Global Games with Strategic Substitutes: An Experimental Investigation*

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Abstract

We experimentally investigate the theory of global games in a simultaneous three-agent market entry game with strategic substitutes. The payoff from staying out is constant, whereas the payoff from entering depends on a random state, a heterogeneous cost of entry, and decreases in the number of entrants. The game predicts multiple Nash equilibria for intermediate state values. The (global) game, however, where agents observe a noisy but precise private signal about the state has a unique equilibrium where agents adopt threshold strategies that are ordered by the entry cost. This equilibrium persists in the limit and characterizes the unique equilibrium that is selected in the game without noise. The experiment provides support for the theory. Aggregate and individual behavior follow comparative static predictions. A majority of subjects adopt threshold strategies with few mistakes. Finally, a majority of outcomes in the game without noise correspond to the equilibrium selected by the theory.

Keywords: Global Games; Strategic Substitutes; Market Entry; Equilibrium Selection; Experiment

JEL Classification: C72; D82;

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1 Introduction

The theory of global games (Carlsson and van Damme, 1993) has been used as an equilibrium selection mechanism to refine predictions in strategic settings with multiple Nash equilibria. Originally developed for two player, binary action games, the theory has been generalized by Frankel et al. (2003) to consider multiple players and multiple actions in games where actions are strategic complements. These are settings in which the incentive to choose an action is increasing in the number of agents choosing the same action. The theory has been used to model several coordination problems in macroeconomics and has considerable experimental support in such settings.[1] Recent theoretical developments have shown that the global games approach can be used as an equilibrium selection device in games where actions are strategic substitutes (Harrison and Jara-Moroni, 2015, 2021). These are settings where the payoff from choosing an action is decreasing in the number of agents choosing the same action.[2] This extension opens the way to apply the global games approach to several microeconomic settings.[3] Unlike strategic complements, however, to the best of our knowledge, there has been no empirical study that looks at behavior in global games when actions are strategic substitutes. This paper adds to the global games literature by experimentally investigating the theory of global games in a setting where actions are strategic substitutes.

We consider a simple setting in which three agents take part in a simultaneous market entry game. Each agent decides between entering or staying out of the market. Choosing to stay out yields a fixed payoff. In contrast, choosing to enter yields a payoff that is dependent on a state drawn from a continuous distribution over a bounded support, the number of agents who choose to enter, and an agent specific entry cost. Unlike previous experiments on global games, however, actions are strategic substitutes: a higher number of entrants decreases the incentive to enter. Furthermore, payoffs are asymmetric in the entry cost which orders agents based on their incentive to enter the market. Under the setting of complete information, when agents have full knowledge about the payoff structure, the game predicts multiple Nash equilibria for intermediate values of the state. These multiple equilibria all agree on the number of agents who choose to enter the market, but are agnostic about which agents enter. The global games theory can be used as an equilibrium selection device in this market entry game. In the global game, agents observe a noisy, yet sufficiently precise, private signal about the state. This game has a unique Bayes-Nash Equilibrium in which each agent adopts threshold strategies wherein they choose to

[1] Theoretical applications in macroeconomics include currency attacks (Morris and Shin, 1998), bank runs (Goldstein and Pauzner, 2005) and regime changes (Szkup and Trevino, 2015). See Morris and Shin (2003) for an excellent survey on early theoretical developments and applications. Experimental work on global games with strategic complements has looked at behavior in models of speculative attacks (Heinemann et al., 2004; Duffy and Ochs, 2012; Szkup and Trevino, 2020; Avoyan, 2022), regime changes (Helland et al., 2021), investment decisions (Darai et al., 2017), and stag hunt games (Van Huyck et al., 2018).

[2] See Hoffmann and Sabarwal (2019a) and Hoffmann and Sabarwal (2019b) for applications to more general payoff structures.

[3] Applications in microeconomics include public goods games (Harrison and Jara-Moroni, 2021) and market entry games (Harrison and Jara-Moroni, 2022).

enter the market if their private signal takes on a value above their threshold and stay out if it takes on a value below their threshold. These thresholds are ordered by the entry costs. The unique equilibrium maintains in the limit as noise vanishes which then characterizes, for each value of the state, a unique equilibrium that is selected in the game with complete information.

The experimental design is motivated by the theoretical predictions of the global games equilibrium selection principle. Subjects take part in 75 rounds of repeated play of the market entry game with random re-matching in between rounds. In each round, the computer randomly generates a value of the state from a known distribution. We consider two treatments, one with complete information and one with incomplete information. In the complete information treatment, the value of the state is publicly observed and common knowledge to all subjects. In the incomplete information treatment, subjects observe a private, noisy signal about the state. In each round, subjects play the game three times, once for each cost type, while playing against the remaining cost types. In each game, subjects choose between two options, A and B, where option A coincides with entering the market and option B coincides with staying out of the market.

The data from the experiment provides support to the validity of using global games as an equilibrium selection mechanism. At the aggregate level, choices are in line with the comparative static predictions of the model. The rate at which subjects choose to enter is monotonically increasing in the signal value and is decreasing in the cost of entry. At the individual level, a majority (67%) of the subject population adopts threshold strategies for each type. Even though the estimated thresholds depart from the point predictions of the model, the comparative static predictions still hold in that the estimated thresholds follow the ordering induced by the agents' costs. More importantly, we find that a majority of outcomes in the complete information game correspond to the equilibrium selected by the global games theory. This is more apparent in regions where the game predicts multiple Nash equilibria where we find only a handful (at most 8.3%) of the outcomes in line with these other equilibria. In particular, the global games equilibrium amounts to 87.5% to 99% of observations that correspond to one of the pure strategy equilibrium in these regions of multiplicity.

We focus on market entry games with strategic substitutes for a couple of reasons. First, as mentioned above, there is considerable experimental work that looks at behavior in global games with strategic complements but none with strategic substitutes. The case of strategic substitutes is not a straightforward extension of strategic complements. There are certain theoretical distinctions when comparing the global games approach for the two settings. With respect to strategic substitutes, the global games approach requires asymmetry in payoffs in order to recover a unique equilibrium. This requirement is not needed for games with strategic complements, and indeed, the experimental literature focuses primarily on settings where payoffs are symmetric.[4] More importantly, the process of recovering a unique equilibrium is also different. In games with strategic complements, uniqueness is obtained through iterated elimination of dominated strategies. In general, however, iterated dominance can fail to select a unique outcome when actions are strategic substitutes.[5] In these settings, the unique equilibrium is obtained through an iterative process which eliminates strategy profiles that are never part of any equilibrium even if they are not dominated. These two distinctions have behavioral implications which make it worthwhile to experimentally investigate the theory in the lab.

Second, the market entry game has been used extensively in empirical industrial organization. This setting has been used to investigate behavior in markets for automobiles (Bresnahan and Reiss, 1990), airlines (Berry, 1992; Ciliberto and Tamer, 2009), construction contractors (Bajari et al., 2010) and others.[6] The prevalence of multiple Nash equilibria in these games creates identification and mis-specification problems in empirical analysis. One way to get around these issues is to adopt an (oftentimes ad-hoc) equilibrium selection rule and estimate the model under the assumption that the selected equilibrium will be played (see, for example, Bjorn and Vuong, 1984 and Jia, 2008). The global games approach can be used as a theoretically founded equilibrium selection rule in such settings. Our paper seeks to provide an empirical basis for using global games as an equilibrium selection rule in applied work.

The rest of this paper is structured as follows. Section 2 presents the theoretical model and predictions. Section 3 presents the experimental design. Section 4 presents the results. Section 5 provides a discussion and our concluding remarks.

2 Model and Predictions

We consider a simultaneous move market entry game with three agents.[7] The game is parameterized by a state of the world θ, which is uniformly distributed over the interval $\Theta = [\underline{\theta}, \overline{\theta}]$. This θ can be interpreted as a parameter that captures the profitability of the market. Each agent i can choose to enter the market (denoted by action $a_i = 1$), or stay out of the market (denoted by action $a_i = 0$). The value of θ is common knowledge among all agents. The payoffs to each agent i are given as:

$$\pi_i(a_i, n, \theta) = \begin{cases} \theta - n\delta - c_i & \text{if } a_i = 1 \\ r & \text{if } a_i = 0 \end{cases}$$

[4] In a recent paper, Heinemann (2018) shows how the global games approach is a poor predictor of behavior in settings with strategic complements and asymmetric payoffs.

[5] See Harrison and Jara-Moroni (2021) for a discussion.

[6] Berry and Reiss (2007) provides a survey on empirical applications of entry games to field data.

[7] See Selten and Güth (1982) and Gary-Bobo (1990) for early theoretical work on market entry games.

where $n = \sum_{j \neq i} a_j \in \{0, 1, 2\}$ is the number of *opponents* that choose to enter, $\delta > 0$ is a penalty term that reduces an agent's payoff from entering if more agents choose to enter, $c_i > 0$ is an agent specific cost to entry, and $r > 0$ is an agent's reservation utility from choosing to stay out. Following the global games literature, denote $\Delta\pi_i(n, \theta) = \pi_i(1, n, \theta) - \pi_i(0, n, \theta) = \theta - n\delta - c_i - r$ to be the marginal benefit to agent i from choosing to enter relative to staying out, given that exactly n opponents choose to enter. Note that payoffs only differ in the cost of entry c_i.

There are a few points worth noting about the payoff structure of the game. First, actions are strategic substitutes. Given a value of the state θ, an increase in the number of opponents choosing to enter *decreases* the incentive to enter. Formally speaking, for each agent i and θ, if $n > n'$ then $\Delta\pi_i(n, \theta) - \Delta\pi_i(n', \theta) = (n' - n)\delta < 0$. Second, the marginal benefit of entry, $\Delta\pi_i(n, \theta)$, is continuous in θ, given n. Finally, given n, the incentive to enter is monotonically increasing in θ. Formally, for each agent i and n, if $\theta \geq \theta'$, then $\Delta\pi_i(n, \theta) - \Delta\pi_i(n, \theta') = \theta - \theta' \geq 0$.

Following convention in the global games literature we assume, for each agent i, the existence of "indifference points" $\{\theta_i^L, \theta_i^H\}$. These are values of the state that make each agent indifferent between entering and staying out when all other opponents are choosing the same action. Formally, θ_i^L, the unique solution to $\Delta\pi_i(0, \theta_i^L) = 0$, is the point which makes agent i indifferent between entering and staying out conditioning on all other agents staying out. Conversely, θ_i^H, the unique solution to $\Delta\pi_i(2, \theta_i^H) = 0$, is the point which makes agent i indifferent when all other agents choose to enter. To guarantee existence of these indifference points, we assume that $\underline{\theta} < \min_i\{\theta_i^L\}$ and $\overline{\theta} > \max_i\{\theta_i^H\}$. This assumption then establishes the existence of dominance regions. For each agent i, staying out is strictly dominant for $\theta < \theta_i^L$ and entering is strictly dominant for $\theta > \theta_i^H$.

Furthermore, given continuity, monotonicity and strategic substitutability, for each agent there exists a value θ_i^M that makes the agent indifferent between entering or staying out when exactly one opponent chooses to enter. This means that θ_i^M uniquely solves $\Delta\pi_i(1, \theta_i^M) = 0$. The payoff structure characterizes the indifference points as follows:

$$\begin{aligned}
\theta_i^L &= c_i + r \\
\theta_i^M &= c_i + \delta + r \\
\theta_i^H &= c_i + 2\delta + r
\end{aligned}$$

Note that the indifference points are monotonically increasing i.e. $\theta_i^L < \theta_i^M < \theta_i^H$ for all agents i.

Finally, we assume that payoffs are asymmetric across agents i.e. $0 < c_1 < c_2 < c_3$. This payoff asymmetry induces an ordering of agents based on their incentive to enter. More specifically, $\Delta\pi_1(n, \theta) >$

$\Delta\pi_2(n,\theta) > \Delta\pi_3(n,\theta)$ for all n and all θ. Thus for any given θ and n, agent 1 has the highest incentive to enter and agent 3 has the lowest incentive to enter. This implies that the indifference points above also follow an order. For any $k \in \{L, M, H\}$, $\theta_1^k < \theta_2^k < \theta_3^k$. We also assume $c_3 - c_1 < \delta$ which implies that $\theta_3^L < \theta_1^M$ and $\theta_3^M < \theta_1^H$.

Our focus is on pure strategy equilibria where a strategy for agent i, denoted $s_i : \Theta \to \{0,1\}$, maps the state to an action. Denote a strategy profile to be a tuple $s(\theta) = (s_1(\theta), s_2(\theta), s_3(\theta))$. Figure 1 traces out choices and equilibrium predictions of the game, conditional on the value of the state θ.

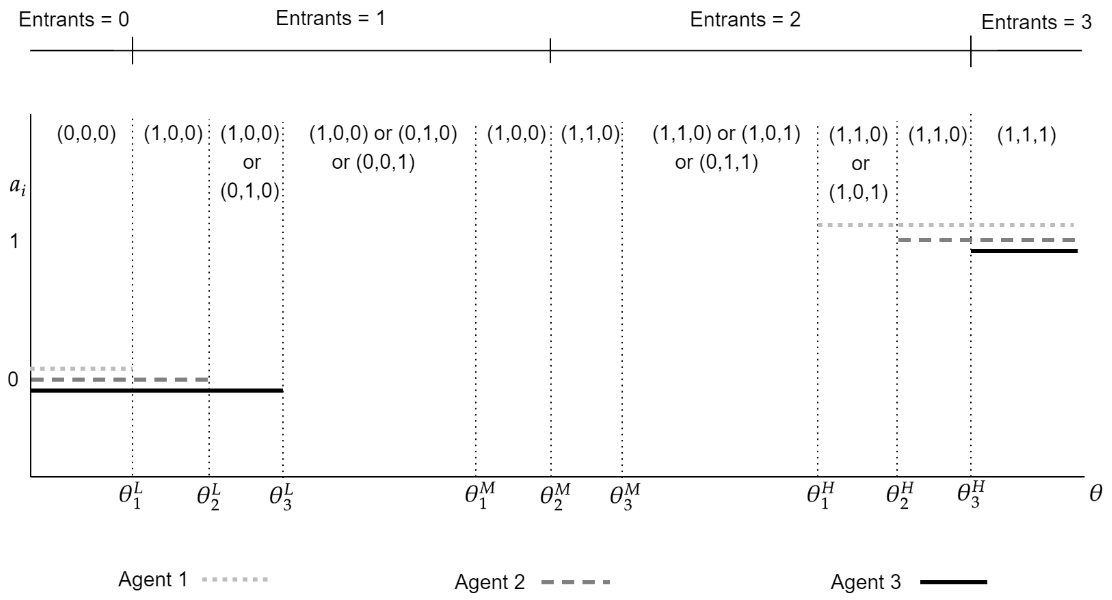


Figure 1: Equilibrium Prediction in Complete Information

Note first that the asymmetry in payoffs results in dominance regions that overlap across agents. As a consequence, for extreme values of θ, the game predicts a unique Nash equilibrium. These unique equilibria are obtained through iterated elimination of dominated strategies. For low values of θ (i.e. $\theta < \theta_2^L$), staying out is strictly dominant for at least agents 2 and 3 and the unique equilibrium has agent 1 choosing to either stay out or enter, depending on the (iterated) dominant strategy. Conversely, for high values of θ (i.e. $\theta > \theta_2^H$), entering is strictly dominant for at least agents 1 and 2 and the unique equilibrium has agent 3 choosing to either stay out or enter, depending on the (iterated) dominant strategy.

There are also regions in the middle where the game predicts a unique equilibrium. For $\theta_1^M < \theta < \theta_2^M$, there is one unique Nash equilibrium in which only agent 1 chooses to enter and agents 2 and 3 choose to stay out. For $\theta_2^M < \theta < \theta_3^M$, there is one unique Nash equilibrium in which agents 1 and 2 choose to enter and agent 3 chooses to stay out. Intuitively, this uniqueness stems from the fact that in these regions, the value of θ is high enough that for agent 1 (and at most agent 2), entering still yields a higher payoff than staying out even if one other agent enters. Unlike other regions with a unique prediction, however, this uniqueness is not obtained through iterated elimination of dominated strategies. In fact, both strategies are rationalizable for all agents in these regions since, for all agents, choosing to enter is a best response to no opponents entering and choosing to stay out is a best response to all opponents entering.

Figure 1 also shows that, for intermediate values of the state, the game predicts multiple Nash equilibria. For $\theta_2^L < \theta < \theta_1^M$, the game predicts multiple Nash equilibria in which exactly one agent chooses to enter and the remaining agents choose to stay out. For $\theta_3^M < \theta < \theta_2^H$, the game predicts multiple Nash equilibria in which exactly 2 agents choose to enter and the remaining agent chooses to stay out. Put in other words, for any value of θ in the regions of multiplicity, all equilibria agree with the number of agents that choose to enter, but are agnostic about the types of agents that choose to enter. Another point of note is that each region of multiplicity is sandwiched between regions where the game predicts a unique equilibrium. This unique equilibrium is the same in these surrounding regions and it is also one of the pure strategy Nash equilibrium in the region of multiplicity.[8]

We are interested in equilibrium selection in the regions of multiplicity. Harrison and Jara-Moroni (2021) show that we can use the global games approach as an equilibrium selection mechanism for this market entry game with strategic substitutes. The global games approach works on the principle that one can recover a unique equilibrium prediction in a similar game where, instead of observing the true value of the state, each agent observes a noisy signal about the state. In the equilibrium for this game with *incomplete* information, agents adopt threshold strategies in which they choose to enter if the value of their private signal exceeds some threshold, and choose stay out if the signal is below their threshold. This equilibrium persists in the limit when noise vanishes, resulting in a unique equilibrium being selected in the original *complete* information game without noise. This is formalized below.

2.1 The Global Game and Equilibrium Selection

Consider the incomplete information (global) game where, instead of observing the value of θ, each agent observes a private signal $\theta_i = \theta + \sigma\varepsilon_i$ where ε is an i.i.d random variable drawn from a uniform distribution over $[-0.5, 0.5]$ and $\sigma > 0$ is a scale parameter. Note that the signals θ_i lie in $\tilde{\Theta} \equiv [\underline{\theta} - 0.5\sigma, \overline{\theta} + 0.5\sigma]$. We again focus on pure strategies $s_i : \tilde{\Theta} \to \{0, 1\}$ where s_i prescribes, for each signal θ_i, a pure action. The following proposition shows that, for sufficiently small noise, there is a unique Bayes-Nash Equilibrium (BNE) of this game with incomplete information, in which agents follow threshold

[8]As an example, consider the region (θ_2^L, θ_1^M). The surrounding regions (θ_1^L, θ_2^L) and (θ_1^M, θ_2^M) both have a unique prediction (1,0,0) which is also one of the Nash equilibrium in (θ_2^L, θ_1^M).

strategies.

Proposition 1. *For $\sigma > 0$ sufficiently small, the unique BNE of the game with incomplete information s^σ takes the form:*

$$s_i^\sigma(\theta_i) = \begin{cases} 0 \text{ if } \theta_i < \theta_i^\sigma \\ 1 \text{ if } \theta_i > \theta_i^\sigma \end{cases}$$

where $\theta_1^\sigma = \theta_1^L \equiv c_1 + r$, $\theta_2^\sigma = \theta_2^M \equiv c_2 + r + \delta$ and $\theta_3^\sigma = \theta_3^H \equiv c_3 + r + 2\delta$.

Proof. It is easy to see that the model satisfies assumptions of *strategic substitutability, continuity, monotonicity, indifference points* and *payoff asymmetry* (Assumptions A1–A5) of Harrison and Jara-Moroni (2021). Let $\sigma < \overline{\sigma}$ where $\overline{\sigma} = \frac{1}{2}\left(\min\{c_2 - c_1, c_3 - c_2\} - \alpha\right)$ for $\alpha > 0$ small.[9] Denote

$$\Delta\overline{\Pi}_i(n, \theta_i) = \int_{\theta_i - 0.5\sigma}^{\theta_i + 0.5\sigma} \Delta\pi_i(n, \theta) dP_{\sigma,i}(\theta|\theta_i) = \int_{\theta_i - 0.5\sigma}^{\theta_i + 0.5\sigma} (\theta - n\delta - c_i - r) dP_{\sigma,i}(\theta|\theta_i)$$

to be the *expected* marginal gain to agent i from choosing to enter, conditioning on them observing signal θ_i *and* exactly n opponents choosing to enter. Define the strategy s^σ as follows: for each agent i,

$$s_i^\sigma(\theta_i) = \begin{cases} 0 \text{ if } \theta_i < \theta_i^\sigma \\ 1 \text{ if } \theta_i > \theta_i^\sigma \end{cases}$$

where θ_i^σ is the signal that makes agent i indifferent between entering and staying out, given that $i - 1$ agents choose to enter. Thus, θ_i^σ is the unique solution to $\Delta\overline{\Pi}_i(i-1, \theta_i) = 0$. Note that, since ε_i and θ are uniformly distributed, for each agent i, the posterior distribution of $\theta|\theta_i$ is uniformly distributed over $[\theta_i - 0.5\sigma, \theta_i + 0.5\sigma]$.[10] Then for each agent i, $dP_{\sigma,i}(\theta|\theta_i) = \frac{1}{\sigma} d\theta$ and θ_i^σ solves

$$\frac{1}{\sigma}\int_{\theta_1^\sigma - 0.5\sigma}^{\theta_1^\sigma + 0.5\sigma} (\theta - c_1 - r) d\theta = 0$$
$$\frac{1}{\sigma}\int_{\theta_2^\sigma - 0.5\sigma}^{\theta_2^\sigma + 0.5\sigma} (\theta - c_2 - \delta - r) d\theta = 0$$
$$\frac{1}{\sigma}\int_{\theta_3^\sigma - 0.5\sigma}^{\theta_3^\sigma + 0.5\sigma} (\theta - c_3 - 2\delta - r) d\theta = 0$$

[9] This is a direct application of Lemma 2 (specifically Equation A1) and the upper bound for the noise threshold for Proposition 1 in Harrison and Jara-Moroni (2021). In particular, we need $\alpha < \min_{j>i}\{c_j - c_i\}$.

[10] We assume that the cutoffs $\theta_i^\sigma \in (\underline{\theta} + 0.5\sigma, \overline{\theta} - 0.5\sigma)$ for all i. This holds true, so long as $\underline{\theta} < c_1 + r - 0.5\sigma$ and $\overline{\theta} > c_3 + r + 2\delta + 0.5\sigma$.

and therefore:

$$\theta_1^\sigma = c_1 + r;$$
$$\theta_2^\sigma = c_2 + r + \delta;$$
$$\theta_3^\sigma = c_3 + r + 2\delta;$$

An application of Lemma 3 in Harrison and Jara-Moroni (2021) shows that s^σ is a Bayes-Nash equilibrium of the game with incomplete information. Uniqueness follows from the application of Proposition 1 in the same paper. ■

Note that the thresholds are independent of the noise parameter σ. This is a consequence of the distributional assumptions of the game and the fact that the payoffs are linear in the state θ.[11]

It is worth mentioning that this unique equilibrium is obtained through an iterative process where, at each stage, strategies that are never part of any equilibrium profile are eliminated. This iterative process "extends" the regions where agents choose only one action.[12] This process is markedly different compared to iterated elimination of (strictly) dominated strategies, the latter of which has been used to recover a unique equilibrium in games where actions are strategic complements. In general, games with strategic substitutes may not be dominance solvable (see section 5 of Harrison and Jara-Moroni, 2021). Even though the market entry game is not guaranteed to be dominance solvable, the equilibrium is, nevertheless, unique.[13]

We now turn towards equilibrium selection in the original complete information game without noise. Proposition 2 below establishes the *limit uniqueness* result that characterizes the equilibrium selected in the game with complete information.

Proposition 2. *As $\sigma \longrightarrow 0$, the unique equilibrium involves threshold strategies of the following form:*

$$s_i^*(\theta_i) = \begin{cases} 0 \text{ if } \theta_i < \theta_i^* \\ 1 \text{ if } \theta_i > \theta_i^* \end{cases}$$

where $\theta_1^* = c_1 + r$, $\theta_2^* = c_2 + r + \delta$ and $\theta_3^* = c_3 + r + 2\delta$.

[11]The result of Harrison and Jara-Moroni (2021) is more general and does not require any distributional assumptions, so long as the supports of θ and ε are bounded and the distributions are continuous. For any given distributional assumptions:

$$\theta_1^\sigma \in [\theta_1^L - 0.5\sigma, \theta_1^L + 0.5\sigma]$$
$$\theta_2^\sigma \in [\theta_2^M - 0.5\sigma, \theta_2^M + 0.5\sigma]$$
$$\theta_3^\sigma \in [\theta_3^H - 0.5\sigma, \theta_3^H + 0.5\sigma]$$

[12]For details, see the proof of Proposition 1 in Harrison and Jara-Moroni (2021).

[13]There are instances in which the market entry game is dominance solvable. See Appendix A for a discussion.

Proof. This is a direct application of Theorem 1 in Harrison and Jara-Moroni (2021). ■

Proposition 2 characterizes, for each θ, the equilibrium that is selected in the game with complete information. For each θ, there exists some agent $j \in \{1, 2, 3\}$ such that agents $i < j$ choose to enter and agents $k \geq j$ choose to stay out. This characterization is illustrated in Figure 2. Only agent 1 chooses to enter in the region $\theta_1^L < \theta < \theta_2^M$ and only agents 1 and 2 choose to enter in the region $\theta_2^M < \theta < \theta_3^H$. In particular, the equilibrium selected in the region (θ_2^L, θ_1^M) is (1,0,0), where only agent 1 enters and the equilibrium selected in the region (θ_3^M, θ_2^H) is (1,1,0) where both agents 1 and 2 enter. Note that there is a natural interpretation for the selected equilibrium: given some value of θ, only the most efficient agents, i.e. the ones with the lowest cost of entry and thus the highest incentive to enter, choose to enter the market.

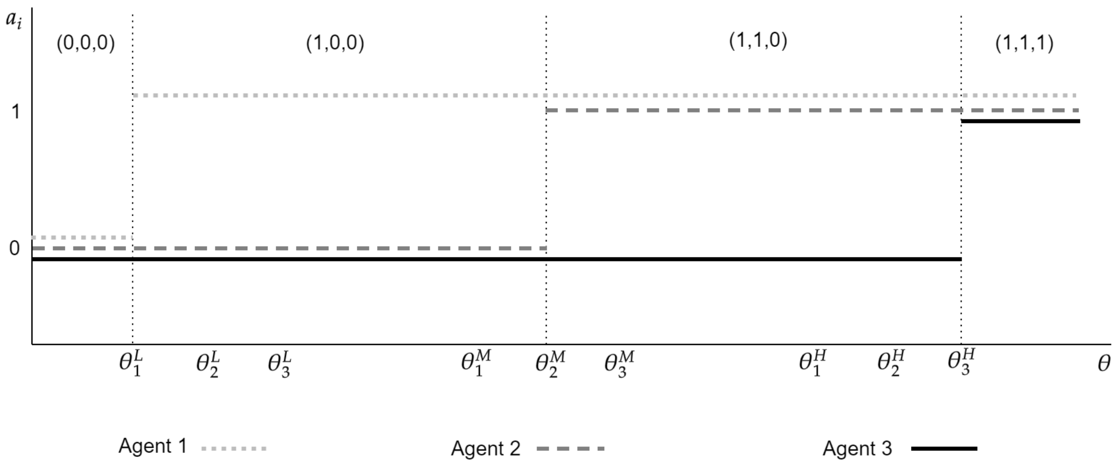


Figure 2: Equilibrium Selection

There are a few key points to note. First, agents follow threshold strategies in equilibrium for both the complete and incomplete information games. Furthermore, these threshold strategies are identical for both games. This is driven by the fact that the thresholds are independent of noise in the incomplete information game. Second, the theoretical thresholds follow the same ordering as the agents, i.e. $\theta_1^* < \theta_2^* < \theta_3^*$. These thresholds are precisely the indifference points for each agent. Agent 1's threshold is the value that makes them indifferent between entering and staying out when no other opponent enters. Agent 2's threshold is the value that makes them indifferent between entering and staying out when exactly one other opponent enters. Finally, agent 3's threshold is the value that makes them indifferent between entering and staying out when both agents 1 and 2 choose to enter.

3 Experimental Design and Hypotheses

The experimental design is driven by two main sets of comparative statics implied by the results in Section 2. The first set compares behavior in settings when θ is common knowledge (the complete information game) and when θ is observed with a small amount of noise (the incomplete information game). Proposition 1 suggests that agents should adopt threshold strategies in the incomplete information game and Proposition 2 suggests that this behavior should persist (and is identical) in the complete information game. This behavior then characterizes the selected equilibrium in the complete information game. The second set of comparative statics lies in comparing behavior across different types. The theory shows that agent thresholds are ordered by their costs, meaning that agents with low costs have lower thresholds for entering. This payoff asymmetry is a key assumption in characterizing the unique equilibrium since only the agents with the higher incentive to enter (lower costs) choose to enter the market.

3.1 Experimental Design

The experiment consists of two treatments: a complete information treatment and an incomplete information treatment. The treatment is fixed for all subjects in a given experimental session. Each session consists of 75 independent and identical rounds in which subjects take part in either the complete information market entry game or the incomplete information market entry game outlined in Section 2. The parameter values used for the experiment are given in Table 1.

Parameter	$\underline{\theta}$	$\overline{\theta}$	δ	r	c_1	c_2	c_3	σ
Value	100	350	75	100	25	50	75	10 (Incomplete Information)

Table 1: Parameters

At the beginning of each round, subjects are first randomly re-assigned into groups of 3.[14] Following the random re-matching, the computer then randomly generates a value of θ from a uniform distribution over the interval [100, 350] with values being reported up to 2 decimal places. Subjects are then shown a signal about θ. In the complete information treatment, the signal is in fact the true value of θ. In the incomplete information treatment, the signal is a noisy private signal generated as $\theta_i = \theta + \sigma\varepsilon_i$ where ε_i is (independently) uniformly distributed over [-0.5,0.5] and $\sigma = 10$. In other words, subjects receive a private signal $\theta_i \in [\theta - 5, \theta + 5]$ in the incomplete information treatment. We set $\sigma = 10$ to satisfy the condition for uniqueness given in Proposition 1.

[14]The random matching protocol was chosen to minimize the possibility of repeated play behavior usually seen in experiments with fixed matching and a large number of periods.

For implementation purposes, the sequences of θ were generated ex-ante. There were 2 reasons for this. First, the large range of the state space meant that there was always the possibility of a randomly generated sequence having significantly large gaps which could result in imprecise estimation of the threshold strategies. Second, we wanted to mitigate any differences across treatments that could be attributed to wildly differing state draws. For these reasons, we generated several entire sequences of 75 state values prior to each session. Care was taken to ensure that, within a sequence, the values of θ were generated independently of other values within the same sequence. We then selected the sequences which had few gaps and had a couple of state values each in the intervals (120, 130), (220, 230) and (320, 330) in the last 60 rounds. The sequence of state draws was fixed for all subjects in a given session. These sequences were then matched across treatments, meaning that a session with complete information had a corresponding session with incomplete information that used the same sequence of state draws.

After observing the value of their signal, each subject in a group then takes part in *three* simultaneous market entry games. For purposes of the experiment, the games are presented in neutral language without any context. Specifically, for each game, subjects are asked to choose between 2 options. Option A coincides with the action to enter the market (action 1 in the model) and Option B coincides with the action to stay out of the market (action 0 in the model). Subjects earn points in each game. Table 2 shows the payoff structure for each game that is shown to the subjects. Subjects are told that the payoff from choosing option A depends on the value of the state, the number of people in their group who also choose A and that "each additional group member choosing A reduces your payoff by 75 points if you choose A." Option B always gives a payoff of 100 points.

		Number of Players Choosing A		
		1	2	3
Your Choice	A	$\theta - c_i$	$\theta - c_i - 75$	$\theta - c_i - 150$
	B	100		
Player 2's Choice	A	$\theta - c_j$	$\theta - c_j - 75$	$\theta - c_j - 150$
	B	100		
Player 3's Choice	A	$\theta - c_k$	$\theta - c_k - 75$	$\theta - c_k - 150$
	B	100		

Table 2: Payoff Structure in the Experiment

Subjects take part in 3 games, one for each cost type (25, 50, 75) and in each game play against the remaining two cost types. They make their decisions for all 3 games on the same screen. This design choice was implemented to allow for a within-subjects comparison of choices across different cost types. Once all subjects in the group have made their decisions, the round ends and they receive feedback on

1) the value of θ and their signal,

2) their decisions for each game,

3) the number of players choosing A for each game, and[15]

4) their payoffs for the round.

At the end of the experiment, subjects are paid for the outcome of all 3 games in one randomly selected round at the rate of 25 points to $1.

3.2 Hypotheses

This section outlines the main hypotheses. Table 3 shows the indifference points implied by the parameter values used for the experiment. Mapping these points to the theory shows that the game with complete information yields multiple equilibrium predictions for $150 < \theta < 200$ and for $250 < \theta < 300$ which amounts to 40% of the state space. Propositions 1 and 2 suggest that, under the global games

c_i	θ_i^L	θ_i^M	θ_i^H	θ_i^*
25	125	200	275	125
50	150	225	300	225
75	175	250	325	325

Table 3: Indifference Points and Equilibrium Thresholds

prediction, subjects should follow threshold strategies in both treatments. Furthermore, these thresholds should be identical across treatments since they are independent of the degree of noise σ. The corresponding thresholds are shown in the last column of Table 3. These thresholds characterize the unique equilibrium that is selected for each θ in the complete information treatment, which are shown in Table 4.

The first set of hypotheses deals with aggregate behavior which leverage the comparative statics of the game. The payoff structure is such that the incentive to enter (option A) is monotonically increasing in the state θ. Furthermore, for fixed θ and n, the incentive to enter is decreasing in the cost c_i. As such, aggregate behavior should follow these monotone comparative statics.

[15]Note that, for each subject, there were two possible ways to assign group members to Players 2 and 3. This results in 6 possible combinations per round. For feedback and payment purposes, we randomly selected one possible assignment for each subject and selected the appropriate decisions for that assignment. The assignments were selected to ensure consistency of payoffs across all subjects within a group.

Range of θ	Equilibrium
$100 < \theta < 125$	(0,0,0)
$125 < \theta < 225$	(1,0,0)
$225 < \theta < 325$	(1,1,0)
$325 < \theta < 350$	(1,1,1)

Table 4: Equilibrium selected under Global Games

Hypothesis 1 (Aggregate behavior)**.** *Entry increases with the signal and decreases with entry costs*

The second set of hypotheses deals with individual subject behavior. The theory provides sharp point predictions about the strategies undertaken by subjects under both treatments. As such, subjects should follow some kind of threshold strategy with these thresholds increasing in c_i.

Hypothesis 2 (Individual behavior)**.** *Subjects adopt threshold strategies in line with theoretical predictions.*

The last set of hypotheses compares behavior in both complete and incomplete information treatments. The theoretical predictions show that agents follow threshold strategies in both treatments and that these thresholds are identical in both treatments. As such, behavior should be very similar, if not identical, across both treatments.

Hypothesis 3 (Complete and Incomplete Information)**.** *Behavior is similar across complete and incomplete information treatments*

3.3 Procedures

Sessions were conducted at the Ohio State Experimental Economics Laboratory in the months of January through March of 2022. Subjects were predominantly students at the Ohio State University and were recruited using the online recruitment system ORSEE (Greiner, 2015). Subjects were provided with paper copies of the instructions which are reproduced in Appendix B. Instructions were read out loud at the beginning of the experimental session and subjects were allowed to ask clarifying questions.[16] Instructions were also programmed into the software, so after the oral description, subjects were able to read the instructions again at their own pace prior to starting the first round. Subjects were paid for the outcome of one randomly determined round at the end of the session. Earnings averaged around $19.90, including a $5 show-up fee, for sessions lasting around 1 hour and 30 minutes. The experiment was programmed using oTree (Chen et al., 2016).

[16] At the end of the experiment, subjects were asked to indicate if they were able to understand the structure of the experiment. All but three subjects responded in the affirmative.

3.4 Data Description

We conducted 3 sessions for each treatment. Each session had either 12 or 15 participants. A total of 42 subjects participated in the complete information treatment and 45 subjects participated in the incomplete information treatment. No subject participated in more than one session. The analysis is restricted to behavior after 15 rounds of play. This is to ensure that subjects had gained enough experience with the experiment and were able to make consistent choices. In a post experiment survey, we asked subjects if there were any sources of confusion for them in understanding the experiment. Several subjects responded that they were better able to understand the experiment after a few rounds of play.

4 Results

We first provide a brief overview of the results in relation to the hypotheses outlined in Section 3.2. To summarize the key findings:

1. Aggregate behavior follows the comparative static predictions of the model. The rate of entry increases with the signal value and decreases with the costs.

2. A majority of the outcomes in the complete information treatment correspond to the global games prediction.

3. Around 67% of the subject population follows some form of a threshold strategy. The estimated thresholds for these subjects are significantly different from the theoretical predictions for $c = 25$ and $c = 75$.

4. There is a significant difference in behavior across treatments. For $c = 25$, the rate at which subjects choose to enter is higher (for low signals) under complete information. Complementing this, the estimated thresholds for $c = 25$ are *lower* in the complete information treatment.

The following subsections provide more detailed results. In what follows, the term signal is used to indicate the value of the state θ in the complete information treatment, and the value of the noisy private signal in the incomplete information treatment.

4.1 Aggregate Behavior

This section focuses on Hypothesis 1 which looks at aggregate behavior. Recall that, under hypothesis 1, subjects are expected to enter at a higher rate as they observe a higher signal. Furthermore, the rate of entry should decline (conditioning on the observed signal) as the cost c_i increases. Figure 3 shows, for all cost types c_i, the rate, along with standard error bars, at which subjects choose to enter (option A) across realized values of the signal in both treatments. The dashed lines represent the theoretical thresholds for each cost type. The findings are similar across both treatments.

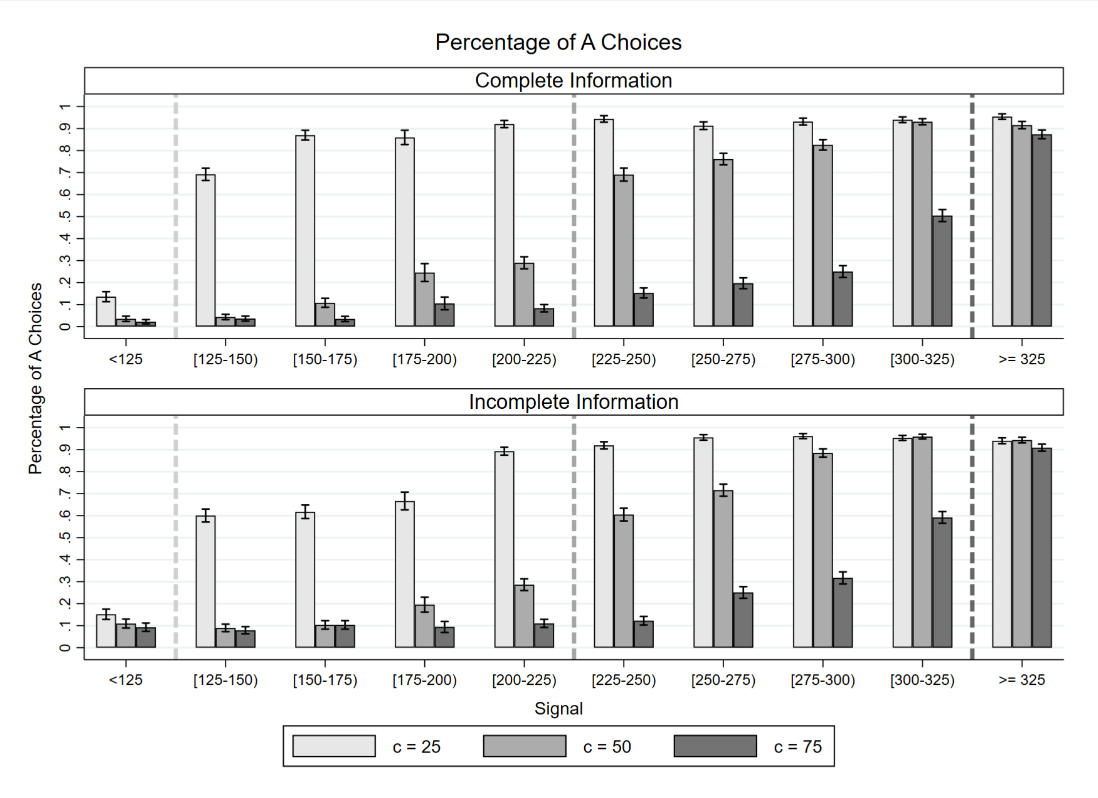


Figure 3: Entry Rates

Firstly, behavior is close to the predictions in the dominance regions. Consider first $c = 25$. In the region where entering is *dominated* (signals below 125), subjects choose to enter 13.6% of the time under complete information and 15.2% under incomplete information. Conversely, in the region where entering is *dominant* (signals above 275), this proportion increases to 94.2% and 95.1% under complete and incomplete information respectively. For $c = 50$, subjects choose to enter 4% and 9.9% of the time under complete and incomplete information respectively when it is the dominated strategy (signals below 150). This proportion jumps up to 92.4% under complete information and 95.1% under incomplete information when entering is dominant (signals above 300). Finally, for $c = 75$, enter is chosen 3.1% and 9.1% of the time when it is dominated (signals below 175) compared to 87.4% and 90.9% when it is dominant (signals above 325) under complete and incomplete information respectively.

The rate of entry is also (weakly) increasing in the signal value for all cost types under both treatments. Results from logistic regressions of choice on the signal show that the signal has a positive and significant effect on the probability of entering for all cost types and treatments ($p < 0.01$ for all regressions with bootstrapped standard errors clustered at the session level).

Furthermore, there are jumps in the entry rates around the theoretical thresholds. Recall that the theoretical thresholds are 125, 225 and 325 for $c = 25$, $c = 50$ and $c = 75$ respectively. For $c = 25$, subjects choose to enter around 13.6% (15.2%) of the time for signals below 125 and 69.2% (60.1%) of the time for signals between 125 and 150 under the complete (incomplete) information treatment. For $c = 50$, subjects choose to enter around 29% of the time for signals between 200 and 225 and around 69.1% (60.5%) of the time for signals between 225 and 250 under the complete (incomplete) information treatment. Finally, for $c = 75$, subjects choose to enter 50.5% (59.2%) of the time for signals between 300 and 325 and 87.4% (90.9%) of the time for signals above 325 under the complete (incomplete) information treatment. To quantify this effect, Table 5 shows results from logistic regressions of choosing to enter on the signal value and a dummy variable indicating whether the signal is above the theoretical threshold. The effect of the signal being above the threshold is positive and significant in all but one case. The effect is positive but insignificant ($p = 0.15$) for $c = 50$ in the incomplete information treatment.

	Complete Info			Incomplete Info		
	$c = 25$	$c = 50$	$c = 75$	$c = 25$	$c = 50$	$c = 75$
Signal	0.04**	0.02	0.05***	0.04***	0.04***	0.06***
	(0.019)	(0.022)	(0.010)	(0.013)	(0.006)	(0.015)
Above Threshold	1.76***	1.25***	0.79***	1.25***	0.46	0.56***
	(0.272)	(0.189)	(0.218)	(0.443)	(0.320)	(0.154)
Constant	-6.32***	-5.44	-16.61***	-6.19***	-9.56***	-19.44***
	(2.140)	(5.047)	(3.372)	(1.515)	(1.122)	(5.131)
Signal Range	≤ 150	[200, 250]	≥ 300	≤ 150	[200, 250]	≥ 300
Observations	504	525	618	515	576	662

Notes: Bootstrapped standard errors (in parentheses) with 500 replications clustered at the session level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Logistic Regressions for the effect of signal being above threshold

Lastly, for signals outside of the overlapping dominance regions (i.e. signals between 175 and 275), the rate of entry follows a monotone ordering in c_i. Specifically, conditioning on the value of the signal, the rate of entry for $c = 25$ is higher than that for $c = 50$ which is higher than that for $c = 75$. These results are supported by a logistic regression of choosing to enter on signals and cost dummies shown in Table 6.

In contrast, for signals in the lower dominance regions (less than 150), the entry rate is similar for

	Complete Info	Incomplete Info
Signal	0.02***	0.03***
	(0.004)	(0.005)
$1\{c = 50\}$	-2.41***	-2.36***
	(0.479)	(0.645)
$1\{c = 75\}$	-4.52***	-4.21***
	(0.788)	(1.090)
Constant	-3.00***	-4.58***
	(0.441)	(0.690)
Observations	2709	2955

Notes: Bootstrapped standard errors (in parentheses) with 500 replications clustered at the session level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Coefficients for $c = 50$ and $c = 75$ are significantly different $p < 0.01$. Signals between 175 and 275.

Table 6: Logistic Regression for the effect of cost on choice

$c = 50$ and $c = 75$ and for signals in the upper dominance regions (above 300), the entry rate is similar for $c = 25$ and $c = 50$. These results are summarized below.

Result 1. *Aggregate behavior follows the predicted comparative statics. The rate of entry is close to the predictions in the dominance regions, is (weakly) increasing in the value of the signal and (weakly) decreasing in the cost c_i. In almost all cases, the rate of entry jumps up around the predicted threshold values.*

4.1.1 On Equilibrium Selection

The global games theory predicts that agents should follow threshold strategies which characterize, for each value of the state θ, the unique equilibrium that is selected in the game with complete information. This subsection looks at the degree to which behavior is in line with the equilibrium selected by the global games prediction in the complete information treatment.

Table 7 shows the percentage of outcomes corresponding to the equilibrium selected by the global games theory, outcomes corresponding to other pure strategy equilibria (when applicable) and outcomes that do not correspond to any pure strategy equilibria.[17] A majority of the outcomes correspond to the global games equilibrium prediction. In regions where the game predicts a unique Nash equilibrium, the global games prediction coincides with the unique equilibrium. The percentage of outcomes corresponding to the unique equilibrium ranges from 42.9% to 81.1%. The percentage is highest in regions

[17] 1 corresponds to enter (A), 0 corresponds to staying out (B). Calculations are done over the outcomes used for feedback and payment purposes. See Appendix C for additional analysis on the number of entrants in the complete information treatment.

where all agents have a strictly dominant strategy ($\theta < 125$ and $\theta > 325$). For $300 < \theta < 325$, where the percentage is the lowest at 42.9%, around 44.1% of the observations correspond to the outcome (1,1,1) where all 3 agents choose to enter. This can be attributed to the fact that around 50% of the choices for $c = 75$ have subjects choosing to enter in this region.

Range of θ	Prediction		Outcomes		
	Global Games NE	Other NE	Global Games NE	Other NE	Non-Equilibrium
$100 < \theta < 125$	(0,0,0)	–	81.1%	–	18.9%
$125 < \theta < 150$	(1,0,0)	–	63.0%	–	37.0%
$150 < \theta < 175$	(1,0,0)	(0,1,0)	74.0%	0.9%	25.1%
$175 < \theta < 200$	(1,0,0)	(0,1,0) or (0,0,1)	57.9%	3.5%	38.6%
$200 < \theta < 225$	(1,0,0)	–	62.3%	–	37.7%
$225 < \theta < 250$	(1,1,0)	–	55.0%	–	45.0%
$250 < \theta < 275$	(1,1,0)	(1,0,1) or (0,1,1)	58.3%	8.3%	33.3%
$275 < \theta < 300$	(1,1,0)	(1,0,1)	57.6%	4.9%	37.5%
$300 < \theta < 325$	(1,1,0)	–	42.9%	–	57.1%
$325 < \theta < 350$	(1,1,1)	–	76.5%	–	23.5%

Table 7: Outcomes in Complete Information

More important is the comparison of the global games prediction to other pure strategy Nash equilibria in regions of multiplicity. These are regions where $150 < \theta < 200$ and $250 < \theta < 300$. The global games prediction corresponds to 57.6% to 74% of the outcomes whereas only a handful of outcomes (at most 8.3%) correspond to other pure strategy equilibrium. In other words, when restricting to observations that coincide with any pure strategy equilibrium, the global games prediction accounts for 87.5% to 99% of the realized outcomes.[18] Thus, the results provide some evidence suggesting that the global games theory is a valid equilibrium selection mechanism in regions with multiple equilibria.

Result 2. *A majority of outcomes in the complete information treatment are in line with the global games equilibrium prediction.*

4.2 Individual Behavior

This section focuses on Hypothesis 2 and looks at behavior at the individual subject level. Recall that Hypothesis 2 states that subjects should adopt threshold strategies. To determine if this is the case, we consider the following approach. We first, following the literature on global games, fit a logistic distribution to each individual subject's data. Specifically, for each subject and for each type, we conduct

[18] Computed as the ratio between global games outcomes and the sum of global games and other equilibrium outcomes.

a logistic regression of the subject's choice, either enter or stay out, on their observed signal. The CDF of the logistic distribution, for each subject i, can be expressed as

$$\Pr(Enter) = \frac{1}{1 + \exp(a_i + b_i \theta_i)}$$

where θ_i is the signal observed by the subject. The threshold is then "backed out" using the estimated parameters. The threshold is the signal for which the estimated probability of entry is 0.5 and can be calculated as $\hat{\theta}_i = -\frac{a_i}{b_i}$. For subjects following a clear threshold strategy (i.e. with a single switching point), their threshold is estimated as the average between the highest signal for which they choose to stay out and the lowest signal for which they choose to enter. We drop subjects who follow a constant strategy where they choose the same action for (almost) all signal realizations.

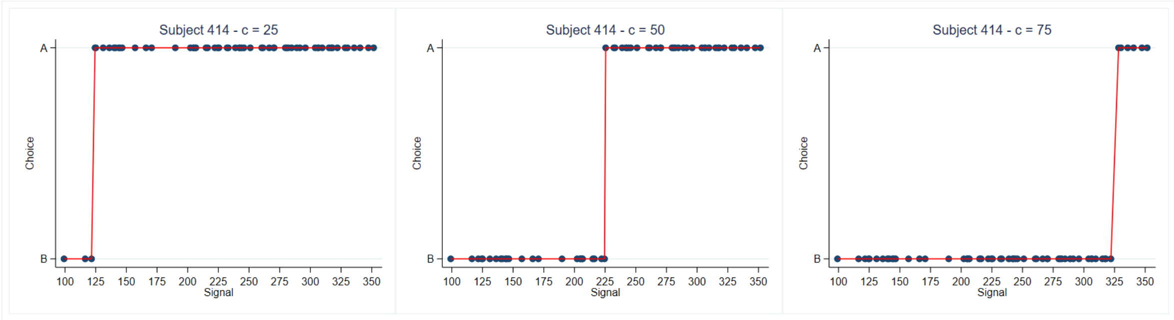
There is considerable heterogeneity in subject behavior. Very few subjects follow clear threshold strategies with a single switching point. However, there is some regularity in behavior across a majority of subjects that indicates that subjects follow a monotone strategy with some degree of noise. To capture this noise, we estimate the number of "mistakes" a subject makes in their choices. An observation is classified as a mistake if a subject chooses to enter and the signal is below their estimated threshold. Likewise, an observation is also considered a mistake if a subject chooses to stay out and the signal is above their estimated threshold.

We partition the subjects into four degrees of noise based on the number of mistakes. These categories are no noise, low noise, moderate noise and high noise. Under the *no noise* category, a subject follows a threshold strategy with no mistakes meaning they have a single switching point. Under *low noise* a subject follows a threshold strategy with at least 1 mistake and at most 5 mistakes. Under *moderate noise*, a subject follows a threshold strategy with at least 6 mistakes and at most 10 mistakes. Finally, under *high noise* a subject follows a threshold strategy with more than 10 mistakes. Subjects whose behavior is consistent with a random strategy are categorized as part of the high noise category. We do not consider subjects who follow a constant strategy.

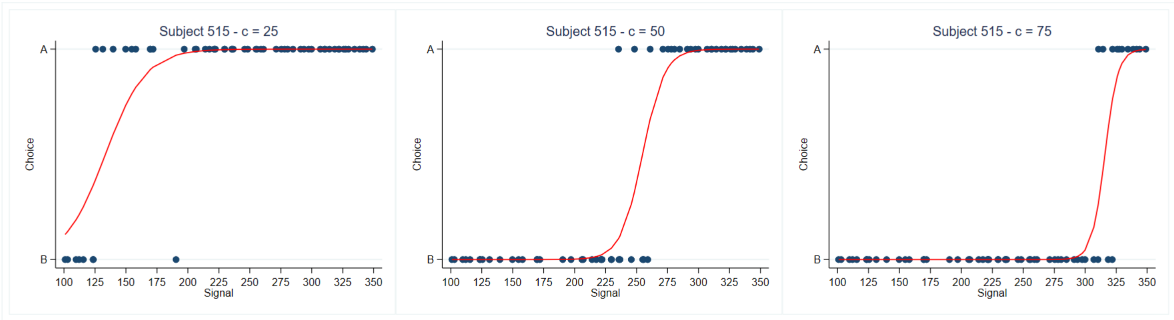
Figure 4 shows some examples of subject behavior. Panel (a) shows a subject whose behavior is in line with a threshold strategy with a single switching point and is thus categorized as no noise. Panel (b) shows a subject who follows a threshold strategy with 3 to 5 mistakes and is thus categorized as low noise. Panel (c) shows the behavior of a subject who follows a threshold strategy with 7 to 8 mistakes and is categorized as moderate noise. Panel (d) shows the behavior of a subject whose behavior is similar to that of an agent choosing uniformly over the options and is categorized as high noise.

Table 8 shows the percentage of subjects that fall into each category for each cost type.[19] Very few

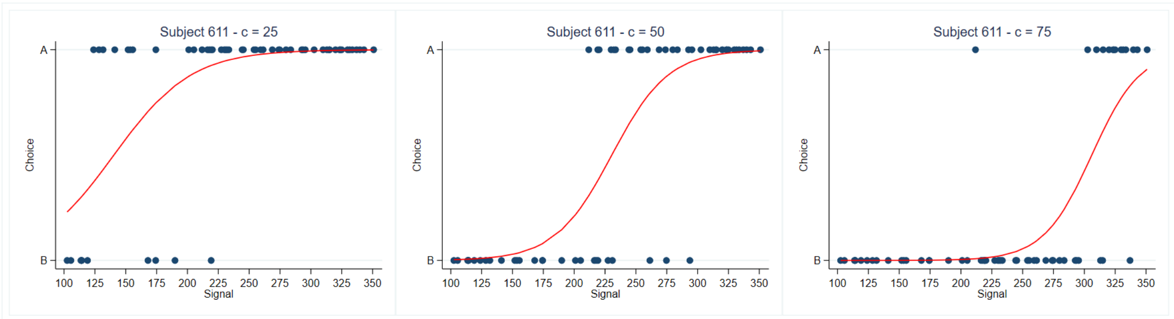
[19]Not included are the subjects who follow a constant strategy.



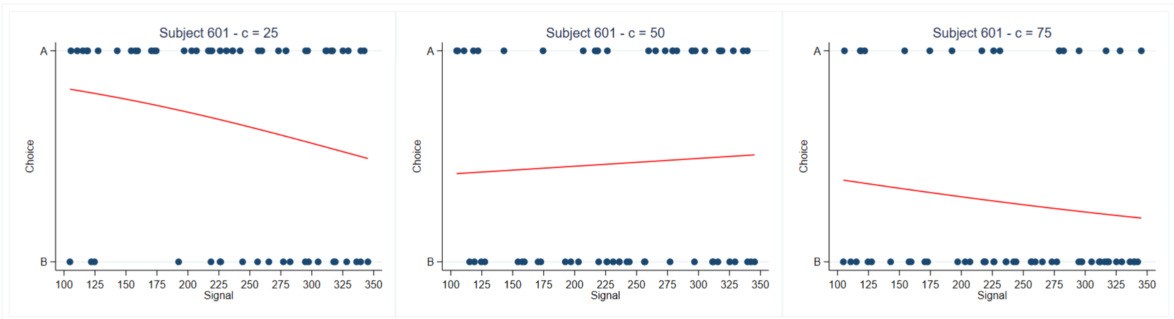
(a) No Noise



(b) Low Noise



(c) Moderate Noise



(d) High Noise

Figure 4: Examples of Subject Behavior and Estimated Logistic Distributions

subjects follow a clear threshold strategy with a single switching point (at most 25.3%). The modal classification of subjects is the low noise category (between 1 and 5 mistakes) which accounts for 36.8%, 39.1% and 44.8% of the population for cost types 25, 50 and 75 respectively.

Category	$c = 25$	$c = 50$	$c = 75$
No Noise	25.3%	10.3%	14.9%
Low Noise	36.8%	39.1%	44.8%
Moderate Noise	23.0%	28.7%	14.9%
High Noise	9.2%	16.1%	19.5%

Table 8: Categorization of Subjects into Noise Categories

We consider an individual subject to follow a threshold strategy if they make *at most* 10 mistakes for each cost type c_i.[20] In other words, a subject is considered to follow a threshold strategy if their behavior is categorized under no noise, low noise or moderate noise for each type. A total of 58 subjects (67%), 26 (62%) in the complete information treatment and 32 (71%) in the incomplete information treatment, satisfy this criteria.[21] This result is summarized below.

Result 3. *A majority (67%) of the subjects follow a threshold strategy with at most 10 mistakes for each cost type.*

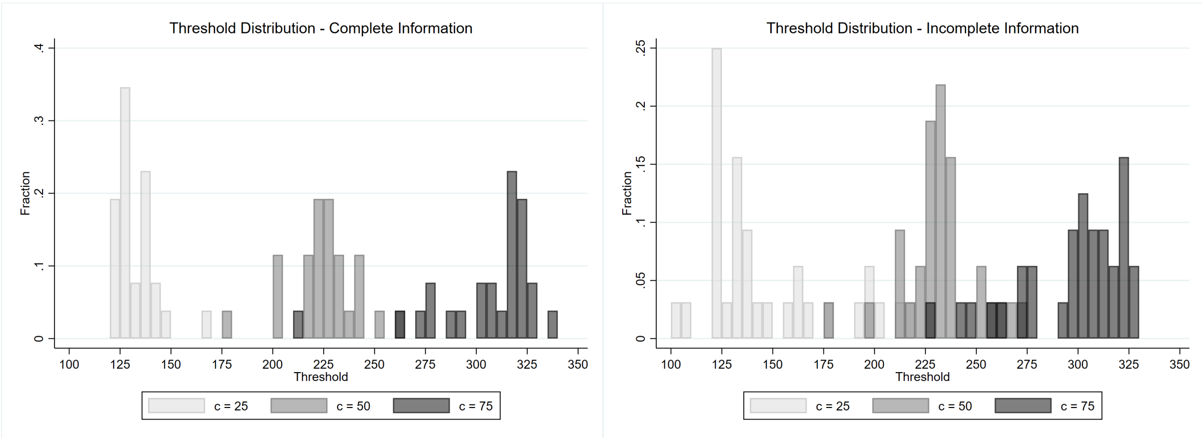
The remainder of this subsection focuses on only these 58 subjects. Figure 5 shows the distribution of estimated thresholds for each cost type under both complete and incomplete information treatments. There is a clear separation in the distribution of thresholds across types for the complete information treatment. For each type, the estimated thresholds are clustered close to each other. In contrast, there is a considerable degree of overlap in the threshold distributions under the incomplete information treatment. This is more evident when considering the distributions for $c = 50$ and $c = 75$.

Table 9 provides a quantitative comparison of the thresholds with respect to the theoretical predictions. The average estimated threshold for $c = 25$ is significantly higher than the theoretical prediction in both the complete and incomplete information treatments ($p < 0.01$ for complete information and $p < 0.05$ for incomplete information). In contrast, the average for $c = 75$ is significantly lower than the theoretical prediction ($p < 0.01$ for both). For $c = 50$, the average is not significantly different from the theoretical prediction for the complete information treatment. However, it is significantly higher than the theoretical prediction under the incomplete information treatment ($p < 0.01$).

It is also worth noting that the estimated thresholds are in line with the comparative static predictions for both treatments. The average estimated threshold for $c = 25$ is significantly lower than that for

[20] An alternative classification could be based on the total number of mistakes a subject makes across all types. Results under this alternative characterization are similar and discussed in Appendix D.

[21] The average number of total mistakes across these subjects is 10.44.



(a) Complete Information

(b) Incomplete Information

Figure 5: Distribution of Estimated Threshold

	c = 25	c = 50	c = 75
Prediction	125	225	325
Mean (Complete Info)	132.9***	225.9	304.4***
	(1.38)	(3.40)	(7.21)
Mean (Incomplete Info)	148.0**	231.8***	297.1***
	(11.0)	(1.42)	(8.89)

Predicted Difference	100	100
Difference (Complete Info)	93.0***	78.5***
	(2.36)	(5.41)
Difference (Incomplete Info)	83.8*	65.3***
	(9.70)	(10.3)

Notes: Mean values reported with bootstrapped standard errors in parentheses clustered at the session level. ***, ** and * indicate estimates are different from prediction at the 1%, 5% and 10% significance level respectively. Tests conducted using bootstrapped regressions with 500 replications and standard errors clustered at the session level.

Table 9: Threshold Estimates

$c = 50$, which again is significantly lower than that for $c = 75$. However, the average distance between the thresholds is significantly lower than the predicted value for both treatments. These results are summarized below

Result 4. *Estimated thresholds for subjects following a threshold strategy follow comparative static predictions. The average thresholds are significantly higher than predicted for* $c = 25$*, but lower for* $c = 75$ *in both treatments. The average threshold is significantly higher than predicted for* $c = 50$ *in the incomplete information treatment.*

4.3 Comparison between Complete and Incomplete Information

This section focuses on Hypothesis 3 and compares behavior between the complete and incomplete information treatments. Recall that under Hypothesis 3, behavior is expected to be similar, if not identical, across both treatments for all types. This is a consequence of the global games theory which predicts that subjects should follow identical threshold strategies in both treatments.

We first take a look at aggregate behavior. Figure 6 compares the rate at which subjects choose to enter between complete and incomplete information across all cost types. There are significant differences in behavior for low signal realizations and cost $c = 25$. For signals between 150 and 200, subjects in the complete information treatment choose to enter at a higher rate than subjects in the incomplete information treatment. Results from a logistic regression of choosing to enter on signal and treatment dummy show that this difference is significant ($p < 0.05$ with bootstrapped standard errors clustered at the session level). However, entry rates become statistically indistinguishable across both treatments for higher signal values.

For $c = 50$, subjects choose to enter at a higher rate in the incomplete information treatment for signals in the lower dominance region (below 150). Behavioral differences are qualitatively similar for $c = 75$ in the lower dominance region. Subjects choose to enter at a higher rate under the incomplete information treatment for signals below 175. However, these differences are not statistically significant ($p > 0.1$ from logistic regressions of choice on signal and treatment dummy with bootstrapped standard errors clustered at the session level).

Result 5. *For low signals, the entry rate is significantly higher under complete information for* $c = 25$*. In contrast, the entry rate is higher for low signals under incomplete information for* $c = 50$ *and* $c = 75$*, however this difference is not statistically significant.*

We now turn towards analyzing individual thresholds. Recall that 26 subjects in the complete information treatment and 32 subjects in the incomplete information treatment satisfy the criteria for a threshold strategy. Figure 7 compares the distributions of these estimated thresholds across all types.

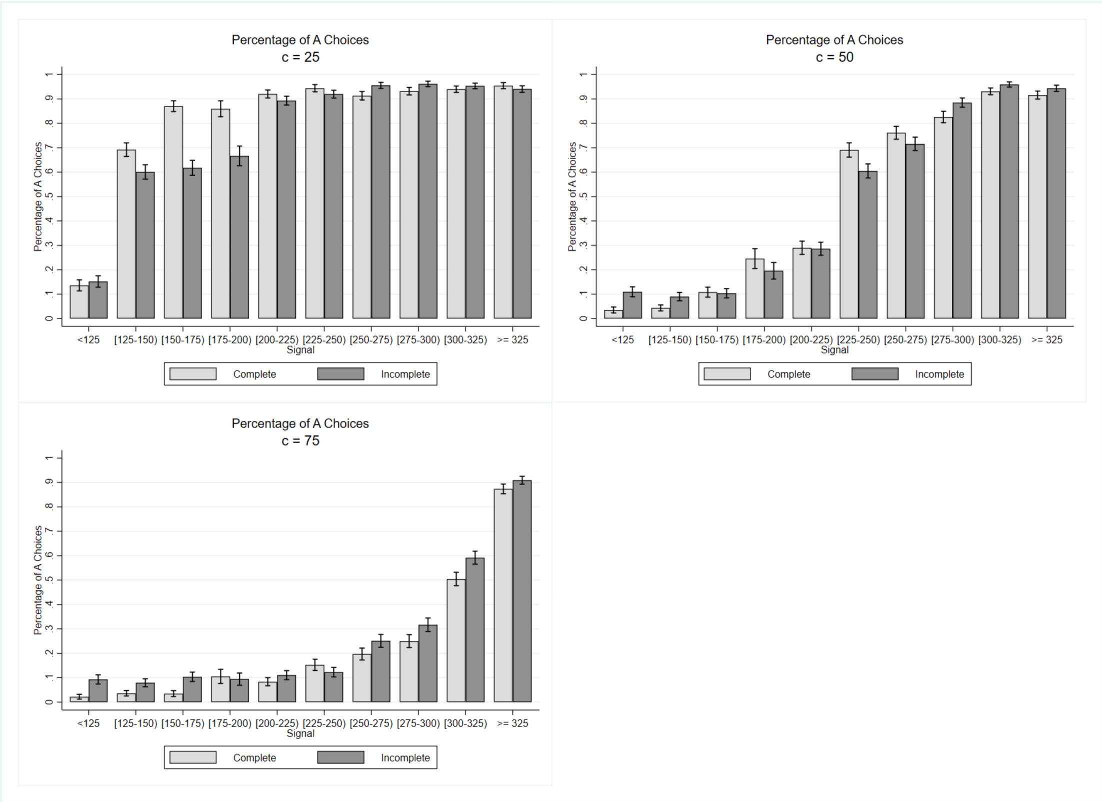


Figure 6: Comparison of Entry Rates (Complete and Incomplete Information)

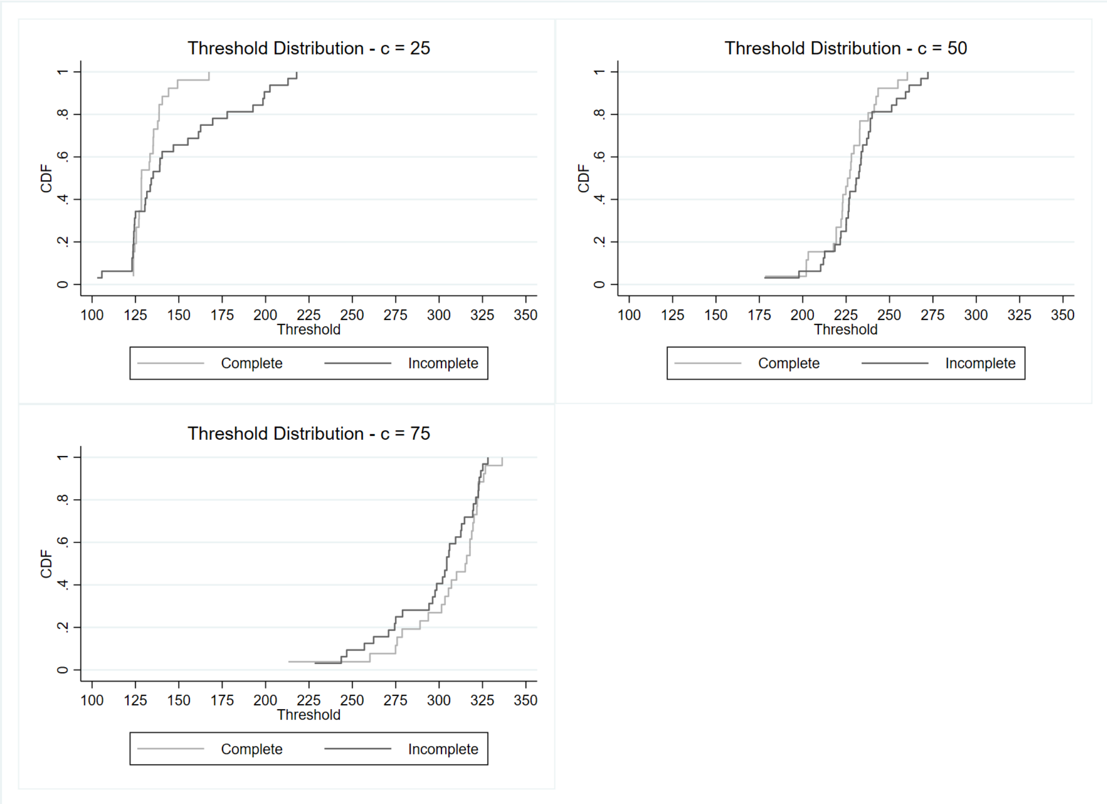


Figure 7: Comparison of Thresholds (Complete and Incomplete Information)

The difference in distributions is only statistically significant for $c = 25$ (Kolmogorov-Smirnov $p < 0.1$) with thresholds being lower under the complete information treatment. We cannot reject the null hypothesis of no difference in distributions for $c = 50$ and $c = 75$ (Kolmogorov-Smirnov $p > 0.1$). This result is summarized below

Result 6. *Estimated thresholds for subjects following a threshold strategy are similar across treatments for $c = 50$ and $c = 75$. Estimated thresholds for $c = 25$ are significantly lower under the complete information treatment.*

This discrepancy at low signals can potentially be attributed to the additional degree of uncertainty in the incomplete information treatment. Unlike the complete information treatment, subjects only observe a noisy signal about the state which can lie anywhere within a 5 point neighborhood of the realized signal. Furthermore, subjects only have noisy information about their group members' signals which can range from either 10 points below their signal to 10 points above. This adds to the degree of strategic uncertainty since there is a positive chance that others observe a higher private signal and choose actions accordingly.

5 Discussion

This paper experimentally investigates behavior in a global game where actions are strategic substitutes. In the experiment, subjects take part in a three agent, market entry game where payoffs are asymmetric across agents in the cost of entry and depend on some underlying state. Depending on the value of the state, the game with complete information permits regions with multiple equilibria. We test the global games equilibrium selection result of Harrison and Jara-Moroni (2021) by having subjects take part in the game with complete *and* incomplete information. The experimental results provide support to the theoretical predictions. A majority (67%) of the subjects adopt threshold strategies, as outlined by the theory, with at most 10 mistakes for each cost type. While the estimated thresholds depart from theoretical predictions, the comparative static predictions still hold in that the rate of entry is monotonically increasing with the signal value and decreasing with the cost of entry. Furthermore, a majority of outcomes in regions of multiplicity in the complete information game correspond to the unique equilibrium selected by the global games theory.

These results have some implications for applied work. As mentioned above, the market entry game has been used extensively in empirical industrial organization. The existence of multiple Nash equilibria in these games creates identification and misspecification problems when estimating these models using field data. Our results provide evidence suggesting that researchers can impose an equilibrium selection assumption when estimating these models by following the prediction outlined by the theory of global games. As an application, consider the same market entry game described in Section 2 restricted to just two agents.[22] Without loss of generality, suppose $c_1 < c_2$ and $r = 0$. Also assume that the market profitability θ is drawn from a distribution over $[\underline{\theta}, \overline{\theta}]$ where $\underline{\theta} < c_1$ and $\overline{\theta} > c_2 + \delta$. This ensures that for some values of θ, the market is profitable enough to support both agents ($\theta > c_2 + \delta$), but for others it can support neither ($\theta < c_1$). The game structure, shown below, and the value of θ is common knowledge to all players.

	Out	Enter
Out	$(0, 0)$	$(0, \theta - c_2)$
Enter	$(\theta - c_1, 0)$	$(\theta - \delta - c_1, \theta - \delta - c_2)$

This setting is similar to the two agent market entry game discussed in Bresnahan and Reiss (1990). There are regions where the game predicts multiple Nash equilibria. Specifically, for $\theta \in (c_2, c_1 + \delta)$, we have 2 pure strategy Nash equilibria where either of the 2 agents choose to enter, and the other agent chooses to stay out. The global games approach can be used to select an equilibrium in this region. Under the global games prediction, agent 1 chooses enter when $\theta > c_1$ and agent 2 chooses enter when $\theta > c_2 + \delta$. This strategy then characterizes the selected equilibrium in the region of multiplicity $(c_2, c_1 + \delta)$. The selected equilibrium has agent 1 choosing Enter and agent 2 choosing Out. This equilibrium has a natural interpretation in the context of firms: the more efficient firm (i.e. the firm with the higher payoff from entering) enters the market.

There is empirical evidence suggesting that play conforms to this equilibrium. In a recent paper, Mahmood and Rehbeck (2022) experimentally investigate behavior in two person, two action entry games as shown above under a large range of payoff structures. They find that, in regions of multiplicity, subjects are better able to coordinate on a pure strategy equilibrium when there are payoff asymmetries. Furthermore, most of this coordination is on the equilibrium in which the more efficient player chooses to enter. Our findings are similar in that, for 3 agent market entry games, a majority of the observations in regions of multiplicity correspond to the equilibrium where the more efficient agents (lower costs) choose to enter the market.[23]

There are several avenues for future research. This paper considers the market entry game which is just one class of games with strategic substitutes. One avenue could be to investigate behavior in different classes of games with strategic substitutes. Other avenues could explore how behavior changes in the

[22]Harrison and Jara-Moroni (2022) show how this framework can be applied to a 2 stage market entry game where entrants engage in Cournot competition.

[23]We note that there is considerable experimental work on market entry games (see, e.g., Sundali et al., 1995, Erev and Rapoport, 1998, Rapoport et al., 1998, Zwick and Rapoport, 2002, and Duffy and Hopkins, 2005). These papers focus on coordination on equilibria with large groups (sizes 6, 12 or 20) and *symmetric payoffs*. Our paper departs from the previous literature by looking at equilibrium selection via global games in small group settings (size 3) with *asymmetric payoffs*.

incomplete information game with a higher degree of noise. Past experimental studies under strategic complements (see, e.g., Helland et al., 2021 and Szkup and Trevino, 2020) have shown a surprising reversal in comparative statics of threshold strategies relative to the theory. Furthermore, for high enough noise, the threshold equilibrium in Proposition 1 may not be unique.[24] As such, it would be worthwhile to conduct a study to document comparative statics in behavior in settings with a higher degree of noise. Finally, another direction could be to incorporate communication into the framework as in Avoyan (2022). We leave these directions for future research.

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[24]In this case, any other equilibria would involve agents adopting non-monotone strategies.

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Appendix A A comment on dominance solvability

A point of note is that the unique equilibrium obtained in Proposition 1 is achieved through an iterative process that eliminates strategies that are never part of an equilibrium profile. In contrast, in settings with strategic complements, the unique equilibrium is obtained through the iterated elimination of dominated strategies. Harrison and Jara-Moroni (2021) provide a discussion as to why iterated dominance might fail in settings with strategic substitutes. However, it is possible to find a sufficient condition when the game is dominance solvable even when actions are strategic substitutes (see Morris and Shin, 2005 and Harrison and Jara-Moroni, 2015 for examples). The insight lies in establishing a sufficient degree of strategic substitutability with respect to the payoffs. This is true for the three agent market entry game described in Section 2. The result is recorded below.

Proposition 3. *Let $c_3 - c_1 > \delta$. Then there exists a $\bar{\sigma} > 0$ such that for any $\sigma < \bar{\sigma}$, $s^\sigma \equiv s^*$ is the unique strategy profile surviving iterated elimination of dominated strategies.*

Proof. It is worth mentioning that our game structure is similar to the three agent game in Harrison and Jara-Moroni (2015). The only asymmetry in payoffs comes from the heterogeneity in the cost of entry c_i. As such, we can write the marginal benefit of entry, for each agent, as $\Delta\pi_i(n,\theta) = \Delta\pi(n,\theta) - c_i$ where, in our setting, $\Delta\pi(n,\theta) = \theta - n\delta - r$. The proof then follows along the same arguments as the proof of Proposition 1 in Harrison and Jara-Moroni (2015), replacing the expression for $\Delta\pi(n,\theta)$ where applicable. ■

Note that the setting in Section 2 is under the assumption that $c_3 - c_1 < \delta$, so it is not guaranteed that the game is dominance solvable.

To see why dominance solvability holds, note that the sufficiency condition $c_3 - c_1 > \delta$ has implications for the overlapping dominance regions. Under this assumption, $\theta_1^M = c_1 + \delta + r < \theta_3^L = c_3 + r$ and $\theta_1^H = c_1 + 2\delta + r < \theta_3^M = c_3 + \delta + r$. This situation is illustrated in Figure 8.

The game permits multiple equilibria for $\theta \in [\theta_2^L, \theta_1^M] \cup [\theta_3^M, \theta_2^H]$ like before. However, there are a few key distinctions compared to the situation in Figure 1 where $c_3 - c_1 < \delta$. First, in both regions of multiplicity, exactly one agent has a strictly dominant strategy. For $\theta \in [\theta_2^L, \theta_1^M]$, agent 3's dominant strategy is to stay out, whereas for $\theta \in [\theta_3^M, \theta_2^H]$, agent 1 has a strictly dominant strategy to enter. This is in contrast to the setting in Section 2, where for some values of θ, none of the agents have a strictly dominant strategy in the regions of multiplicity.

Second, the unique equilibrium in the immediate regions surrounding the regions of multiplicity is achieved through iterated dominance. For $\theta \in (\theta_1^L, \theta_2^L)$, out is strictly dominant for agents 2 and 3. For $\theta \in (\theta_1^M, \theta_3^L)$, out is strictly dominant for agent 3. Given this, enter becomes strictly dominant for

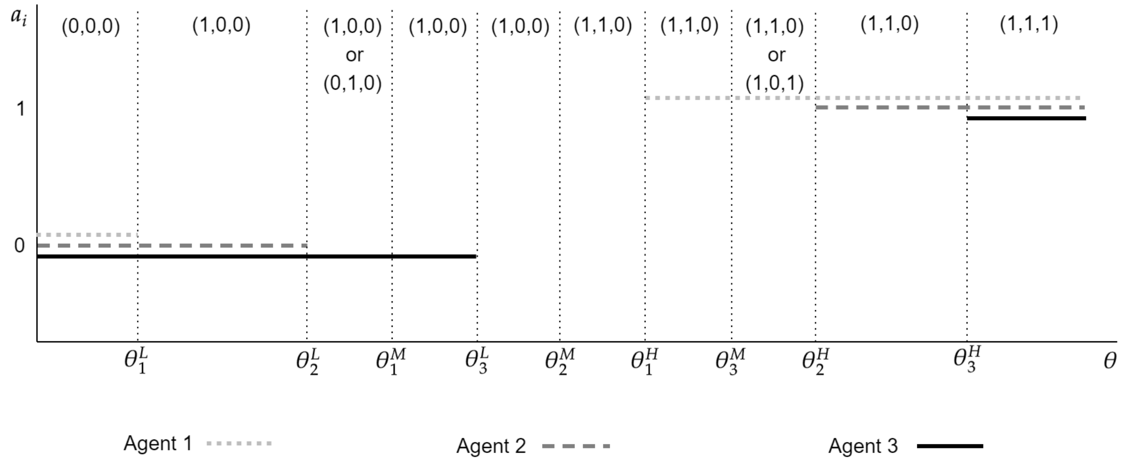

Figure 8: Equilibrium in the Dominance Solvable Game

agent 1 (since $\theta > \theta_1^M$) and consequently, out becomes strictly dominant for agent 2 (since $\theta < \theta_2^M$). Similar arguments can be made to show how iterated dominance holds in the regions (θ_1^H, θ_3^M) and (θ_2^H, θ_3^H). The setting in Section 2 also has regions with a unique equilibrium that surround the regions of multiplicity. However, these equilibria are not always obtained through iterated dominance.[25]

These two observations, coupled with incomplete information facilitate the contagion effect which drives the arguments for dominance solvability in the global games literature. Intuitively, due to the presence of uncertainty about the state, the existence of strictly dominant actions in some states can influence behavior in states in which no agent has strictly dominant actions. For an example, consider a setting where agent 2 observes a signal $\theta_2 \in (\theta_2^L, \theta_1^M)$. Note that, for sufficiently small noise, agent 2 will know that for any possible value of θ in the posterior distribution out is strictly dominant for agent 3. However, if θ_2 is close to either θ_2^L or θ_1^M, then agent 2 puts a positive probability on the fact that, for some states, agent 1 will have a strictly dominant strategy to enter which would make out strictly dominant for agent 2. Each iteration of eliminating dominated strategies would then rule out neighboring signals where entering is strictly dominant for agent 2.

Appendix B Instructions for the Experiment

We reproduce the instructions for the incomplete information treatment below. For the instructions, we use the letter X to denote the value of the state θ.

[25]For example, Figure 1 shows that (1,0,0) is the unique equilibrium in (θ_1^M, θ_2^M) but this is not dominance solvable

Instructions

Welcome and thank you for taking part in this Economics Experiment. This experiment will last for around 1.5 hours. If you read the instructions carefully, you can earn a considerable amount of money depending on your decisions, the decisions of others and chance. Your earnings will be paid out to you in cash after the experiment.

Please turn off your cell phones for the duration of the experiment. Only use the software provided to you on your devices. Failure to comply with these rules will result in dismissal from this experiment and as a result, you will not be paid any earnings you may have otherwise received. If you have any questions, please raise your hands.

Overview

This experiment consists of 75 rounds. At the beginning of each round, you will be randomly matched into a group with 2 other participants. You will be re-matched randomly into different groups every round and you will never know the identity of your group members in any round.

In each round you will make 3 decisions with your group members. You will earn points in each round for each decision. Your payment for this experiment will depend on the points you earn **in one randomly selected round.** Your payment will be converted to dollars at the rate of

$1 = 25 points

You will also earn a show-up fee of $5 in addition to your payment from the experiment.

Next

Instructions

Rounds

At the beginning of each round, the computer will randomly generate a number X. Each period, the computer will generate a new value for X from a **uniform distribution ranging from 100.00 to 350.00.** This means that any number between 100.00 and 350.00, in increments of 0.01, is equally likely to be generated. The value of X will be drawn independently for each round, meaning that each draw is unaffected by the draws in earlier or later periods. **Note that this number will be the same for all decisions and group members for a given round.**

Private Signal: Instead of observing the actual value of X, you will observe the value of a *private signal*. This signal will serve as a hint for the value of X and is constructed as follows.

Your private signal = X + your private Y

In each round, the computer will randomly generate a private number Y from a **uniform distribution ranging from -5.00 to 5.00.** This means that any number between -5.00 and 5.00, in increments of 0.01, is equally likely to be generated. This number will be drawn independently of X and for each round, meaning that the draw of Y is not affected by the true value of X or by the value of your Y in any other round. This number Y is private, meaning that the computer will draw a number for each of the group members and your number Y is drawn independently of the numbers drawn for the other group members. **You will not see the value of Y or X; you will only see your private signal.**

You will not know the values of your group members' private signals.

Each round has 3 decisions. For each decision, you must choose between two options: **Option A and Option B.** You will make your decisions at the same time as your group members. Your earnings for each decision will depend on:

1. Your choice,
2. The number of participants in your group choosing option A and,
3. The random number X generated at the start of the round.

On your screen, you will see the value of your private signal (X + Y) as well as the payoff tables for each decision. You will then, for each decision, click the choice (either A or B). To submit your choices, click the Next button.

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Instructions

Payoffs

The following tables summarize your, and your group members' earnings for each decision and combination of choices.

Decision 1

		Number of Players Choosing A		
		1	2	3
Your Choice	A	X - 25	X - 100	X - 175
	B	100		
Player 2's Choice	A	X - 50	X - 125	X - 200
	B	100		
Player 3's Choice	A	X - 75	X - 150	X - 225
	B	100		

Decision 2

		Number of Players Choosing A		
		1	2	3
Your Choice	A	X - 50	X - 125	X - 200
	B	100		
Player 2's Choice	A	X - 75	X - 150	X - 225
	B	100		
Player 3's Choice	A	X - 25	X - 100	X - 175
	B	100		

Decision 3

		Number of Players Choosing A		
		1	2	3
Your Choice	A	X - 75	X - 150	X - 225
	B	100		
Player 2's Choice	A	X - 25	X - 100	X - 175
	B	100		
Player 3's Choice	A	X - 50	X - 125	X - 200
	B	100		

Each cell represents the payoff to the relevant person for each decision and choice scenario. If you choose A and are the only person choosing A in your group for that decision, your payoff for that decision is X-25 (decision 1), X-50 (decision 2) or X-75 (decision 3). Each additional group member choosing A *reduces your payoff by 75 points if you choose A*. Choosing B always gives you a payoff of 100 points for any decision.

How the choices of other group members for each decision are selected is explained as follows:

For each round, the computer will randomly assign one of your group members as Player 2, and the remaining group member as Player 3. The relevant choices to determine the number of people choosing A for each decision are given below:

	Payoff for Decision 1	**Payoff for Decision 2**	**Payoff for Decision 3**
Your Choice	Decision 1	Decision 2	Decision 3
Player 2's Choice	Decision 2	Decision 3	Decision 1
Player 3's Choice	Decision 3	Decision 1	Decision 2

In words, to compute your payoffs for Decision 1, we look at your choice in Decision 1, Player 2's choice in Decision 2 and Player 3's choice in Decision 3. To compute your payoffs for Decision 2, we look at your choice in Decision 2, Player 2's choice in Decision 3 and Player 3's choice in Decision 1. Finally, to compute your payoffs for Decision 3, we look at your choice in Decision 3, Player 2's choice in Decision 1 and Player 3's choice in Decision 2.

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Instructions

Feedback

Once everyone has submitted their choices, you will be shown the outcome for the round. On this screen, you will see

1. The value of X,
2. Your private signal (X + Y),
3. The payoff tables for each decision,
4. Your choices for each decision,
5. The number of people who chose A in your group and,
6. Your payoffs for each decision and the total payoff for the round.

At the end of the 75 rounds, the computer will randomly select one round for payment. Your screen will show the following information for that round:

1. The round chosen for payment,
2. The value of X for that round,
3. Your private signal (X + Y),
4. Your choices for each decision,
5. The number of people who chose A in your group for each decision and,
6. Your payoffs (and final payment) for that round.

At the end of the experiment, we will ask you some survey questions.

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Instructions

Summary

To summarize:

1. The experiment consists of 75 rounds.
2. You will be randomly re-assigned into a group of 3 participants at the beginning of every round.
3. At the beginning of each round, the computer will randomly generate a number X between 100.00 and 350.00 (each number is equally likely).
4. Instead of observing the value of X, you will be shown a *private signal* X+Y, where Y is a private number randomly generated between -5.00 and 5.00 (any number in between is equally likely).
5. You and your group members will take part in 3 decisions. Each decision involves you choosing between Option A and Option B
6. Your payoff for each decision depends on your choice, the number of people choosing A and the value of X.
7. After 75 rounds are completed, the computer will select one round at random for payment.
8. Payment will be at the rate of $1=25 points. You will also earn a $5 show-up fee.

Please click the next button to continue on to the experiment.

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Appendix C Analysis on the Number of Entrants

Table 10 shows, for the complete information treatment, the percentage of outcomes corresponding to the number of entrants ranging from 0 to 4. For almost all cases, the majority of outcomes correspond to the predicted number of entrants, save for the range $300 < \theta < 325$, where around 49.3% of the time, the predicted number of 2 agents choose to enter the market. A closer inspection of the table reveals a consistent pattern. Conditioning on the predicted number of entrants, there is a cycle in that there is *under-entry* for low values of the state and *excess-entry* for high values of the state.

Consider the range $125 < \theta < 225$ where all possible Nash Equilibria predict 1 entrant. For $\theta < 175$, around 87–93.9% of the outcomes coincide with *at most* 1 entrant, whereas for $\theta > 175$, around 90.3–96.4% of the outcomes coincide with *at least* 1 entrant. This pattern is also observed in the range $225 < \theta < 325$ where all Nash equilibria predict 2 entrants. For $\theta < 275$, around 89% of the observations coincide with *at most* 2 entrants whereas for $\theta > 275$, 82.6–93.4% of the observations coincide with *at least* 2 entrants.

Range of θ	Prediction (Entrants)	Outcomes (Entrants)			
		0	1	2	3
$100 < \theta < 125$	0	81.1%	18.4%	0.4%	0.0%
$125 < \theta < 150$	1	29.0%	64.9%	6.2%	0.0%
$150 < \theta < 175$	1	12.1%	74.9%	12.6%	0.4%
$175 < \theta < 200$	1	9.7%	61.4%	27.2%	1.8%
$200 < \theta < 225$	1	3.6%	65.9%	27.9%	2.5%
$225 < \theta < 250$	2	2.0%	27.7%	59.8%	10.4%
$250 < \theta < 275$	2	1.5%	20.8%	66.7%	11.0%
$275 < \theta < 300$	2	1.1%	16.3%	63.3%	19.3%
$300 < \theta < 325$	2	0.0%	6.6%	49.3%	44.1%
$325 < \theta < 350$	3	0.0%	2.1%	21.4%	76.5%

Table 10: Number of Entrants in Complete Information

Appendix D Robustness Checks for Individual Behavior

In this section, we conduct some additional robustness checks regarding behavior at the individual level. In particular, we look at the sensitivity of the threshold estimates to different selection criteria. In the main text, we considered a subject to adopt a threshold strategy if they made at most 10 mistakes across each type. An alternative classification could be based on the *total* number of mistakes a subject makes across all types. We consider the sensitivity of the threshold estimates to this classification.

Table 11 provides the mean values of the estimated thresholds when the analysis is restricted to subjects who made at most 15, 20 and 25 mistakes respectively. The estimated values are very similar to the values presented in Table 9. Most of the qualitative patterns still hold. Across all cases, the estimated thresholds are significantly higher than predicted for $c = 25$ and significantly lower than predicted for $c = 75$. We also observe that thresholds under the incomplete information treatment are significantly higher for $c = 50$ across all samples. Quantitatively, the values are near identical to those from Table 9 (232.6 compared to 231.8). In comparing the distributions across treatments, we find no significant differences in the distributions of thresholds (Kolmogorov-Smirnov $p > 0.1$ for all comparisons).

At most 15 total mistakes (n=45)			
	c=25	c=50	c=75
Prediction	125	225	325
Mean (Complete)	131.7***	226.5	307.7***
	(0.572)	(2.49)	(4.10)
Mean (Incomplete)	140.7**	232.9***	302.5***
	(7.40)	(1.09)	(5.94)

At most 20 total mistakes (n=58)			
	c=25	c=50	c=75
Prediction	125	225	325
Mean (Complete)	136.4***	229.3*	308.8***
	(1.34)	(2.23)	(3.60)
Mean (Incomplete)	145.5**	232.6***	299.5***
	(9.98)	(1.38)	(7.92)

At most 25 total mistakes (n=65)			
	c=25	c=50	c=75
Prediction	125	225	325
Mean (Complete)	134.0***	226.1	303.6***
	(2.93)	(4.53)	(8.11)
Mean (Incomplete)	147.6**	232.7***	299.2***
	(10.04)	(2.48)	(7.17)

Notes: Mean values reported with bootstrapped standard errors in parentheses clustered at the session level. ***, ** and * indicate estimates are different from prediction at the 1%, 5% and 10% significance level respectively. Tests conducted using bootstrapped regressions with 500 replications and standard errors clustered at the session level.

Table 11: Sensitivity of Threshold Estimates