. In the second stage (the production stage), player 1 chooses a production level x. The payoff to player 1 is $\pi_1 = rx - c(x) - p_2x - \alpha(p_1 - p_2)^2$, while the payoff to player 2 is $\pi_2 = p_1x - e(x)$, where $\alpha > 0$ is a free punishment parameter chosen by the designer.

We study a generalized version of the compensation mechanism (Cheng 1998), which adds a punishment term, $-\beta(p_1 - p_2)^2$, to player 2's payoff function, thus making the payoff functions:

$$\pi_1 = rx - c(x) - p_2x - \alpha(p_1 - p_2)^2, \text{and} \quad \pi_2 = p_1x - e(x) - \beta(p_1 - p_2)^2. \tag{1}$$

[4] Cox and Walker (1998) study whether subjects can learn to play Cournot duopoly strategies in games with two kinds of interior Nash equilibrium. Their type I duopoly has a stable interior Nash equilibrium under Cournot best-reply dynamics and therefore is dominance solvable (Moulin 1984). Their type II duopoly has an unstable interior Nash equilibrium and two boundary equilibria under Cournot best-reply dynamics, and therefore is not dominance solvable. They found that after a few periods subjects did play stable interior, dominance solvable equilibria, but they did not play the unstable interior equilibria nor the boundary equilibria. It is interesting to note that these duopoly games are submodular games. Being two-player games, they are also supermodular (Amir 1996). Results of Cox and Walker (1998) illustrate the importance of uniqueness together with supermodularity in inducing convergence.

Using the generalized version, we solve the game by backwards induction. In the production stage, player 1 chooses the quantity that solves the following problem:

$$\max_{x} rx - c(x) - p_2 x - \alpha(p_1 - p_2)^2.$$

The first order condition is

$$r - c'(x) - p_2 = 0,$$

which characterizes the best response in the second stage, $x(p_2)$. In the announcement stage, player 1 solves

$$\max_{p_1} rx - c(x) - p_2 x - \alpha(p_1 - p_2)^2.$$

The first order condition is

$$\frac{\partial \pi_1}{\partial p_1} = -2\alpha(p_1 - p_2) = 0, \tag{2}$$

which yields the best response function for player 1 as $p_1 = p_2$. Player 2 simultaneously solves

$$\max_{p_2} p_1 x(p_2) - e(x(p_2)) - \beta(p_1 - p_2)^2.$$

The first order condition is

$$\frac{\partial \pi_2}{\partial p_2} = p_1 x'(p_2) - e'(x) x'(p_2) + 2\beta(p_1 - p_2) = 0, \tag{3}$$

which characterizes player 2's best response function.

The unique subgame-perfect equilibrium has $p_1 = p_2 = p^*$, where p^* is the Pigovian tax which induces the efficient quantity, x^*. As the equilibrium does not depend on the value of β, it holds for the original version where $\beta = 0$. However, when β is set appropriately, the generalized version is a supermodular mechanism. The following proposition characterizes the necessary and sufficient condition for supermodularity.

PROPOSITION 1 (Cheng (1998)) *The generalized version of the compensation mechanism is supermodular if and only if $\alpha > 0$ and $\beta \geq -\frac{1}{2}x^{'}(p_2)$.*

The proof is simple. First, as the strategy space is one-dimensional, the supermodularity condition is automatically satisfied. Second, we use Theorem 1 to check for increasing differences. For player 1, from Equation (2), we have $\frac{\partial^2 \pi_1}{\partial p_1 \partial p_2} = 2\alpha > 0$, while for player 2, from Equation (3), we have $\frac{\partial^2 \pi_2}{\partial p_1 \partial p_2} = x'(p_2) + 2\beta$. Therefore, $\frac{\partial^2 \pi_2}{\partial p_1 \partial p_2} \geq 0$ if and only if $\beta \geq -\frac{1}{2}x^{'}(p_2)$.

To obtain analytical solutions, we use a quadratic cost function $c(x) = cx^2$, where $c > 0$, and a quadratic externality function $e(x) = ex^2$, where $e > 0$. We now summarize the best response functions, equilibrium solutions and stability analysis in this environment.

PROPOSITION 2 *Quadratic cost and externality functions yield the following characterizations:*

1. *The best response functions for players 1 and 2 are:*

$$p_1 = p_2; \tag{4}$$
$$p_2 = \frac{\beta - \frac{1}{4c}}{\beta + \frac{e}{4c^2}} p_1 + \frac{\frac{er}{4c^2}}{\beta + \frac{e}{4c^2}}; \text{ and} \tag{5}$$
$$x = \max\{0, \frac{r - p_2}{2c}\}.$$

2. *The subgame-perfect Nash equilibrium is characterized as*

$$(p_1^*, p_2^*, x^*) = \left(\frac{er}{e+c}, \frac{er}{e+c}, \frac{r}{2(e+c)} \right).$$

3. *If players follow Cournot best-reply dynamics, (p_1^*, p_2^*) is a globally asymptotically stable equilibrium of the continuous time dynamical system for any $\alpha > 0$ and $\beta \geq 0$.*

4. *The game is supermodular if and only if $\alpha > 0$ and $\beta \geq \frac{1}{4c}$.*

Proof: See Appendix A. ∎

The best-response functions presented in Part 1 of Proposition 2 reveal interesting incentives. While player 1 has an incentive to always match player 2's price, player 2 has an incentive to match *only* when player 1 plays the equilibrium strategy. Also, at the threshold for strategic complementarity, $\beta = \frac{1}{4c}$, player 2 has a dominant strategy, $p_2 = \frac{er}{e+c} = p_2^*$. Part 3 of Proposition 2 extends Cheng (1998), who shows that the original version of the compensation mechanism ($\beta = 0$) is globally stable under continuous time Cournot best-reply dynamics.[5] However, Cournot best-reply is a relatively poor description of human learning, e.g., Boylan and El-Gamal (1993). Therefore, global stability under Cournot best reply for any $\beta \geq 0$ does not imply equilibrium convergence among human subjects. Part 4 characterizes the threshold for strategic complementarity in our experiment, a more robust stability criterion than that characterized by Part 3.

An intuition for how strategic complementarities affect the outcome of adaptive learning can be gained from analysis of the best response functions, Equations (4) and (5). While player 1's best response function is always upward sloping, player 2's best response function, Equation (5), is nondecreasing if and only if $\beta \geq \frac{1}{4c}$, i.e., when the game is supermodular. Beyond the threshold for strategic complementarity, both best response functions are upward sloping and they intersect at the equilibrium. It is easy to verify (graphically) that adaptive learners, e.g., Cournot best reply, will converge to the equilibrium regardless of where they start.

[5] Cheng (1998) also shows that the original mechanism is locally stable under discrete time Cournot best-reply dynamics.

To examine how α, which is unrelated to strategic complementarity, might affect behavior, we observe that when player 1 deviates from the best response by ε, i.e., $p_1 = p_2 + \varepsilon$, his profit loss is $\Delta\pi_1 = -\alpha\varepsilon^2$. This profit loss, which is proportional to the magnitude of α, is the deviation cost for player 1. Based on previous experimental evidence, the incentive to deviate from best response decreases when the deviation cost increases. Chen and Plott (1996) call it the General Incentive Hypothesis, i.e., the error of game theoretic models decreases as the level of incentive increases. We therefore expect that an increase in α improves player 1's convergence to equilibrium. When player 1 plays equilibrium strategy, player 2's best response is to play equilibrium strategy as well. Therefore, we expect that an increase in α might improve player 2's convergence to equilibrium as well. It is not clear, however, whether the α-effects systematically change the effects of the supermodularity parameter β. We rely on experimental data to test the interaction of the α-effects on β-effects.

3 Experimental Design

Our experimental design reflects both theoretical and technical considerations. Specifically, we chose an environment that allows significant latitude in varying the free parameters to better assess the performance of the compensation mechanism around the threshold of strategic complementarity. We describe this environment and the experimental procedures below.

3.1 The Economic Environment

We use the general payoff functions presented in Equation (1) with quadratic cost and externality functions to obtain analytical solutions: $c(x) = cx^2$ and $e(x) = ex^2$. We use the following parameters: $c = 1/80, e = 1/40, r = 24$. From Proposition 2, the subgame perfect Nash equilibrium is $(p_1^*, p_2^*, x^*) = (16, 16, 320)$ and the threshold for strategic complementarity is $\beta = \frac{1}{4c} = 20$.

In the experiment, each player chooses $p_i \in \{0, 1, \cdots, 40\}$. Without the compensation mechanism, the profit-maximizing production level is $x = 960$, three times higher than the efficient level. To reduce the complexity of player 1's problem, we use a grid size of 10 for the quantity and truncate the strategy space, i.e., player 1 chooses $X \in \{0, 1, \cdots, 50\}$, where $X = x/10$. The payoff functions presented to the subjects are adjusted accordingly (see Appendix B). Truncating the strategy space to $X \leq 50$ also reduces the possibility of player 2's bankruptcy. To reduce payoff asymmetry, we give player 1 a lump sum payment of 250 points each round. Therefore, the equilibrium payoffs for the two players are $\pi_1 = 1530$ and $\pi_2 = 2560$.

The functional forms and specific parameter values are chosen for several reasons. First, equilibrium solutions are integers. Second, equilibrium prices and quantities do not lie in the center of the strategy space, thus avoiding equilibrium convergence as a result of focal points. Third, there is a salient gap between efficiency with and without the mechanism. Without the mechanism, the profit-maximizing production level is $X = 50$, resulting in an efficiency level of 68.4%. With the mechanism, the system achieves 100% efficiency in equilibrium. Finally, since the threshold for strategic complementarity is $\beta = 20$, there are a large number of β values to choose from both below and above the threshold.

To study how strategic complementarity affects equilibrium convergence, we keep $\alpha = 20$, and vary $\beta = 0, 18, 20,$ and 40. To study whether α affects convergence, we also keep $\alpha = 10$, and vary $\beta = 0, 20$.

3.2 Experimental Procedures

Our experiment involves 12 players per session — six player 1's (called Red players in the instructions) and six player 2's (Blue players). Each player remains the same type throughout the experiment. At the beginning of each session, subjects randomly draw a PC terminal number. Each then sits in front of the corresponding terminal, and is given printed instructions. After the instructions are read aloud, subjects are encouraged to ask questions. The instruction period varies between fifteen to thirty minutes.

Each round a player 1 is randomly matched with a player 2. Subjects are randomly re-matched each round to minimize repeated game effects. The random re-matching protocol also minimizes the possibility that players collude on a high subsidy and low tax outcome.[6] Each session consists of 60 rounds. As we are interested in learning, there are no practice rounds. Each round consists of two stages:

1. Announcement Stage: Each player simultaneously and independently chooses a price, $p_i \in \{0, 1, \cdots, 40\}$.

2. Production Stage: After (p_1, p_2) are chosen, player 1's computer displays player 2's price and a payoff table showing her payoff for each $X \in \{0, 1, \cdots, 50\}$. Player 1 then chooses a quantity, X. The server calculates payoffs and sends each player his payoff, the quantity chosen, and the prices submitted by him and his match.

To summarize, each subject knows both payoff functions, the choices made each round by himself and his match, as well as his per period and cumulative payoffs. At any point, subjects have ready access to all of this information. The mechanism is thus implemented as a game of complete information. However, we

[6] If the players could commit to maximizing joint profits, they would choose, by Equation (1), $(p_1, p_2, x) = \left(\frac{4(\alpha+\beta)er}{4(\alpha+\beta)(e+c)-1}, \frac{r(4e(\alpha+\beta)-1)}{4(\alpha+\beta)(e+c)-1}, \frac{2r(\alpha+\beta)}{4(\alpha+\beta)(e+c)-1}\right)$. With our choice of parameters, we get: $p_1 = 24, p_2 = 12$ for $\alpha = 20$ and $\beta = 0$; $p_1 = 19.2, p_2 = 14.4$ for $\alpha = 20$ and $\beta = 20$; and $p_1 = 18, p_2 = 15$ for $\alpha = 20$ and $\beta = 40$; etc.

do not know how subjects processed this information, nor do we know their beliefs about the rationality of others. Both of these factors introduce uncertainty in the environment.

[Table 1 about here.]

Table 1 presents features of the experimental sessions, including parameters, number of independent sessions in each treatment, whether the mechanism is supermodular in that treatment and equilibrium prices and quantities. Overall, 27 independent computerized sessions were conducted in the RCGD lab at the University of Michigan from April to July, 2001, and in April 2003. We used zTree to program our experiments. Our subjects were students from the University of Michigan. No subject was used in more than one session, yielding 324 subjects. Each session lasted approximately one-and-a-half hours. The exchange rate for all treatments was one dollar for 4250 points. The average earning was $22.82. Experimental instructions are included in Appendix B. Data are available from the authors upon request.

4 Hypotheses

Given the above design, we next identify our hypotheses. To do so, we first define and discuss two measures of convergence: the level and speed of convergence.[7] In theory, convergence implies that all players play the stage game equilibrium and no deviation is observed. However, this is not realistic in an experimental setting. Therefore, we define the following measures.

DEFINITION 1 *The level of convergence at round t, $L(t)$, is measured by the proportion of Nash equilibrium play in that round. The level of convergence for a block of rounds, $L_b(t_1, t_2)$, measures the average proportion of Nash equilibrium play between rounds t_1 and t_2, i.e., $L_b(t_1, t_2) = \sum_{t=t_1}^{t_2} L(t)/(t_2 - t_1 + 1)$, where $0 \leq t_1 \leq t_2 \leq T$ and T is the total number of rounds.*

We define the level of convergence for both a round and a block of rounds. The block convergence measure smooths out inter-round variation. However, a particular convergence level does not capture the change in equilibrium play over time. The following definition captures the change in equilibrium play induced by the mechanism and reduces cohort effects.

DEFINITION 2 *The convergence-level change, $\Delta L(\tau)$ is measured by the difference in the proportion of Nash equilibrium play in the last and first τ rounds, i.e., $\Delta L(\tau) = L_b(T - \tau + 1, T) - L_b(1, \tau)$, where $0 < \tau < T/2$, and T is the total number of rounds.*

[7] We thank anonymous referees for suggesting this separation and appropriate measures.

Ideally, the speed of convergence should measure how quickly all players converge to equilibrium strategies. However, in our experimental setting, we never observe perfect convergence. We therefore use a more general definition for the speed of convergence.

DEFINITION 3 *For a given level of convergence, $L^* \in (0, 1]$, the speed of convergence is measured by the first round in which the level of convergence reaches L^* and does not subsequently drop below this level, i.e., τ such that $L(t) \geq L^*$ for any $t \geq \tau$. Alternatively, we measure the speed of convergence by the first block in which the level of convergence reaches L^* and does not subsequently drop below this level, i.e., $\tau_1 \leq \tau_2$ such that $L_b(t_1, t_2) \geq L^*$ for any $t_1 \geq \tau_1$, $t_2 \geq \tau_2$ and $t_2 - t_1 = (\tau_2 - \tau_1)n$, where n is a positive integer.*

We sometimes use the slope of $L(t)$ as a measure of the speed of convergence for computational ease. We now relate the slope of $L(t)$ and the initial level of convergence $L(1)$ to the speed of convergence. Assuming $L_y(t)$ is differentiable, where y is a treatment, we establish the following observation.

OBSERVATION 1 *If $L_1(1) \geq L_2(1)$ and $dL_1(t)/dt > dL_2(t)/dt$ for all $t \in [1, T]$, then, given any $L^* \in (0, 1]$, the first treatment converges more quickly than the second treatment, i.e., $\tau_1 < \tau_2$.*

Based on theories presented in Section 2, we now form our hypotheses about the level and speed of convergence. While theories of strategic complementarities do not make any predictions about the speed of convergence, we form our hypotheses based on previous experiments that incidentally address games with strategic complementarities.

HYPOTHESIS 1 *When $\alpha = 20$, increasing β from 0 to 20 significantly increases (a) the level and (b) the speed of convergence.*

Hypothesis 1 is based on the theoretical prediction that games with strategic complementarities converge to the unique Nash equilibrium, as well as on previous experimental findings that supermodular games perform robustly better than their non-supermodular counterparts.

HYPOTHESIS 2 *When $\alpha = 20$, increasing β from 0 to 18 significantly increases (a) the level and (b) the speed of convergence.*

Hypothesis 2 is based on the findings of Falkinger et al. (2000), that average play is close to equilibrium when the free parameter is slightly below the supermodular threshold.

HYPOTHESIS 3 *When $\alpha = 20$, increasing β from 18 to 20 significantly increases (a) the level and (b) the speed of convergence.*

Since we have not found any previous experimental studies which compare the performance of games with strategic complementarities with those near the threshold, Hypothesis 3 is pure speculation.

HYPOTHESIS 4 *When $\alpha = 20$, increasing β from 20 to 40 does not significantly increase either (a) the level or (b) the speed of convergence.*

Since we have not found any previous experimental studies within the class of games with strategic complementarities, Hypotheses 4 is again our speculation.

HYPOTHESIS 5 *When $\beta = 0$ or 20, increasing α from 10 to 20 significantly increases (a) the level and (b) the speed of convergence.*

HYPOTHESIS 6 *Changing α from 10 to 20 significantly increases the improvement in (a) the level and (b) the speed of convergence that results from increasing β from 0 to 20.*

Hypothesis 5 is based on experimental findings supporting the General Incentive Hypothesis. Hypothesis 6 is our speculation.

Hypotheses 1 to 6 are concerned with only one measure of performance, convergence to equilibrium. Other measures, such as efficiency and budget balance, can be largely derived from convergence patterns. Therefore, although we omit the formal hypotheses, we present results regarding these measures in Sections 5 and 6.

5 Experimental Results

In this section, we compare the performance of the mechanism as we vary α and β. At the individual level, we look at both the level and speed of convergence to subgame-perfect equilibrium and near-equilibrium in each of the six different treatments. At the aggregate level, we examine the efficiency and budget imbalance generated by each treatment. In the following discussion, we focus on prices rather than on quantity. Recall that player 1's best response in the production stage is uniquely determined by p_2, and that player 1 has all of the information needed to select this best response. In our experiment, deviations in the production stage tend to be small (the average absolute deviation is less than one in 23 of 27 sessions) and does not differ significantly among treatments. Therefore, it is not surprising that, in all of our analyses, the results for quantities largely mirror the results for player 2's price.[8]

Recall that subgame perfect Nash equilibrium for a stage game is $(p_1^*, p_2^*, X^*) = (16, 16, 32)$. Since the strategy space in this experiment is rather large and the payoff function is relatively flat near equilibrium, a small deviation from equilibrium is not very costly. For example, in the $\alpha 20 \beta 20$ treatment, a one-unit unilateral deviation from equilibrium prices costs player 1 \$0.005 and player 2 \$0.014. Therefore, we check the ϵ-equilibrium play by looking at the proportion of price announcements within ± 1 of the equilibrium price, and the quantity announcement within ± 4 of the equilibrium quantity, since a one-unit price change results in a four-unit best-response quantity change. Therefore, the ϵ-equilibrium prediction is $(\epsilon\text{-}p_1^*, \epsilon\text{-}p_2^*, \epsilon\text{-}x^*) = (\{15, 16, 17\}, \{15, 16, 17\}, \{28, \cdots, 32, \cdots, 36\})$.

[Figure 1 about here.]

[Figure 2 about here.]

Figures 1 and 2 contain box and whiskers plots for the prices for each treatment for all 60 rounds by players 1 and 2, respectively. The box represents the ranges of the 25th and 75th percentiles of prices, while the whiskers extend to the minimum and maximum prices in each round. The horizontal line within each box represents the median price. Compared with the $\beta = 0$ treatments, equilibrium price convergence is clearly more pronounced in the supermodular and near-supermodular treatments.

[Table 2 about here.]

To analyze the performance of the compensation mechanism, we first compare the convergence level achieved in the last 20 rounds of each treatment. Table 2 reports the level of convergence ($L_b(41, 60)$) to subgame-perfect Nash equilibrium (top two panels) and ϵ-Nash equilibrium (bottom two panels) for each session under each of the six different treatments, as well as the alternative hypotheses and the corresponding p-values of one-tailed permutation tests[9] under the null hypothesis that the convergence level in the two treatments are the same. While the proportion of ϵ-equilibrium play is much higher than the proportion

[8] Tables are available from the authors upon request.

[9] The permutation test, also known as the Fisher randomization test, is a nonparametric version of a difference of two means t-test. (See, e.g., Siegel and Castellan (1988), p.95-100.) The idea is simple and intuitive: by pooling all independent observations, the p-value is the exact probability of observing a separation between the two treatments as the one observed when the pooled observations are randomly divided into two equal-sized groups. This test uses all of the information in the sample, and thus has 100% power-efficiency. It is among the most powerful of all statistical tests.

of equilibrium play, the results of the permutation tests largely follow similar patterns. We now formally test our hypotheses regarding convergence level. Parts 1-3 of Result 1 present the effects of the degree of strategic complementarity (β-effects). Parts 4 and 5 present effects due to changes in α (α-effects).

RESULT 1 (Level of Convergence in the Last 20 Rounds) :

1. *When* $\alpha = 20$, *increasing* β *from* 0 *to* 18 *and from* 0 *to* 20 *significantly*[10] *increases the level of convergence in* p_1^*, p_2^* *and* ϵ-p_2^*.

2. *When* $\alpha = 20$, *increasing* β *from* 18 *to* 20 *does not change the level of convergence significantly.*

3. *When* $\alpha = 20$, *increasing* β *from* 20 *to* 40 *does not change the level of convergence significantly.*

4. *When* $\beta = 0$, *increasing* α *from* 10 *to* 20 *weakly increases the level of convergence in* p_2^*, *and significantly increases the level of convergence in* ϵ-p_2^*, *but has no significant effects on* p_1^* *or* ϵ-p_1^*.

5. *When* $\beta = 20$, *increasing* α *from* 10 *to* 20 *weakly increases the level of convergence in* p_1^*, *but not in* ϵ-p_1^*, p_2^*, *or* ϵ-p_2^*.

SUPPORT: The last two columns of Table 2 report the corresponding alternative hypotheses and permutation test results. ∎

By Part 1 of Result 1, we accept Hypotheses 1(a) and 2(a). Part 1 also confirms previous experimental findings that supermodular games perform significantly better than those far from the supermodular threshold. Furthermore, near-supermodular games also perform significantly better than those far from the threshold.

However, by Part 2, we reject Hypothesis 3(a). This is the first experimental result which shows that, from a little below the supermodular threshold ($\beta = 18$) to the threshold ($\beta = 20$), improvement in convergence level is statistically insignificant. In other words, we do not see a dramatic improvement at the threshold. This implies that the performance of near-supermodular games, such as the Falkinger mechanism, ought to be comparable to that of supermodular games.

By contrast, we accept Hypothesis 4(a) by Part 3. This is the first experimental result systematically comparing convergence levels of supermodular games, where theory is silent. The convergence level does not significantly improve as β increases from the threshold, 20, to 40. Therefore, the marginal returns for being "more supermodular" diminish once the payoffs become supermodular.

[10]When presenting results throughout the paper, we follow the convention that a significance level of 5% or less is *significant*, while a significance level between 5% and 10% is *weakly significant*.

Proposition 2 predicts convergence under Cournot best reply for any $\beta \geq 0$. However, there is a significant difference in convergence level as β increases from 0 to 18, 20 and beyond. We investigate in Section 6 whether this difference persists in the long run.

While Parts 1-3 present the β-effects, Parts 4 and 5 examine the α-effects and we partially accept Hypothesis 5(a). Recall from Equation (5) and subsequent discussions that, at the threshold of strategic complementarity $\beta = 20$, player 2's Nash equilibrium strategy is also a dominant strategy. The finding of no α-effect on player 2's equilibrium play when $\beta = 20$ is consistent with this observation.

The above results highlight the convergence level achieved towards the end of the game. However, these results do not indicate whether players have learned equilibrium strategies. Therefore, we now look at the improvement in convergence over time as we change the parameters. Our measure, $\Delta L(20) = L_b(41, 60) - L_b(1, 20)$, is the difference in convergence level between the first and last twenty rounds.

[Table 3 about here.]

Table 3 reports the convergence-level change between the first and last 20 rounds, $\Delta L(20)$, to subgame-perfect Nash equilibrium (top two panels) and ϵ-Nash equilibrium (bottom two panels) for each session under each of the six different treatments, as well as the alternative hypotheses and the corresponding p-values of one-tailed permutation tests. Comparing the permutation test results of Table 3 to those of Table 2, we notice that the β-effects in Result 1 persist (although sometimes they are only weakly significant). However, the α-effects disappear, as higher α weakly increases the level of convergence in the first 20 rounds as well.[11]

[Table 4 about here.]

To determine the effects of strategic complementarities and other factors on convergence level and speed, we use logit models with clustering at the individual level. The results from these models are presented in Table 4. The dependent variable is ϵ-p_1^* in specifications (1) and (3), and ϵ-p_2^* in specifications (2) and (4).

In specifications (1) and (2), the independent variables are: treatment dummies, D_y, where $y = \alpha10\beta00$, $\alpha20\beta00$, $\beta18$, $\alpha10\beta20$ and $\beta40$; $\ln(Round)$; and a constant. We omit the dummy for $\alpha20\beta20$. Therefore, in these two specifications, restricting learning speed to be the same across treatments, the estimated coefficient of D_y captures the difference in the convergence level between treatments y and $\alpha20\beta20$. We use dummies for different values of α and β, rather than direct parameter values, to avoid assuming a linear relationship

[11]For example, the permutation test of the null hypothesis of equal proportion against H_1: $\alpha10\beta20 < \alpha20\beta20$ yields a p-value of 0.091.

of parameter effects. Results from these specifications are largely consistent with Result 1 which uses a more conservative test. The coefficients of $\ln(Round)$ are both positive and highly significant, indicating that players learn to play equilibrium strategies over time. The concave functional form, $\ln(Round)$, which yields a better log-likelihood than either the linear or quadratic functional form, indicates that learning is rapid at the beginning and decreases over time. We will examine learning in more detail in Section 6.

In specifications (3) and (4), we use $\ln(Round)$, interaction of each of the treatment dummies with $\ln(Round)$, and a constant[12] as dependent variables. The interaction term allows different slopes for different treatments. Compared with the coefficient of $\ln(Round)$, the coefficient for the interaction term, $D_y \ln(Round)$, captures the slope differences between treatment y and $\alpha 20 \beta 20$. By Observation 1, we use the slope of each treatment as a measure for the convergence speed.

RESULT 2 (Speed of Convergence) :

1. *When* $\alpha = 20$, *increasing* β *from* 0 *to* 18 *and from* 0 *to* 20 *significantly increases the speed of convergence in* ϵ-p_1^* *and* ϵ-p_2^*.
2. *When* $\alpha = 20$, *increasing* β *from* 18 *to* 20 *has no significant effect on convergence speed.*
3. *When* $\alpha = 20$, *increasing* β *from* 20 *to* 40 *has no significant effect on convergence speed.*
4. *When* $\beta = 0$, *increasing* α *from* 10 *to* 20 *has no significant effects on convergence speed.*
5. *When* $\beta = 20$, *increasing* α *from* 10 *to* 20 *has no significant effects on convergence speed.*

SUPPORT: Models (3) and (4) in Table 4 report analyses on convergence speed. For each independent variable, the coefficients, standard errors (in parentheses) and significance levels are reported. The second Wald test looks at whether the coefficient of $D_{\alpha 10 \beta 00} \ln$(Round) equals that of $D_{\alpha 20 \beta 00} \ln$(Round). ∎

Part 1 of Result 2 supports Hypotheses 1(b) and 2(b), while by Part 2 we reject Hypothesis 3(b). Part 3 supports Hypothesis 4(b). Parts 4 and 5 reject Hypothesis 5(b). Result 2 provides the first empirical evidence on the role of strategic complementarity and the speed of convergence.

Although Part 2 indicates that increasing β from 18 to 20 does not significantly change convergence speed, we now investigate whether there are any differences between $\beta 18$ and the supermodular treatments.

[12] This specification restricts the same intercept across all treatments, i.e., initial round proportion of equilibrium play is assumed to be the same. When including treatment dummies, Wald tests on the hypothesis that the treatment dummy coefficients are all zero yield p-values of 0.2703 for ϵ-p_1^*, and 0.3383 for ϵ-p_2^*.

In particular we compare $\alpha20\beta18$ with $\alpha20\beta20$ and $\alpha20\beta40$.[13] In Result 1, we show that these treatments achieve the same convergence level. Also, we cannot reject the hypothesis that round one prices for each player are drawn for the same distribution for each treatment.[14] As the treatments all start and converge to similar levels of equilibrium play, we use a more flexible functional form to look for differences in speed.

[Table 5 about here.]

In Table 5, we report the results of logit regressions comparing $\alpha20\beta18$ with the two $\alpha20$ supermodular treatments. We use Round, ln(Round), and their interactions with $\alpha20\beta18$ as independent variables to allow different convergence speeds to the same level of convergence. In model (1), the dependent variable is player 1 ϵ-equilibrium play. There is no significant difference between $\alpha20\beta18$ and the $\alpha20$ supermodular treatments. In model (2), the dependent variable is player 2 ϵ-equilibrium play. There are significant differences between the near-supermodular and $\alpha20$ supermodular treatments. In early rounds, ln(Round) is large relative to Round. The negative and weakly significant coefficient on $D_{\alpha20\beta18}$ln(Round) implies a lower probability of early-round equilibrium play in $\alpha20\beta18$ relative to the supermodular treatments. The $\beta18$ treatment does catch up to these treatments, which is reflected in the positive and significant coefficient on $D_{\alpha20\beta18}$ interacted with Round. This result suggest a difference between supermodular and near-supermodular treatments: while they achieve similar convergence levels, the supermodular treatments perform better in early rounds and thus might reach certain convergence levels faster than their near-supermodular counterparts.

The previous discussion examines the separate effects of strategic complementarity (β-effects) and α (α-effects) on convergence. However, varying α allows us to test the importance of strategic complementarity relative to other features of mechanism design. Having a full factorial design in the parameters $\alpha = 10, 20$ and $\beta = 0, 20$, we can study whether α affects the role of strategic complementarity. In particular, as β increases from 0 to 20, we expect improvement in convergence level and speed. We study whether this improvement changes when α increases from 10 to 20.

The last two Wald tests in the bottom panel of Table 4 separately examine the α-effects on convergence level and speed resulting from increasing β from 0 to 20 (α-effects on β-effects). Changing α from 10 to 20 does not significantly change either the level or speed of convergence. This is the first empirical result examining the effects of other factors on the role of strategic complementarity.

So far, we have discussed the performance of the mechanism relative to equilibrium predictions and individual behavior. We now turn to group-level welfare results. Since the compensation mechanism balances

[13] We omit $\alpha10\beta20$ from this analysis. First, it does not achieve the same ϵ-p_1^* convergence level as the other supermodular treatments. Second, omitting it avoids the possibility of an α-effect.

[14] Kolmogorov-Smirnov test result tables are available by request.

the budget only in equilibrium, total payoffs off the equilibrium path can be only weakly related to efficient payoffs. Therefore, we use two separate measures to capture welfare implications, an efficiency measure and a measure of budget imbalance.

We first define the per-round efficiency measure which includes neither the tax/subsidy nor the penalty terms, i.e.,

$$e(t) = \frac{rx(t) - c(x(t)) - e(x(t))}{rx^* - c(x^*) - e(x^*)},$$

where x^* is the efficient quantity. The efficiency achieved in a block, $e(t_1, t_2)$, where $0 \leq t_1 \leq t_2 \leq 60$, is then defined as:

$$e(t_1, t_2) = \sum_{t=t_1}^{t_2} \frac{e(t)}{t_2 - t_1 + 1}.$$

RESULT 3 (Efficiency in the Last 20 Rounds) :

1. *When* $\alpha = 20$*, increasing* β *from* 0 *to* 18 *significantly improves efficiency, while increasing* β *from* 0 *to* 20 *weakly improves efficiency.*
2. *When* $\alpha = 20$*, increasing* β *from* 18 *to* 20 *has no significant effect on efficiency.*
3. *When* $\alpha = 20$*, increasing* β *from* 20 *to* 40 *weakly improves efficiency.*
4. *When* $\beta = 0$*, increasing* α *from* 10 *to* 20 *weakly improves efficiency.*
5. *When* $\beta = 20$*, increasing* α *from* 10 *to* 20 *has no significant effect on efficiency.*

[Table 6 about here.]

SUPPORT: Table 6 presents the efficiency measure for each session in each treatment in the last 20 rounds (top panel) and the change in efficiency between the first and last 20 rounds (bottom panel), the alternative hypotheses and the results of one-tailed permutation tests. ∎

Result 3 is largely consistent with Result 1, indicating that supermodular and near-supermodular mechanisms induce a significantly higher proportion of equilibrium play than mechanisms far from the supermodular threshold. The new finding is that increasing β from the threshold 20 to 40 weakly improves efficiency. We note that the efficiency change between the first and last 20 rounds is not significantly different across treatments.

Second, the budget surplus at round t is the sum of the penalty terms, plus tax, minus subsidy in that round, i.e., $s(t) = (\alpha + \beta)(p_1(t) - p_2(t))^2 + p_2(t)x(t) - p_1(t)x(t)$. Examining the session-level budget surplus across all rounds, we find the following results. First, 22 out of 27 sessions result in a budget surplus. This comes from a combination of our choice of parameters and the dynamics of play. Second, the only significant difference across treatments is that budget surpluses under $\alpha 20\beta 18$ and $\alpha 20\beta 20$ are significantly lower than those under $\alpha 20\beta 40$ (p-values $= 0.029$ and 0.024 respectively). This finding points to a potential cost of driving up the punishment parameter, β. In other words, before the system equilibrates, a high punishment parameter can worsen the budget imbalance problem inherent in the mechanism.

Overall, Results 1 through 3 suggest the following observations regarding games with strategic complementarities. First, in terms of convergence level and speed, supermodular and near-supermodular games perform significantly better than those far under the threshold. Second, while there is no significant difference between supermodular and near-supermodular games in terms of convergence level, early performance differences may lead to supermodular treatments reaching lower convergence levels more quickly. Third, beyond the threshold, increasing β has no significant effect on either the level or the speed of convergence. Last, For a given β, increasing α has partial effects on convergence level, but no significant effect on convergence speed. To check the persistence of these experimental results in the long run, we use simulations in Section 6.

6 Simulation Results: Continued Dynamics

Our experiment examines the relationship between strategic complementarity and convergence to equilibrium. Learning theory predicts long-run convergence. Figures 1 and 2 show that convergence continues to improve in later rounds for several treatments, suggesting continued dynamics. Due to time, attention and resource constraints, it was not feasible to run the experiment for much longer than 60 rounds. Therefore, we rely on simulations to study continued convergence beyond 60 rounds.

To do so, we look for a learning algorithm which, when calibrated, closely approximates the observed dynamic paths over 60 rounds. The large empirical literature on learning in games (see, e.g., Camerer (2003), for a survey) suggests many models. Our interest here is not to compare the performance of various learning models. We look for learning models that match two criteria. First, we require a model that performs well in a variety of experimental games. Second, given that our experiment has complete information about the payoff structure, the model needs to incorporate this information. In the following subsections, we first introduce three learning models which meet our criteria. We then look at how well the learning models predict the experimental data by calibrating each algorithm on a subset of the experimental data, and then validating the models on a hold-out sample. We then report the forecasting results using one of the calibrated algorithms.

6.1 Three Learning Models

The models we examine are stochastic fictitious play with discounting (hereafter shortened as **sFP**) (Cheung and Friedman (1997) and Fudenberg and Levine (1998)), functional EWA (**fEWA**) (Ho, Camerer and Chong 2001) and the payoff assessment learning model (**PA**) (Sarin and Vahid 1999). We now give a brief overview of each model. Interested readers are referred to the originals for complete descriptions.

The particular version of sFP that we use is logistic fictitious play (see, e.g., Fudenberg and Levine (1998) p.199). A player predicts the her match's price in the next round, $p_{-i}(t+1)$ according to,

$$p_{-i}(t+1) = \frac{p_{-i}(t) + \sum_{\tau=1}^{t-1} r^{\tau} p_{-i}(t-\tau)}{1 + \sum_{\tau=1}^{t-1} r^{\tau}}, \tag{6}$$

for some discount factor, $r \in [0,1]$. Note $r = 0$ corresponds to the *Cournot best reply* assessment, $p_{-i}(t+1) = p_{-i}(t)$. When $r = 1$, it yields the standard *fictitious play* assessment. The usual *adaptive learning model* assumes $0 < r < 1$. All observations influence the expected state but more recent observations have greater weight.

As opposed to standard fictitious play, stochastic fictitious play allows decision randomization and thus better captures the human learning process. Omitting time subscripts, the probability that a player announces price p_i is given by:

$$Prob(p_i|p_{-i}) = \frac{exp(\lambda \pi(p_i, p_{-i}))}{\sum_{j=0}^{40} exp(\lambda \pi(p_j, p_{-j}))}. \tag{7}$$

Given a predicted price, a player is thus more likely to play strategies that yield higher payoffs. How much more likely is determined by λ, the sensitivity parameter. As λ increases, the probability of a best response to p_{-i} increases.

The second model we consider, fEWA, is a one-parameter variant of the experience weighted attraction model (EWA, Camerer and Ho (1999)). In this model, strategy probabilities are determined by logit probabilities similar to Equation (7) with actual payoffs ($\pi(p_i, p_{-i})$) replaced by strategy *attraction*. In both variants, strategy attraction, $A_i^j(t)$, and an experience weight, $N(t)$, are updated after every period. The experience weight is updated according to $N(t) = \phi(1-\kappa) \cdot N(t-1) + 1$, where ϕ is the change-detection parameter and κ controls exploration (low κ) versus exploitation. Attractions are updated according to the following rule:

$$A_i^j(t) = \frac{\phi N(t-1) A_i^j(t-1) + [\delta + (1-\delta) I(p_i^j, p_i(t))] \pi_i(p_j, p_{-i}(t))}{N(t)}, \tag{8}$$

where the indicator function $I(p_i^j, p_i(t))$ equals one if $p_i^j = p_i(t)$ and zero otherwise, and $\delta \in [0,1]$ is the imagination weight. In EWA, all parameters are estimated, whereas in fEWA these parameters (except for

λ) are endogenously determined by the following functions. The change-detector function, $\phi_i(t)$, is given by:

$$\phi_i(t) = 1 - .5 \left(\sum_{j=1}^{m_{-i}} \left[\frac{I(p_{-i}^j, p_{-i}(t))}{1} - \frac{\sum_{\tau=1}^{t} I(p_{-i}^j, p_{-i}(t))}{t} \right]^2 \right). \tag{9}$$

This function will be close to 1 when recent history resembles previous history. The imagination weight $\delta_i(t)$ equals $\phi_i(t)$, while κ equals the Gini coefficient of previous choice frequencies. EWA models encompass a variety of familiar learning models: cumulative reinforcement learning ($\delta = 0, \kappa = 1, N(0) = 1$), weighted reinforcement learning ($\delta = 0, \kappa = 0, N(0) = 1$), weighted fictitious play ($\delta = 1, \kappa = 0$), standard fictitious play ($\delta = \phi = 1, \kappa = 0$), and Cournot best reply ($\phi = \kappa = 1, \delta = 1$).

Finally, we introduce the main components of the PA model. For simplicity, we omit all subscripts which represent player i, and let $\pi_j(t)$ represent the actual payoff of strategy j in round t. Since the game has a large strategy space, we incorporate similarity functions into the model to represent agent use of strategy similarity. As strategies in this game are naturally ordered by their labels, we use the Bartlett similarity function, $f_{jk}(h, t)$, to denote the similarity between the played strategy, k, and an unplayed strategy, j, at period t:

$$f_{jk}(h, t) = \begin{cases} 1 - |j - k|/h & \text{if } |j - k| < h, \\ 0 & \text{otherwise.} \end{cases}$$

In this function, the parameter h determines the $h-1$ unplayed strategies on either side of the played strategy to be updated. When $h = 1$, $f_{jk}(1, t)$ degenerates into an indicator function equal to one if strategy j is chosen in round t and zero otherwise.

The PA model assumes that a player is a myopic subjective maximizer. That is, she chooses strategies based on assessed payoffs, and does not explicitly take into account the likelihood of alternate states. Let $u_j(t)$ denote the subjective assessment of strategy p_j at time t, and r the discount factor. Payoff assessments are updated through a weighted average of his previous assessments and the payoff he actually obtains at time t. If strategy k is chosen at time t, then:

$$u_j(t+1) = (1 - r f_{jk}(h, t)) u_j(t) + r f_{jk}(h, t) \pi_k(t), \forall j. \tag{10}$$

Each period, the assessed strategy payoffs are subject to zero-mean, symmetrically distributed shocks, $z_j(t)$. The decision maker chooses on the basis of his shock-distorted subjective assessments, $\tilde{u}_j(t) = u_j(t) + z_j(t)$. At time t he chooses strategy p_k if:

$$\tilde{u}_k(t) - \tilde{u}_j(t) > 0, \forall p_j \neq p_k. \tag{11}$$

Note that mood shocks affect only his choices and not the manner in which assessments are updated.

6.2 Calibration

Literature assessing the performance of learning models contains two approaches to calibration and validation. The first approach calibrates the model on the first t rounds and validates on the remaining rounds. The second approach uses half of the sessions in each treatment to calibrate and the other half to validate. We choose the latter approach for two reasons. First, this approach is feasible as we have multiple independent sessions for each treatment. Second, we need not assume that the parameters of later rounds are the same as those in earlier rounds. We thus calibrate the parameters of each model in blocks of 15 rounds using the experimental data from the first two sessions of each treatment. We then evaluate each model by measuring how well the parameterized model predicts play in the remaining two or three sessions.

For parameter estimation, we conduct Monte Carlo simulations designed to replicate the characteristics of the experimental settings. In all calibrations, we exclude the last two rounds (59 and 60) to avoid any end-of-game effects. We then compare the simulated paths with the experimental data to find those parameters which minimize the mean-squared deviation (MSD) scores. Since the final outcome distributions of our data are unimodal, the simulated mean is an informative statistic and is well captured by MSD (Haruvy and Stahl 2000). In all simulations, we use the *k*-period-ahead rather than the one-period-ahead approach[15] because we are interested in forecasting the long-run mechanism performance. In doing so, we choose $k = 10, 15, 20, 30$ and 58. We look at blocks of 10, 15, 20 and 30 rounds because as players gain information and experience, information use may change over time. We use $k = 15$ rather than the other values because it best captures the actual dynamics in the experimental data.

Each simulation consists of 1,500 games (18,000 players) and the following steps:

1. Simulated players are randomly matched into pairs at the beginning of each round.
2. Simulated players select price announcements.
   (a) Initial round: Based on Kolmogorov-Smirnov tests on the actual round-one price distribution, we reject the null hypotheses of uniform distribution ($d = 0.250$, p-value = 0.000) and normal distribution ($d = 0.381$, p-value = 0.000). We thus follow the convention (e.g., Ho et al. (2001)) and use the actual first-round empirical distribution of choices to generate the first round choices.

[Figure 3 about here.]

[15] Erev and Haruvy (2000) discuss the tradeoffs of the two approaches.

Figure 3 presents the actual first round empirical distribution of choices for players 1 and 2, respectively.

   (b) Subsequent rounds: Simulated player strategies are determined via Equation (7) for sFP and fEWA, and (11) for PA.

3. Simulated player 1's quantity choice is based on the following steps:

   (a) Determine each player 1's best response to p_2.

   (b) Determine whether player 1 will deviate from the best response via the actual probability of errors for each block.

   (c) If yes, deviate via the actual mean and standard deviation for the block. Otherwise, play the best response.

4. Payoffs are determined by the payoff function of the compensation mechanism, Equation (1), for each treatment.

5. Assessments are updated according to Equation (8) for fEWA and (10) for PA.

6. Proceed to the next round.

The discount factor, $r \in [0, 1]$, is searched at a grid size of 0.1. The parameter λ is searched at a grid size of 0.1 in the interval $[1.5, 10.5]$ for fEWA, and $[1.5, 25.0]$ for sFP. The size of the similarity window, $h \in [1, 10]$, is searched at a grid size of 1. Mood shocks, z, are drawn from a uniform distribution[16] on an interval $[-a, a]$, where a is searched on $[0, 500]$ with a step size of 50. For all parameters, intervals and grid sizes are determined by payoff magnitude.

[Table 7 about here.]

Table 7 reports the calibrated parameters (discount factor, sensitivity parameter, mood shock interval and similarity window size) for the first two sessions of each treatment in 15-round blocks.[17] Estimated parameters for the supermodular and near-supermodular treatments are consistent with the increased level of convergence over time, while the $\beta00$ treatments are not. The second column (**sFP**) reports the best-fit

[16]Chen and Khoroshilov (2003) compare three versions of PA models where shocks were drawn from uniform, logistic and double exponential distributions on two sets of experimental data and find that the performance of the three versions of PA were statistically indistinguishable.

[17]We also calibrate all parameters for the entire 60 rounds, but do not report results due to space limitations.

parameters for the stochastic fictitious play model. With the exception of treatment $\alpha 20\beta 00$, the discount factor is close to 1.0, indicating that players keep track of all past play when forming beliefs about opponent's next move. [18] Given these beliefs, the increasing sensitivity parameter, λ, for all treatments except $\alpha 10\beta 00$ indicates that the likelihood of best response increases over time. The third column reports calibration results for the fEWA model. Again, with the exception of treatment $\alpha 10\beta 00$, the parameter λ increases over time. The final column reports calibration of parameters in the PA model. For each treatment except $\alpha 10\beta 00$, a middle block has the highest discount factor, indicating more weight on new information about a strategy's performance. The second parameter in the PA model represents the upper bound of the interval from which shocks are drawn, a. Experimentation should decrease in the final rounds. Indeed, for all treatments, the estimated mood-shock ranges (weakly) decrease from the third to the last block. Finally, the decreasing similarity windows from the third to final block indicate decreasing strategy spill-over. Relatively large discount factors in the third block, combined with relatively large similarity windows, flatten the payoff assessments around the most recently played strategies, consistent with the local experimentation (or relatively stabilized play) observed in the data.

6.3 Validation

Using the parameters calibrated on the first two sessions of each treatment, we next compare the performance of the three learning models in predicting play in the hold-out sample. For comparison, we also present the performance of two static models. The **random choice model** assumes that each player randomly chooses any strategy with equal probability for all rounds. This model only incorporates number of strategies, and thus provides a minimum standard for a dynamic learning model. The **equilibrium model** assumes that each player plays the subgame perfect Nash equilibrium every round. This model conveys the same information as the proportion of equilibrium play presented in Section 5, but with a different metric (MSD).

[Table 8 about here.]

Table 8 presents each model's MSD scores for each hold-out session. Recall that two of each treatment's four or five independent sessions are used for calibration, and the rest for validation. The results indicate that all three learning models perform significantly better than the random choice model (p-value < 0.01, one-sided permutation tests) and, by a larger margin, significantly better than the equilibrium model (p-value < 0.01, one-sided permutation tests). While the equilibrium model does a poor job of explaining overall ex-

[18] As the discount factor is zero in Cournot best reply, we can reject this model based on our estimation of the discount factors.

perimental data, its performance improvement over time[19] justifies the use of learning models to explain the dynamics of play. Within each of the top three panels (i.e., learning models), session-level MSD scores are lower for the supermodular and near-supermodular treatments, indicating that each learning model does a better job explaining behavior in those treatments. Indeed, in the empirical learning literature learning models fit better in experiments with better equilibrium convergence (see, e.g., Chen and Khoroshilov (2003)).

RESULT 4 (Comparison of Learning Models) *The performance of PA is weakly better than that of fEWA and strictly better than that of sFP. The performances of fEWA and sFP are not significantly different.*

SUPPORT: Table 8 reports the MSD scores for each independent session in the hold-out sample under each model. The Wilcoxon signed-ranks tests show that the MSD scores under PA are weakly lower than those under fEWA ($z = -0.085$, p-value $= 0.068$), and strictly lower than those under sFP ($z = -0.028$, p-value $= 0.023$). Using the same test, we cannot reject the hypothesis that fEWA and sFP yield the same MSD scores ($z = 0.662$, p-value$= 0.508$). ∎

Although the the performance of PA is only weakly better than that of fEWA, the overall MSD scores for PA are lower than those for fEWA for every treatment. Therefore, we use PA for forecasting beyond 60 rounds.

[Figure 4 about here.]

Figure 4 presents the simulated path of the calibrated PA model and compares it with the actual data in the hold-out sample by superimposing the simulated mean (black line) plus and minus one standard deviation (grey lines) on the actual mean (black box) and standard deviation (error bars). The simulation does a good job of tracking both the mean and the standard deviation of the actual data. However, in treatments $\alpha 10 \beta 00$ and $\alpha 20 \beta 40$, the reduction in variance lags that seen in the middle rounds of the experiment.

6.4 Forecasting

We now report the results from the PA model. As the strategic complementarity predictions concern long-run performance, we use the calibrated parameters for the first 58 rounds to simulate play in later rounds. This exercise allows us to study convergence and efficiency in long but finite horizons.

In all forecasting exercises we base all post-58 round parameters on those from the last block (calibrated from rounds 46–58). Since we do not know how these parameters might change beyond 60 rounds, we use

[19] We omit the table to show the performance of the equilibrium model in blocks of 15 rounds, as the information is repetitive with Figures 1 and 2.

three different specifications. First, we retain all final-block parameters. Second, we exponentially decay in subsequent blocks the probability of deviation from the best response in the production stage.[20] Third, we exponentially decay the shock interval in subsequent blocks. As all three specifications yield qualitatively similar results, we report results from only the third specification due to space limitations.[21] In presenting the results, we use the shorthand notation $x > y$ to denote a measure under treatment x is significantly higher than that under treatment y at the 5% level or less, and $x \sim y$ to denote that the measures are not significantly different at the 5% level.

[Figure 5 about here.]

The top and bottom rows of Figure 5 report the simulated and actual proportion of ϵ-equilibrium play, respectively. We report only the results for the first 500 rounds since the dynamics do not change much thereafter. In our simulation, all treatments reach higher convergence levels than those achieved in the 60 rounds of the experiment. Since the simulated variance reduction lags that of the experiment, round 60 results are not achieved until approximately 90 rounds of simulation. We further note that these improvements slow down after 200 rounds. The proportion of ϵ-equilibrium play is bounded by 72% for player 1 and 93% for player 2. We now outline the simulation results.

RESULT 5 (Level of Convergence in Round 500) : *In the simulated data for player 1, at round 500, we have the following level of convergence ranking in:*

1. p_1^*: $\alpha 20\beta 18 \sim \alpha 20\beta 40 > \alpha 20\beta 20 > \alpha 10\beta 20 > \alpha 20\beta 00 > \alpha 10\beta 00$,
2. ϵ-p_1^*: $\alpha 20\beta 18 > \alpha 20\beta 40 > \alpha 20\beta 20 > \alpha 10\beta 20 > \alpha 20\beta 00 > \alpha 10\beta 00$,
3. p_2^*: $\alpha 20\beta 40 > \alpha 20\beta 18 \sim \alpha 10\beta 20 > \alpha 20\beta 20 > \alpha 20\beta 00 > \alpha 10\beta 00$, *and*
4. ϵ-p_2^*: $\alpha 20\beta 40 > \alpha 20\beta 18 > \alpha 10\beta 20 > \alpha 20\beta 20 > \alpha 20\beta 00 > \alpha 10\beta 00$.

[Table 9 about here.]

[20] In block $k > 4$, we use the probability of deviation, $Prob_k = \min\{\frac{Prob_4}{(k-4)^2}, 10^{-8}\}$. We set a lower bound of 10^{-8} to avoid the division by zero problem.

[21] Different sequences of random numbers produce slightly different parameters estimates. While the convergence level of a given treatment for a given set of parameter estimates is not affected by the sequence of random numbers, this convergence level is somewhat sensitive to the exact parameter calibration. We therefore conduct four different calibrations for each treatment, and select the parameters which yield the highest level. The relative rankings of treatments are quite robust with respect to which ordinal selected.

SUPPORT: The fourth and seventh columns of Table 9 report p-values for t-tests of the preceding alternative hypotheses for players 1 and 2 respectively. ∎

Comparing Results 1 and 5, we first note that the four supermodular and near-supermodular treatments continue to dominate the $\beta 00$ treatments. In fact, the simulations suggest that the gap remains constant compared with $\alpha 20 \beta 00$, and actually increases compared with $\alpha 10 \beta 00$. Unlike Result 1, however, the four dominant treatments differ. In particular, $\alpha 20 \beta 18$ performs better in terms of player 1's convergence, and $\alpha 20 \beta 40$ in terms of player 2's , although the differences within the top four treatments are smaller than the differences between these four and the $\beta 00$ treatments. In addition, an increase in α significantly improves convergence by a large margin (40-80%) for both players when $\beta = 0$.

It is instructive to compare these results with those concerning the speed of convergence in our experimental treatments. In terms of convergence to ϵ-p_2, our regression results (Table 5) indicate that $\alpha 20 \beta 18$'s performance in later rounds enables it to achieve the same convergence level as the supermodular treatments. This trend continues in our simulations, as $\alpha 20 \beta 18$ performs robustly well compared to the supermodular treatments. Likewise, in our analysis of the experimental results, the convergence speed of $\alpha 20 \beta 40$ was not significantly different than those of the other dominant treatments. However, in our simulations, this treatment dominates all treatments in player 2 equilibrium play.

In our simulations, the convergence improvement due to increasing β from 0 to 20 does depend on α (α-effect on β-effect). An increase in α significantly decreases the improvement in convergence level (all p-values for one-sided t-tests are less than 0.01). Due to the relatively poor performance of $\alpha 10 \beta 00$ in our simulations, increasing α from 10 to 20 when $\beta = 0$ improves convergence more dramatically in round 500 than in rounds 40-60. In the long run, an increase in α is a partial substitute for an increase in β.

[Table 10 about here.]

We now use Definition 3 to examine the convergence speed in the long run. Table 10 presents results for the first time a treatment reaches the level of convergence, L^*. We omit the two $\beta 00$ treatments since they do not converge to the same levels as the other treatments. In terms of player 1, $\alpha 20 \beta 18$ achieves the fastest convergence for all levels L^*. However, the picture for player 2 convergence is more subtle. First, for the $\beta 20$ and $\beta 18$ treatments, the speeds of convergence to all L^* are remarkably similar. While $\alpha 20 \beta 40$ lags the other treatments in terms of achieving 80% ϵ-equilibrium play for player 2, it is the only treatment to achieve $L^* = 90\%$.

Apart from convergence to equilibrium, it is also important to look at long-run welfare properties. We evaluate mechanism performance using the measures presented in Section 5.

[Figure 6 about here.]

Figure 6 summarizes the short-run and long-run efficiency achieved by each of the treatments. The top panel reports simulated results, while the bottom row reports the actual data. In the long run, supermodular and near-supermodular treatments continue to differ from the $\beta00$ treatments, with $\alpha20$ superior to $\alpha10$ in the $\beta00$ treatments. We now present our efficiency results.

RESULT 6 (Efficiency in Round 500) :

1. *In the simulated data, the following relative efficiency ranking of the treatments in round 500 is significant:*

$$\alpha20\beta40 > \alpha20\beta18 > \alpha10\beta20 > \alpha20\beta20 > \alpha20\beta00 > \alpha10\beta00.$$

2. *At round 500, efficiency of treatment $\alpha10\beta00$ is approximately 78%, that of $\alpha20\beta00$ approaches 93%, while that of other four treatments is over 98%.*

[Table 11 about here.]

SUPPORT: Table 11 reports results of t-tests comparing efficiency in different treatments. ∎

Efficiency is determined solely by the quantity produced, which in turn is a function of p_2. Therefore, efficiency rankings match those for p_2-convergence (Result 5). Another interesting welfare result is the overall budget balance. After 500 rounds, the magnitude of budget imbalance is significantly closer to zero for all treatments except for $\alpha10\beta00$. In fact, decreasing α from 20 to 10 significantly increases the deficit for both $\beta00$ and $\beta20$. Finally, $\alpha20\beta40$ is the only treatment that has an overall budget surplus after 500 rounds, although this surplus is approaching zero.

7 Interpretation and Discussion

The underlying force for convergence in games with strategic complementarities is the combination of the slope of the best-response functions and adaptive learning by players. In the compensation mechanisms, the slope of player 2's best response function is determined by β. As α and β determine the penalty for mismatched prices, we seriously consider the possibility that convergence in supermodular and near-supermodular treatments to an equilibrium where both players announce the same price is not due to strategic complementarities, but rather is due to increases in α and β making the penalty terms more prominent and matching strategies more focal.[22] We thus have two hypotheses to explain the observed improvement

[22]We thank an anonymous referee and the co-editor for pointing this out.

in convergence to equilibrium play in supermodular and near-supermodular treatments: a best-response hypothesis and a matching hypothesis. In this section, we present evidence that the improvement in convergence is due to payoff-relevant changes to best responses and not due to matching becoming more focal.

While the focal point hypothesis suggests that players converge to a match, it does not specify the price at which they match. In the first round of our experiments (Figure 3), almost 50% of all prices were 20, and less than 10% were in the ϵ-equilibrium range of $[15, 17]$. In the final rounds of our experiments, play in the four supermodular or near-supermodular treatments converges strongly to this range, suggesting more than simple matching.

By Equation (4), player 1's best response is always to match regardless of p_2. By the General Incentive Hypothesis, we expect more matching behavior by player 1 as α increases. However, by Equation (5), matching is a best response for player 2 only in equilibrium. Therefore, player 2 data can help us separate the best-response and matching hypotheses.

We first investigate which model better explains our experimental data. We operationalize the the best response hypothesis by the stochastic fictitious play model of Section 6 and the matching hypothesis with a stochastic matching model.[23] In both models, the predicted player 1 price is specified by Equation (6). In the matching model, player 2 plays this price with probability $1 - \epsilon$, and one of the other 40 prices with probability $\epsilon/40$. We estimate ϵ using the first two sessions of each treatment.[24] We then compare the performance of the matching model with the sFP model using the hold-out sample. Using the Wilcoxon signed-rank tests to compare the MSD scores in the hold-out sample, we conclude that sFP explains player 2's behavior significantly better than the matching model (p-value = 0.006). We conclude that best response to a predicted price explains behavior significantly better than the matching model.

We next investigate whether differences in the cost of matching, defined as the difference between matching and best-response profits, can explain all of the differences in matching behavior among treatments, or whether there exists additional matching behavior that cannot be explained by payoff-relevant factors.

We examine the probability that player 2 tries to match the anticipated player 1 price. We do not know what price player 2 anticipates. To estimate how players weigh history, we calibrate a matching model in a manner similar to that outlined in Section 6.2. We assume a player matches the price he anticipates, given by Equation (6), and we find the discount rate for each treatment that minimizes MSD.[25] This gives us the

[23] We do not report the results of the deterministic matching model as it performs significantly worse than its stochastic counterpart.

[24] Estimated ϵ in each block are as follows: $\alpha10\beta00 = \{1.0, .7, .6, .8\}; \alpha20\beta00 = \{.7, .6, .5, .4\}; \alpha20\beta18 = \{.7, .2, .3, .3\}; \alpha10\beta20 = \{.5, .3, .3, .2\}; \alpha20\beta20 = \{.1, 0, 0, 0\}; \alpha20\beta40 = \{.2, 0, 0, .1\}$.

[25] In all treatments, the calibrated discount rate is $r = 0.1$.

anticipated price that best explains the matching hypothesis. Using this discount rate, we calculate, for each $t > 1$, an anticipated player 1 price, $\bar{p}_1$, for each player 2. We also calculate the opportunity cost of matching $\bar{p}_1$, equal to the difference between best-response and matching profits. This opportunity cost captures the payoff relevant effects of β and also depends on the price to be matched.

We next regress the probability that player 2 matches the anticipated price, Prob($p_2 = \bar{p}_1$), on $\ln(Round)$, treatment dummies, and treatment dummies interacted with $\ln(Round)$. In one specification, we include the cost of matching as a regressor. If parameter changes make matching more focal, then changes in the cost of matching will not explain all of the changes in probability of matching.

[Table 12 about here.]

Table 12 presents the results of two random-effects probit models. In the first specification, we do not include the cost of matching as a regressor. In this specification, the coefficient for $\beta = 0$ is negative and significant; thus reducing β from 20 to 0 decreases the probability that player 2 will try to match player 1's price. Including the cost of matching in the regression, however, we find that neither the dummies nor their interactions are significant, while the coeffecient on the cost of matching is significant and negative. This finding suggests that the rise in matching that occurs when we increase β from 0 to 20 is not because matching is more focal, but rather because an increase of β decreases the cost of matching.[26]

8 Concluding Remarks

The appeal of games with strategic complementarities is simple: as long as players are adaptive learners, the game will, in the limit, converge to the set bounded by the largest and smallest Nash equilibria. This convergence depends on neither initial conditions nor the assumption of a particular learning model. Unfortunately, while many competitive environments are supermodular,[27] many are not. In this study, we examine whether there are non-supermodular games which have the same convergence properties as supermodular ones. We also study whether there exists a clear convergence ranking among games with strategic complementarities.

Our results confirm the findings of previous experimental studies that supermodular games perform significantly better than games far below the supermodular threshold. However, from a little below the threshold to the threshold, the change in convergence level is statistically insignificant. This results suggests

[26] We consider other specifications of anticipated price, including the averages of the last 1, 2, 3 and 4 prices seen. In only one specification was a dummy or its interaction with $\ln(Round)$ significant. In that specification, the coefficient $\beta = 18$ is *positive*, and its interaction with $\ln(Round)$ is negative, a finding which is not consistent with a focal point hypothesis.

[27] Milgrom and Roberts (1990) and Topkis (1998) both present numerous examples of games with strategic complementarities.

that in the context of mechanism design, the designer need not be overly concerned with setting parameters that are firmly above the supermodular threshold—close is just as good. It also enlarges the set of robustly stable games. For example, the Falkinger mechanism (Falkinger 1996) is not supermodular, but close. This results suggest that near-supermodular games perform like supermodular ones.

Our next result concerns convergence performance within the class of games with strategic complementarities. Variations in the degree of complementarities have no significant effect on performance within the 60 experimental rounds. However, our simulations suggest an increased degree of strategic complementarities leads to improved convergence in the long run.

Finally the generalized compensation mechanism we use to study convergence issues has a parameter unrelated to the degree of complementarities. We use this parameter to study the effects factors not related to strategic complementarities on the performance of supermodular games. For a given level of strategic complementarity, the factors have partial effects on convergence level and speed, but the effects of strategic complementarities are largely robust to variations in these other factors. In the long run, these effects persist, and we find evidence that strengthening the strategic complementarities in one player's strategy can partially substitute for the lack of strategic complementarities in the other's.

A word of caution is in order. In a single experimental setting, it is infeasible to study a large number of games in a wide range of complex environments. While this is the first systematic experimental study of the role of strategic complementarities in equilibrium convergence, the applicability of our results to other games needs to be verified in future experiments. In the only other study of this kind, Arifovic and Ledyard (2001) study similar questions using the Groves-Ledyard mechanism. Their results are encouraging, as their results are consistent with ours.

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Appendix A. Proof of Proposition 2

Proof of Proposition 2: We omit the proofs of Parts 1, 2 and 4, as they follow directly from the previous analysis and Proposition 1. We now present the proof for Part 3. If players follow Cournot best reply dynamics, we can rewrite Equations (4) and (5) as

$$\begin{aligned} p_1(t+1) &= p_2(t); \\ p_2(t+1) &= mp_1(t) + n, \end{aligned}$$

where $m = \frac{\beta - \frac{1}{4c}}{\beta + \frac{e}{4c^2}}$ and $n = \frac{\frac{er}{4c^2}}{\beta + \frac{e}{4c^2}}$. This is equivalent to

$$\begin{aligned} p_1(t+1) - p_1(t) &= p_2(t) - p_1(t); \\ p_2(t+1) - p_2(t) &= mp_1(t) - p_2(t) + n. \end{aligned}$$

The analogous differential equation system is

$$\begin{aligned} \dot{p}_1 &= p_2 - p_1; \\ \dot{p}_2 &= mp_1 - p_2 + n. \end{aligned} \tag{12}$$

We now use the Lyapunov second method to show that system (12) is globally asymptotically stable. Define

$$V(p_1, p_2) \equiv \frac{(p_1 - p_2)^2}{2} + \int_{p_0}^{p_1} (p - mp - n)dp,$$

where $p_0 \geq 0$ is a constant. We now show that $V(p_1, p_2)$ is the Lyapunov function of system (12).

Define $G(p_1) \equiv \int_{p_0}^{p_1} (p - mp - n)dp$. We get

$$G(p_1) = \frac{1}{2}(1-m)p_1^2 - np_1 - \frac{1}{2}(1-m)p_0^2 + np_0.$$

As $c > 0$ and $e > 0$, for any $\beta \geq 0$, we always have $m < 1$. Therefore, the function $G(p_1)$ has a global minimum, which is characterized by the following first order condition:

$$\frac{dG(p_1)}{dp_1} = (1-m)p_1 - n = 0.$$

Therefore, $p_1 = \frac{n}{1-m} = \frac{er}{e+c} \equiv p^*$ is the global minimum. When $p_1 = p_2 = p^*$, $\frac{(p_1-p_2)^2}{2}$ also reaches its global minimum. Therefore, $V(p_1, p_2)$ is at its global minimum when $p_1 = p_2 = p^*$.

Next we show that $\dot{V} \leq 0$.

$$\begin{aligned} \dot{V} &= \frac{\partial V}{\partial p_1}\dot{p}_1 + \frac{\partial V}{\partial p_2}\dot{p}_2 \\ &= (p_1 - p_2 + (1-m)p_1 - n)(p_2 - p_1) + (p_2 - p_1)(mp_1 - p_2 + n) \\ &= (p_2 - p_1)(2p_1 - 2p_2) \\ &= -2(p_1 - p_2)^2 \leq 0 \end{aligned}$$

Let B be an open ball about (p_1^*, p_2^*) in the plane. For all $(p_1, p_2) \neq (p_1^*, p_2^*)$, $\dot{V} < 0$. Therefore, (p_1^*, p_2^*) is an globally asymptotically stable equilibrium of (12). ∎

Appendix B. Experiment Instructions

Instructions for the $\alpha 20 \beta 20$ treatment is attached. Instructions for other treatments are identical except for the parameters involving α and β.

Experiment Instructions – Mechanism A20 B20

Introduction

- You are about to participate in a decision process in which one of numerous alternatives is selected in each of 60 rounds. This is part of a study intended to provide insight into certain features of decision processes. If you follow the instructions carefully and make good decisions you may earn a considerable amount of money. You will be paid in cash at the end of the experiment.

- *During the experiment, we ask that you please do not talk to each other.* If you have a question, please raise your hand and an experimenter will assist you.

Procedure

- You will be randomly assigned to one of two groups: the Blue group or the Red Group. There will be 6 players in each group. You will stay in the same group for the entire experiment.

- In each of 60 rounds, you will be randomly matched with a player from the other group. You will not know the identity of your Match. Your payoff each round depends only on the decisions made by you and your Match.

- In each of 60 rounds, Red will produce a quantity, Q. Red gets a revenue of $240 \cdot Q + 250$ and pays the production cost of $\frac{5}{4} \cdot Q^2$. Red's production imposes a loss of $\frac{5}{2} \cdot Q^2$ on Blue.

- In order to compensate Blue's loss, prior to production, Blue and Red simultaneously announce a price, P_{Blue} and P_{Red}, respectively. Red will pay a tax of $10 \cdot P_{Blue} \cdot Q$. Blue will receive a compensation of $10 \cdot P_{Red} \cdot Q$. Note that Blue's announcement, P_{Blue}, determines Red's tax rate; and Red's announcement, P_{Red}, determines Blue's compensation rate.

- If P_{Blue} and P_{Red} are not the same, each will pay a penalty proportional to $(P_{Blue} - P_{Red})^2$.

- Each round consists of two stages: the Announcement Stage and the Production Stage.
  - Announcement Stage: Blue selects P_{Blue}, an integer between 0 and 40. At the same time, Red selects P_{Red}, also an integer between 0 and 40.
  - Production Stage: Red then selects the quantity for that period, Q, an integer between 0 and 50. *This quantity is affected by* P_{Blue}. When Red chooses Q, Red's terminal will display a payoff table listing Red's payoff for each Q.

Payoffs

- **Per Round Payoffs: Red**

$$\text{Payoff}_{Red} = \underbrace{240 \cdot Q + 250}_{\text{Revenue}} - \underbrace{\frac{5}{4} \cdot Q^2}_{\text{Production Cost}} - \underbrace{10 \cdot P_{Blue} \cdot Q}_{\text{Tax}} - \underbrace{20 \cdot (P_{Blue} - P_{Red})^2}_{\text{Penalty}}$$

  Revenue: Red receives 240 points for each unit Red produces plus 250 points.

  Production Cost: This term represents the cost of producing Q units.

  Tax: Red pays a tax to compensate Blue. The tax rate, P_{Blue}, is announced by Blue.

  Penalty: Red is penalized for any difference between P_{Blue} and P_{Red}.

- **Per Round Payoffs: Blue**

$$\text{Payoff}_{Blue} = \underbrace{10 \cdot P_{Red} \cdot Q}_{\text{Compensation}} - \underbrace{\frac{5}{2} \cdot Q^2}_{\text{Loss}} - \underbrace{20 \cdot (P_{Blue} - P_{Red})^2}_{\text{Penalty}}$$

  Compensation: Blue receives a compensation. The compensation rate, P_{Red}, is announced by Red.

  Loss: This term represents Blue's loss due to Red's production.

  Penalty: Blue is penalized for any difference between P_{Blue} and P_{Red}.

- There will be 60 rounds. There will be no practice rounds. From the first round, you will be paid for each decision you make.

- Your total payoff is the sum of your payoffs in all rounds.

- The exchange rate is $1 for ____________ points.

Information At the end of each **round**, you are informed of your result of the round:

- Your Price
- The Price of your Match for that round
- The Quantity selected that round
- Your Payoff

We encourage you to earn as much cash as you can. Are there any questions?

Parameters and Treatments				Properties	Equilibrium
		α			
		10	20	Supermodular	(p_1^*, p_2^*, X^*)
β	0	$\alpha 10 \beta 00$ (4 sessions)	$\alpha 20 \beta 00$ (5 sessions)		
	18		$\alpha 20 \beta 18$ (4 sessions)	No	(16, 16, 32)
	20	$\alpha 10 \beta 20$ (5 sessions)	$\alpha 20 \beta 20$ (5 sessions)		
	40		$\alpha 20 \beta 40$ (4 sessions)	Yes	(16, 16, 32)

Table 1: Features of Experimental Sessions

Proportion of Nash Price 1 (p_1^*)							Permutation Tests	
Treatment	Session 1	Session 2	Session 3	Session 4	Session 5	Overall	H_1	p-value
$\alpha 10 \beta 00$	0.000	0.008	0.158	0.008		0.044	$\alpha 10 \beta 00 < \alpha 20 \beta 00$	0.397
$\alpha 20 \beta 00$	0.000	0.083	0.083	0.042	0.058	0.053	$\alpha 20 \beta 00 < \alpha 20 \beta 20$	0.008***
$\alpha 20 \beta 18$	0.125	0.117	0.100	0.192		0.133	$\alpha 20 \beta 00 < \alpha 20 \beta 18$	0.008***
$\alpha 10 \beta 20$	0.242	0.067	0.067	0.067	0.208	0.130	$\alpha 10 \beta 20 < \alpha 20 \beta 20$	0.064*
$\alpha 20 \beta 20$	0.325	0.267	0.208	0.058	0.367	0.245	$\alpha 20 \beta 18 < \alpha 20 \beta 20$	0.064*
$\alpha 20 \beta 40$	0.175	0.400	0.158	0.133		0.217	$\alpha 20 \beta 20 < \alpha 20 \beta 40$	0.643
Proportion of Nash Price 2 (p_2^*)							Permutation Tests	
Treatment	Session 1	Session 2	Session 3	Session 4	Session 5	Overall	H_1	p-value
$\alpha 10 \beta 00$	0.025	0.042	0.025	0.067		0.040	$\alpha 10 \beta 00 < \alpha 20 \beta 00$	0.056*
$\alpha 20 \beta 00$	0.067	0.083	0.033	0.075	0.050	0.062	$\alpha 20 \beta 00 < \alpha 20 \beta 20$	0.032**
$\alpha 20 \beta 18$	0.133	0.292	0.108	0.258		0.198	$\alpha 20 \beta 00 < \alpha 20 \beta 18$	0.008***
$\alpha 10 \beta 20$	0.392	0.108	0.175	0.067	0.667	0.282	$\alpha 10 \beta 20 < \alpha 20 \beta 20$	0.504
$\alpha 20 \beta 20$	0.308	0.117	0.483	0.017	0.450	0.275	$\alpha 20 \beta 18 < \alpha 20 \beta 20$	0.238
$\alpha 20 \beta 40$	0.325	0.492	0.233	0.233		0.321	$\alpha 20 \beta 20 < \alpha 20 \beta 40$	0.365
Proportion of ϵ-Nash Price 1 (ϵ-p_1^*)							Permutation Tests	
Treatment	Session 1	Session 2	Session 3	Session 4	Session 5	Overall	H_1	p-value
$\alpha 10 \beta 00$	0.108	0.200	0.350	0.158		0.204	$\alpha 10 \beta 00 < \alpha 20 \beta 00$	0.183
$\alpha 20 \beta 00$	0.067	0.458	0.358	0.183	0.425	0.298	$\alpha 20 \beta 00 < \alpha 20 \beta 20$	0.087*
$\alpha 20 \beta 18$	0.317	0.625	0.300	0.583		0.456	$\alpha 20 \beta 00 < \alpha 20 \beta 18$	0.103
$\alpha 10 \beta 20$	0.475	0.200	0.300	0.375	0.492	0.368	$\alpha 10 \beta 20 < \alpha 20 \beta 20$	0.194
$\alpha 20 \beta 20$	0.450	0.558	0.475	0.133	0.775	0.478	$\alpha 20 \beta 18 < \alpha 20 \beta 20$	0.444
$\alpha 20 \beta 40$	0.458	0.492	0.375	0.442		0.442	$\alpha 20 \beta 20 < \alpha 20 \beta 40$	0.643
Proportion of ϵ-Nash Price 2 (ϵ-p_2^*)							Permutation Tests	
Treatment	Session 1	Session 2	Session 3	Session 4	Session 5	Overall	H_1	p-value
$\alpha 10 \beta 00$	0.133	0.200	0.242	0.225		0.200	$\alpha 10 \beta 00 < \alpha 20 \beta 00$	0.016**
$\alpha 20 \beta 00$	0.300	0.400	0.200	0.275	0.333	0.302	$\alpha 20 \beta 00 < \alpha 20 \beta 20$	0.016**
$\alpha 20 \beta 18$	0.717	0.667	0.342	0.700		0.606	$\alpha 20 \beta 00 < \alpha 20 \beta 18$	0.016**
$\alpha 10 \beta 20$	0.650	0.517	0.542	0.400	0.892	0.600	$\alpha 10 \beta 20 < \alpha 20 \beta 20$	0.564
$\alpha 20 \beta 20$	0.533	0.592	0.642	0.225	0.900	0.578	$\alpha 20 \beta 18 < \alpha 20 \beta 20$	0.556
$\alpha 20 \beta 40$	0.825	0.792	0.467	0.517		0.650	$\alpha 20 \beta 20 < \alpha 20 \beta 40$	0.294

Note: Significant at: * 10% level; ** 5% level; *** 1% level.

Table 2: Level of Convergence in the Last 20 Rounds

Change in Proportion of Nash Price 1 (p_1^*)							Permutation Tests	
Treatment	Session 1	Session 2	Session 3	Session 4	Session 5	Overall	H_1	p-value
$\alpha10\beta00$	-0.025	-0.017	0.083	-0.017		0.006	$\alpha10\beta00 < \alpha20\beta00$	0.302
$\alpha20\beta00$	0.000	0.050	0.000	0.042	0.000	0.018	$\alpha20\beta00 < \alpha20\beta20$	0.004***
$\alpha20\beta18$	0.100	0.083	0.050	0.092		0.081	$\alpha20\beta00 < \alpha20\beta18$	0.016**
$\alpha10\beta20$	0.242	0.017	0.050	-0.067	0.192	0.087	$\alpha10\beta20 < \alpha20\beta20$	0.155
$\alpha20\beta20$	0.225	0.192	0.083	0.042	0.233	0.155	$\alpha20\beta18 < \alpha20\beta20$	0.103
$\alpha20\beta40$	0.100	0.383	0.158	0.092		0.183	$\alpha20\beta20 < \alpha20\beta40$	0.381
Change in Proportion of Nash Price 2 (p_2^*)							Permutation Tests	
Treatment	Session 1	Session 2	Session 3	Session 4	Session 5	Overall	H_1	p-value
$\alpha10\beta00$	0.000	0.017	0.017	0.008		0.010	$\alpha10\beta00 < \alpha20\beta00$	0.183
$\alpha20\beta00$	0.033	0.067	-0.042	0.042	0.050	0.030	$\alpha20\beta00 < \alpha20\beta20$	0.044**
$\alpha20\beta18$	0.108	0.250	0.000	0.167		0.131	$\alpha20\beta00 < \alpha20\beta18$	0.054*
$\alpha10\beta20$	0.275	0.025	0.100	0.017	0.592	0.202	$\alpha10\beta20 < \alpha20\beta20$	0.492
$\alpha20\beta20$	0.217	0.058	0.333	0.008	0.400	0.203	$\alpha20\beta18 < \alpha20\beta20$	0.238
$\alpha20\beta40$	0.208	0.467	0.208	0.117		0.250	$\alpha20\beta20 < \alpha20\beta40$	0.349
Change in Proportion of ϵ-Nash Price 1 (ϵ-p_1^*)							Permutation Tests	
Treatment	Session 1	Session 2	Session 3	Session 4	Session 5	Overall	H_1	p-value
$\alpha10\beta00$	-0.058	0.058	0.167	0.075		0.060	$\alpha10\beta00 < \alpha20\beta00$	0.222
$\alpha20\beta00$	-0.025	0.300	0.067	0.042	0.233	0.123	$\alpha20\beta00 < \alpha20\beta20$	0.099*
$\alpha20\beta18$	0.192	0.425	0.150	0.267		0.258	$\alpha20\beta00 < \alpha20\beta18$	0.087*
$\alpha10\beta20$	0.367	0.033	0.142	0.092	0.433	0.213	$\alpha10\beta20 < \alpha20\beta20$	0.349
$\alpha20\beta20$	0.283	0.333	0.183	0.033	0.442	0.255	$\alpha20\beta18 < \alpha20\beta20$	0.492
$\alpha20\beta40$	0.158	0.300	0.283	-0.017		0.181	$\alpha20\beta20 < \alpha20\beta40$	0.779
Change in Proportion of ϵ-Nash Price 2 (ϵ-p_2^*)							Permutation Tests	
Treatment	Session 1	Session 2	Session 3	Session 4	Session 5	Overall	H_1	p-value
$\alpha10\beta00$	0.000	0.092	0.050	0.092		0.058	$\alpha10\beta00 < \alpha20\beta00$	0.183
$\alpha20\beta00$	0.200	0.217	-0.100	0.117	0.183	0.123	$\alpha20\beta00 < \alpha20\beta20$	0.032**
$\alpha20\beta18$	0.483	0.492	0.025	0.333		0.333	$\alpha20\beta00 < \alpha20\beta18$	0.064*
$\alpha10\beta20$	0.425	0.142	0.192	0.083	0.583	0.285	$\alpha10\beta20 < \alpha20\beta20$	0.508
$\alpha20\beta20$	0.283	0.192	0.333	0.142	0.450	0.280	$\alpha20\beta18 < \alpha20\beta20$	0.683
$\alpha20\beta40$	0.308	0.583	0.317	0.033		0.310	$\alpha20\beta20 < \alpha20\beta40$	0.373

Note: Significant at: * 10% level; ** 5% level; *** 1% level.

Table 3: Level-of-Convergence Change: Last 20 Rounds-First 20 Rounds

Model	(1)	(2)	(3)	(4)
Dependent Variable	ϵ-p_1^*	ϵ-p_2^*	ϵ-p_1^*	ϵ-p_2^*
$D_{\alpha10\beta00}$	-0.826	-1.405		
	(0.310)***	(0.325)***		
$D_{\alpha20\beta00}$	-0.485	-1.065		
	(0.326)	(0.297)***		
$D_{\beta18}$	-0.021	0.019		
	(0.334)	(0.287)		
$D_{\alpha10\beta20}$	-0.421	0.108		
	(0.313)	(0.301)		
$D_{\beta40}$	-0.004	0.332		
	(0.316)	(0.322)		
$\ln(Round)$	0.599	0.752	0.676	0.807
	(0.067)***	(0.072)***	(0.095)***	(0.092)***
$D_{\alpha10\beta00}\ln(Round)$			-0.248	-0.416
			(0.092)***	(0.097)***
$D_{\alpha20\beta00}\ln(Round)$			-0.151	-0.317
			(0.097)	(0.089)***
$D_{\beta18}\ln(Round)$			-0.003	0.018
			(0.099)	(0.088)
$D_{\alpha10\beta20}(Round)$			-0.119	0.035
			(0.093)	(0.093)
$D_{\beta40}\ln(Round)$			-0.011	0.100
			(0.094)	(0.101)
Constant	-2.614	-2.635	-2.865	-2.820
	(0.298)***	(0.293)***	(0.212)***	(0.208)***
Observations	9720	9720	9720	9720
Number of groups	162	162	162	162
Log Likelihood	-4588.718	-4807.181	-4564.832	-4750.630
$D_{\alpha10\beta00} = D_{\alpha20\beta00}$	1.46	1.27		
$D_{\alpha10\beta00}\ln(Round)$=$D_{\alpha20\beta00}\ln(Round)$			1.32	1.21
$D_{\alpha10\beta20} - D_{\alpha10\beta00} = -D_{\alpha20\beta00}$				
	0.04	1.11		
$D_{\alpha10\beta20}\ln(Round) - D_{\alpha10\beta00}\ln(Round) = -D_{\alpha20\beta00}\ln(Round)$			0.03	1.06

Notes:

1. Robust standard errors in parentheses are adjusted for clustering at the individual level.
2. Significant at: * 10% level; ** 5% level; *** 1% level.
3. D_y is the dummy variable for treatment y.
4. The bottom panel presents null hypotheses and Wald $\chi^2(1)$ test statistics.

Table 4: Speed of Convergence: Logit Models with Clustering

Model	(1)	(2)
Dependent Variable	ϵ-p_1^*	ϵ-p_2^*
ln(Round)	0.2682	0.9289
	(0.1826)	(0.1851)***
Round	0.0170	-0.0052
	(0.0100)*	(0.0079)
$D_{\alpha 20 \beta 18}$ln(Round)	-0.0529	-0.2688
	(0.1496)	(0.1445)*
$D_{\alpha 20 \beta 18}$Round	0.0053	0.0239
	(0.0107)	(0.0121)**
Constant	-2.0785	-2.9053
	(0.3179)***	(0.3789)***
Observations	4680	4680
Log Likelihood	-2879.15	-2994.20

Notes:

1. Standard errors in parentheses.
2. Significant at: * 10% level; ** 5% level; *** 1% level.
3. D_y is the dummy variable for treatment y.

Table 5: Convergence Speed: Logit models with individual-level clustering comparing $\alpha 20 \beta 18$ with the $\alpha 20$ supermodular treatments achieving similar convergence levels.

Efficiency Induced: Last 20 Rounds								
Treatment	Session 1	Session 2	Session 3	Session 4	Session 5	Overall	H_1	p-value
$\alpha10\beta00$	0.600	0.671	0.804	0.858		0.733	$\alpha10\beta00 < \alpha20\beta00$	0.087*
$\alpha20\beta00$	0.650	0.870	0.907	0.873	0.825	0.825	$\alpha20\beta00 < \alpha20\beta20$	0.095*
$\alpha20\beta18$	0.963	0.952	0.889	0.959		0.941	$\alpha20\beta00 < \alpha20\beta18$	0.016**
$\alpha10\beta20$	0.958	0.919	0.905	0.881	0.984	0.929	$\alpha10\beta20 < \alpha20\beta20$	0.714
$\alpha20\beta20$	0.888	0.937	0.939	0.780	0.971	0.903	$\alpha20\beta18 < \alpha20\beta20$	0.833
$\alpha20\beta40$	0.973	0.962	0.943	0.949		0.957	$\alpha20\beta20 < \alpha20\beta40$	0.064*

Change in Efficiency Induced: Last 20 Rounds-First 20 Rounds								
Treatment	Session 1	Session 2	Session 3	Session 4	Session 5	Overall	H_1	p-value
$\alpha10\beta00$	0.024	0.045	0.126	0.256		0.113	$\alpha10\beta00 < \alpha20\beta00$	0.198
$\alpha20\beta00$	0.181	0.295	0.105	0.194	0.083	0.171	$\alpha20\beta00 < \alpha20\beta20$	0.333
$\alpha20\beta18$	0.323	0.286	0.111	0.173		0.223	$\alpha20\beta00 < \alpha20\beta18$	0.214
$\alpha10\beta20$	0.238	0.147	0.194	0.018	0.220	0.163	$\alpha10\beta20 < \alpha20\beta20$	0.397
$\alpha20\beta20$	0.204	0.188	0.173	0.177	0.212	0.191	$\alpha20\beta18 < \alpha20\beta20$	0.793
$\alpha20\beta40$	0.119	0.316	0.417	0.127		0.245	$\alpha20\beta20 < \alpha20\beta40$	0.222

Note: Significant at: * 10% level; ** 5% level; *** 1% level.

Table 6: Efficiency measure

Model:	sFP				fEWA				PA			
Block:	1	2	3	4	1	2	3	4	1	2	3	4
	Discount Rate (r)								**Discount Rate (r)**			
$\alpha 10 \beta 00$	1.0	0.7	0.9	1.0					0.1	0.0	0.9	1.0
$\alpha 20 \beta 00$	0.7	0.6	0.1	0.1					0.5	1.0	0.2	0.1
$\alpha 20 \beta 18$	1.0	1.0	0.9	0.9					0.2	1.0	0.3	0.2
$\alpha 10 \beta 20$	1.0	1.0	1.0	0.9					0.1	0.3	0.6	0.3
$\alpha 20 \beta 20$	1.0	1.0	1.0	0.9					0.2	0.1	0.5	0.2
$\alpha 20 \beta 40$	1.0	1.0	1.0	0.7					0.1	1.0	0.4	0.3
	Sensitivity (λ)				**Sensitivity (λ)**				**Shock Interval (a)**			
$\alpha 10 \beta 00$	1.5	4.4	4.5	2.8	1.6	4.5	4.4	3.7	500	500	250	50
$\alpha 20 \beta 00$	1.5	4.3	14.0	18.0	1.7	4.0	5.1	7.4	50	100	150	50
$\alpha 20 \beta 18$	1.6	8.0	11.5	18.3	1.5	5.3	6.2	9.5	50	300	500	150
$\alpha 10 \beta 20$	1.9	5.9	8.6	13.8	1.8	4.7	6.2	8.2	100	500	450	300
$\alpha 20 \beta 20$	2.8	5.6	8.1	11.2	2.4	3.8	6.1	6.7	200	300	350	350
$\alpha 20 \beta 40$	3.4	6.5	14.0	20.5	3.2	4.9	6.7	9.9	150	50	150	50
									Similarity Window (h)			
$\alpha 10 \beta 00$									1	1	10	9
$\alpha 20 \beta 00$									10	10	9	6
$\alpha 20 \beta 18$									5	4	6	1
$\alpha 10 \beta 20$									1	1	8	3
$\alpha 20 \beta 20$									2	2	7	1
$\alpha 20 \beta 40$									1	3	2	2

Table 7: Calibration of Three Learning Models in Fifteen-Round Blocks

			Stochastic Fictitious Play			
Session	$\alpha10\beta00$	$\alpha20\beta00$	$\alpha20\beta18$	$\alpha10\beta20$	$\alpha20\beta20$	$\alpha20\beta40$
1	0.955	0.934	0.940	0.930	0.888	0.940
2	0.960	0.946	0.890	0.917	0.973	0.878
3		0.948		0.883	0.873	
Overall	0.957	0.943	0.915	0.910	0.912	0.909
			fEWA			
1	0.956	0.934	0.942	0.928	0.887	0.948
2	0.960	0.946	0.890	0.922	0.978	0.886
3		0.946		0.879	0.871	
Overall	0.958	0.942	0.916	0.910	0.912	0.917
			Payoff Assessment			
1	0.952	0.933	0.914	0.941	0.888	0.916
2	0.957	0.944	0.899	0.922	0.917	0.898
3		0.947		0.894	0.903	
Overall	0.955	0.941	0.907	0.919	0.902	0.907
			Equilibrium Play			
1	1.867	1.853	1.833	1.833	1.489	1.792
2	1.889	1.919	1.606	1.839	1.953	1.669
3		1.917		1.447	1.539	
Overall	1.878	1.896	1.719	1.706	1.660	1.731
			Random Play			
Overall	0.976	0.976	0.976	0.976	0.976	0.976

Table 8: Validation on Hold-out Sessions

Treatment	Player 1 Equilibrium Price Probability	H_1	p-value	Player 2 Equilibrium Price Probability	H_1	p-value
$\alpha 10\beta 00$	0.073			0.082		
$\alpha 20\beta 00$	0.188	$\alpha 20\beta 00 > \alpha 10\beta 00$	0.000***	0.213	$\alpha 20\beta 00 > \alpha 10\beta 00$	0.000***
$\alpha 20\beta 18$	0.265	$\alpha 20\beta 18 > \alpha 20\beta 40$	0.187	0.381	$\alpha 20\beta 18 > \alpha 10\beta 20$	0.264
$\alpha 10\beta 20$	0.211	$\alpha 10\beta 20 > \alpha 20\beta 00$	0.000***	0.376	$\alpha 10\beta 20 > \alpha 20\beta 20$	0.001***
$\alpha 20\beta 20$	0.243	$\alpha 20\beta 20 > \alpha 10\beta 20$	0.000***	0.353	$\alpha 20\beta 20 > \alpha 20\beta 00$	0.000***
$\alpha 20\beta 40$	0.259	$\alpha 20\beta 40 > \alpha 20\beta 20$	0.007***	0.442	$\alpha 20\beta 40 > \alpha 20\beta 18$	0.000***
	Player 1 ϵ-Equilibrium Price			Player 2 ϵ-Equilibrium Price		
Treatment	Probability	H_1	p-value	Probability	H_1	p-value
$\alpha 10\beta 00$	0.216			0.232		
$\alpha 20\beta 00$	0.519	$\alpha 20\beta 00 > \alpha 10\beta 00$	0.000***	0.573	$\alpha 20\beta 00 > \alpha 10\beta 00$	0.000***
$\alpha 20\beta 18$	0.713	$\alpha 20\beta 18 > \alpha 20\beta 40$	0.045**	0.870	$\alpha 20\beta 18 > \alpha 10\beta 20$	0.008***
$\alpha 10\beta 20$	0.584	$\alpha 10\beta 20 > \alpha 20\beta 00$	0.000***	0.857	$\alpha 10\beta 20 > \alpha 20\beta 20$	0.000***
$\alpha 20\beta 20$	0.662	$\alpha 20\beta 20 > \alpha 10\beta 20$	0.000***	0.834	$\alpha 20\beta 20 > \alpha 20\beta 00$	0.000***
$\alpha 20\beta 40$	0.701	$\alpha 20\beta 40 > \alpha 20\beta 20$	0.000***	0.925	$\alpha 20\beta 40 > \alpha 20\beta 18$	0.000***

Table 9: Results of t-tests comparing level of convergence of simulations of experimental treatments. Values are for round 500 and based on 1500 simulated games.

	Player1				Player 2					
Threshold:	0.4	0.5	0.6	0.7	0.4	0.5	0.6	0.7	0.8	0.9
$\alpha 20\beta 18$	54	83	126	316	38	52	62	87	127	-
$\alpha 10\beta 20$	129	221	-	-	36	48	63	91	148	-
$\alpha 20\beta 20$	61	91	149	-	39	51	61	84	137	-
$\alpha 20\beta 40$	101	166	263	496	30	38	56	94	166	339

Table 10: Speed of Convergence in Simulated Data: Threshold is the percent of players playing epsilon-equilibrium strategy. Entry indicates round in which went over threshold for good, where “-” indicates that treatment never achieved threshold.

Treatment	Efficiency	H_1	p-value
$\alpha 10\beta 00$	0.7804		
$\alpha 20\beta 00$	0.9280	$\alpha 20\beta 00 > \alpha 10\beta 00$	0.000***
$\alpha 20\beta 18$	0.9831	$\alpha 20\beta 18 > \alpha 10\beta 20$	0.000***
$\alpha 10\beta 20$	0.9813	$\alpha 10\beta 20 > \alpha 20\beta 20$	0.003***
$\alpha 20\beta 20$	0.9800	$\alpha 20\beta 20 > \alpha 20\beta 00$	0.000***
$\alpha 20\beta 40$	0.9862	$\alpha 20\beta 40 > \alpha 20\beta 18$	0.000***

Table 11: Results of t-tests comparing efficiency in simulations of experimental treatments. Values are for round 500 and based on 1500 simulated games.

Model	(1)	(2)
Dependent Variable	Prob($p_2 = \bar{p}_1$)	Prob($p_2 = \bar{p}_1$)
$D_{\alpha 10}$	0.0684	0.1538
	(0.4750)	(0.4830)
$D_{\beta 00}$	-1.0744	-0.6576
	(0.4898)**	(0.5048)
$D_{\beta 18}$	-0.6428	-0.4973
	(0.7929)	(0.8156)
$D_{\beta 40}$	0.0862	-0.6319
	(0.6322)	(0.6560)
ln(Round)	0.4256	0.3166
	(0.1216)***	(0.1210)***
Match Cost		-0.0004
		(0.0000)***
$ln(Round)D_{\alpha 10}$	-0.1255	-0.1227
	(0.1390)	(0.1396)
$ln(Round)D_{\beta 00}$	0.0775	0.0350
	(0.1473)	(0.1498)
$ln(Round)D_{\beta 18}$	0.0929	0.0515
	(0.2308)	(0.2371)
$ln(Round)D_{\beta 40}$	0.0085	0.1888
	(0.1858)	(0.1890)
Constant	-3.1366	-2.5983
	(0.4154)***	(0.4140)***
Observations	9588	9588
Log Likelihood	-3243.55	-3178.81
$H_0 : D_{\alpha 10} = D_{\beta 00} = D_{\beta 18} = D_{\beta 40} = 0$		
$\chi^2(4)$	6.16	3.11
p-value	0.19	0.54
$H_0 : ln(Round)D_{\alpha 10} = ln(Round)D_{\beta 00} = ln(Round)D_{\beta 18} = ln(Round)D_{\beta 40} = 0$		
$\chi^2(4)$	1.75	3.38
p-value	0.78	0.50
$H_0 : ln(Round)D_{\alpha 10} = ln(Round)D_{\beta 00} = ln(Round)D_{\beta 18} = ln(Round)D_{\beta 40} = D_{\alpha 10} = D_{\beta 00} = D_{\beta 18} = D_{\beta 40} = 0$		
$\chi^2(8)$	62.74	28.38
p-value	0.00	0.00

Note: Significant at: * 10% level; ** 5% level; *** 1% level.

Table 12: Probability that player 2 announces a price equal to the anticipated player 1 price.

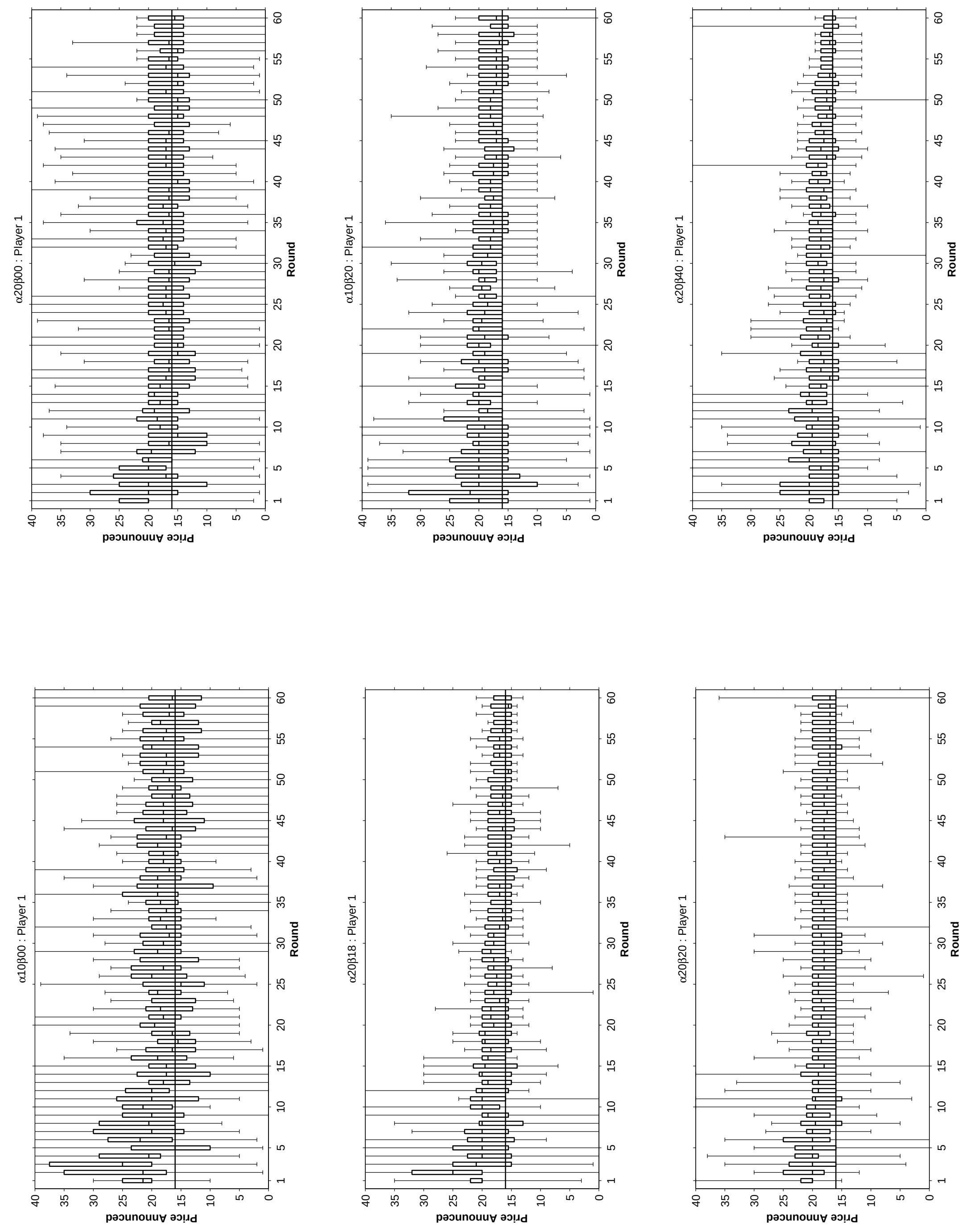


Figure 1: Distribution of Announced Prices in Experimental Treatments: Player 1

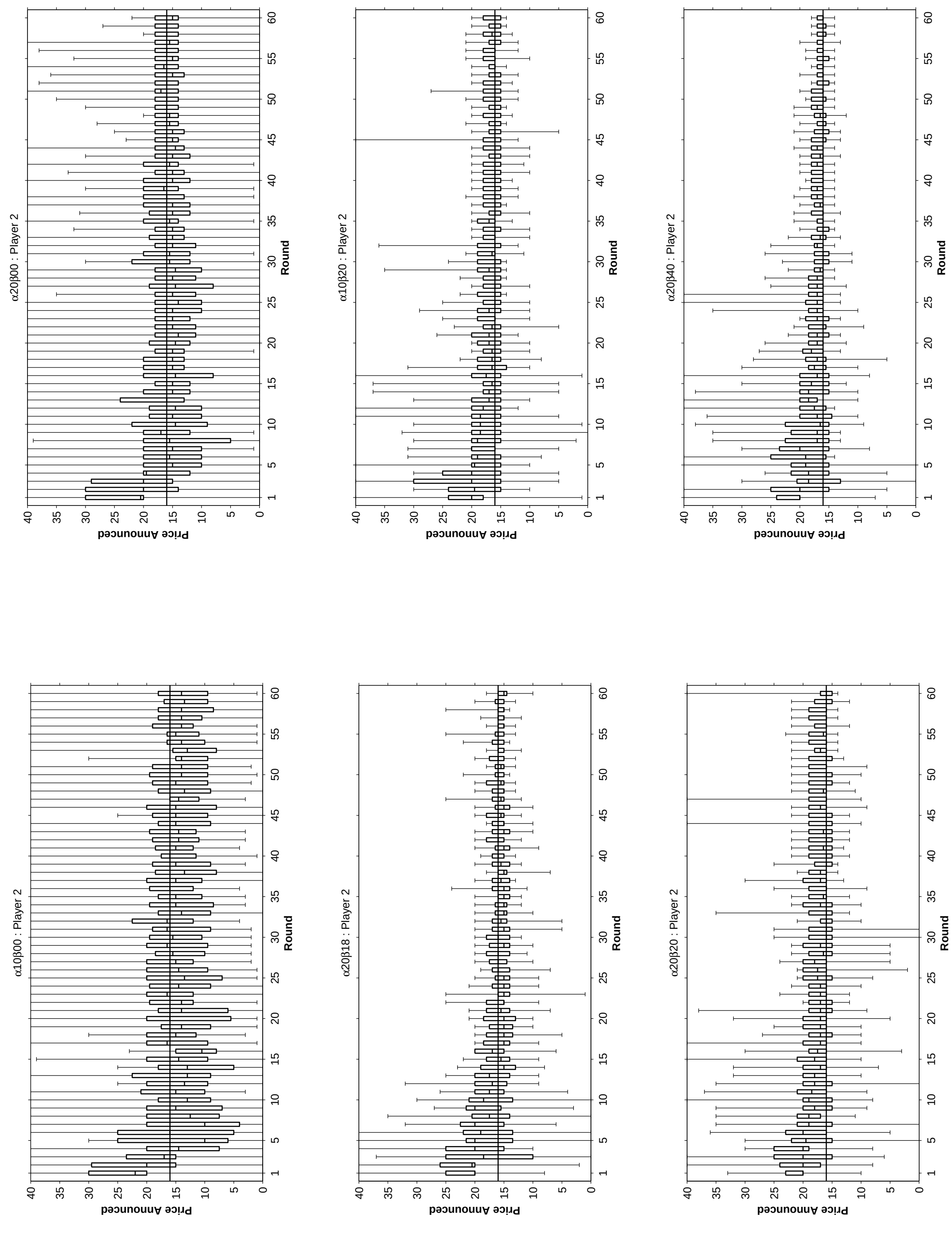


Figure 2: Distribution of Announced Prices in Experimental Treatments: Player 2

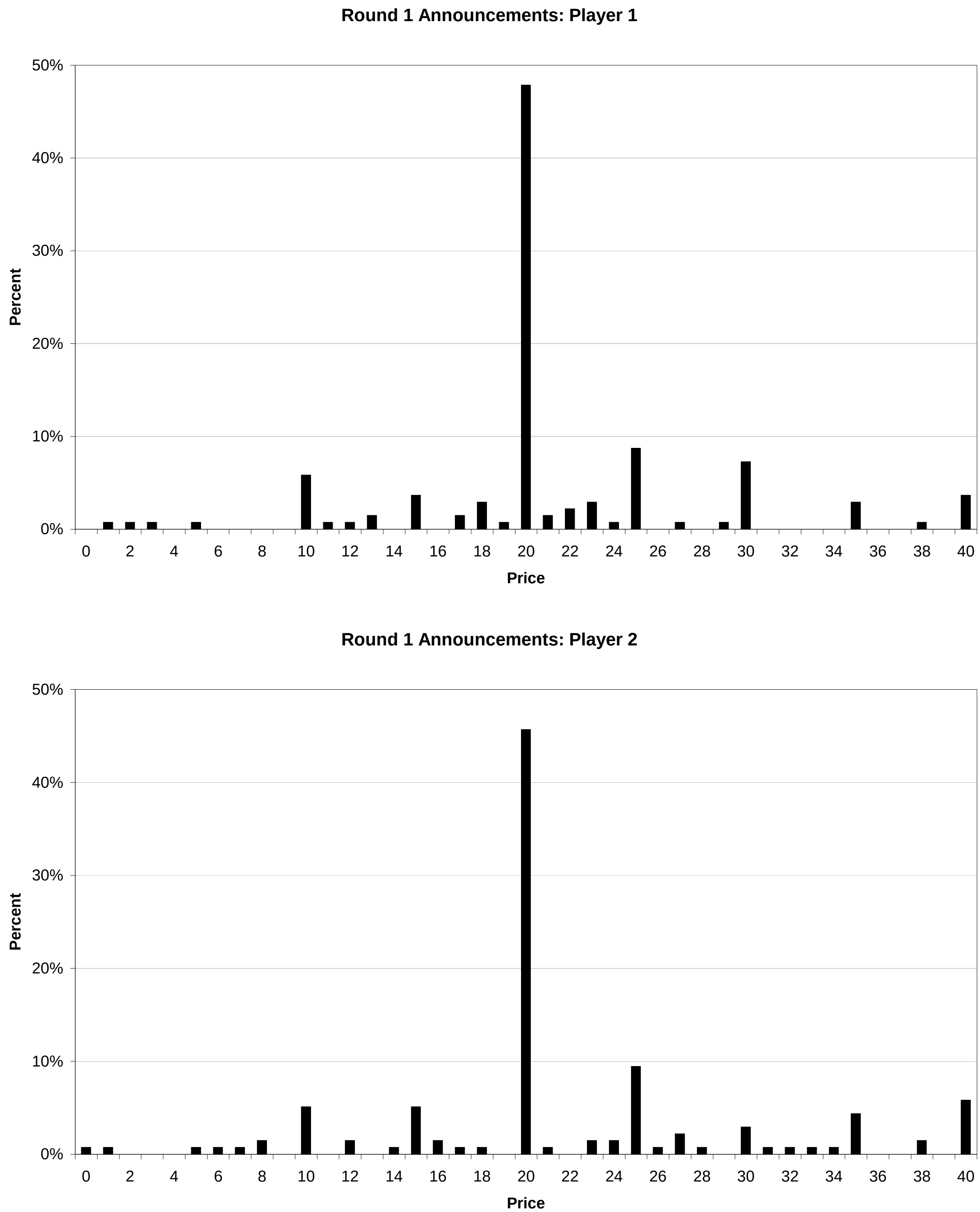


Figure 3: Distribution of first round choices

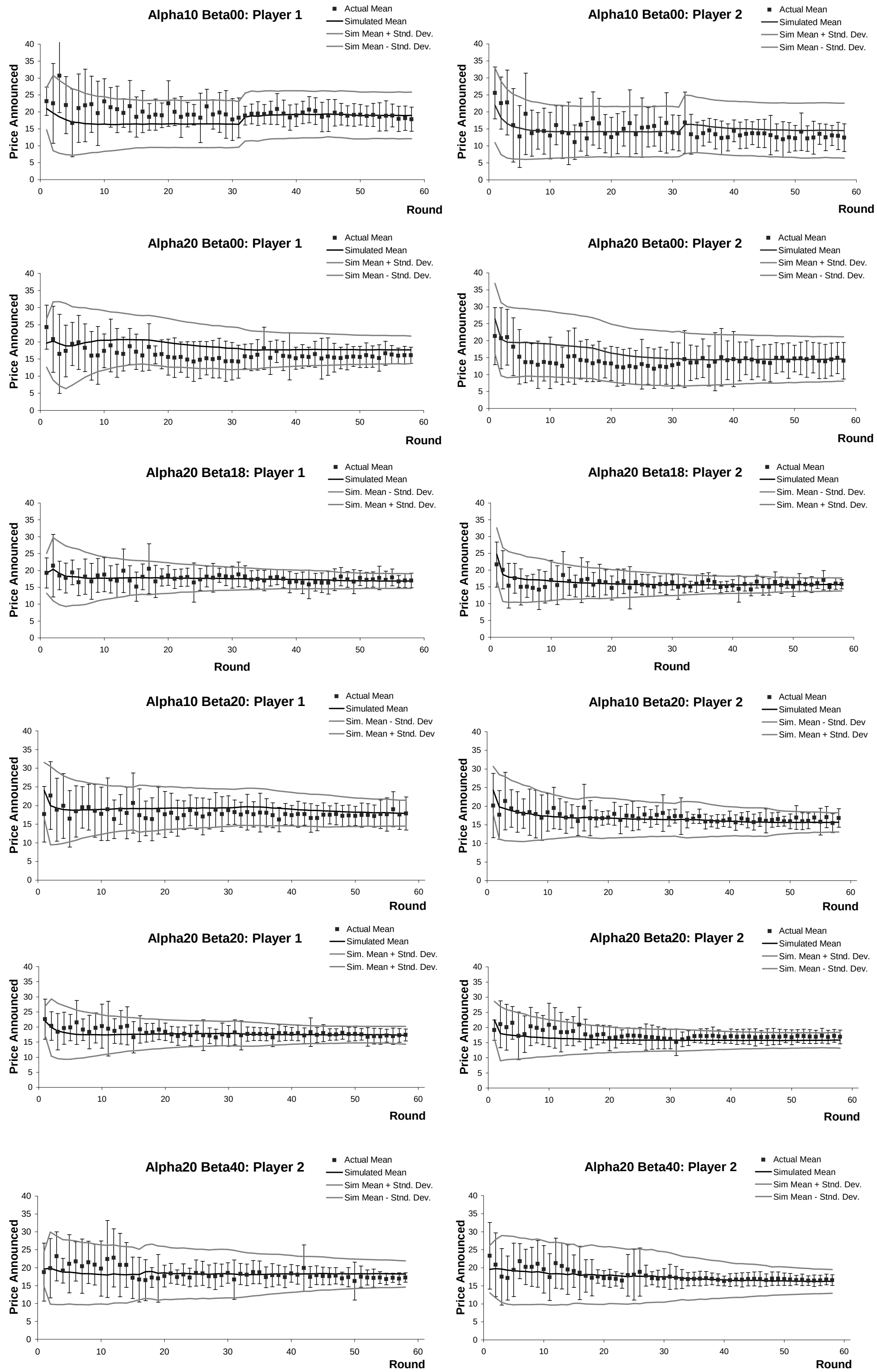


Figure 4: Simulated dynamic path vs. actual data

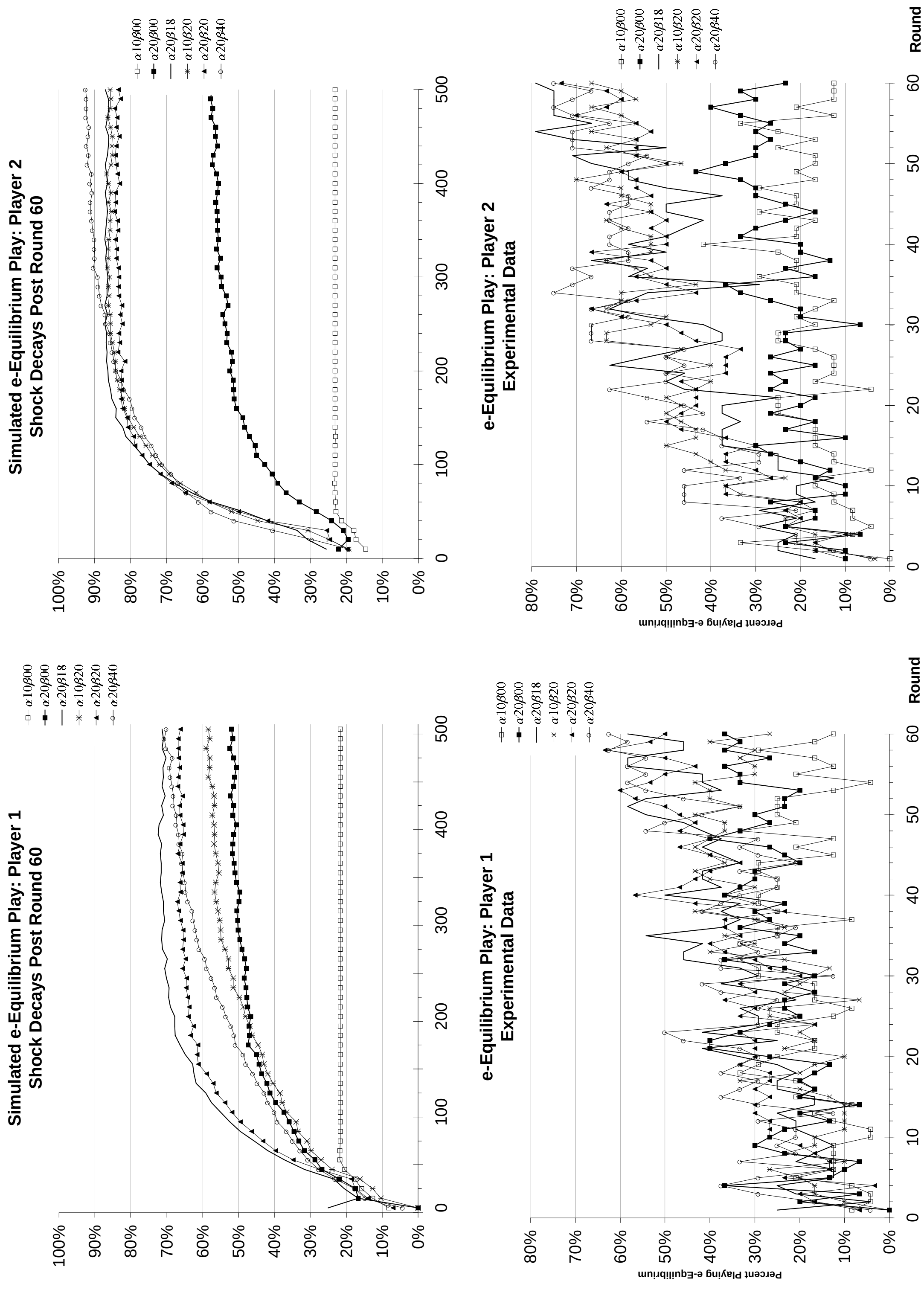
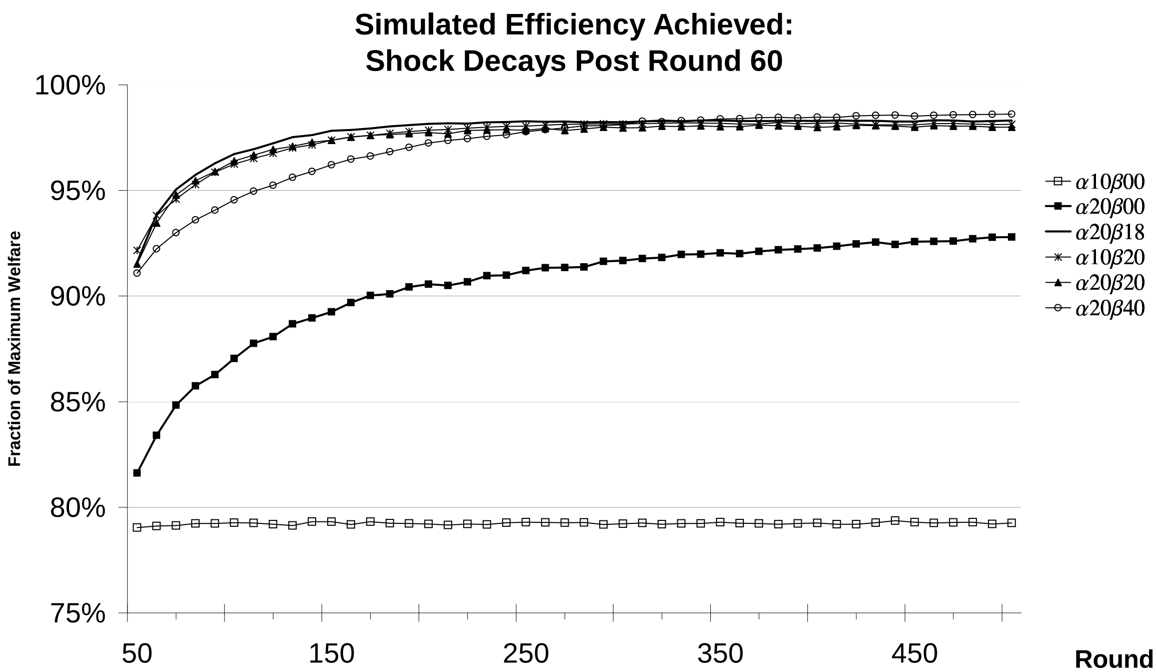


Figure 5: Simulated and actual ϵ-equilibrium play



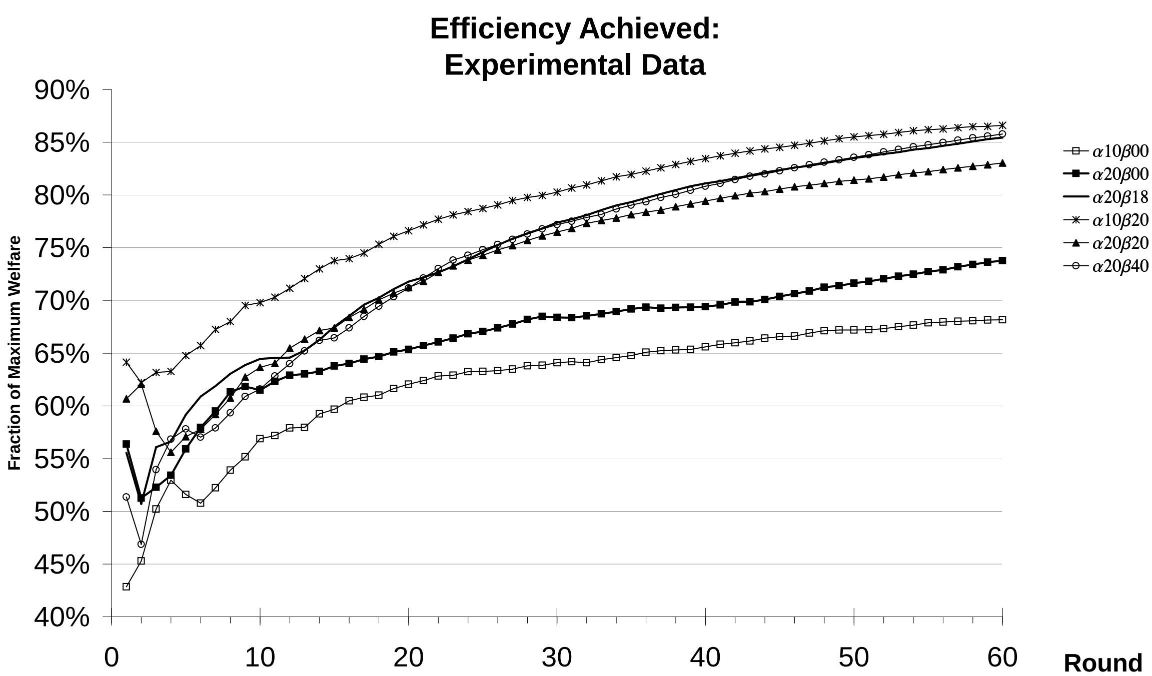


Figure 6: Efficiency in the simulated and actual data