Equilibrium Selection in Static and Dynamic Entry Games*

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Abstract. We experimentally examine equilibrium refinements in static and dynamic binary choice games of complete information with strategic complementarities known as "entry" games. Examples include speculative attacks, bank runs and refinancing decisions by multiple lenders. We explore behavior when the value of a payoff relevant state variable is known to all players in advance of making their action choices. Such games give rise to multiple equilibria and coordination problems. Our specific aim is to assess the predictive power of two different equilibrium selection principles. In static entry games, we test the theory of *global games* as an equilibrium selection device. This theory posits that players play games of complete information *as if* they were playing a related global game of incomplete information. In dynamic entry games, individuals decide not only whether to enter but also *when to enter*. Once entry occurs it is irreversible. The number of people who have already entered is part of the state description, and individuals can condition their decisions on that information. If the state variable does not indicate that entry is dominated, the efficient subgame perfect equilibrium prediction calls for all players to immediately choose to enter, thereby resolving the coordination problem. This subgame perfect entry threshold in the dynamic game will generically differ from the global game threshold in static versions of the same entry game. Nevertheless, our experimental findings suggest that entry thresholds in both static and dynamic versions of the same entry game are surprisingly similar. The mean entry threshold in the static game lies below the global game equilibrium threshold while the mean entry threshold in the dynamic game lies above the efficient subgame perfect equilibrium threshold. An important implication of this finding is that if one were to observe only the value of the state variable and the number of people who enter by the end of the game one could not determine whether the static or the dynamic game had been played.

Keywords: Coordination problems, entry games, strategic complementarities, speculative attacks, equilibrium selection, global games, dynamic games, subgame perfection, experiments.

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1 Introduction

Many games of complete information with strategic complementarities have multiple equilibria. An important class of such games may be labeled ‘entry games’. In an entry game an individual has two possible actions, ‘enter’ and ‘not enter’. The payoff to a player who does not enter is a fixed amount, *F*, while the payoff to entering, $\pi(e) = G(m,Y),$ depends in a monotonic way on the number of people who enter, *m*, and on a payoff-relevant parameter, *Y*, of the game. In this class of games there exists a value of *Y*, $\underline{Y}$, such that for $Y < \underline{Y}$ the dominant strategy is ‘not enter’. There exists another value $\overline{Y} > \underline{Y}$, such that for $Y > \overline{Y}$ the dominant strategy is ‘enter’. For intermediate values $Y \in [\underline{Y}, \overline{Y}],$ there are two equilibria in pure strategies, all ‘enter’ or all ‘not enter’.

Financial markets provide important examples of such ‘entry’ games. For instance, this game form may represent situations of speculative attack on a currency (Obstfeld (1996), Morris and Shin (1998)), with $\overline{Y}$ representing a state in which the fundamentals are such that the currency is certain to be devalued if a single speculator sells the currency short, so that a short sale is certain to be profitable, while $\underline{Y}$ represents a state in which the State holds sufficient reserves that it will certainly withstand any feasible attack by all currency speculators. For other states, $\underline{Y} < Y < \overline{Y}$ the State can withstand short sales from a fraction, $f(Y)$, of currency speculators. If less than $f(Y)$ agents ‘enter’ all those who enter lose money while if more than $f(Y)$ ‘enter’ all those who enter make a profit. The same game form can be used to characterize the situation faced by a group of lenders, all of whom have debts that have come due from a particular borrower and find that the borrower has insufficient cash on hand to pay off more than some fraction of the outstanding debt (Morris and Shin (2006)). Given the borrower’s cash holdings, *Y*, if a sufficient fraction $f(Y)$ of lenders agree to roll over the debt, the borrower need not default, but if too few lenders agree to a roll-over, a default occurs.

Viewed as static games of complete information, standard game theory yields no prediction of how these entry games will be played when there are multiple equilibria. However, Carlsson and van Damme (1993) propose an equilibrium refinement for 2×2 entry games that is based on the assumption that when players face the uncertainty associated with the multiplicity of equilibria in these games they effectively transform the game ***in their own minds*** to a related game of incomplete information. The related game is called a ‘global game’. The global game consists of a game of incomplete information drawn from the set of all games, *G*, with the same form as that of the game of interest. The initial common prior beliefs of the players with regard to the game actually being played are represented by a probability distribution with support on some subclass of *G.* This support includes those games with unique Nash equilibria in dominant strategies. Prior to any choice of action by the players, Nature draws the values of the parameters of the payoff function from a commonly known distribution of those values. Each player then gets private information, possibly imprecise, with regard to the game $g \in G$ that Nature has selected. Players then choose their actions. As each player’s signal is private information and it is common knowledge that these private signals are correlated, “the global game approach provides a natural way to force players to link (all possible) games together and to analyze them simultaneously” (Carlsson and van Damme (1993 p.1013)). As shown by Carlsson and van Damme for the case of 2×2 games of complete information, in the related global game the required equilibrium strategies for all possible realizations are *cut-off* strategies. In the global game a player always chooses one action upon receiving a signal that comes from one portion of the probability distribution of signals and the other action when the realized signal comes from outside this set. This result has been generalized by Morris and Shin (2003) to a class of $2 \times N$ symmetric games. Unlike the original game of complete information with its multiplicity of equilibria, the global game of incomplete information has a unique Bayesian perfect equilibrium. Therefore, if all players play the game of complete information as though there were a common understanding that all players will play that game *as if* they were playing the related global game, the coordination problem is resolved. In section 2 we describe an experiment that is designed to test the predictive power of the global game equilibrium with regard to the play of a related entry game of complete information.

The theory of global games offers an equilibrium selection criterion for a *static* entry game. However, many entry games of interest are inherently dynamic, as individuals must decide not only whether to enter but also *when to enter*. Therefore, we also study how individuals play a *dynamic entry game of complete information* in order to determine whether or not the ultimate pattern of entry is different in the dynamic entry game than in the static entry game. In section 2 we describe the portion of our experiment that was designed to test whether play in the dynamic game corresponds to the sub-game perfect equilibrium and, more generally, whether the entry decisions in the dynamic game differ significantly from the entry decisions in the static version of the same complete information game.

2 Related Literature

In this section we situate our work within the current theoretical and experimental literature on static and dynamic entry games. The paper most closely related to this one is the experimental study of Heinemann et al. (2004) testing Morris and Shin's (1998) model of speculative attacks. In the Heinemann et al. design, subjects play sequences of static entry games under several treatment conditions that are chosen to test the comparative static implications of the theory. Their main treatment variable is whether there is common, complete information or private, noisy information about the state of fundamentals. Their principal finding is that there is little difference in observed behavior under the different information treatment conditions. They further find that behavior responded to variations in the threshold fundamental in the direction predicted by the theory of global games. As we elaborate upon below, their design provides only an indirect test of the hypothesis that the global game provides an equilibrium refinement of the game of complete information.

Angeletos, Hellwig and Pavan (2007) present a model of a dynamic global game that is composed of a sequence of global games with the same fundamentals. The sequence ends when the number of people who have entered crosses the threshold for a successful attack. At each game in the sequence each player gets a new, imperfect signal and knows that no successful attack has already occurred. They show that the knowledge that the game has not ended allows for a pattern of updating of priors that can produce multiple global game equilibria. Shurchkov (2007) provides an experiment based on a two-period variant of this model. She finds behavior that is qualitatively consistent with the theory.

Costain (2007) provides a model of a dynamic global game in which asynchronous moves allows learning from the past actions of others about the likely value of the underlying fundamentals. Costain shows that herding behavior can lead to multiple outcomes from the same underlying fundamentals. Costain et al. (2007) provide experimental evidence of herding behavior that produce multiple outcomes in a dynamic asynchronous move global game with private signals.

The multiplicity of global game outcomes in these dynamic games is related to learning about the underlying fundamentals that repeated play allows. Therefore, these studies do not speak directly to the hypotheses we wish to test.

Cheung and Friedman (2008) have conducted an experiment with an entry game played in continuous time. Each player can at every point in time, *t*, choose to attack or to be passive. An attack is costly and the cost accumulates as long as the subject is in attack mode. When player *i* attacks at time *t* he contributes mass $a_i(t)$ to the total mass of attackers at *t*, *B(t)*. At time *t* there is a threshold for a successful attack *T(t)* such that, if $B(t) \geq T(t)$, the game ends and those individuals whose attack was successful earn a positive net payoff at that point in time. In their experiment, *T(t)* is not constant, but evolves over time. The path of *T* is not common knowledge, but in some treatments individuals are either given the history of *T(t)* up to *t* or an imprecise history of its past values. In these treatments subjects could, therefore, forecast the current and future path of *T(t)*. Their experiment is designed to test various hypotheses that have been suggested with regard to the determinants of success of speculative attacks. It does not allow for any comparison of play of a static entry game of complete information with the play of a dynamic entry game of complete information.

Gale (1995) considers an N-player, dynamic "monotone" entry game that is similar to the dynamic game we study. In Gale's game, a player's decision to enter ("invest") can take place at discrete periods in time, t=1,2,…, is irreversible, and provides a flow of benefits that depends on the number of other players who have already entered by date t. There is a critical number of players, n*, who must enter before entry is profitable. As the number of players, N, increases so does n*. Gale shows that there is a subgame perfect equilibrium in which everyone delays entry until n* -1 periods have elapsed. This equilibrium is supported by the off-equilibrium belief that if anyone were to enter before n*-1 periods have elapsed, no one else will enter prior to period n*-1 so early entry will be unprofitable. Gale's game differs from the one we consider in that his game is indefinitely repeated and has payoffs that vary with the date of entry.

Dasqupta, Steiner and Stewart (2007) analyze a dynamic entry game in which each player receives a sequence of signals about the true value of the fundamental. If the fundamental exceeds a critical value and all players enter, then all receive a positive payoff. If the fundamental is favorable, but not all enter, those who do enter receive a negative payoff. A player may enter at any time, but entry is irreversible. Each entrant secures a payoff that is decreasing in absolute value with the time of entry. As time passes, information becomes more nearly precise. They show that for any fundamental above the critical value, the probability that everyone will enter approaches 1 as time passes. Furthermore, they show that when information is precise, if the fundamental exceeds the value at which all enter is the Pareto Optimal pattern of actions, everyone enters immediately. This result is analogous to the characterization of the sub-game perfect equilibrium of our version of the dynamic entry game.

3 Experimental Design

Our experimental design builds upon and complements an earlier experiment by Heinemann, Nagel and Ockenfels (2004). In their experiment, subjects play a sequence of entry games under one of two information conditions: complete information or incomplete information. Only one information condition was used in a given experimental session. In each of their sessions, all N subjects played the same sequence of N-person entry games. Let A denote the strategy "don't enter" and B the strategy "enter."   In all treatments studied by Heinemann et al. (2004), each subject i has a payoff function of the form:

$$\pi_i(A) = F > 0$$
$$\pi_i(B) = \begin{cases} Y \text{ if } \#B \geq f(Y) \\ 0 \text{ if } \#B < f(Y) \end{cases} \quad (1)$$

Here, F is a fixed payoff that is independent of the actions chosen by the other N-1 players, $\#B$ denotes the number of the N players including i who choose action B, Y is a random payoff parameter drawn from a known uniform distribution, that completely characterizes each game, and $f(Y)$ is a monotonically decreasing function of Y that is fixed across all games in a session.

In the Heinemann et al. (2004) study, subjects are repeatedly presented with lists of entry games each of which differs in the value of Y.   In their complete information game treatment, every subject in a session receives the same list. In their incomplete information treatment, random Y values (games) are drawn as before, but subjects are not given a list of different values of Y. Instead, for each value of Y drawn, each subject i is given a signal, X_i which is a random draw from a commonly known, uniform distribution centered on the unknown value of Y and having known support $[Y-\lambda, Y+\lambda]$. Each individual's signal of Y is drawn independently of the signals of others. In both treatments, a subject is asked to specify an *action* A (no entry), or B (entry) for each game on the list. Once all subjects submitted their action list, the outcomes of the games on that list were presented to them. This procedure was repeated for 16 rounds. Heinemann et al. find that in both information treatments the pattern of action choices of most subjects corresponds to a "cut-off" strategy in which entry is chosen only if the commonly observed *Y* value or the private signal *X* exceeds a certain threshold. The estimated mean threshold was smaller in the complete information treatment than in the incomplete information treatment. In both treatments, the estimated thresholds were consistently below the global game equilibrium threshold. Heinemann et al. found that the estimated mean thresholds varied in response to changes in the payoff function in the direction predicted by the global game equilibrium and that the variance in the individual estimated thresholds decreased with experience.

The equilibrium of the global game is defined in terms of a cut point strategy for all possible values of the true state *Y*, given a measure of noise in the signal, λ. Therefore, the fact that Heinemann et al. found that the actions they elicited from subjects tended to conform to cut-off strategies in both of their information treatments provides support for the refinement hypothesis proposed by Carlsson and van Damme. However, the support is only indirect. A *direct* test would elicit both strategy choices for the global game and a sequence of action choices under different known values for the state variable, Y, from the *same* subjects in order to determine whether the actions of particular individuals when playing games of complete information conform to the actions that are implied by their strategy choice when playing the global game, as the proposed refinement hypothesizes. This calls for a within-subject design and for the direct elicitation of cut-point strategy thresholds when playing the global game. We build these features into our experimental design.[1]

In addition, in Heinemann et al.'s design, subjects gained experience by repeatedly playing with the same group of subjects. Consequently, the reduction in variance of individual thresholds as subjects gained experience might have reflected fixed group efforts at improving coordination in addition to learning in response to individual experience. In our design, we

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[1] Commenting on the finding of Heinemann et al. (2004) of little difference in the way subjects play a game of complete information and a game of incomplete information, Hellwig (2002) notes that uncertainty with regard to the value of the state variable is not the only uncertainty that may lead individuals to follow a cut-point strategy in a market entry game. Uncertainty about risk preferences or other aspects of utility functions of players may also induce such behavior. Of course, we are testing the assumption that in a game where there is no uncertainty with respect to the state variable individuals will choose actions that are consistent with the cut-off strategies we elicit from them. The fact that we may not have complete control over individual utility functions simply biases the results in favor of subjects playing the game in action mode as they would play it under the strategy method.

attempt to reduce the likelihood of group efforts at coordination by running two games in a session simultaneously and randomly reassigning individuals to one or the other group after the play of each game.

While the global game refinement applies to simultaneous move entry games, in many settings of interest, e.g., bank runs, refinancing decisions, etc., entrants do not have to move simultaneously. Consequently, in our design we also study behavior in a *dynamic* entry game with the same payoffs as used in the static entry game sessions, but where each of the subjects chooses not only whether to enter but also *when* to enter. For the dynamic entry game, we continue to predict threshold behavior in entry decisions, however, the threshold is determined not via the global game solution concept but instead by subgame perfection as explained below.

Finally, like Heinemann et al. (2004), we also consider the comparative static implications of changes in the model parameters. Specifically, we consider two different values of the fixed payment F in both the static and dynamic treatments. Changes in the value of F affect both the global game and subgame perfect equilibrium predictions.

3.1 Specific Details

The specific details of our experimental design are as follows. The experiment was conducted using Fischbacher's (2007) z-Tree software over networked PC workstations in the Pittsburgh Experimental Economics Laboratory. Each experimental session consisted of 20 subjects with no prior experience in any of our treatments. Subjects were recruited from the general college student population of the University of Pittsburgh and Carnegie-Mellon University. Each session begins with the reading aloud of the written instructions (provided in the appendix) followed by play of a series of either 60 static or 30 dynamic entry games.

At the start of each new entry game our computer program randomly assigns the 20 subjects to one of two groups of size $N=10$. Subjects are informed of their random assignment to either "group 1" or to "group 2" at the start of each entry game, but the composition of the members of each group is anonymous, and no communication is possible among group members. This design thus avoids the possibility of repeated game strategies that might arise under fixed groups of players (as in the design of Heinemann et al. (2004)). Subjects are instructed that they will participate in a series of games where their payoff function is as described in (1) with the threshold number of players needed for entry to yield a positive payoff equal to

$$f(Y) = 10(80 - Y)/60.$$

In the experiment, we use $\hat{f}(Y)$, denoting the round-up of $f(Y)$ to the nearest integer in the set {1,2,…,10}. While this formula and the round-up rule *are* presented to subjects, we also provide subjects with tables using this formula for ease of reference – see the instructions for the details. Thus, our payoff function is essentially identical to that used by Heinemann et al. (2004), except for the fact that we have groups of size 10 while they had groups of size 15 (we have modified $f(Y)$ accordingly). The Y values characterizing each "game" are random draws from a uniform distribution over the interval [10, 90]. The distribution and support of the Y values, the payoff function (1), and $f(Y)$ are all public information in all sessions of our experiment, as provided in the written instructions and written on a chalkboard for all to see.

There are three treatment variables in our design. The first treatment variable is the strategy space. In treatments labeled 'C', the strategy space consists of two possible actions, {A, B}, corresponding to "not enter" and "enter". In this treatment the randomly drawn Y value is announced publicly prior to the choice of a strategy. In treatments labeled 'G', the Y value is not drawn until all 10 subjects have submitted their "cut-point" strategies. The strategy space in G treatments consists of the set of integers, I, where $\{10 \leq I \leq 90\}$. These correspond to cut-point strategies such that if the randomly drawn value $Y \geq I$, the action that will be automatically chosen for the subject (by the computer program) is "enter" (choice B) otherwise the action that will be automatically chosen for the subject is "not enter" (choice A).

The second treatment variable is whether the game is 'static' or 'dynamic'. In the static treatment, a game consists of a single decision round. In the dynamic game treatment, each game consists of $n=10$ decision rounds. Following the first round of a dynamic game, all individuals are informed at the start of each new round about the number of individuals in their group of 10 who have previously entered in that game. Each individual who has not already entered (chosen B) then decides whether to enter in that round (choice B) or to stay out (choice A). Entry is irreversible. Thus, to preserve the right to enter at a later round of a dynamic game, a subject would have to choose not to enter (choice A). The dynamic game ends after 10 rounds.

The payoff to a player who enters (choice B) in a game is determined by the number of players in their group of 10 who have entered by the *end* of the static or dynamic game (round

10) and by the value of the state variable, *Y*. If the number of entrants, #B, meets or exceeds $f(Y)$, rounded to the nearest integer, $\hat{f}(Y)$, then all those who have chosen to enter receive the payoff, *Y*. Otherwise, those who have chosen to enter receive 0. The payoff to a player who chooses not to enter (choice A) is always fixed at $F>0$.

Our third treatment variable concerns the value of this fixed payoff, *F*. Variations in this parameter shift the theoretical equilibrium cut-point strategy in the global game in which the noise of the signal goes to zero and also affect the subgame perfect equilibria of the dynamic game as explained below. We consider two values for *F*, $F=20$ and $F=50$; we use only one of these two values of *F* in each experimental session.

The timing of events in a static game is as follows. At the start of each static game, subjects are randomly assigned to one of two, 10-player groups and a value of *Y* is drawn at random. The *Y* number chosen is the same for both groups. In the C treatment, this *Y* number is announced to the subjects on their computer screens. Each subject then uses their mouse to click on their choice, either not enter (A) or enter (B). After all subjects submitted their choices, the game is over. Each subject is then reminded of the *Y* number and their own choice (A or B). They are further informed of their own payoff for the game, the number in their group of 10 who "entered" (chose B) in that game and the payoff earned by those who "entered" (*Y* or *0*); the payoff to non-entry is a known constant, *F*. In the G treatment, the *Y* number is not announced until *after* the game has been played. Instead, each subject chooses a cut-off strategy—an integer from the set {10≤I≤90}—for the game and enters it when prompted by their computer terminal. Once all subjects had submitted their cut-off numbers, the computer program automatically selects an action, A or B for each subject, based on the value of *Y* chosen for that game and the subject's cut-off strategy. Subjects were then informed of the *Y* number, reminded of their cut-off value and shown the action chosen for them by the computer program based on their cut-off value. As in the C treatment, they were then informed of their individual payoff for the game, the number in their group of 10 who had (via their threshold) chosen to enter in that game and the payoff earned by those who chose to enter (*Y* or *0*). Before the next static game begins, subjects are once again randomly assigned to one of the two groups of size 10.

In all 'static' game sessions, we used a within-subjects design where subjects played half of the 60 games under condition C and the other half under condition G. The order of play of the two conditions C and G was varied from session to session. In each session, the changeover from condition G to C or from condition C to G was *not* announced in advance; instead, following the first 30 entry games, the session was briefly paused while subjects were given new 'continuation' instructions on the rules of play for the remaining 30 entry games (see the instructions in the appendix for further details).

All dynamic game sessions are conducted only under the C treatment strategy space. The timing of events in a dynamic game is as follows. At the start of each dynamic game (as in the static-C game) a value of Y is drawn at random and shown to all group members. In the dynamic treatment, this value of Y remains fixed over all 10 rounds of the dynamic game, as does the composition of the group. Subjects then decide whether to enter or not (B or A) by using their mouse to click on their action choice. At the end of each round of the dynamic game, subjects were told the cumulative number in their group of size 10 (including themselves) who had chosen to enter in all prior rounds. If the 10^{th} round had not yet been played, the dynamic game continued with another round. Subjects were informed that a decision to enter (a B choice) once made, was *irreversible* and that they could only preserve the right to enter in a later round of the game (or never enter at all) by using their mouse to click on choice A (not enter) in each round in which they wanted to delay entry. Subjects who had chosen to enter in any prior round of the dynamic game (by clicking on choice B) did not have to make any further choice for the remaining rounds of that dynamic game. Thus, there was a small physical cost—in terms of repeated mouse clicks (and possibly a decision/psychic cost as well)—associated with preserving the option to enter at a later date; once a subject chose to enter (option B) this cost was no longer born for the remainder of that dynamic game. The payoff function for entry in the dynamic game is the same one used in the static game. However, in the dynamic game, the payoff depended on the number who had entered by the end of the final, 10^{th} round; this number was compared with $\hat{f}(Y)$ to determine the payoff to those who chose to enter (payoffs were either Y or 0), as in the static game. In each dynamic game session, 30, 10-round dynamic games are played.

Subjects earned their payoff in "points" (which were equal to either F, the randomly drawn Y number, or 0) from all games played in a session. In the static treatment, points were converted into dollars at the rate of 1 point =1/2 cent, while in the dynamic treatment which had half as many games, the conversion factor was 1 point=1 cent. In addition, subjects in all sessions received a $5 show-up payment. Total payments for the 60 games played in the static-game sessions averaged $19.95 for a 75 minute session. Total payments for the 30 games played in the dynamic-game sessions averaged $20.21 for a 75 minute session.

3.2 Predictions

In the static game, we have the following predictions. First, if $Y < \underline{Y} = F,$ the maximal payoff from entering, *Y*, is dominated by the payoff from not entering, *F*, so "not enter" (choice A) is a player's dominant strategy.[2] Similarly, if $Y \geq \overline{Y} = \hat{f}^{-1}(1) > F$ (as in our set-up), a decision to enter by a single individual (the 1 in the inverse mapping, $\hat{f}^{-1}$) *guarantees* a payoff of $Y > F$, so "enter" (choice B) is a player's dominant strategy. Given our specification for *f* and our rounding rule, we have $\overline{Y} = 72$. The lower bound, $\underline{Y}$ varies directly with the treatment variable F: $\underline{Y} = 20,\ \underline{Y} = 50.$ For $\underline{Y} < Y < \overline{Y}$ there are two equilibria in pure strategies: all-enter and all-not-enter. This multiplicity is resolved in the global game approach of Morris and Shin (1998) by assuming that players do not know the true value of the state variable Y; instead each player i receives a private signal X_i of the Y value that is drawn randomly from a uniform distribution over $[Y-\lambda, Y+\lambda]$, where λ represents a small amount of noise. Morris and Shin show that this private information game has a unique threshold X^* below which players choose not to enter and above which players choose to enter. Heinemann (2000) further shows that in the limit, as the noise term converges to zero, the threshold signal X^* converges to a threshold value, Y^*. As we do not consider the case of noisy signals – subjects in our experiment are either informed in advance of the value of Y or learn it after all have submitted their cut-off thresholds – this limiting threshold value Y^* is the relevant global game prediction for our static game. In our parameterization, Y^* is the solution to $Y^*[10 - \hat{f}(Y^*) + 1] = 10F.$ Intuitively, Y^* is the value of Y for which players are indifferent between entering and not entering. For *F=20*, we have $Y^* = 42$ and for *F=50*, we have $Y^* = 62$.

In the dynamic game it remains a dominant strategy for players to not enter if $Y < \underline{Y} = F$ and to enter if $Y \geq \overline{Y} = \hat{f}^{-1}(1).$ Unlike the static game, in the dynamic game, the N=10 individuals face a game involving N=10 rounds of play. A player's decision to enter prior to the

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[2] If $Y = F = \underline{Y}$, risk neutral individuals should be indifferent between choosing enter or not enter.

last (10th) round of the dynamic game has an influence on the decisions of other players in future rounds. This feature of the dynamic game implies that subgame perfection is an appropriate solution concept.

In the dynamic game, the number of players who have entered prior to round k is part of the description of the state of the game at round k. If Y>F and the number who have already entered is $\hat{f}(Y)-1,$ then in round k the optimal response for a player who has not previously entered is to choose `enter'. This observation has two important implications: (1) Since the strategy of a player in the dynamic game must specify an action in each round for all possible states of that round, if Y>F there cannot be any symmetric subgame perfect equilibrium strategy profile in which no one enters; (2) When Y>F there cannot be any symmetric subgame perfect equilibrium in mixed strategies, since the play of mixed strategies in the dynamic game can produce a state in which $\hat{f}(Y)-1$ players have previously entered and in that state, the decision to enter strictly dominates non-entry. It follows from observations (1-2) that if Y>F, then in any symmetric subgame perfect equilibrium it must be the case that all N players choose to enter.

When Y>F, it is straightforward to show, via backward induction, the existence of subgame perfect equilibria in which everyone enters. For any value of *Y,* the minimum number who must have entered for all those who chose enter to receive a positive payoff is given by $\hat{f}(Y)$. Thus in round *k* there is a critical number, $c(Y,k),$ who must have entered by the beginning of round *k* for it to possibly be a best response for someone who has not yet entered to enter in round *k*. For *k=N* the critical number is $\hat{f}(Y)-1.$ Consequently, the critical number for `entry' to be a best response in round *N-1* is $c(\hat{f}(Y),N-2)=\hat{f}(Y)-2.$ By backward induction, the critical number at the beginning of round *N-k* is $c(\hat{f}(Y),k)=\hat{f}(Y)-(N-k)-1.$ Since $\hat{f}(Y)\leq N$ for all Y, the value of $c(Y, k=1) \leq 0$ for all *Y*. As noted earlier, in the static game it is never a best response to enter if $Y<F=\underline{Y}.$ Therefore, for *any* $Y>\underline{Y}=F$, there is a symmetric, subgame perfect equilibrium in which everyone enters *immediately* (i.e., in round 1), but if $Y<\underline{Y}$ no one enters (in any round). Note that until a player makes a decision to enter (which is irreversible) that player must continue to make decisions up until the 10th round of play. Therefore if there is any psychic cost at all to making a decision it is a strictly dominant strategy to enter immediately in the first round whenever Y>F so that the subgame perfect equilibrium is unique. If there is no cost to delay there exist other symmetric subgame perfect equilibria of the form "if Y>F, then enter in period k."[3]

Notice that this subgame perfect equilibrium refinement leads to a sharp difference from the global game equilibrium refinement of the static game. In the static game the global game refinement predicts no entry for Y* > Y > F while in the dynamic game, symmetric subgame perfection implies that every one enters for all Y>F. This subgame perfect equilibrium is also *Pareto efficient*, whereas the global game equilibrium for the static game is not, as the latter involves a threshold that is greater than F .

Summarizing, the global game refinement for the static game predicts a significantly higher and less efficient entry threshold for the state variable, *Y*, than the subgame perfect refinement predicts for the dynamic game. Our aim is to assess the extent to which these thresholds characterize actual behavior within and across the two treatments. In addition, our variation in the value of *F* (the certain payoff to non-entry) enables us to assess the comparative static implications of both the global game (GG) and subgame perfect (SGP) solution concepts within a single class of games (static or dynamic).

4. Empirical findings

Table 1: Experimental Design and Predicted Entry Thresholds

Treatment Conditions			No. of Sessions	Equilibrium Concept GG or SGP, Predicted Entry Threshold for Y
Game Type: Static/Dynamic	Strategy Space, No. Rounds	F		
Static	C 30 Rounds, G 30 Rounds	20	2	GG, 42
Static	G 30 Rounds, C 30 Rounds	20	2	GG, 42
Static	C 30 Rounds, G 30 Rounds	50	2	GG, 62
Static	G 30 Rounds, C 30 Rounds	50	2	GG, 62
Dynamic	C 30 Rounds	20	4	SGP, 21
Dynamic	C 30 Rounds	50	4	SGP, 51

[3] We chose not to have an explicit monetary cost to delay in the dynamic game so that the payoffs in that game would be comparable to those of the static game. However, as we noted earlier, in our design those choosing to delay were required to continually use their mouse to click on either option A (not enter) or option B (enter). Once a subject had chosen option B he had no further choice to make, as entry was irreversible. Thus, the small physical (mouse clicks) and decision/psychic costs associated with delaying a decision to enter should have sufficed to rule out any subgame perfect equilibrium of the dynamic game where rational actors all enter in any round k>1.

We report results from 16 sessions involving 20 subjects each – a total of 320 subjects. Our experimental design, treatment conditions, the number of sessions conducted of each treatment and our equilibrium predictions are outlined in Table 1.

The presentation of our findings is organized around the predictions described in the previous section.

4.1 Dominated strategies and efficiency

A basic test of rationality is whether subjects avoided play of dominated strategies. Recall that if $Y < \underline{Y} = F$, the dominant strategy is to *not enter,* while if $Y \geq \overline{Y} = \hat{f}^{-1}(1)$, ($\hat{f}^{-1}(1) = 72$ in our set-up), the dominant strategy is to *enter*. For all other values of *Y*, neither strategy (non-entry or entry) is dominant. Table 2 reports the percentage of subjects who never played a dominated strategy in any of the 30-60 games of each session. Among the subjects who *did* play dominated strategies, Table 2 reports the average frequency with which dominated strategies were played.

Table 2: Dominated Strategies and Efficiency

Session Number	Treatment Conditions	F=	Percent of subjects who never play a dominated strategy*	Average frequency of the play of dominated strategies by those playing them.	Payoff efficiency relative to equilibrium prediction	Equilibrium Concept-Predicted Entry Threshold
1	Static C,G	20	0.80	0.04	1.03	GG-42
2	Static G,C	20	0.55	0.07	1.02	GG-42
3	Static C,G	20	0.60	0.03	0.99	GG-42
4	Static G,C	20	0.75	0.02	1.12	GG-42
5	Dynamic, C	20	0.95	0.03	0.91	SGP-21
6	Dynamic, C	20	1.00	0.00	0.94	SGP-21
7	Dynamic, C	20	0.80	0.04	0.96	SGP-21
8	Dynamic, C	20	1.00	0.00	0.97	SGP-21
9	Static C,G	50	0.65	0.04	0.98	GG-62
10	Static G,C	50	0.70	0.04	0.99	GG-62
11	Static C,G	50	0.75	0.02	1.00	GG-62
12	Static G,C	50	0.35	0.05	1.00	GG-62
13	Dynamic, C	50	0.90	0.01	0.99	SGP-51
14	Dynamic, C	50	0.70	0.02	0.98	SGP-51
15	Dynamic, C	50	0.80	0.01	0.99	SGP-51
16	Dynamic, C	50	1.00	0.00	0.99	SGP-51
Sessions 1-16 Overall Avgs:			0.77	0.03	0.99	

*Dominated strategies are entering (choice B) when $Y < F$ or not entering (choice A) when $Y > \overline{Y}$. For the Dynamic treatment, entry decisions are assessed as of the final (10^{th}) round of the game.

These frequencies, shown in columns 4-5 of Table 2, provide support for the notion that most subjects are frequently behaving rationally. Specifically, we have:

Finding 1: More than three quarters of subjects *never* played a dominated strategy in any (static or dynamic) entry game. Among the remaining subjects, the frequency of play of dominated strategies is low, averaging just 3%.

Finding 1 is consistent with Heinemann et al.'s (2004) finding that subjects in their design largely avoided the play of dominated strategies.

Table 2 also reports on a measure of *payoff efficiency*, specifically, how subjects' payoffs compare with those they could have earned if all had played according to the threshold strategies specified by the equilibrium solution concept for the class of entry games examined in each session. For instance, session 1 involved play of a static entry game with F=20. Under the global game (GG) solution concept, the threshold prediction is that subjects enter if $Y \geq 42$ and don't enter otherwise. Our payoff efficiency measure takes the sum of all subjects' payoffs for all rounds played in the session and divides that number by the sum of the payoffs that all subjects would have earned had they faced the exact same sequence of randomly drawn Y numbers and played according to the global game equilibrium strategy. For session 1, the payoff efficiency number of 1.03 indicates subjects earned 3% more, on average, than they would have by playing according to the "GG-42" equilibrium prediction. For the dynamic game sessions, the solution concept is subgame perfection, SGP, and the threshold is the lower, Pareto efficient one where all choose to enter whenever Y>F. Based on data in the next-to-last column of Table 2 we have:

Finding 2: Subjects earned payoffs that averaged 99% of the payoffs they could have earned by following either the global game (static treatment) or the subgame perfect (dynamic treatment) equilibrium threshold strategies.

We further note that, using a nonparametric, Wilcoxon-Mann-Whitney test on session level averages, there are no statistically significant differences in payoff efficiency between the static sessions where F=20 and the static sessions where F=50 (p>.10). However, we find that payoff efficiency is significantly larger in the dynamic F=50 treatment as compared with the dynamic F=20 treatment (p=.02). Finding 2 suggests that both equilibrium refinements may be characterizing subject behavior rather well. However, as we shall see, in the next two sections, the payoff efficiency evidence does not indicate that subjects were playing according to the prescribed equilibrium threshold strategies.

4.2 Elicited entry thresholds

Finding 3: The elicited thresholds in the static-G treatment games are consistently different from the global game prediction.

Table 3: Elicited Entry Thresholds, Static G-treatment Sessions

Sess No.	Treatment Conditions	F=	Mean Y^G	Std Dev.	Equilibrium Concept-Pred. Entry Threshold
1	Static C,G	20	31.24	12.93	GG-42
2	Static G,C	20	29.25	16.81	GG-42
3	Static C,G	20	27.97	12.10	GG-42
4	Static G,C	20	40.77	15.46	GG-42
9	Static C,G	50	61.80	14.46	GG-62
10	Static G,C	50	55.32	15.36	GG-62
11	Static C,G	50	50.20	8.49	GG-62
12	Static G,C	50	55.36	11.98	GG-62

Table 3 reports the mean and standard deviation of the elicited thresholds, Y^G, from all static-G treatment sessions of our design. (For C-treatment sessions (static or dynamic), the thresholds were not elicited and can only be estimated on the basis of *observed choices* as we do in the following section). Specifically, for each static-G session, we calculated the mean elicited cut-off value provided by all 20 subjects over all 30 rounds of the session. For the four static-G treatment sessions (numbers 1-4) with F=20, the average elicited cut-off value for Y is 32.3 while in the four static-G treatment sessions (numbers 9-12) with F=50, the average elicited cut-off value for Y is 55.67. Both of these averages, as well as most of the session-level averages lie *well below* the global game predictions of 42 and 62 respectively, though there is a greater departure from the global game prediction in the case of F=20 than in the case of F=50. The latter difference mainly reflects the difference between the global game prediction, Y^* and the value of *F*, a difference of 22 in the case of F=20 but a difference of only 12 in the case of F=50. If we instead consider the *proportion* of the distance, $Y^* - F$, we find that in the F=20 treatment subjects' average entry threshold is 55.9% of this distance, whereas in the F=50 treatment, subjects' average entry threshold is lower, at 47.25% of this distance, so in this sense, the global game prediction is closer to characterizing behavior in the F=20 than in the F=50 treatment of the static-G treatment. Also, contrary to the global game prediction, we find that there is significant variance in the distributions of these elicited thresholds, i.e., the standard deviations are not zero.

4.3 Estimated entry thresholds

For the static- and dynamic-C treatment sessions, empirical entry thresholds have to be estimated from observed entry decisions. We follow Heinemann et al. (2004) and *estimate* a logit regression model in which the binary entry decision depends on a constant and the Y value, using all data (binary entry decisions and associated Y values) from a given session. That is, we use maximum likelihood estimation to find the coefficient estimates a and b, that are a best fit to the logit response function

$$\Pr(B) = \frac{e^{a+bY}}{1+e^{a+bY}},$$

where a is the coefficient on the constant term and b is the coefficient on the Y-value. Since Pr(B)=.5 when $Y=-a/b$, we may regard $-a/b$ as an *estimate of the entry threshold*, as it represents the mean of the fitted logit distribution. The associated standard deviation is given by $\frac{\pi}{b\sqrt{3}}$. We estimate the entry threshold and its standard deviation for the static- and dynamic- C treatment sessions as well as for the static-G treatment sessions; in the latter case, we can compare the logit estimated thresholds and standard deviations with the actual mean and standard deviation of the elicited cut-points as reported in Table 3. For the dynamic-C treatment, we use entry decisions as of the final, 10^{th} round of each game.

For each of our 16 sessions, Table 4 reports the logit estimates of a, b, the ratio $-a/b$, and the associated standard deviations. Note that we divide the static game sessions up according to the information treatment, C or G. There were 30 games played of each static information treatment. For the dynamic game, we use entry outcomes as of the 10^{th} round of each of the 30 games. Thus, each estimate in Table 4 is based on data from 30 games played by 20 subjects (600 individual observations).

Table 4 Logit Coefficient Estimates, Implied Entry Threshold and Standard Deviation

Ses No.	Session Characteristics			C Treatment Estimates				G Treatment Estimates				Equilib. Concept -Pred.
	F	Game Type	Order	A	b	-a/b	$\frac{\pi}{b\sqrt{3}}$	a	b	-a/b	$\frac{\pi}{b\sqrt{3}}$	
1	20	Static	C, G	-4.63	0.15	31.65	12.40	-4.10	0.13	**31.30**	**13.85**	GG-42
2	20	Static	G, C	-6.77	0.24	28.57	7.65	-2.26	0.09	**25.39**	**20.38**	GG-42
3	20	Static	C, G	-7.90	0.24	32.92	7.56	-3.85	0.15	**25.67**	**12.09**	GG-42
4	20	Static	G, C	-8.60	0.38	22.63	4.77	-4.70	0.12	**39.17**	**15.11**	GG-42
5	20	Dynamic	C	-6.63	0.21	31.89	8.72	n/a	n/a	n/a	n/a	SGP-21
6	20	Dynamic	C	-11.18	0.45	24.77	4.02	n/a	n/a	n/a	n/a	SGP-21
7	20	Dynamic	C	-6.88	0.30	22.77	6.00	n/a	n/a	n/a	n/a	SGP-21
8	20	Dynamic	C	-6.28	0.24	26.17	7.56	n/a	n/a	n/a	n/a	SGP-21
9	50	Static	C, G	-9.54	0.18	54.47	10.35	-7.87	0.13	**59.99**	**13.83**	GG-62
10	50	Static	G, C	-18.89	0.36	52.36	5.03	-5.03	0.09	**55.21**	**19.92**	GG-62
11	50	Static	C, G	-16.97	0.34	51.46	5.41	-11.42	0.22	**51.71**	**8.21**	GG-62
12	50	Static	G, C	-14.40	0.29	49.65	6.36	-7.08	0.13	**54.46**	**14.52**	GG-62
13	50	Dynamic	C	-41.33	0.83	49.95	2.19	n/a	n/a	n/a	n/a	SGP-51
14	50	Dynamic	C	-15.31	0.31	48.90	5.79	n/a	n/a	n/a	n/a	SGP-51
15	50	Dynamic	C	-19.60	0.38	51.58	4.82	n/a	n/a	n/a	n/a	SGP-51
16	50	Dynamic	C	-49.81	0.97	51.35	1.87	n/a	n/a	n/a	n/a	SGP-51

Comparing the elicited entry thresholds in Table 3 with the estimated thresholds in Table 4 for the static-G treatment sessions we have:

Finding 4: Estimated entry thresholds and standard deviations for the static-G treatments (shown in bold in Table 4) are not significantly different from (and are a good approximation to) the elicited entry thresholds and standard deviations for the static-G treatments (as given in Table 3).

Using a two-sided, Wilcoxon matched-pairs signed ranks test, we cannot reject the null hypothesis of no difference between the mean elicited entry thresholds and standard deviations as reported in Table 3 and the estimated entry thresholds and standard deviations as reported in Table 4 using session-level data for both the F=20 and F=50 treatments (p>.10 for all tests). This finding provides us with some assurance that the logit-estimated thresholds and associated standard deviations are a good approximation to those that were elicited from subjects in our static-G treatment.

Finding 5: In the F=20 treatment, the estimated thresholds in the static-G treatment are not significantly different from the estimated thresholds in the static-C treatment. However, in the F=50 treatment, we reject the null hypothesis of no difference between the estimated thresholds in the static-G and static C-treatments.

When the four estimated entry thresholds for the C-treatment of the F=20 static game are compared with the corresponding four entry thresholds for the G-treatment of the same game, we find no significant difference (Wilcoxon matched-pairs signed-ranks test (2-sided test, p=.37). However, the four estimated entry thresholds for the G-treatment of the static F=50 game are significantly higher than the corresponding estimated entry thresholds for the C-treatment of the same game (Wilcoxon matched-pairs signed-ranks test (2-sided test, p=.07).

Finding 6: Estimated entry thresholds in the static-C treatment sessions are indistinguishable from estimated entry thresholds in the corresponding dynamic treatment sessions (with the same F-value).

Using a nonparametric Wilcoxon-Mann-Whitney test, we find that there is no significant difference between the four estimated entry thresholds for the C-treatment of the static, F=20 game and the four estimated thresholds for the dynamic, F=20 game (two-sided test, p=.56). For the F=50 game, the Wilcoxon-Mann-Whitney test again indicates that we cannot reject the null hypothesis that the four estimated thresholds for the C-treatment of the static, F=50 game come from the same distribution as the four estimated thresholds for the dynamic, F=50 game (2-sided test, p=.24).

For further evidence confirming the findings above, we report the results of two simple OLS regressions of the 24 logit-estimated entry thresholds in Table 4 (the values of -a/b) and the 24 estimated standard deviations ($\frac{\pi}{b\sqrt{3}}$) on several dummy variables: $\delta^G = 1$ if the G, "cut-point strategy" treatment was used, 0 otherwise; $\delta^{50} = 1$ if F=50, 0 otherwise, $\delta^D = 1$ if the entry game was dynamic, 0 otherwise, as well as two multiplicative dummies, $\delta^G \times \delta^{50}$ and $\delta^{50} \times \delta^D$. The OLS regression results—with standard errors (in parentheses) that have been corrected for clustering of estimates within (static-treatment) sessions using a Huber-White sandwich estimator— are presented in Table 5.

For the regression involving the entry threshold we see that the change in the value of F from 20 to 50 significantly increases the entry threshold, as predicted, from an estimated mean of about 29 to about 52. However, all other treatment conditions appear to be irrelevant for the determination of the entry threshold, as the coefficient estimates on the dummy variables δ^D, δ^G, $\delta^G \times \delta^{50}$ and $\delta^G \times \delta^{50}$ are not significantly different from zero.

Table 5: Linear Regression Examining Treatment Effects: Coefficient Estimates (Standard Error)

Variable	Entry threshold, -a/b	Standard deviation, $\pi/(b\sqrt{3})$
Intercept	28.94*** (1.19)	8.10*** (1.60)
δ^G	1.44 (5.29)	7.26*** (2.62)
δ^{50}	23.04*** (2.53)	-1.31 (2.02)
δ^D	-2.54 (3.05)	-1.52 (1.91)
$\delta^G \times \delta^{50}$	1.92 (5.42)	0.07 (3.85)
$\delta^{50} \times \delta^D$	1.00 (3.28)	-1.60 (2.47)
R^2	0.93	0.71

Statistically significant at the: .01 level, ***; .05 level, **; .10 level, *.

For the regression involving the standard deviation as the dependent variable, we find that the only treatment condition with a significant effect on the standard deviation of entry decisions is whether subjects submitted cut-off strategies or made action choices as indicated by the significant coefficient estimate on the δ^G dummy variable. In particular, we observe that the standard deviation of entry decisions is significantly larger in the static G-treatment where we elicited cut-off strategies than in the C-treatment where actions were chosen. In the G treatment unlike the C treatment, the Y value is *not* known at the time a strategy choice must be submitted and this different timing likely explains the significantly higher variance in entry choices (cut-off values) in the G treatment relative to the C treatment.[4]

[4] Heinemann et al. (2004, result 7) also find that the standard deviation of entry decisions is higher in treatments with private information as compared with treatments with common information.

Finally, we test for differences between the logit-estimated entry thresholds in Table 4 and the global game or subgame perfect equilibrium predictions. Using a simple t-test, we consider whether the four independent session level entry thresholds in the static, F=20 game are statistically different from the global game prediction. In both the C and G treatments, we may reject the null of no difference from the global game threshold of 42 (two-sided t-test, p=.01 in the C treatment, p=.04 in the G treatment). For the F=20 dynamic game, we use a *one*-sided version of the t-test to determine whether the four session level entry thresholds in the dynamic F=20 game are greater than the subgame perfect equilibrium threshold prediction of 21 (it would not be rational for these thresholds to be lower than 21). We again find that we can reject the null of no difference (one-sided t-test, p=.04) in favor of the alternative that entry thresholds are greater than 21. We conclude that in the F=20 case, entry thresholds in the static game lie below the global game threshold and, in the dynamic game they lie above the subgame perfect equilibrium prediction, which is consistent with our earlier finding of no significant difference in the distribution of entry thresholds between these two treatments.

For the F=50 static game sessions, a t-test indicates that we may also reject the null of no difference between the four estimated session-level entry thresholds and the predicted global game threshold of 62 for both the C and G treatments (two-sided test, p=.01 in the C treatment, p=.03 in the G treatment). However, for the F=50 dynamic game, a one-sided t-test indicates that we *cannot* reject the null of no difference between the four session level estimated entry thresholds and the subgame perfect (and efficient) equilibrium threshold prediction of 51 (one-sided test, p=.79). Given that we earlier found no difference in the distribution of entry thresholds between the static C-treatment and the dynamic treatment of the F=50 game, it would seem that entry thresholds in the static C-treatment should also not differ significantly from the efficient equilibrium threshold of 51 for the dynamic game. Indeed, a t-test confirms that we cannot reject the null hypothesis of no difference between the estimated entry thresholds in the static C-treatment and a hypothesized entry threshold of 51 (one-sided test, p=.20).[5] As noted earlier, observed and estimated entry thresholds in the static game where F=50 are a smaller proportion of the distance $Y^* - F$ than are entry thresholds in the static game where F=20. This

[5] We *can* reject the null of no difference between the estimated entry thresholds in the static-G treatment and a hypothesized entry threshold of 51 in favor of the alternative that the static G-treatment thresholds are greater than 51 (one-sided test, p=.04). However, the timing of information concerning the Y-value in the G treatment is different from that in the static-C and dynamic game treatments, so the more natural comparison to make (as in the text above) is between the static-C and dynamic treatments with the same value of F.

difference most likely reflects the greater likelihood that entry will succeed in the F=50 treatment as compared with the F=20 treatment, as in the F=20 case, more subjects must choose entry on average for entry to yield a non-zero payoff than in the F=50 case.

Summarizing, these last findings with regard to our equilibrium predictions we have:

Finding 7: Estimated entry thresholds in both the F=20 and F=50 *static* game treatments are significantly below the global game predictions. A comparison of the distribution of entry thresholds between *static-C* game and *dynamic* game treatments with the *same F value* reveal no significant differences. In the F=50 treatment, the efficient strategy of entering if $Y>F$ and not entering otherwise can be used to characterize behavior in *both* the static-C and dynamic game treatments.

4.4 Distribution of entry frequencies

[Figures 1a-1b here.]

In addition to considering whether there are differences in estimated or inferred entry thresholds for Y between treatments, it is also of interest to examine whether the *entire distribution* of entry frequencies (over all Y numbers) differs between the static and dynamic treatments. Figures 1a-1b show the average frequency of entry by participants in all four static and all four dynamic sessions for each F-value (20, 50) disaggregated by Y-numbers. The Y-numbers have been grouped into the same "bins" that were used to determine the number of entrants needed for entry to yield a positive payoff (as given in the experimental instructions). We observe that the distributions of entry frequencies over these Y-bins are strikingly similar. Indeed, using a two-sample, Friedman rank test, we find that we cannot reject the null hypothesis that the ranking of entry frequencies (higher or lower) between static and dynamic treatments within the 10 Y-number bin is equally likely $p>.05$ for both the F= 20 and F=50 cases. In the F=20 case, this null hypothesis can be rejected in favor of the alternative that entry frequencies rank higher in the dynamic case than in the static case, at the higher, 10% significance level. We summarize this finding as follows:

Finding 8: There is little difference in the distribution of entry frequencies over Y-numbers between static and dynamic entry games with the same F-value.

Finding 8 provides further confirmation that subjects adopted very similar strategies in their play of either the static or the dynamic version of the entry game with strategic complementarities.

4.5 Consistency of cut-point strategies with action choices in the static game

We next restrict attention to our *static* game treatment where we used both the action choice method (treatment C) and the strategy method (treatment G). We have the following finding:

Finding 9: Individual's chosen cut-point strategies are a poor predictor of their actions when the payoff relevant state variable, Y, lies between F and the global game equilibrium threshold.

For each subject in the static-G treatment, we calculated the mean of that subjects' entry cut-point in the last five games played, as subjects should have had sufficient experience by then to have settled on an entry threshold that seemed reasonable to them. Using each subject's mean cut-off from the static-G treatment, we then calculated the sequence of actions implied by that strategy in the static-C treatment using the same sequence of Y values subjects faced in the C-treatment part of the session. We use these predicted actions to calculate a *consistency metric* for each subject, where a value of 1 corresponds to perfect consistency between a subject's mean strategy threshold (as determined by end behavior in the G-treatment) and his action choices in all rounds of the C-treatment and a value of 0 corresponds to complete inconsistency.

Figures 2a-2b provide weighted average values of the consistency measure over all subjects who participated in the static F=20 and F=50 treatments. These averages are again disaggregated according to the 10 non-overlapping "bin" values for the Y-number used in the experiment.

[Figures 2a-2b here.]

Notice that for Y-values that lie either below F or above the hypothesized global game thresholds (42 when F=20 and 62 when F=50), the average consistency metric is generally very high, often close to 100%. However, there is a sharp fall-off in this consistency measure in the neighborhood of the empirically observed thresholds, bins 24-29, 30-35 and 36-41 in the F=20 sessions and bins 48-53 and 54-59 in the F=50 sessions. In the F=20 case, when Y is between 30-35, subjects' strategies from the G-treatment part of the session predict their actions in the C treatment part of the session only 50% of the time. This finding leads us to conclude that there is only mixed support for an important implication of the global game solution—that individuals approach the play of a sequence of coordination games, which differ only in a payoff-relevant variable, by adopting a unique threshold strategy.

This finding is not inconsistent with the finding that inferred or estimated entry thresholds in the F=20 static-C and static-G game treatments are not significantly different from one another as the *variance* of entry thresholds is significantly greater in the G-treatment as compared with the C-treatment (see, e.g., Table 4). And indeed, we earlier reported (Finding 5) that both the mean entry threshold and its variance in the F=50 static-G treatment were significantly higher than in the corresponding F=50 static-C treatment. The observation that subjects are varying their cut-off thresholds to a greater degree than the variation in their entry choices is what appears to account for the inconsistencies observed in Figure 2.

Recall also that we varied the *order* of the static-C and static-G treatments in our within-subjects design; in 2 out of the 4 sessions for each value of F, the static-C treatment was played first followed by the static-G treatment, while in the remaining 2 sessions, the reverse order was followed. Restricting attention to these 8 static game sessions, we find no evidence for any *order effect* on the consistency metric. Specifically we calculated the individual consistency metric described above for each subject using their average cut-off from the last five rounds of the G treatment to predict their actions in *all 30* rounds played of the C treatment (that is, using all 30 values of Y they actually faced in the C treatment). We ran a regression of these 160 individual observations for the consistency metric on a constant and two dummies: $\delta^{GC} = 1$ if the treatment order was 30 rounds of the static-G treatment (strategy method) followed by 30 rounds of the static-C treatment, 0 for the reverse order, and $\delta^{50} = 1$ if F was *50*, *0* otherwise. The OLS regression results, with standard errors (in parentheses) that have been corrected for clustering of the consistency metric within sessions using a Huber-White sandwich estimator, are as follows:

$$\text{Consistency} = \underset{(0.021)}{0.869} - \underset{(0.031)}{0.013}\,\delta^{GC} + \underset{(0.031)}{0.068}\,\delta^{50} \qquad R^2 = 0.09$$

The regression results reveal that the coefficient on the order dummy, δ^{GC}, is not significantly different from zero, suggesting that the static game treatment order did not affect the consistency between subjects' elicited thresholds (G treatment) and their action choices (C treatment). The absence of an order effect is not only indicative of the neutrality of our within-subject designs. It further suggests that there is indeed a consistency between subjects' action choices and the use of threshold strategies as Heinemann et al. (2004) asserted in their study.

The regression above also reveals that there is a statistically significant increase in the consistency metric in the *F=50* treatment as compared with the *F=20* treatment. We observe that consistency over all values of Y averages around 87% when F=20 and rises to an average of around 94% when F=50. While these average consistency levels seem high, note that they are calculated for all values of $Y \in [10, 90]$. We know from Finding 9 (and Figures 2a-2b) that most of variance in the consistency metric arises when the Y number lies in the critically important region between F and the global game equilibrium threshold, Y^*. As the region Y^*-F is smaller when F=50 than when F=20, this difference is what accounts for the greater consistency between elicited thresholds and action choices in the F=50 as compared with the F=20 treatment.

Finding 10: The overall consistency (all values of Y) between elicited cut-point strategies and action choices averages 87% in the F=20 treatment and 94% in the F=50 treatment. The consistency measure is unaffected by whether strategies were elicited in the first or second half of static game sessions.

4.6 Timing of entry decisions in the dynamic game

Finally, we focus attention on the *dynamic* game treatment and examine the timing of entry decisions. We have the following finding:

Finding 11: There is clear evidence against backward induction.

For the dynamic game, the subgame perfect (and efficient) equilibrium in which an individual enters whenever the number who have already entered exceeds a specific threshold predicts that, via backward induction, entry should occur *immediately*, in the first of the 10 rounds of each dynamic game for any value of $Y > F$. However, as Figures 3a-3b reveal, this prediction finds only conditional support. Figure 3a(b) is constructed using pooled data from the four dynamic sessions where F=20 (F=50). Using the 10 bins for Y values (indicated by the vertical lines) these figures show the mean number of the 10 subjects who choose to enter at each of the 10 rounds of the dynamic game (indicated by tick marks within each Y-bin).[6]

[Figures 3a-3b here.]

These figures reveal that decisions to enter or not enter are, on average, immediate (occur in round 1) only when Y is below the value of F or well above the global game threshold of 42 in the F=20 case and 62 in the F=50 case. For intermediate values of Y, there is clear evidence that subjects are *conditioning* their entry decisions on the number of subjects who have previously entered, that is, some subjects are playing a "wait-and-see" strategy that is inconsistent with the subgame perfect equilibrium prediction. Notice, for example, the bin for Y values 30-35 in Figure 3a of the F=20 treatment: on average, slightly less than 4 of the 10 players enter immediately in round 1 (marked with a vertical line in the figure) and on average, about 7.5 of the 10 players have entered by round 10 (for Y values in this bin, 8 players must enter for entry to yield a positive payoff).[7] This is clear evidence against the backward induction logic of the subgame perfect equilibrium prediction.

The incidence of this wait-and-see behavior is less pronounced in the dynamic F=50 games, as it is less risky for individual subjects to immediately enter in the first round of such games when Y>50; in that case, *at most* 5 of the 10 group members must choose to enter for an entry decision to yield the larger, Y payoff. However, entry hesitation nevertheless persists in the F=50 treatment. For example, consider the bin for Y values 54 to 59 in Figure 3b: an average of just 6.4 of the 10 players choose to enter in the first round of games with those Y values; in that bin, only 4 out of the 10 players must choose to enter for entry to succeed. The average number of entrants in the 54-59 bin climbs to 9.9 by the 10th round.

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[6] The 10th tick for each bin, representing the 10th round should not be connected to first tick of the next bin representing the 1st round ; the connection is unavoidable using our graphical software.

[7] While the average number of entrants by round 10 is about 7.5, this masks some variance across games/sessions; in some of these games, entry is successful as more than 8 have entered and in others entry is unsuccessful as less than 8 have entered.

5 Summary and Concluding Remarks

Games with strategic complementarities give rise to a multiplicity of equilibria. An important class of such games are entry games in which the payoff to a player who ‘enters’ is a monotonic increasing function of the number of other players who enter. These games have been used to model speculative attacks, bank runs, and other situations in which actions by a critical mass can produce a regime change. The theory of global games has been proposed as a model of how people resolve the coordination that is inherent in such games. That theory implies that an individual will play all entry games whose payoff functions differ only with respect to the value of a threshold parameter using the same cut-point strategy and that in equilibrium all individuals will choose the same strategy. We test these implications by directly eliciting the strategies subjects choose to play in all entry games that vary only with respect to the threshold parameter, Y. We then compare those strategies with the actual action choices the same subjects make in a series of entry games in which the value of Y varies from one game to another. We find only mixed support for the theoretical predictions. In support of the proposed refinement, we find that individual actions are generally consistent with the actions that are implied by the strategies they chose when asked to choose a cut-point strategy. Further, the lack of any order effect suggests that individuals are employing a cut-point strategy when selection which action to take in these entry games. These strategies and actions chosen are responsive to changes in the payoff to not entering in the direction predicted by the theory. However, inconsistent with the theory, there is substantial variance among individuals in their elicited cut-point strategies. Furthermore, the mean of the elicited or estimated entry threshold in the static game is significantly below the global game equilibrium strategy and the mean of the estimated dynamic entry threshold is above the subgame perfect equilibrium prediction in the F=20 case, though not significantly different from it in the F=50 case.

The theory of global games is a theory of a game played in a static environment. However, most phenomena that are modeled as entry games have an inherently dynamic property in that individuals do not have to move simultaneously and when they do act, they may possess information about how close the system is to the threshold that would make entry individually profitable. Theoretically, the equilibrium of the dynamic version of the entry game we study is quite different from the equilibrium of the global game. Surprisingly, we find that despite the large, predicted difference in the play of the static and dynamic games, the actual pattern of behavior in these different games is statistically indistinguishable. The latter finding suggests that the modeling of N-player entry games with strategic complementarities as static, one-shot games –ignoring the dynamic element of those interactions -- may not be leaving out empirically important determinants of behavior observed in such environments.

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Appendix: Instructions Used in the Experiment

A.1 Instructions used in static game sessions where F=20 and subjects played 30 rounds of the G treatment followed by 30 rounds of the C treatment. Other static game treatments involve similar instructions, or reverse the order of play of the G and C treatments.

Overview

Welcome to this experiment in economic decision-making. Please read these instructions carefully as they explain how you earn money from the decisions you make in today's session. There is *no talking* for the duration of the session. If you have a question, please raise your hand and your question will be answered in private.

There are 20 participants in today's session. The rules are the same for all participants. In the first phase of this experiment you will participate in 30 rounds of decision-making. At the beginning of each round you will be assigned randomly to one of two groups of 10 participants, Group 1 or Group 2. The group to which you are assigned for that round appears on your screen. In each round you will be asked to enter a number. After a round is over, all participants will be randomly divided between these two groups again. While you may be assigned to the same group number (1 or 2) more than once in succession, the composition of participants in the group to which you are assigned will differ from round to round.

The Decision You Face Each Round

Prior to the start of each round, an integer number labeled the "Y number" will be randomly drawn from the interval 10 to 90 inclusive. All numbers in this interval have the same probability of being drawn. The Y number drawn in each round is the same for all participants. The Y number will *not* be revealed to you or any other participant in your group until the end of the round, *after* you have made your decision.

In each round you will be asked to specify a cut-off value, corresponding to an integer number in the interval between 10 and 90 inclusive. Simply enter your number in this range in the box on your screen. When you are satisfied with your choice click the submit button.

If the Y number drawn is less than your cut-off number, your choice for the round will be action A. If the Y number drawn is greater than or equal to your cut-off number, your choice for the round will be action B. These choices will be made for you automatically by the computer program, given your cut-off value.

Example 1. You specify a cut-off number of 12. The Y number is 32. Since the Y number is greater than or equal to your cut-off number, the action chosen for you is action B.

Example 2. You specify a cut-off number of 74. The Y number is 71. Since the Y number is less than your cut-off number, the action chosen for you is action A.

Your cut-off value implies a certain choice of A or B each round.

<u>If your choice is A</u> then you earn 20 points for the round.

<u>If your choice is B</u>, then the number of points you earn depends on 1) how many other people in your group also choose B and 2) the value of the Y number. Generally, the more people in your group who choose B and the larger the Y number, the greater will be your points from choosing B. Specifically if the number of participants in your group who choose B is at least 10×(80-Y)/60, rounded to the next integer,

or greater, then each of those choosing B earns Y points. If the number of participants in your group who choose B is less than 10×(80-Y)/60, then each of those choosing B earns 0 points. For your convenience, we provide a table below showing, for different values of Y, the minimum number of players who must choose B for B to yield Y points.

After all cut-off decisions have been made, the round is over and the results of the round will appear on your computer screen. The value of Y for the round will be revealed to you and you will be reminded of your cut-off number. The choice that was made for you (A or B) based on your cut-off value is also revealed, as is the number of points you earned from your choice, the total number of players in your group of 10 who chose action B in the last round and the payoff in points earned by the members of your group who chose action B. The payoff to choosing action A is always 20 points. Please record this information on your record sheet under the appropriate headings. When you have completed this task, click the OK button to continue to the next decision round. Your history of play will also appear at the bottom of your decision screen for ready reference.

Earnings

<u>Each point earned is equal to 1/2 cent</u>, so 10 points = 5 cents, etc. The more points you earn the greater is your dollar payoff. You will be paid your earnings from all rounds played today in cash at the end of the session.

Table

Recall that if the number of participants who chose B is at least 10×(80-Y)/60, then each player who chose B earns Y>0 points. Otherwise, each player who chose B earns 0 points. The table below presents this formula in tabular form for your convenience.

Y is a number drawn between 10 and 90 inclusive. If the Y number drawn is in the interval:	…then at least this number of the 10 participants must choose B in order for each of them to get Y>0 points.
10 to 23	10
24 to 29	9
30 to 35	8
36 to 41	7
42 to 47	6
48 to 53	5
54 to 59	4
60 to 65	3
66 to 71	2
72 to 90	1

Some Examples

The numbers in these examples are merely illustrative. Actual numbers in the session may be quite different.

Example 3. Suppose Y turns out to be 64. Four of the 10 participants in your group had cut-off values greater than 64 so their choice was A, earning 20 points each. The other 6 had cut-off values less than or equal to 64 so their choice was B. The payoff to those choosing B depends on whether the total number of participants choosing B is greater than or equal to 10×(80-Y)/60. Since Y=64, the critical number is 10×(80-64)/60 = 2.67. Rounded up to the next integer, the critical number is 3. Since 6 players chose B, and 6 is greater or equal to 3, each player whose cut-off value caused them to choose B earns Y=64 points for the round. Alternatively, one could use the table above to come up with the same answer. With Y=64, the table reveals that the minimum number of players needed to choose action B for a B choice to yield Y=64 points is 3. Since 6 players choose B, each of those choosing B earns Y=64 points.

Example 4. Suppose Y turns out to be 31. Six of the 10 participants in your group had cut-off values greater than 31 so their choice was A, earning 20 points each. The other 4 had cut-off values less than or equal to 31 so their chose was B. With Y=31, the critical number, 10×(80-31)/60 = 8.17 rounded to the next integer is 8. Since just 4 players chose B, each player who chose B earns 0 points for the round.

Practice Questions

We now pause to ask you to answer two practice questions. We will review the answers shortly.

Question 1. You specify a cut-off of 52. Y is revealed to be 64. A total of 3 players chose B. What is your action choice and how many points did you earn?

Question 2. You specify a cut-off of 38. Y is revealed to be 26. A total of 7 players chose B. What is your action choice and how many points did you earn?

Questions

Now is the time for questions about the rules or how you make decisions. If you have a question, please raise your hand and we will attempt to answer your question in private.

Continuation Instructions (Read following the first 30 rounds of play)

You will play 30 more rounds in which you will have to make decisions. However, the rules as to how you make decisions are different from the rules used in the first 30 rounds. As in the first 30 rounds, after each round you will be randomly assigned to either Group 1 or to Group 2. The following rules apply to all participants.

The Decision You Face Each Round

Prior to the start of each round, an integer number labeled the “Y number” will be randomly drawn from the interval 10 to 90 inclusive. All numbers in this interval have the same probability of being drawn. The Y number drawn in each round is the same for all participants. Unlike the first 30 rounds however, the Y number will be revealed to you and all other participants in your group *before* you have to make your decision.

After the Y number is revealed, you will have to make a decision between choice A or choice B. Click on the radio button next to your choice. You can change your mind any time prior to clicking the red Submit button.

Notice that you no longer specify a cut-off number. You directly choose either action A or action B after observing the Y number for the round. The number of points you earn from action A is the same as before, 20 points. Similarly, the number of points you earn from action B is determined in the same manner as before. Specifically, if at least 10×(80-Y)/60 participants (rounded to the nearest integer) choose B, then all those choosing B earn Y points; otherwise they earn 0 points. The table given in the earlier set of instructions remains useful to you in figuring out your points from a B choice, given the value of the Y number announced at the start of each round.

After all decisions have been made, the round is over and the results of the round appear on your computer screen. You will be reminded of the Y number for the round and your choice for the round, (A or B). You will also see the number of points you earned from your choice, the total number of players in your group of 10 who chose action B in the last round and the points earned by the members of your group who chose action B. (The payoff to choosing action A is always 20 points and so it is not displayed). As before, please record the information appearing on your screen on your record sheet under the appropriate headings. When you have completed this task, click the OK button to continue to the next decision round. Your history of play will appear at the bottom of your decision screen for ready reference. Before the next round begins you will be randomly assigned to one of the two groups.

Earnings

As in the first 30 rounds, in these last 30 rounds, each point is worth 1/2 cent. Following the completion of these last 30 rounds, the session will be over. Your point total from all 60 rounds will be converted into dollars and you will be paid your earnings in cash and in private.

Some Examples

The numbers in these examples are merely illustrative. Actual numbers in the session may be quite different.

Example 1. Suppose Y=40 and you chose B. 5 of the 10 participants chose A each earning 20 points. The other 5, including you, chose B. With Y=40 the critical number of players needed to earn Y points from playing B, $10\times(80-40)/60 = 6.67$, Rounded up to the next integer, the critical number is 7. Since only 5 players chose B, you and each of these players choosing B earns 0 points for the round.

Example 2. Suppose Y=68 and you chose A. The 4 members of your group, including yourself, who chose A earn 20 points each. The other 6 players chose B. With Y=68, the critical number of players needed to earn a Y points from playing B, $10\times(80-68)/60 = 2$. Since 6 players chose B, each of those players earns 68 points for the round.

Practice Questions

We now pause to ask you to answer two practice questions. We will review the answers shortly.

Question 1. The Y number is 45. 8 players choose A and 2 choose B. How many points are earned by those choosing A? How many points are earned by those choosing B?

Question 2. The Y number is 74. 3 players choose A and 7 choose B. How many points are earned by those choosing A? How many points are earned by those choosing B?

Questions

Now is the time for questions about the rules or how you make decisions. If you have a question, please raise your hand and we will attempt to answer your question in private.

A.2 Instructions used in dynamic game sessions where F=20 (Instructions for the F=50 case are identical except that the payment for action A is 50 rather than 20).

Overview

Welcome to this experiment in economic decision-making. Please read these instructions carefully as they explain how you earn money from the decisions you make in today's session. There is *no talking* for the duration of the session. If you have a question, please raise your hand and your question will be answered in private.

There are 20 participants in today's session. The rules are the same for all participants. You will participate in 30 sequences of decision-making. At the beginning of each sequence you will be assigned randomly to one of two groups of 10 participants, Group 1 or Group 2. The group to which you are assigned for that sequence appears on your screen. Each sequence consists of 10 rounds. At the end of each sequence you will be randomly assigned again to one of the two groups.

The Decision You Face Each Sequence

At the beginning of a sequence an integer number labeled the "Y number" will be randomly drawn from the interval 10 to 90 inclusive. All numbers in this interval have the same probability of being drawn. The Y number drawn is the same for all participants and will be shown on your computer screen. This number remains unchanged for all 10 rounds of the sequence.

In the first round of a sequence you will be asked to choose between one of two choices, labeled "A" or "B". You make your choice by clicking on the radio button next to your choice. You then click the red 'submit' button. At the end of this first round (and at the end of the subsequent 9 rounds) of the sequence, you will be reminded of your choice and you will be informed as to how many people in your group of 10 have chosen "B" so far in that sequence. The next round of the sequence is then played. If you chose "B" in a previous round then the computer automatically chooses "B" for you in this and every remaining round of the sequence. You must simply click the red "OK" button to advance the program to the next round in the sequence. However, if you have not chosen "B" in a previous round in the sequence – you have instead chosen A in all prior rounds of the sequence – then you must decide in the current round whether to repeat your choice of "A" or to choose "B" instead. That is, a choice of "B" in any round in the sequence 'locks' you into choosing B for duration of that sequence. But a choice of "A" preserves your option to choose either "A" or "B" in a future round of the sequence, or to completely avoid making a B choice.

In the first round of each new 10-round sequence, you are again free to choose A or B, regardless of your action choices in any previous sequence.

After all 10 rounds of a sequence have been played; your point earnings for that sequence will be calculated as follows:

> If you chose "A" in all 10 rounds you earn 20 points for that sequence.
>
> If you chose "B" in any round, then your earnings for the sequence depend upon the Y number drawn for that sequence and on the total number of people in your group of 10 who chose "B" in the sequence. Generally, the more people in your group who choose B and the larger the Y number, the greater will be your points from choosing B. Specifically if the number of participants in your group who choose B is at least $10\times(80-Y)/60$, rounded to the next integer, or

greater, then each of those choosing B earns Y points. If the number of participants in your group who choose B is less than 10× (80-Y)/60, then each of those choosing B earns 0 points. For your convenience, we provide a table below showing, for different values of Y, the minimum number of participants who must choose B for B to yield Y points.

At the end of a sequence the results for that sequence appear on your computer screen. Displayed will be the Y number for the sequence, your final choice for the sequence, (A or B), the number of points you earned from your choice, the total number of participants in your group of 10 who chose action B and the payoff earned by the members of your group who chose action B. (The payoff to always choosing action A is fixed at 20 points and so it is not displayed). Please record the information appearing on your screen on your record sheet under the appropriate headings. When you have completed this task, click the OK button to continue on to the next 10-round sequence. Your history of play will appear at the bottom of your decision screen for ready reference. After a sequence is over, all participants will be randomly divided between these two groups again. While you may be assigned to the same group number (1 or 2) more than once in succession, the composition of participants in the group to which you are assigned will differ from sequence to sequence.

Earnings

Each point earned is equal to 1 cent. You will be paid your earnings from all rounds played today in cash at the end of the session.

Table

Recall that if the number of participants in your group who chose B during a sequence is at least 10×(80-Y)/60, then each participant who chose B in that sequence earns Y>0 points. Otherwise, each participant who chose B during a sequence earns 0 points. The table below presents this formula in tabular form for your convenience.

Y is a number drawn between 10 and 90 inclusive. If the Y number drawn is in the interval:	…then at least this number of the 10 participants must choose B in order for each of them to get Y>0 points.
10 to 23	10
24 to 29	9
30 to 35	8
36 to 41	7
42 to 47	6
48 to 53	5
54 to 59	4
60 to 65	3
66 to 71	2
72 to 90	1

Some Examples

The numbers in these examples are merely illustrative. Actual numbers in the session may be quite different.

Example 1. Suppose Y turns out to be 64. Following the 10th round of the sequence, 4 of the 10 participants' final choice was A, earning them 20 points each and the other 6 participants' final choice was B. The payoff to those choosing B depends on whether the total number of participants choosing B is greater than or equal to 10×(80-Y)/60. Since Y=64, the critical number is 10× (80-64)/60 = 2.67. Rounded up to the next integer, the critical number is 3. Since 6 participants chose B, and 6 is greater or equal to 3, each participant choosing B earns Y=64 points for the round. Alternatively, one could use the table above to come up with the same answer. With Y=64, the table reveals that the minimum number of participants needed to choose action B for a B choice to yield Y=64 points is 3. Since 6 participants choose B, each of those choosing B earns Y=64 points.

Example 2. Suppose Y turns out to be 31. Following the 10th round of the sequence, 6 of the 10 participants' final choice is A, earning them 20 points each and the other 4 participants' final choice is B. With Y=31, the critical number, 10× (80-31)/60 = 8.17 rounded to the next integer is 8. Since just 4 participants choice was B, each participant who chose B earns 0 points for the round.

Practice Questions

We now pause to ask you to answer two practice questions. We will review the answers shortly.

Question 1. The Y number is 45. Following the 10th round of the sequence, 8 participants have chosen A and 2 have chosen B. How many points are earned by those choosing A? How many points are earned by those choosing B?

Question 2. The Y number is 74. Following the 10th round of the sequence, 3 participants have chosen A and 7 have chosen B. How many points are earned by those choosing A? How many points are earned by those choosing B?

Questions

Now is the time for questions about the rules or how you make decisions. If you have a question, please raise your hand and we will attempt to answer your question in private.

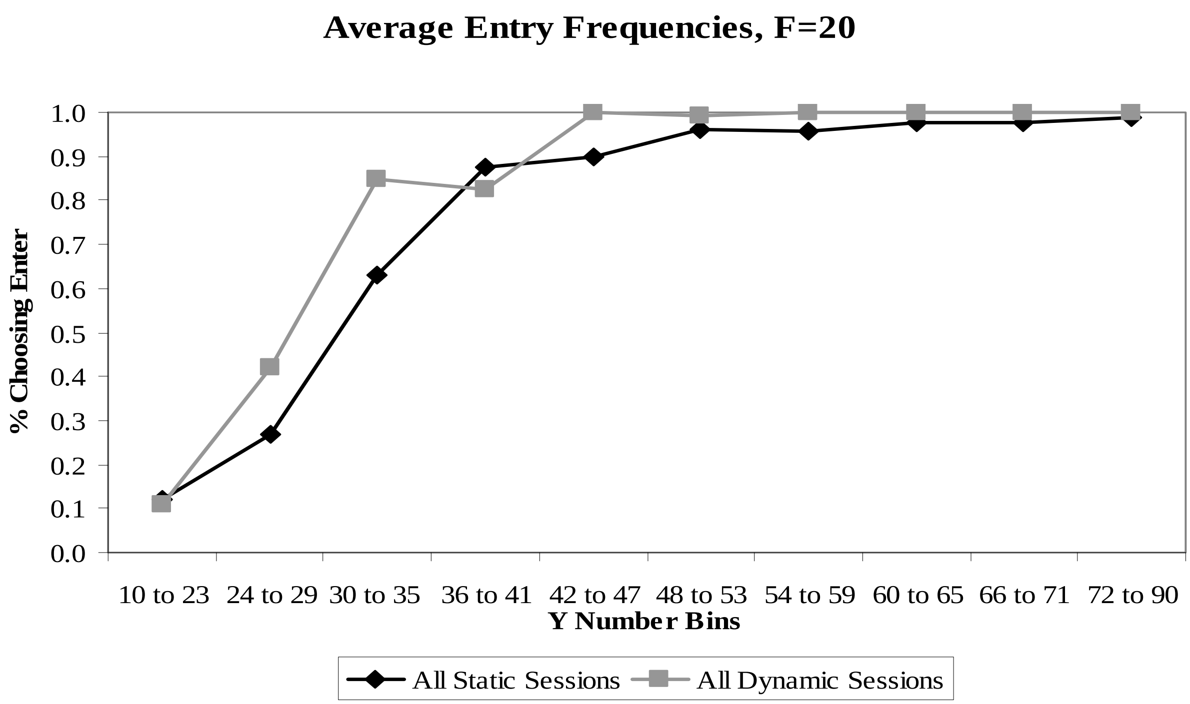

Figure 1a: Average Entry Frequencies According to Y Number Bins in Static and Dynamic Game Sessions (Pooled Data from All Sessions where F=20)

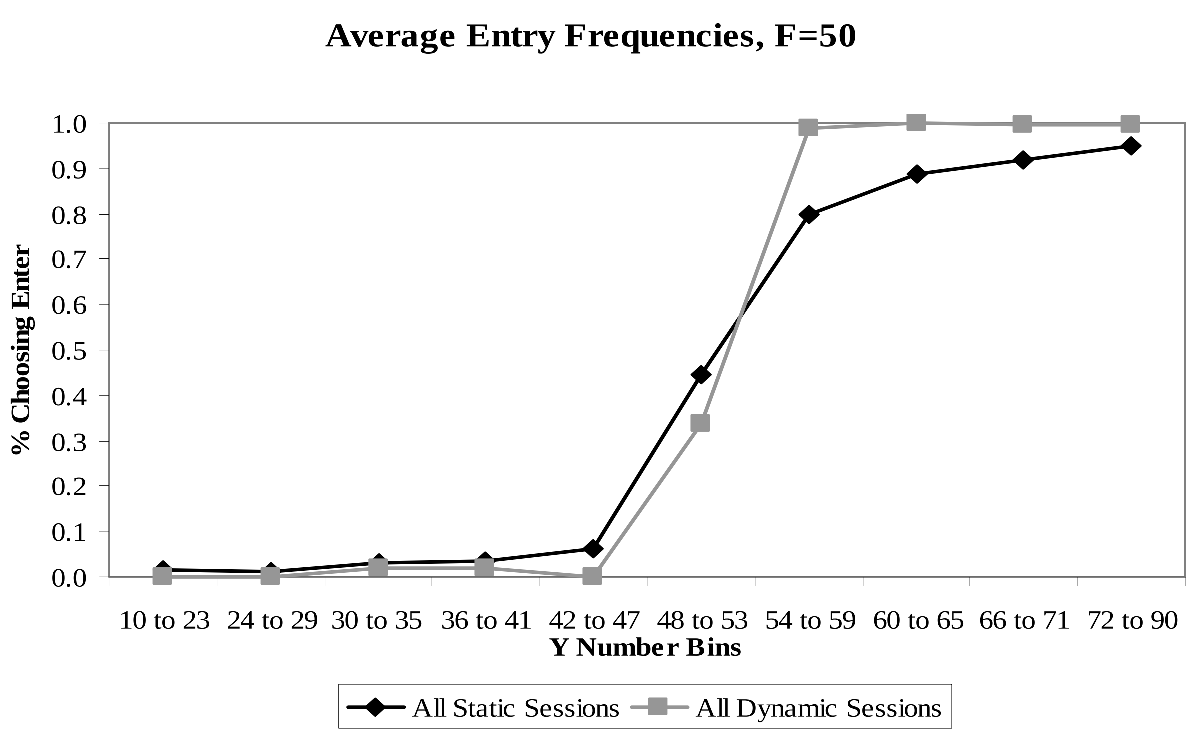

Figure 1b: Average Entry Frequencies According to Y Number Bins in Static and Dynamic Game Sessions (Pooled Data from All Sessions where F=50)

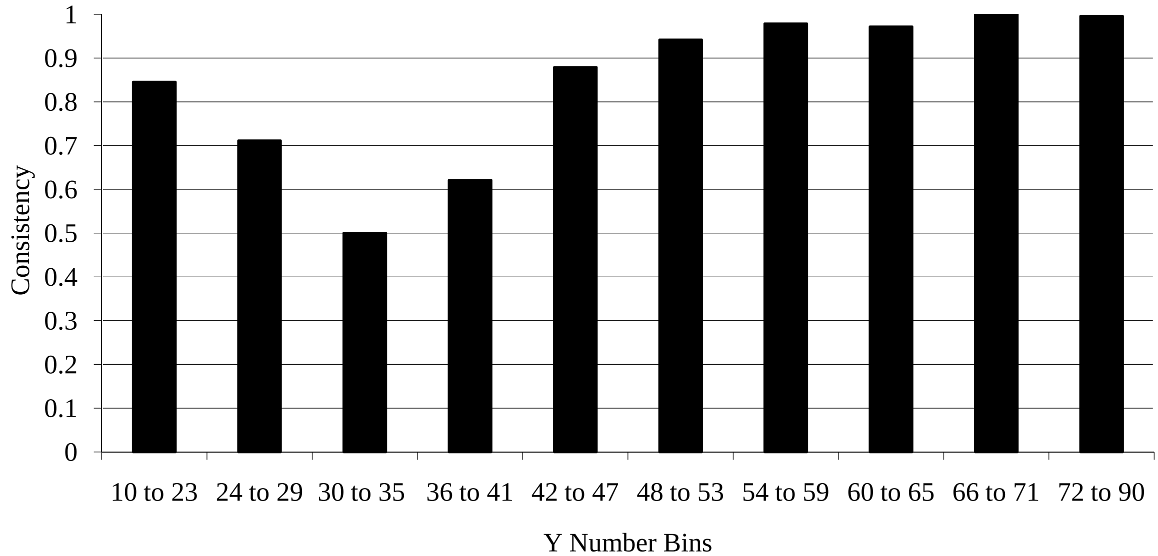

Figure 2a: Average Accuracy of Predicted Entry Decisions Using Elicited Cut-Points: Pooled Data from Four Static Game Sessions where F=20

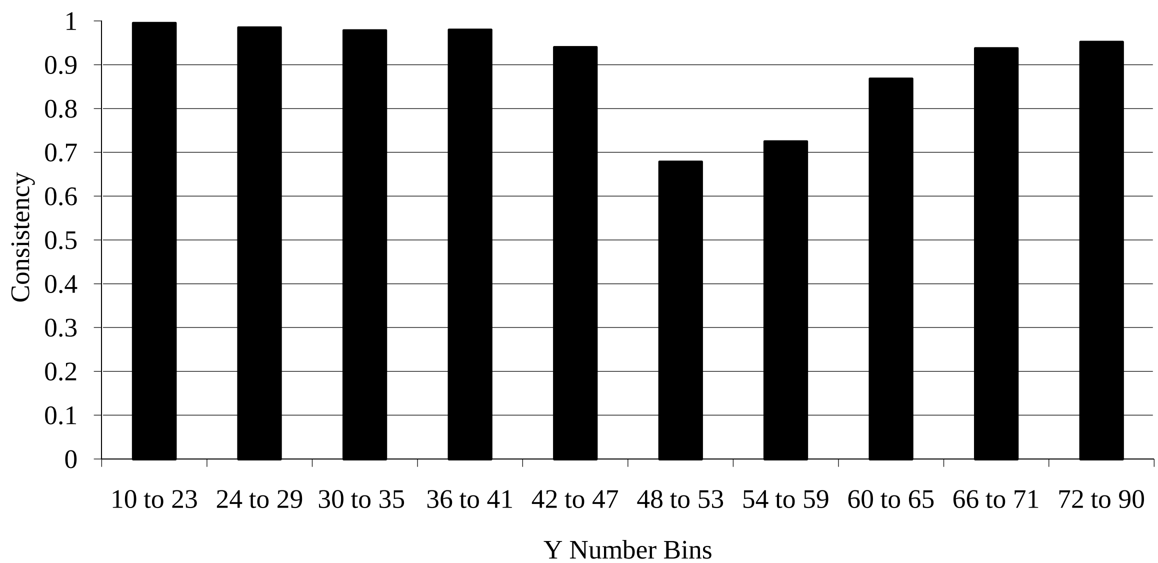

Figure 2b: Average Accuracy of Predicted Entry Decisions Using Elicited Cut-Points: Pooled Data from Four Static Game Sessions where F=50

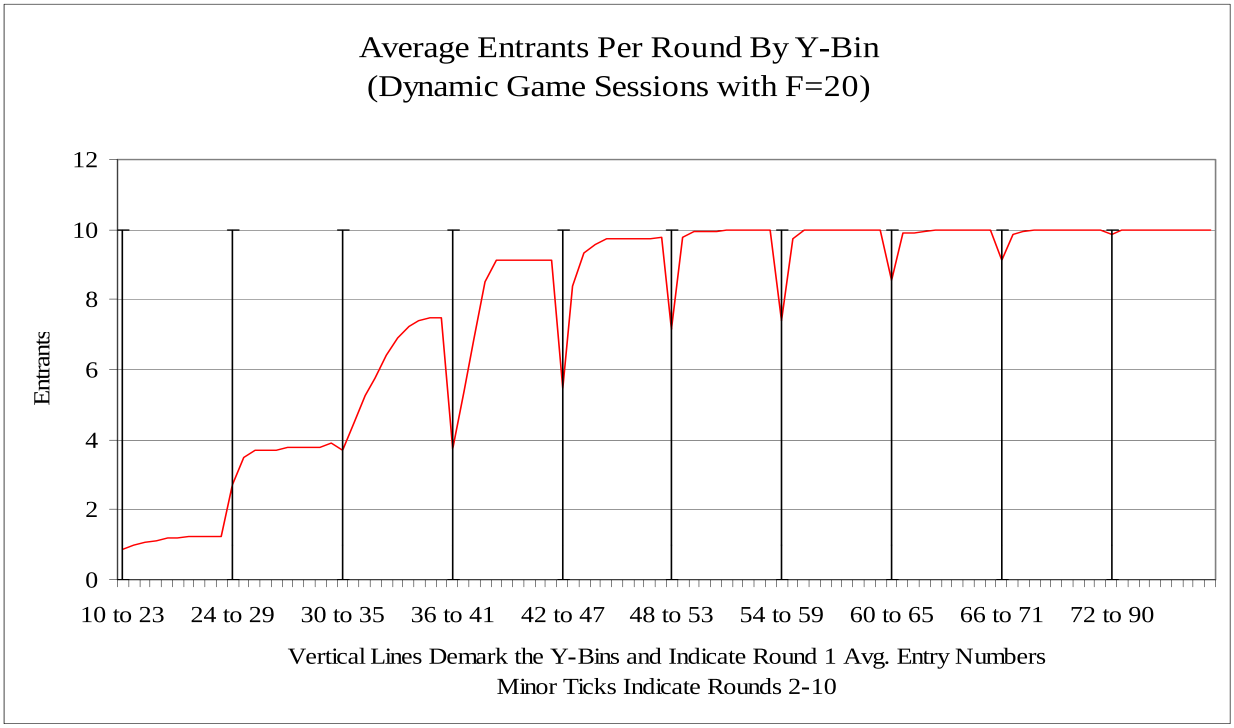

Figure 3a: Average Number of Entrants in Rounds 1-10 of All Dynamic Game Sessions with F=20, Grouped According to Y-bins

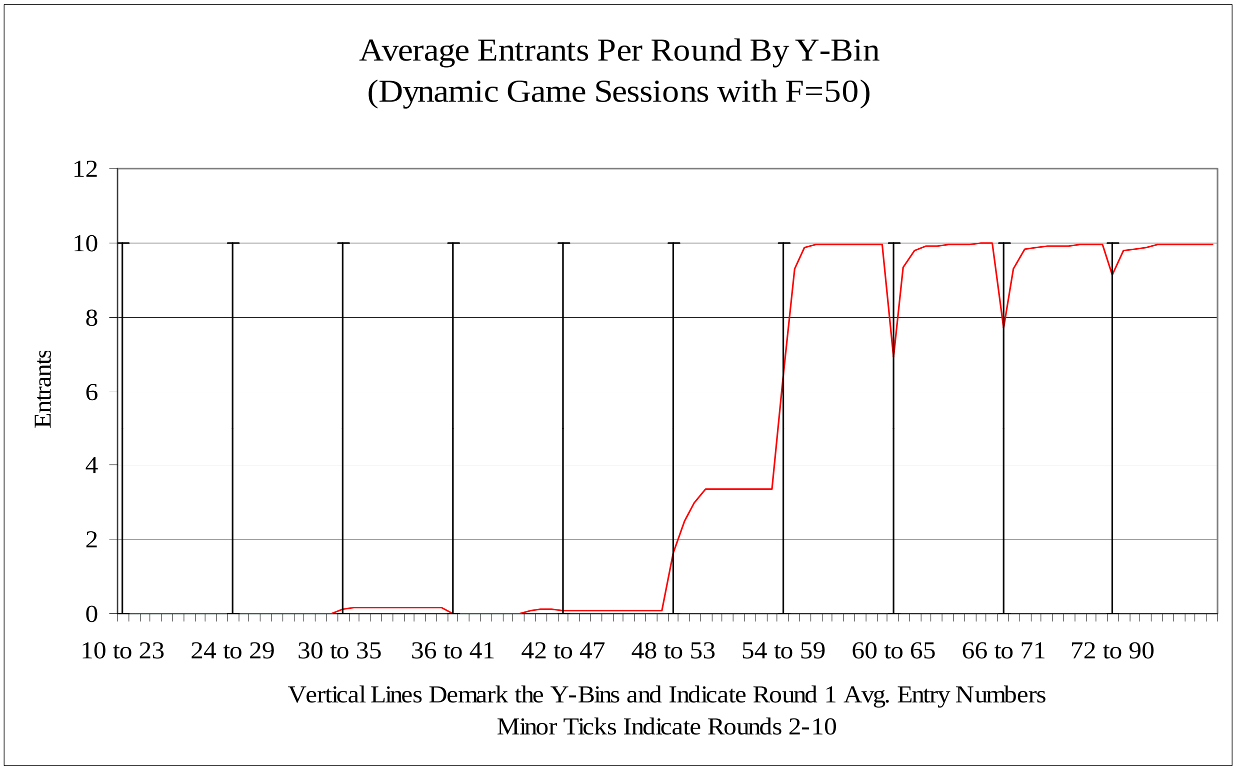

Figure 3b: Average Number of Entrants in Rounds 1-10 of All Dynamic Game Sessions with F=50, Grouped According to Y-bins