Understanding Entry Games using Laboratory Experiments*

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Abstract

This laboratory experiment examines whether individuals follow Nash equilibrium predictions in the two-player one-shot complete information entry game of Bresnahan and Reiss (1990) while varying payoff parameters. This entry game is regularly used in empirical industrial organization, but has not been examined experimentally. We find that subjects regularly play dominant strategies (98.2% on average), however there are violations of iterated dominance (13.6% on average). While Nash predictions are silent on coordination, we find more coordination in regions of multiple equilibrium when there are payoff asymmetries (67.3% on average) compared to payoff symmetry (38.4% on average). We also find behavior is monotonic with respect to own and opponent's payoffs.

JEL Classification Numbers: C72; C92; L1
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1 Introduction

To understand market structure, it is important to understand how strategic agents perform in market entry games. Work in empirical industrial organization often uses structural models of entry to facilitate estimation, tighten predictions, and perform welfare analysis. However, it is difficult to justify whether strategic agents obey the structural assumptions (e.g. play follows Nash equilibrium) in the empirical settings of interest. While it is difficult to verify these assumptions on strategic agents in the field, we can see whether these assumptions hold in an idealized laboratory study. Regardless of the outcome of the laboratory study, it is likely to reveal useful information for an empirical study. For example, if the experiment shows individuals satisfy the assumptions, then a researcher can have more confidence in the structure of the model. Even when the experimental data is not described by the structural model, it may be possible to organize comparative statics of behavior from the lab to obtain shape restrictions (e.g. monotonicity) that could be used to analyze data from the field.

In this paper, we perform a laboratory experiment to examine whether strategic agents follow Nash equilibrium predictions in the one-shot complete information entry game described in Bresnahan and Reiss (1990), Berry (1992), and Tamer (2003) with two agents. For this class of games, each agent can choose to be either In or Out of the market where the payoff when all agents play Out is normalized to zero. When only one agent plays In, that agent makes a monopoly profit subject to a "shock." Lastly, when both agents play In, each receives their monopoly profit plus the "shock" and less a penalty term. The penalty term captures competition or congestion that results when both agents are in the market. We examine one-shot behavior of 88 subjects in 64 different full information games varying the level of monopoly profit, the penalty when both agents enter, and the "shocks." Since this is a laboratory study, all of these parameters including the "shocks" are experimentally controlled which allows us to look at rich comparative statics of behavior in entry games.

We focus our exploratory analysis on two main questions to evaluate the entry game model of Bresnahan and Reiss (1990), Berry (1992), and Tamer (2003).

Question 1. Do Nash equilibrium predictions describe strategic behavior in the lab?

Question 2. Are there comparative statics that are consistent across games?

Question 1 is essentially one of testing Nash equilibrium predictions. We evaluate Question 1 by looking at failure to play dominant strategies, failure to apply iterated dominance, and failure to coordinate play. Question 2 looks for regularities regardless of the structural model. Question 2 is essentially independent of the first question. For example, Nash equilibrium often has no prediction on comparative statics as discussed in Goeree and Holt (2001). Thus, any findings from Question 2 could be used to place additional restrictions on Nash equilibrium or best response behavior even when the data agrees with Nash predictions. Analogues of these questions could be examined for most structural models in empirical industrial organization where the first question looks at the model structure and the second at comparative statics.

We briefly summarize some main results. Regarding Question 1, we find deviations from Nash predictions, but they are sensitive to payoffs. We find few violations of playing dominant strategies where on average 1.8% of all relevant play deviates from the dominant strategy. We find larger errors when examining iterated dominance. A violation of iterated dominance occurs when an individual fails to realize the other player has a dominant strategy that they should take into account. For situations where violations of iterated dominance are possible, we find on average 13.6% of play violates iterated dominance. We also find that payoffs of individuals facilitate coordination of actions when there are multiple equilibrium. In particular, we find individuals are more likely to coordinate when payoffs for entry are asymmetric. When there are multiple equilibrium, on average 67.3% of play follows Nash predictions when payoffs are asymmetric compared to only 38.4% of play on average with symmetric payoffs. These results also mean individuals violate Nash equilibrium predictions 32.7% on average with asymmetric payoffs and 61.6% on average with symmetric payoffs.

Regarding Question 2, we find evidence of several comparative statics. For example, we find that subjects are more likely to play “In” when there is a higher payoff “shock” to enter. We also find that players are less likely to play “In” as the other player’s “shocks” increase. Thus, individuals are sensitive to their own payoffs as well as their opponents payoffs. We discuss how the comparative statics we find could be used to help identify and estimate coefficients in our final remarks. Overall, we view

Nash equilibrium predictions as most useful in situations of dominance and less useful elsewhere, but the monotonicity restrictions appear robust from the experimental results. Whether these monotonicity restrictions would impose enough structure to recover useful information empirically is an open question.

We focus on the one-shot complete information market entry game of Bresnahan and Reiss (1990), Berry (1992), and Tamer (2003) since this framework has been used extensively in empirical industrial organization. For example, these models have been estimated using field data from the automobile retail market in Bresnahan and Reiss (1990), markets for airline routes in Berry (1992); Ciliberto and Tamer (2009), markets for professional occupations such as doctors, plumbers, and veterinarians in Bresnahan and Reiss (1991), and markets for construction contractors in Bajari et al. (2010) among others.[1] While there are many empirical studies on market entry games using this structure, we were unable to find work examining behavior in this type of entry game using a controlled laboratory environment. More generally, we think that looking at structures used in empirical industrial organization is a fruitful avenue for experimental researchers.

However, laboratory research faces its' own set of drawbacks. Many of these issues are discussed at length in the survey on experimental work in industrial organization from Holt (1995). For example, some might be skeptical of laboratory studies since incentives are relatively small, subjects in the lab may not have experience with the entry game, and the laboratory lacks the "real world" context of the field. While these are valid concerns, laboratory studies have benefits relative to field studies in several ways. For example, one does not need to estimate payoff parameters to evaluate the model since the payoffs are set ex-ante. We are also able to guarantee that both players have full information which is difficult to imagine in a "real world" setting. Lastly, control of payoffs allows us to examine comparative statics that would be difficult to examine in the field since the components of a firm's payoff such as price is often determined endogenously. We think that laboratory methods can complement the empirical industrial organizations literature by giving a more nuanced understanding of how individuals behave when interacting with an idealized setting of the model. Ideally, the features seen in the lab would be incorporated in a structural model to be applied on field data. One could then compare whether imposing the

[1] See Berry and Reiss (2007) for a survey on estimating models of market entry on field data.

restrictions seen in the lab improve predictions or better describe "real world" field data.

We also note that experiments like the one studied here might be of interest for econometricians studying strategic games of complete information.[2] For example, there are often complications that result when using game theoretic models since there are regions with multiple equilibrium. One approach to handle multiple equilibrium is to assume and estimate equilibrium selection mechanisms as done in Sweeting (2009) and Bajari et al. (2010). Another approach makes no assumptions on equilibrium selection and instead bounds the probabilities that can result from equilibrium play to facilitate analysis as in Tamer (2003) and Ciliberto and Tamer (2009). One approach that falls in-between the previously mentioned approaches uses shape restrictions on how often equilibrium are played as in Galichon and Henry (2011) to get tighter predictions. Whether shape restrictions are appropriate is difficult to analyze from field data, but could be easily verified in an laboratory experiment. Thus, experiments could inform shape restrictions used in the field. An alternative approach is to try and discern solution concepts from the data as discussed in Kashaev and Salcedo (2021).

The remainder of the paper is organized as follows. Section 2 describes the basic model. Section 3 describes the experimental design, how it relates to the theory, and defines how we measure violations of Nash equilibrium play. Section 4 presents the main results from the experiment. Section 5 describes other relevant literature. Section 6 provides our final remarks.

2 Theoretical Preliminaries

We study complete information simultaneous entry games with two players inspired by the decomposition of Bresnahan and Reiss (1990), Berry (1992), and Tamer (2003) represented in Table 1.

We denote the role a player takes in Table 1 by $i \in \{1, 2\}$ where the row role is indexed by 1 and column role is indexed by 2. Here x_1 is a baseline payoff to the player in the row role and x_2 is a baseline payoff to the player in the column role.

[2]There is an extensive literature on this topic. See the surveys by De Paula (2013) and Aradillas-López (2020) for an extensive description of the literature.

	Out	In
Out	(0,0)	(0,$x_2 + u_2$)
In	($x_1 + u_1$,0)	($x_1 + u_1 - \Delta_1$, $x_2 + u_2 - \Delta_2$)

Table 1: A simultaneous entry game

The term $\Delta_1 > 0$ is a penalty to the player in the row role when both players enter the market. The term $\Delta_2 > 0$ is a penalty to the player in the column role when both players enter the market. In Tamer (2003), the u_1 and u_2 terms are interpreted as random payoff shocks to the individual player. For the economic experiment, we choose values for the "shocks" to study comparative statics around a given baseline payoff. The values of these "shocks" are unknown to the players in the laboratory experiment. The entry decision of the player in the ith role is denoted by $y_i \in \{0, 1\}$ where $y_i = 0$ when they play Out and $y_i = 1$ when they play In.

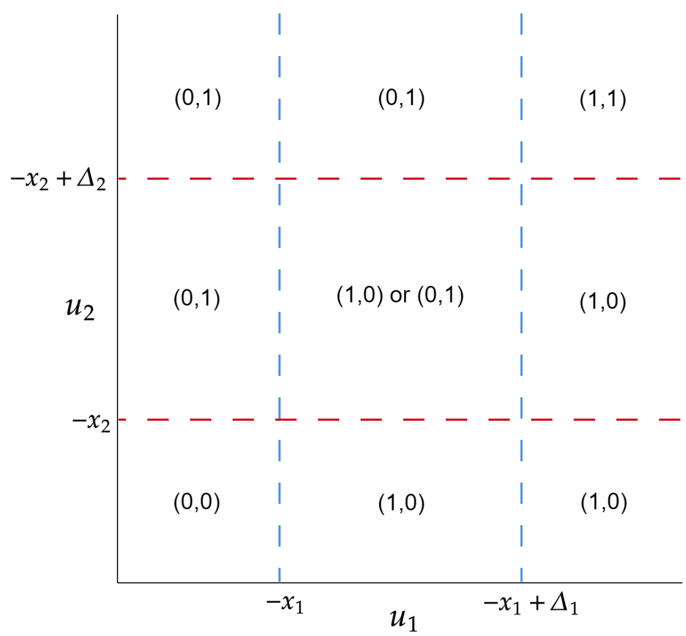

Figure 1: Equilibrium Regions

Throughout the paper, we treat pure strategy Nash equilibrium as the baseline model.[3] A game is defined by the vector of payoff parameters $\Gamma =$

[3]For the region with multiple equilibria, mixed strategy equilibrium are possible. We discuss

$(x_1, x_2, \Delta_1, \Delta_2, u_1, u_2)$. Following Tamer (2003), we can trace out all pure strategy Nash equilibrium predictions for different values of (u_1, u_2) when given $(x_1, x_2, \Delta_1, \Delta_2)$ as in Figure 1 where the equilibrium is represented by (y_1, y_2). Thus, the bottom-left region with $(0, 0)$ is when players in the row and column roles both play Out. While there are many regions with a unique equilibrium, there are multiple equilibrium where one player plays In and the other Out given by (1,0) and (0,1) in the region with $-x_2 < u_2 < -x_2 + \Delta_2$ and $-x_1 < u_1 < -x_1 + \Delta_1$.

We give some examples to better understand Figure 1. First, note that for all regions to the left of $-x_1$, it is a dominant strategy for the player in the row role to play Out. Similarly, for all regions below $-x_2$, it is a dominant strategy for the player in the column role to play Out. We can similarly find regions where it is a dominant strategy to play In. For example, it is dominant for the player in the column role to play In for the region above $-x_2 + \Delta_2$. Several regions allow us to look at violations of iterated dominance. For example, in the region with $-x_2 + \Delta_2 < u_2$ and with $-x_1 < u_1 < -x_1 + \Delta_1$, it is a dominant strategy for player in the column role to play In, but the player in the row role makes a positive payoff playing In when column plays Out. Thus, this region allows us to look at whether individuals are able to recognize iterated dominance when there is some temptation to play In. The same is true for the region to the right of the region with multiple equilibrium with the row and column roles reversed.

To measure violations of equilibrium play, we will examine how often a player does not play their best response. The best response of the player in the ith role conditional on the action of the player in the jth role is given by

$$y_i^*(y_j) = \begin{cases} 1 & \text{if } \; x_i + u_i - \Delta_i y_j \geqslant 0 \\ 0 & \text{otherwise} \end{cases}$$

where $j \neq i$.

this in Appendix D.

3 Experimental design and methods

Our experimental design is motivated by the entry game from Bresnahan and Reiss (1990), Berry (1992), and Tamer (2003). In our experiment, subjects took part in a series of complete information one-shot entry games described in Table 1. Each session consisted of 64 different games. The experiment was coded in oTree (Chen et al., 2016). There were several important design choices that we discuss below. Following the design choices, we provide a screenshot of the experiment. Lastly, we describe how we measure violations of Nash equilibrium.

3.1 Choice of Payoffs

The nature of the decomposition outlined in Table 1 allowed us considerable freedom in selecting the parameters for the experiment. For simplicity and ease of comparability, we selected parameters based on the following considerations:

1. We decided to use a common baseline payoff for each role (i.e. $x_1 = x_2 = x$) and a common penalty when both players enter (i.e. $\Delta_1 = \Delta_2 = \Delta$).

2. To mimic high and low stakes, we let x and Δ to take on high and low values.

The majority of these cases are not without loss of generality.[4] We focused on symmetric baseline payoffs and penalties since we did not want players to introduce concerns about inequality among the participants.

The payoff to each subject is described in points where 1 point = \$0.10. In addition to a show-up fee, we started subjects with 150 points to avoid subjects loosing money from their participation. We note that this means that subjects are subject to experiencing losses in the game. For example, when $-x_i < u_i < -x_i + \Delta_i$ a subject can experience a loss when both players choose In. Similarly, whenever $u_i < -x_i$ the ith player will experience a loss whenever they choose In. For this experiment, we treat individuals as risk neutral in payoffs. Thus, we do not attempt to interact with the literature that examines loss aversion.[5] While this is a source of potential error, it does not change any of the dominance properties or regions of pure

[4] However, we note that when there are symmetric shocks, these are equivalent to an increase or decrease in the baseline payoff.

[5] See the survey article of Barberis (2013) who discusses advances in loss aversion following Kahneman and Tversky (1979).

strategy equilibrium. Moreover, the analysis of comparative statics is independent of the structural model assumed.

x	Δ	Possible u_i Values
50	75	$\{-75, -30, 10, 35\}$
50	125	$\{-60, -5, 30, 85\}$
100	75	$\{-110, -75, -50, -20\}$
100	125	$\{-125, -50, -25, 30\}$

Table 2: Values of the Games (in points)

We considered u_i's from a common set of values for each combination of x and Δ with values in points. Table 2 shows the values in points chosen to create the 64 games we study. For this reason, we also refer to a game as $\Gamma = (x, \Delta, u_1, u_2)$. For a fixed x and Δ, the Nash equilibrium only depends on the shocks (u_1, u_2). For each combination of x and Δ, we choose "shocks" to put payoffs in each of the regions from Figure 1.

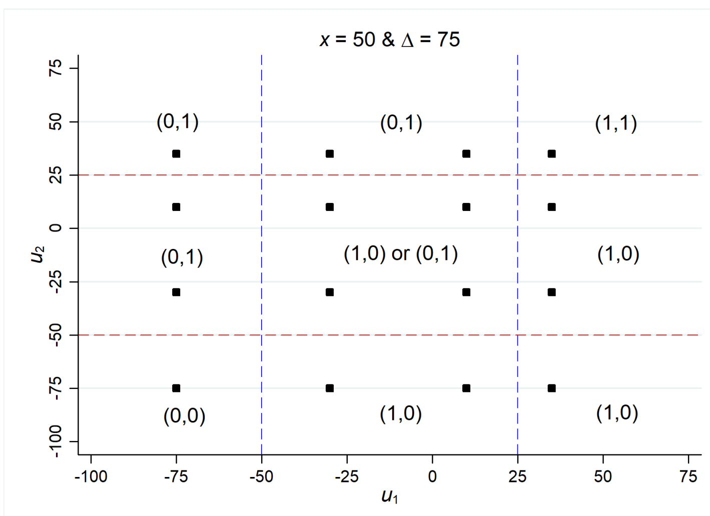

Figure 2: Equilibrium Prediction of Games with $x = 50$, $\Delta = 75$

For each tuple (x, Δ), we have 4 possible values of u_i. This means that we have 16 different combinations of shocks (u_1, u_2). As a result, we have 64 games $\Gamma = (x, \Delta, u_1, u_2)$. Figure 2 shows the pure strategy Nash equilibrium prediction for one set of $(x, \Delta) = (50, 75)$ at different values of (u_1, u_2). As seen in Figure 2, this design gives us a grid over the different equilibrium regions. We have more games in the region with multiple equilibrium since we thought this would be an interesting region to examine. We also had at least one game in every other region to get comprehensive comparative statics.

3.2 Basic setup of the game

Next, we describe how the game was presented to subjects. Subjects were asked to choose between two alternatives: *In* or *Out*. Payoffs depended on their action, as well as their opponent's action. Each subject was presented the game from the perspective of the row role. We made this design choice so that there was no difference in how the individuals made their choices. For example, if we instead had individuals interact with payoffs as a column role, then the results could be driven by the fact that individuals are better/worse are evaluating payoffs in the column role. We wanted to avoid this possibility.

		Other	
		Out	**In**
You	**Out**	(0, 0)	(0, α)
	In	(a, 0)	(b, β)

Table 3: Payoff Table in Experiment

While we designed the payoffs by using the decomposition from Bresnahan and Reiss (1990), Berry (1992), and Tamer (2003), we present subjects with a simpler environment. In particular, the ith subject was shown payoffs as in Table 3 where we have $a = x + u_i$ and $b = x + u_i - \Delta$ while their opponent is indexed by $j \neq i$ and their payoffs are given by $\alpha = x + u_j$ and $\beta = x + u_j - \Delta$. We decided to show subjects the result of the addition to prevent confusion and ensure violations of Nash equilibrium were not coming from computational errors. For example, if we did not add the numbers together for the subject and saw an individual choose a dominated strategy, then this could have occurred from poor computational skills.

3.3 Implementing one-shot games and payments

We now describe how we implement the one-shot nature of the game. First, we wanted to ensure that subjects understand how they earn money in the game. To get subjects to understand the environment, we required subjects answer three un-incentived questions about their payoffs in different situations of play. An example practice question faced by subjects is described in Appendix B. A subject could not continue to the main experiment until these questions were answered correctly. Thus, we believe subjects understand how they are paid for their actions.

In order to mimic the one-shot nature of the games, the subjects were randomly matched for each round of play and did not receive feedback. In more detail, subjects were randomly matched at the beginning of each round with another participant according to the following procedure. Each subject was assigned an ID, (either 1 or 2 which mimic the row and column roles), and was randomly matched with another subject with a different ID. Thus, a subject with ID 1 was always matched with a subject with ID 2 and vice versa. This matching protocol ensured that no participant played the same entry game more than once. We refer to the players with ID 1 as "Row" and those with ID 2 as "Column" to distinguish between these two groups.[6] The matching procedure is implemented using the built-in random matching feature from oTree (Chen et al., 2016). Subjects were not provided with details about the matching procedure. In the instructions, we merely stated that subjects would be randomly matched with another at the beginning of every round.

Subjects faced no time restrictions in making their decision, but could only move on once all subjects finalized their decisions. Once all subjects finalized their decisions, they all moved on to the next round of decisions and were randomly matched to another subject. Thus, subjects did not have an incentive to move through the experiment as fast as possible since they had to wait until all other subjects made their choices. We did not include any feedback stages to limit any learning that could occur during the experiment. Finally, the order of games was randomized *ex-ante* and all participants across all sessions faced the same sequence of games.

Once all 64 rounds were complete, we paid subjects for one randomly chosen round which is incentive compatible under the monotonicity assumptions of Azrieli et al. (2018). For the round chosen for payment, we showed the subject the payoff table, the subject's decision, their randomly matched opponent's decision, and their payoff in points based on actions of both subjects. This payoff was then added to their starting balance of 150 points. The starting balance was common knowledge and was implemented so that subjects could experience losses present in the entry

[6] However, we remind the reader that the payoff tables were always shown to the subjects were from the perspective of the row role.

game of Bresnahan and Reiss (1990), Berry (1992), and Tamer (2003).

3.4 Experiment implementation details

The experiment was conducted at the Ohio State University Experimental Economics Laboratory. We recruited subjects from the undergraduate and graduate student population using ORSEE (Greiner, 2015). We had 88 subjects take part in the experiment over the fall 2021 and spring 2022 semesters. Thus, we have 44 subjects for each role (e.g. row and column) for each of the 64 games. The size of the sessions ranged from 6 to 16 subjects with an average size of 9.8 subjects per session. All sessions were required to have more than 6 people to ensure they would match with several different subjects. The experiment was programmed using oTree (Chen et al., 2016). A screen-shot from the experiment is shown in Figure 3. We recall that all subjects faced the game from the perspective of the row player, but were given an ID for the different roles in the game.

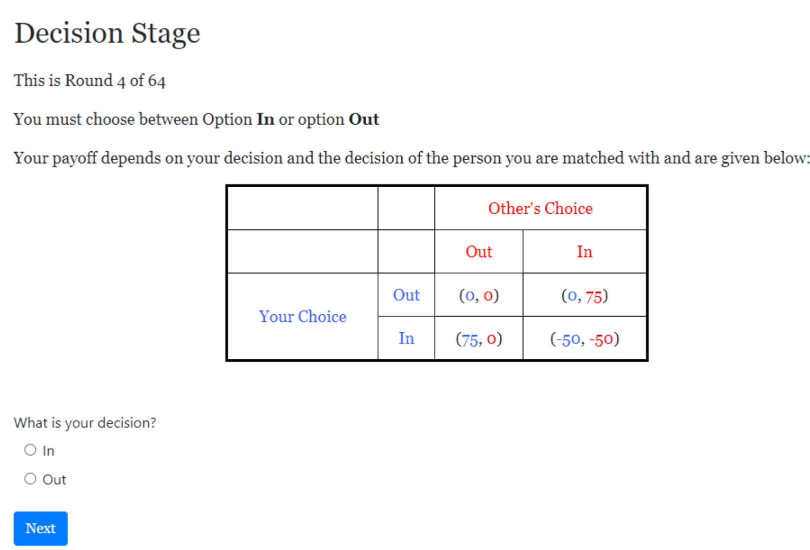

Figure 3: Screenshot of a Round

Instructions were read aloud by the experimenter and were displayed on the subject's computer screen at the start of the experiment. The instructions are reproduced in Appendix A. Regarding payments, subjects earned a $5 show-up fee. In addition, subjects were given an endowment of 150 points from which they could earn or lose additional money where 1 point = \$0.10. The parameters were chosen so that the largest loss would result in a gain of zero points although this never happened in practice. However, some subjects did experience losses from their play. On average, subjects earned \$22.8 including the show up fee. All sessions lasted less than an hour so the average wage exceeds \$22 per hour.

3.5 Types of Violations

We examine violations of Nash equilibrium in the one-shot entry game for each group of subjects where ID 1 is "Row" and ID 2 is "Column." Understanding whether violations of Nash equilibrium are present in the entry game is important since it is regularly used in applications (Bresnahan and Reiss, 1990, 1991; Berry, 1992; Ciliberto and Tamer, 2009; Bajari et al., 2010). Let $\hat{y}_{i,n}(\Gamma)$ be the observed play from the n-th individual in the ith group ("Row" or "Column") for the game $\Gamma = (x_1, x_2, \Delta_1, \Delta_2, u_1, u_2)$. We measure violations from Nash equilibrium play for the ith group in game Γ as

$$\frac{1}{N}\sum_{n=1}^{N} |\hat{y}_{i,n}(\Gamma) - y_i^*(\hat{y}_{j,n}(\Gamma))|$$

for $j \neq i$ where N is the total number of individuals in the ith group.

There are four types of violations that seem qualitatively different. We record the violations and the space of parameters where they can occur in Table 4.

Type of Violation	Region of Violation
Out Dominance	$u_i < -x_i$
In Dominance	$-x_i + \Delta_i < u_i$
Iterated Out Dominance	$-x_i < u_i < -x_i + \Delta_i$ and $-x_j + \Delta_j < u_j$
Iterated In Dominance	$-x_i < u_i < -x_i + \Delta_i$ and $-x_j < u_j$
Coordination	$-x_i < u_i < -x_i + \Delta_i$ and $-x_j < u_j < -x_j + \Delta_j$

Table 4: Types of Violations

We say there is a violation of Out Dominance when it is a dominant strategy to play out. Similarly, we say there is a violation of In Dominance when it is a dominant strategy to play In. There is a failure of iterated dominance when the player fails to recognize that their opponent has a dominant strategy. There are two ways iterated dominance can fail. First, a player might fail to recognize that their opponent has a dominant strategy to choose In and, subsequently chooses In and makes losses. We consider this a violation of Iterated Out Dominance. Secondly, a player might fail to recognize that their opponent has a dominant strategy to choose Out and, subsequently chooses Out, forgoing positive earnings. We call this a violation of Iterated In Dominance. Lastly, we say there is a coordination violation when there are multiple equilibrium and the players fail to coordinate on one of the pure strategy Nash equilibrium.

4 Results

We briefly summarize the main results from the experiment.

1. We observe few violations of Out and In dominance (1.8% of relevant play on average),
2. We observe frequent failure of iterated dominance (13.6% of relevant play on average),
3. In regions of multiplicity, payoff asymmetry helps subjects coordinate on one equilibrium (67.3% of relevant play on average), whereas payoff symmetry results in less equilibrium coordination (38.4% of relevant play on average),
4. We observe evidence of monotonicity of choices wherein the frequency of choosing In is increasing in the "shock" to their payoff for choosing In and decreasing in the "shock" to their opponent's payoff for choosing In.

We go through these results in more detail in the subsections. However, we also note that many of the main results can be seen looking at how observed play changes for fixed values of base payoffs and penalty given by (x, Δ). Thus, before going into more detail, we show how these can be seen from descriptive data in one game.

4.1 Descriptive results

We describe basic results looking at the play from distinct games with a fixed (x, Δ) and varying the shocks (u_1, u_2). Recall, a game is identified by the parameters $\Gamma = (x, \Delta, u_1, u_2)$. Figure 4 shows the frequencies of Row and Column groups of players choosing In for each game when $x = 50$ and $\Delta = 75$. The values in blue indicate Row group frequencies and, values in red indicate Column group frequencies. Results are qualitatively similar for all other games, the figures for which can be found in the Appendix C.

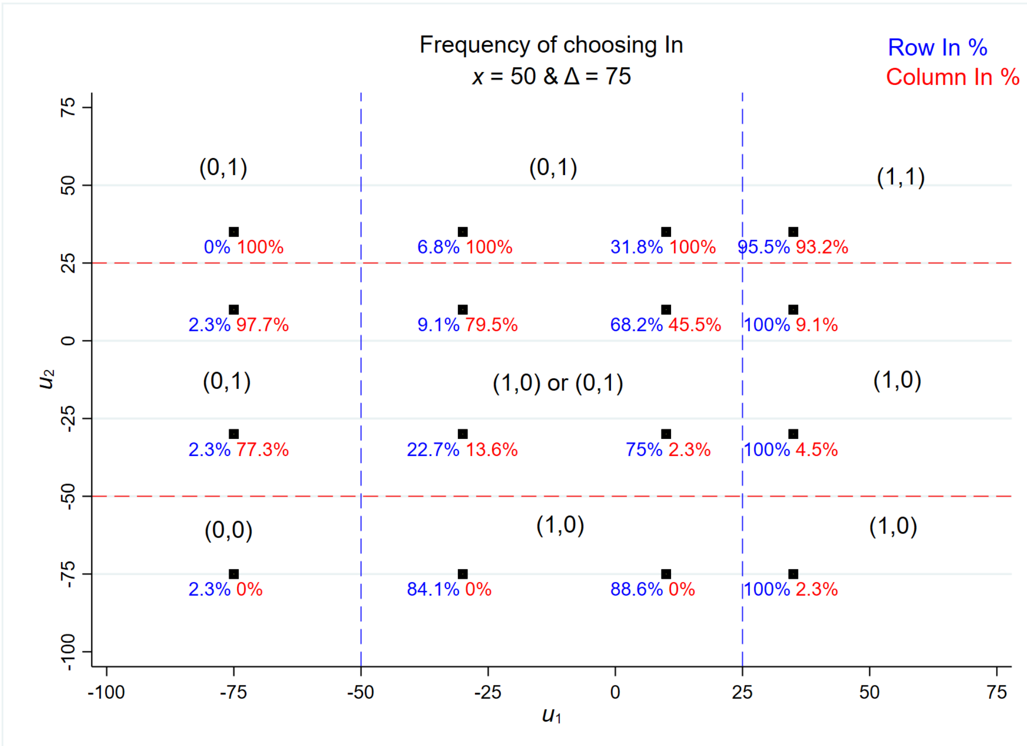

Figure 4: Frequency of In for $x = 50$, $\Delta = 75$

Looking at Figure 4, we can make several observations. First, empirical frequencies of the Row and Column group choosing In almost perfectly match the theoretical predictions in regions of dominance. To see this, consider the situations where either player has Out as the dominant strategy (i.e. $u_i < -50$). At the maximum, we observe only 2.3% of observations within a given game in which subjects choose the dominated strategy In. We observe similar results when looking at the regions where In is the dominant strategy (i.e. $u_i > 25$). The maximum proportion of subjects choosing the dominated strategy Out is 4.5% for the Row group and 6.8% for the Column group.

When looking at regions where iterated dominance plays a role, already we observe instances where subjects fail to best respond to an opponent's dominant strategy. For regions of Iterated Out Dominance ($-50 < u_i < 25$ and $u_j > 25$), we observe at maximum 31.8% of the Row group and 9.1% of the Column group choose In. Similarly, for regions of Iterated In Dominance ($-50 < u_i < 25$ and $u_j < -50$), we observe, at maximum 15.9% of the Row group and 22.7% of the column group choose Out.

In regions of multiplicity ($-50 < u_1, u_2 < 25$), we find evidence suggesting that payoff asymmetry can help subjects coordinate on a pure strategy Nash equilibrium. Consider the games in the upper-left and lower-right of this region. Here, payoffs are asymmetric in the sense that one player has a greater incentive for choosing In than the other. The empirical frequencies show that the player with the higher incentive chooses In substantially more frequently than the other player. We do not observe this pattern in games where payoffs are symmetric.

Finally, we observe that the frequency that Row and Column groups choose In are weakly monotonic in "shocks" in most instances. Specifically, we observe that subjects choose In more frequently as the shock to their payoff increases holding all else fixed. Conversely, subjects choose In less frequently as the shock to their opponent's payoffs increases holding all else fixed. We further substantiate these findings across all games in Section 4.3.

4.2 Violations of Nash equilibrium

We first consider violations in regions with a unique equilibrium. Recall that there are four types of violations we can observe with a unique equilibrium: 1) violations of Out Dominance; 2) violations of In Dominance; 3) violations of Iterated Out Dominance; and 4) violations of Iterated In Dominance. Table 5 below shows summary statistics of the aforementioned violations observed with the level of observation being a game Γ.

We start by looking at the violations of Out Dominance. Recall that *Out* is the dominant strategy for the ith group when $u_i < -x$. We observe few violations of Out Dominance for both Row and Column groups. The number of violations range from 0% to 6.8%, with an average of 2.4% for the Row group. For the Column group, the violations range from 0% to 2.3%, with an average of 0.4%.

	Row			Column		
	Min	Max	Mean	Min	Max	Mean
Out Dominance	0%	6.8%	2.4%	0%	2.3%	0.4%
In Dominance	0%	4.5%	1.9%	0%	9.1%	2.6%
Iterated Out Dominance	6.8%	31.8%	17.9%	4.5%	11.4%	7.4%
Iterated In Dominance	4.5%	29.5%	15.1%	2.3%	22.7%	13.9%

Table 5: Violation Summary Statistics

We find similar results when looking at violations of In Dominance. Recall that *In* is the dominant strategy for the ith group when $u_i > \Delta - x$. We again observe few violations of In dominance for both Row and Column group. For the Row group, violations range from 0% to 4.5% and average 1.9% of play in relevant situations. For the Column group, the range is from 0% to 9.1%, with an average of 2.6% of play in relevant situations. One point to note is that a majority of these violations occur in the region where In is the dominant strategy for both players. In this setting, the payoff gain from choosing In is very small (at most 10 points or $1) so that players may have some degree of altruism.

Our results suggest that subjects are able to recognize when they themselves have a dominant strategy and act accordingly. As mentioned above, another component to entry games is recognizing that opponents have a dominant strategy and best responding. We next look at violations of iterated dominance. There are two instances where iterated dominance plays a role. First, when the opponent has a dominant strategy to play In, iterated dominance yields Out as the best response. Conversely, when the opponent has a dominant strategy to play Out, iterated dominance yields In as the best response.

We observe that subjects frequently fail to best respond to an opponent's dominant strategy. Fixing the case when Out is the best response, we find that violations range from 6.8% to 31.8% for the Row group, averaging 17.9% of play in relevant situations. For the Column group, violations range from 4.5% to 11.4% with an average of 7.4% of play in relevant situations. When looking at the the case when In is the best response, we find violations ranging from 4.5% to 29.5% for the Row group, and 2.3% to 22.7% for the Column group. Thus, it appears subjects may ignore information about their opponent's payoffs even when it is known and readily available.

We next examine behavior in regions with multiple equilibria. Given fixed (x, Δ), multiplicity of equilibria occurs for $-x < u_1, u_2 < \Delta - x$ which corresponds to the middle box in the figures. We focus on the degree to which subjects fail to coordinate on one of the pure strategy Nash equilibrium. We find that coordination failure ranges from 22.7% to 75%, averaging 47.2% across games with multiple equilibria.

Given the wide range of coordination failure, one question to ask is whether payoffs play a role in facilitating coordination on a particular equilibrium. Experimental results on coordination games have shown that payoffs can influence what individuals coordinate on.[7] We now look at whether there is a relationship between coordination rates and the random shocks (u_1, u_2). Table 6 highlights the coordination rates for the (1,0) and (0,1) equilibria respectively across all games with multiple equilibria.

Γ	**Frequency of (1,0)**	**Frequency of (0,1)**	**Total Coordination**
Symmetric Payoffs			
(50, 75, -30, -30)	18.2%	9.1%	27.3%
(50, 75, 10, 10)	31.8%	9.1%	40.9%
(50, 125, -5, -5)	15.9%	15.9%	31.8%
(50, 125, 30, 30)	27.3%	15.9%	43.2%
(100, 75, -75, -75)	13.6%	11.4%	25.0%
(100, 75, -50, -50)	38.6%	18.2%	56.8%
(100, 125, -50, -50)	18.2%	15.9%	34.1%
(100, 125, -25, -25)	38.6%	9.1%	47.7%
	Average Symmetric Coordination :		38.4%
Asymmetric Payoffs			
(50, 75, -30, 10)	2.3%	72.7%	75.0%
(50, 75, 10, -30)	75.0%	2.3%	77.3%
(50, 125, -5, 30)	6.8%	56.8%	63.6%
(50, 125, 30, -5)	61.4%	4.5%	65.9%
(100, 75, -75, -50)	0.0%	68.2%	68.2%
(100, 75, -50, -75)	65.9%	2.3%	68.2%
(100, 125, -50, -25)	2.3%	65.9%	68.2%
(100, 125, -25, -50)	47.7%	4.5%	52.3%
	Average Asymmetric Coordination:		67.3%

Table 6: Coordination Rates

We observe that payoffs play a significant role in facilitating coordination on one of the two pure strategy equilibria. Coordination rates are lowest when payoffs are symmetric (i.e. $u_1 = u_2$), ranging from 25% to 56.8% of play with an average of

[7] See Devetag and Ortmann (2007) for a survey on coordination failure in the lab.

38.3%. In contrast, coordination rates are higher when payoffs are asymmetric (i.e. $u_1 \neq u_2$), ranging from 52.3% to 77.3% of play, with an average of 67.3%.

Furthermore, the relative share of observations is correlated with the advantaged player. For instance, when looking at $\Gamma = (50, 75, -30, 10)$, the Column group has a higher payoff from choosing In compared to the Row group (60 against 20). We observe substantially higher frequencies of (0,1) compared to (1,0) for this game (72.7% vs 2.3%). When looking at the converse of this game (50, 75, 10, -30) where the Row group has a higher payoff, we observe the opposite. Frequencies of (1,0) significantly outweigh frequencies of (0,1) (75% vs 2.3%). We observe this pattern for all instances where one of the players is more advantaged than the other.

4.3 Comparative Statics and Monotonicity

Results from Section 4.2 suggest that Nash equilibrium predictions may not be an accurate model of behavior in one-shot entry games with complete information. However, a closer investigation of the data shows that subject choices are monotonic with respect to payoffs. Empirical frequencies exhibit two patterns. First, keeping the opponent's shocks fixed, an increase in a subject's shock u_i leads to (weakly) higher frequencies of choosing In. Secondly, keeping the subject's shocks fixed, an increase in the opponent's shock u_j leads to (weakly) lower frequencies of choosing In. These findings are particularly salient in regions with multiple equilibria via equilibrium coordination as mentioned in Section 4.2.

To quantify the effect of changes in payoffs on individual actions, we conduct a linear regression analysis.[8] For each pair (x, Δ), we estimate the following regressions for both the Row group and Column group

$$\mathbf{1}\{y_{n,t}^{Row}(x,\Delta) = In\} = \beta_0 + \beta_1 u_{1,t} + \beta_2 u_{2,t} + \eta_{n,t}^{Row}$$
$$\mathbf{1}\{y_{n,t}^{Col}(x,\Delta) = In\} = \gamma_0 + \gamma_1 u_{1,t} + \gamma_2 u_{2,t} + \eta_{n,t}^{Col}$$

where $\mathbf{1}$ is an indicator function that is 1 if subject n chose In in game t and 0 otherwise, $u_{1,t}$ is the shock to the Row group in game t and $u_{2,t}$ is the shock to the column group in game t, and $\eta_{n,t}^{Row}$ and $\eta_{n,t}^{Col}$ are the residuals for the Row and Column

[8] We conduct regressions with non-linear effects and a logistic regression as a robustness check in Appendix E.

group respectively. We cluster standard errors at the individual level. The results are presented in Table 7.

x = 50 & Δ = 75		
	Row (In)	Column (In)
u_1	0.00867	-0.00369
	(0.000191)	(0.000266)
u_2	-0.00299	0.00858
	(0.000339)	(0.000131)
Constant	0.578	0.527
	(0.0156)	(0.0144)
Observations	704	704

x = 50 & Δ = 125		
	Row (In)	Column (In)
u_1	0.00664	-0.00298
	(0.000112)	(0.000215)
u_2	-0.00271	0.00670
	(0.000237)	(0.0000747)
Constant	0.424	0.405
	(0.0151)	(0.0154)
Observations	704	704

x = 100 & Δ = 75		
	Row (In)	Column (In)
u_1	0.0106	-0.00424
	(0.000315)	(0.000388)
u_2	-0.00316	0.0106
	(0.000412)	(0.000173)
Constant	0.942	0.845
	(0.0305)	(0.0340)
Observations	704	704

x = 100 & Δ = 125		
	Row (In)	Column (In)
u_1	0.00613	-0.00279
	(0.000152)	(0.000198)
u_2	-0.00210	0.00610
	(0.000287)	(0.000123)
Constant	0.648	0.584
	(0.0186)	(0.0224)
Observations	704	704

Table 7: OLS Regressions: Linear Effects

The regression results confirm our qualitative findings in Section 4.1. We observe a monotonic increasing response of playing In as their own shock increases. For example, the Row group is more likely to choose In as they receive a higher shock. In particular, in the regression with $(x, \Delta) = (50, 75)$ we see that an increase of two points in own shock increases the Row group choosing In approximately 1.7% holding everything fixed. We also see a monotonic decreasing response of playing In as the opponent's shock increases. For example, the Column group is less likely to choose In as the Row groups shock increases. In particular, in the regression with $(x, \Delta) = (50, 75)$ we see that an increase of three points in the Row group's shock decreases the Column group choosing In approximately 1.8% holding everything fixed. Recall that one point corresponds to a \$0.10 gain in payoff, thus small payoff changes appear to have relatively large changes in behavior.

We also mention some comparative results. First, the probability of choosing In as measured by the constant term increases as the base payoff x increases. Moreover, the probability of choosing In as measured by the constant term decreases as the penalty Δ increases. Another comparison of note is that the effect of an own shock is larger in magnitude than an opponent's shock in all situations. We also note that the base payoff may effect the strength of the monotone effect. For example, the shock to the Row group's payoff has a larger effect when going from $(x, \Delta) = (50, 75)$ to $(x, \Delta) = (100, 75)$. A similar comparative static is not seen for the higher penalty. We also find the going to a higher penalty can affect the response. For example, an increase in Row group's shock has a smaller effect going from $(x, \Delta) = (50, 75)$ to $(x, \Delta) = (50, 125)$ and going from $(x, \Delta) = (100, 75)$ to $(x, \Delta) = (100, 125)$. There seems to be little difference in the response to the opponent's shock across situations. The extent to which these results hold more generally is an open question.

5 Literature review

This paper contributes to several different groups of literature that we briefly review here. We believe this is the first paper to experimentally look at the entry game of Bresnahan and Reiss (1990), Berry (1992), and Tamer (2003). As mentioned in the introduction there is a large literature in empirical industrial organizations that uses this structure in field settings. For example, the surveys of Berry and Reiss (2007), De Paula (2013), and Aradillas-López (2020) give a great overview of the empirical and econometrics literature studying entry games and how the literature has evolved. We believe this study will be of interest to this audience and inform additional restrictions on this game structure.

Our research is also related to the study of coordination games. In particular, the entry game is an anti-coordination game when there is a region of play where opponents need to choose different actions to be in equilibrium. The survey by Cooper and Weber (2020) gives a recent survey of the literature on coordination games, but this entry game does not appear to be studied empirically. One closely related paper is Cooper et al. (1990) which experimentally studies one-shot equilibrium selection looking at normal form coordination games with two players and three actions. Kaplan and Ruffle (2012) study coordination in a simultaneous two person entry game with imperfect information and repeated interactions. They find that repetition allows for subjects to coordinate on an efficient outcome by alternating the decision to enter. Kaplan et al. (2018) expand on the above by looking at a sequential entry game with the same payoffs. In both papers, the payoff structure is set so that the unique Nash Equilibrium in the one-shot game is for both players choosing enter.

We note there has been an extensive experimental literature studying entry games with linear costs of entry following the formulation by Erev and Rapoport (1998) and Rapoport et al. (1998). This experimental work has focused on whether individuals learn to coordinate their actions by having individuals receive feedback from each round. Work following this approach includes Sundali et al. (1995), Camerer and Lovallo (1999), and Zwick and Rapoport (2002) and they all focus on learning.[9] Thus, we differ from this literature by looking at a different structure, focusing on one-shot games, and focusing on comparative statics.

In addition, there is a literature studying one-shot normal form games. For example, the work of Stahl and Wilson (1994), Stahl and Wilson (1995), Stahl (2000), Stahl (2000), and Stahl and Haruvy (2008) all look at various normal form games with two players and three or more actions for each player. This research has mainly focused on examining an individual's ability to predict opponent play according to "level-k" thinking. Other notable examples of papers studying "level-k" thinking include Nagel (1995), Ho et al. (1998), Costa-Gomes et al. (2001), among many others. Relative to this literature, we look at a very specific structure given by the entry games following Bresnahan and Reiss (1990) and focus more on deriving comparative statics in a simple environment. Thus, we complement this existing literature by studying a simple setting that is empirically relevant. One other interesting paper that looks at a wide class of one-shot games and finds some comparative statics with payoffs is Goeree and Holt (2001).

One final area of related research is the work on quantal response equilibrium following McKelvey and Palfrey (1995) and McKelvey and Palfrey (1998). Work following this literature starts from assuming that individuals have some unobserved error that affects their payoffs which creates deviations from Nash equilibrium play.

[9] For a more general overview of the experimental work on industrial organizations we recommend Holt (1995).

Many papers have followed this research. For exammple, Rogers et al. (2009) allows for heterogeneity in the shocks, Goeree et al. (2005) and Goeree et al. (2016) relax the restrictions on the error terms and describe regular quantal response equilibrium, and Allen and Rehbeck (2021a) study general aggregate models that nest the quantal response predictions. One interesting feature about regular quantal response equilibrium is that these models have similar monotonicity predictions that we observe in the data. Therefore, it might be interesting to apply these restrictions on field data following recent statistical results in Melo et al. (2019). Relative to these papers we focus on a simpler class of entry games to examine equilibrium predictions and search for comparative statics. We think estimating quantal response equilibrium models on data from our experiment is interesting. However, we believe this should be done in a more systematic model selection exercise similar to the work by Fudenberg and Liang (2019).

6 Conclusion

We conduct an experiment to investigate behavior in the simple one-shot, complete information two player entry games described in Bresnahan and Reiss (1990); Berry (1992) and Tamer (2003). Our experiment varies the "shocks" to payoffs from choosing to enter the market. This allows us to observe behavior in regions with unique and multiple equilibria. We find very few instances where subjects fail to follow a dominant strategy. However, despite the simple environment, we observe frequent failures of iterated dominance. In regions with multiple equilibria, we find that payoff asymmetry acts as a coordination device wherein subjects coordinate on the equilibrium where the player with the higher incentive to enter chooses In and the other player chooses Out. In contrast, we observe frequent coordination failures in games where payoffs are symmetric. We also observe that group level choices are monotonic with respect to the shocks. Specifically, subjects are more likely to enter when the shock to their payoffs increases, and subjects are less likely to enter when the shock to their opponent's payoff increases.

We note that some of these results could be immediately translated to restrictions for parameter identification and estimation in empirical industrial organization. For example, the monotonicity with respect to payoff shocks can be translated to parameter restrictions following a similar setup to Bresnahan and Reiss (1990), Berry (1992), and Tamer (2003). For example, suppose there are covariates, $Z_i \in \mathbb{R}^K$, associated to the ith player scaled by the vector $\beta_i \in \mathbb{R}^K$. Moreover, assume there is an unobserved random independent error for the ith individual given by $\varepsilon_i \in \mathbb{R}$. Suppose that the ith player enters the market according to the random variable

$$Y_i(Z_i, Z_j, \varepsilon_i, \varepsilon_j) = \mathbf{1}\left\{\beta_i Z_i - \Delta_i Y_j(Z_j, Z_i, \varepsilon_j, \varepsilon_i) + \varepsilon_i > 0\right\}$$

where $j \neq i$ and the product $\beta_i Z_i$ is a vector inner-product. Relative to the laboratory study where $x + u_i$ vary and are observed, we would now place the monotonicity restrictions on $\beta_i Z_i$ where we have additional unobserved error (ε_i) when going to a field setting.

Integrating over the epsilon terms gives the conditional probability of the ith player entering conditional on covariates and is denoted by

$$P_i(Z_i, Z_j) = \int_{\varepsilon_i} \int_{\varepsilon_j} \mathbf{1}\left\{\beta_i Z_i - \Delta_i Y_j(Z_j, Z_i, \varepsilon_j, \varepsilon_i) + \varepsilon_i > 0\right\} f_i(\varepsilon_i) f_j(\varepsilon_j) d\varepsilon_i d\varepsilon_j.$$

We note that this is not a best response function since it does not involve the opponents strategy. Instead, it is an *aggregate response function* which just depends on the probability of choosing an action conditional on observable information. Thus, the restrictions require less information on the play of other individuals.[10]

For realizations of the covariates given by $z_i, \tilde{z}_i, z_j, \tilde{z}_j \in \mathbb{R}^K$ with $z_i \neq \tilde{z}_i$ and $z_j \neq \tilde{z}_j$. Monotonic increasing restrictions in own payoffs when $P_i(z_i, z_j) \neq P_i(\tilde{z}_i, z_j)$ conditional on the opponent having z_j would give

$$\beta_i(z_i - \tilde{z}_i)(P_i(z_i, z_j) - P_i(\tilde{z}_i, z_j)) \geqslant 0.$$

Similarly, monotone decreasing properties in the opponent's payoff when $P_j(z_j, z_i) \neq P_j(\tilde{z}_j, z_i)$ and $P_i(z_i, z_j) \neq P_i(\tilde{z}_i, z_j)$ would give the restrictions

$$\beta_j(z_j - \tilde{z}_j)(P_i(z_i, z_j) - P_i(\tilde{z}_i, z_j)) \leqslant 0.$$

[10] Similar things have been shown theoretically in bundles models by Fox and Lazzati (2017) and Allen and Rehbeck (2021b) where identification only requires aggregate information rather than observing bundles purchased together.

These are a form of conditional moment inequalities similar to Pakes et al. (2015). We note these inequalities are a simpler forms of restrictions used in Shi et al. (2018), Allen and Rehbeck (2019), and Melo et al. (2019). These restrictions do not involve the penalty terms of Δ_i. Further work in this direction might look at when restrictions on Δ_i are appropriate and how they are related to these models.

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Appendix A Experiment Instructions

The instructions to the experiment are reproduced below.

Welcome, and thank you for taking part in this Economics Experiment. This experiment will last for around 1 hour. 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 via cash at the end of the experiment.

Before we begin, we ask that you turn off your cell phones for the duration of this experiment. We also ask that you do not communicate with anyone for the duration of this experiment and 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.

Overview

In this experiment, you will take part in a series of decision tasks. The series will consist of 64 rounds. Your payment will depend on the outcome of **one randomly chosen round.**

At the beginning of every round, you will be randomly matched with another participant to form a group of 2 members. Neither you, nor your group member will know the other's identity.

Decision Task

The decision task will proceed as follows. In each round, both you and your group member must choose between option **In** and option **Out**. Both you and your group member must make this decision without knowing the decision of the other. The outcome will depend on your and your group member's decisions.

For each round, your screen will show you a payoff table as shown below. The rows indicate the possible payoffs from your decision and the columns indicate the possible payoffs resulting from your group member's decision.

The first number in each cell (in blue) represents your payoff. The second number in

		Other's Choice	
		Out	In
Your Choice	Out	$(0, 0)$	$(0, a_2)$
	In	$(a_1, 0)$	(b_1, b_2)

each cell (in red) represents the other person's payoff. Numbers a1, b1, a2 and b2 can be either negative or positive. These numbers will take on different values throughout the experiment. Your payoff will depend on the decision taken by both you and your group member. For example, if you choose In and the other person chooses Out, you will get a1 points and the other person will get 0.

Note: You will not be shown the outcome in any round.

To make your decision, click the radio button for your choice (either **In** or **Out**) and click the Next button. **You will not have the option to revise your decision once you click Next.**

Example

To facilitate your understanding, consider the following example of a decision round. **Note this table is merely for illustration and is not indicative of payoffs used in the actual experiment.**

		Other's Choice	
		Out	In
Your Choice	Out	$(0, 0)$	$(0, 50)$
	In	$(25, 0)$	$(5, 35)$

- If you choose In and the other person chooses In, you get 5 points and the other person gets 35 points.
- If you choose In and the other person chooses Out, you will get 25 points and the other person gets 0 points.
- If you choose Out and the other person chooses In, you get 0 points and the other person gets 50 points.
- If you choose Out and the other person chooses Out, you get 0 points and the other person gets 0 points.

Payment

Your payment will depend on the outcome of **one round** chosen at random from the 64 rounds. At the end of the experiment, you will be notified about the round chosen for payment, your decision in that round, the decision of your group member, and the payoff from these decisions.

Your payoff (in points) for the randomly chosen round will be added to a balance of 150 points. You will be paid for the remaining balance.

Your payment will be calculated using the following conversion rate:

$$1 \text{ point} = \$0.10$$

In addition to this, you will also receive a show up fee of $5. Your payment will be paid to you via cash end of the experiment.

Summary

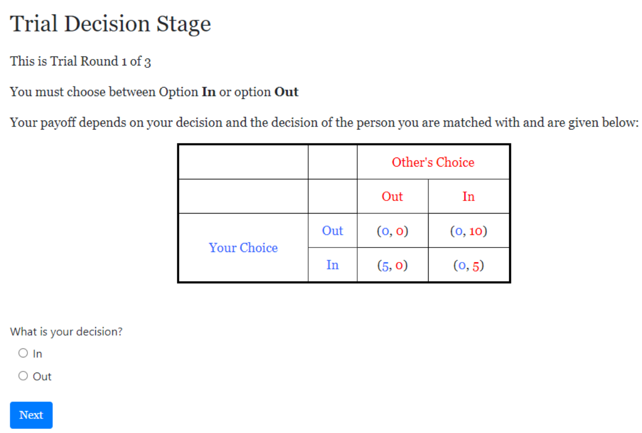
The following points summarize the experiment.

1. You will take part in a series of 64 decision tasks
2. You will be randomly matched with another participant at the start of every round.
3. You and your group member will have to decide between choosing In or Out.
4. The payoffs will depend on your and your group member's decisions and will vary from round to round.
5. You will not know the outcome of any round.
6. At the end of the experiment, you will be notified about the outcome of one randomly chosen round and will be paid for the outcome of that round and a starting balance of 150 points at the rate of 1 point = $0.10.

Before we begin, we will ask you to take part in a short sequence of "Trial" rounds to test your understanding of the experiment.

Appendix B Trial Round Example

Figure 5 shows an example of a trial round that checks a subject's understanding of the experiment. First, the subject makes a decision similar to those in the experiment. Second, they answer a question about the payoffs in a relevant situation.



Trial Decision Stage

This is Trial Round 1 of 3

You must choose between Option **In** or option **Out**

Your payoff depends on your decision and the decision of the person you are matched with and are given below:

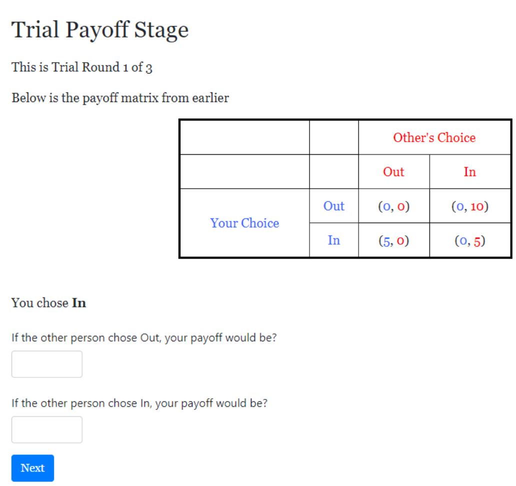
		Other's Choice	
		Out	In
Your Choice	Out	(0, 0)	(0, 10)
	In	(5, 0)	(0, 5)

What is your decision?

- In
- Out

Next

(a) Choice



Trial Payoff Stage

This is Trial Round 1 of 3

Below is the payoff matrix from earlier

		Other's Choice	
		Out	In
Your Choice	Out	(0, 0)	(0, 10)
	In	(5, 0)	(0, 5)

You chose **In**

If the other person chose Out, your payoff would be?

If the other person chose In, your payoff would be?

Next

(b) Questions

Figure 5: Example Trial Round

Appendix C Additional Entry Rates

Figure 6, Figure 7, and Figure 8 show the empirical frequencies of subjects choosing In for the remaining 48 games.

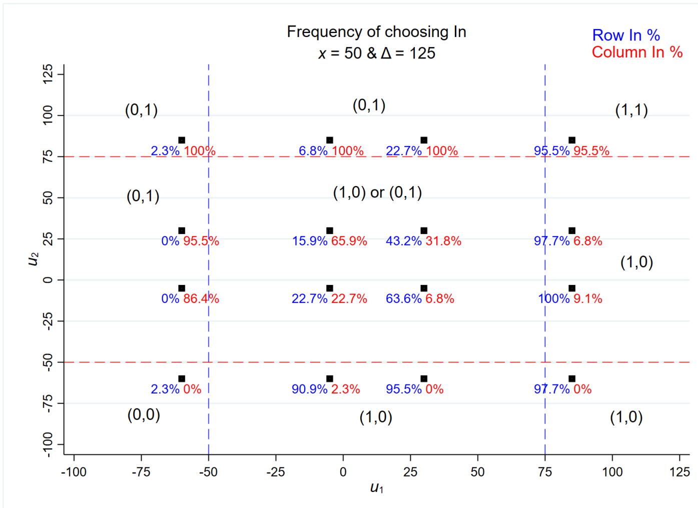


Figure 6: Entry rates when $x = 50$, $\Delta = 125$

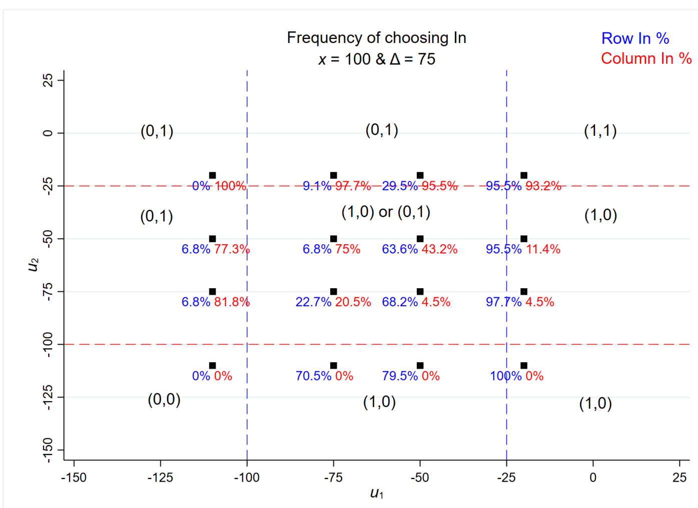


Figure 7: Entry rates when $x = 100$, $\Delta = 75$

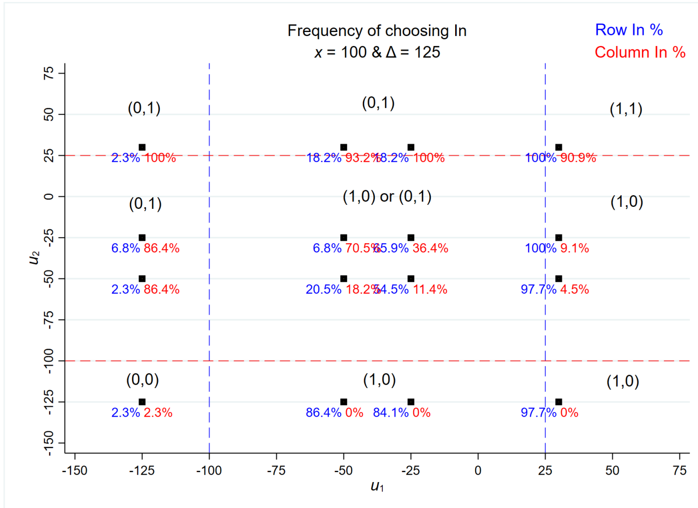


Figure 8: Entry rates when $x = 100$, $\Delta = 125$

Appendix D Mixed Strategy Equilibria

In this section, we compare the empirical frequencies in regions of multiple equilibria to the predictions outlined by the Mixed Strategy Nash Equilibrium (MSNE). Recall that the MSNE for the ith group is given by the probability of choosing In $p_i = 1 - \frac{x_j + u_j - \Delta_j}{-\Delta_j}$. Table 8 below compares the predicted MSNE probabilities for each of the 16 games with multiple equilibria to the realized empirical frequencies.

The mixed strategy equilibrium yields the following comparative static predictions: keeping the ith group's payoff fixed, the frequency of the ith group choosing In increases as jth group's payoffs from choosing In increase. Furthermore, keeping the jth group's payoffs fixed, the frequency of the ith group choosing In is invariant to the ith group's payoffs from choosing In. These predictions stem from the fact that players mix strategies in order to ensure that their opponent is indifferent when choosing their strategies.

Our empirical results show the exact opposite in a majority of cases. The frequency of choosing In *decreases* as the opponent's payoff from choosing In increases. Furthermore, the frequency of choosing In *increases* as a group's payoff from choosing In increases.

Γ	p^{Row}	p^{Col}	Row In (%)	Column In (%)
(50, 75, -30, -30)	26.7%	26.7%	22.7%	13.6%
(50, 75, -30, 10)	80.0%	26.7%	9.1%	79.5%
(50, 75, 10, -30)	26.7%	80.0%	75.0%	2.3%
(50, 75, 10, 10)	80.0%	80.0%	68.2%	45.5%
(50, 125, -5, -5)	36.0%	36.0%	22.7%	22.7%
(50, 125, -5, 30)	64.0%	36.0%	15.9%	65.9%
(50, 125, 30, -5)	36.0%	64.0%	63.6%	6.8%
(50, 125, 30, 30)	64.0%	64.0%	43.2%	31.8%
(100, 75, -75, -75)	33.3%	33.3%	22.7%	20.5%
(100, 75, -75, -50)	66.7%	33.3%	6.8%	75.0%
(100, 75, -50, -75)	33.3%	66.7%	68.2%	4.5%
(100, 75, -50, -50)	66.7%	66.7%	63.6%	43.2%
(100, 125, -50, -50)	40.0%	40.0%	20.5%	18.2%
(100, 125, -50, -25)	60.0%	40.0%	6.8%	70.5%
(100, 125, -25, -50)	40.0%	60.0%	54.5%	11.4%
(100, 125, -25, -25)	60.0%	60.0%	65.9%	36.4%

Table 8: Comparison to MSNE

Appendix E Additional Regression Results

In this section we conduct a more robust comparative static analysis of subject choices. We first estimate the same linear effects regression as in Section 4.3 with individual subject fixed effects. We then estimate non-linear effects of shocks on player choices using OLS. To estimate non-linear effects of the shocks, for each (x, Δ) we order the four shocks for each group $i \in \{1, 2\}$ so $u_i^0 < u_i^1 < u_i^2 < u_i^3$ and assign indicator variables when the shocks take the values u_i^1, u_i^2, or u_i^3 to pick up the effect of each shock relative to the lowest levels u_1^0 and u_2^0. We then estimate both linear and non-linear effects using logistic regressions.

E.1 OLS with Linear Effects including Subject Fixed Effects

Table 9 below shows the results for the linear effects regression using subject fixed effects. Qualitatively the results are the same.

$x = 50$ & $\Delta = 75$		
	Row (In)	Column (In)
u_1	0.00855	-0.00380
	(0.000233)	(0.000300)
u_2	-0.00311	0.00847
	(0.000384)	(0.000164)
Observations	704	704

$x = 50$ & $\Delta = 125$		
	Row (In)	Column (In)
u_1	0.00668	-0.00293
	(0.000114)	(0.000225)
u_2	-0.00267	0.00675
	(0.000238)	(0.0000969)
Observations	704	704

$x = 100$ & $\Delta = 75$		
	Row (In)	Column (In)
u_1	0.00946	-0.00541
	(0.00106)	(0.00108)
u_2	-0.00426	0.00942
	(0.00109)	(0.00102)
Observations	704	704

$x = 100$ & $\Delta = 125$		
	Row (In)	Column (In)
u_1	0.00594	-0.00301
	(0.000237)	(0.000302)
u_2	-0.00228	0.00588
	(0.000357)	(0.000238)
Observations	704	704

Table 9: OLS Regression: Linear Effects with Subject fixed effects

E.2 OLS with Non-Linear Effects

We estimate, for each (x, Δ) combination, a linear regression of the following form for Row and Column groups separately:

$$\begin{aligned}
\mathbf{1}(y^{Row}_{n,t}(x,\Delta) = 1) &= \beta_0 + \beta_1\mathbf{1}\{u_{1,t} = u_1^1\} + \beta_2\mathbf{1}\{u_{1,t} = u_1^2\} + \beta_3\mathbf{1}\{u_{1,t} = u_1^3\} \\
&\quad + \beta_4\mathbf{1}\{u_{2,t} = u_2^1\} + \beta_5\mathbf{1}\{u_{2,t} = u_2^2\} + \beta_6\mathbf{1}\{u_{2,t} = u_2^3\} + \eta^{Row}_{n,t} \\
\mathbf{1}(y^{Col}_{n,t}(x,\Delta) = 1) &= \gamma_0 + \gamma_1\mathbf{1}\{u_{1,t} = u_1^1\} + \gamma_2\mathbf{1}\{u_{1,t} = u_1^2\} + \gamma_3\mathbf{1}\{u_{1,t} = u_1^3\} \\
&\quad + \gamma_4\mathbf{1}\{u_{2,t} = u_2^1\} + \gamma_5\mathbf{1}\{u_{2,t} = u_2^2\} + \gamma_6\mathbf{1}\{u_{2,t} = u_2^3\} + \eta^{Col}_{n,t}
\end{aligned}$$

where $y^j_{n,t}$ is the nth subject's choice from group $j \in \{Row, Column\}$ and game t, $\mathbf{1}$ is an indicator function that is 1 when the statement in parenthesis is satisfied. In these regressions, the coefficients $\beta_1 - -\beta_6$ give the change in the probability of choosing In for the Row player relative to the lowest values (u_1^0 and u_2^0). The same is true for the coefficients $\gamma_1 - -\gamma_6$ for the Column player. We cluster standard errors at the individual subject level. The results are shown in Table 10.

We observe monotonicity with respect to the shocks on the probability of subjects choosing In. All coefficients are statistically significant at the 5% level. Furthermore, the magnitude of the effects are increasing in the size of the shocks.[11] For the Row group, all u_1 shocks have a positive coefficient, suggesting that an increase in Row group's payoffs leads to an increase in the probability of choosing In with the effect increasing in the size of the shock. Conversely, all u_2 shocks have a negative coefficient which suggests that an increase in the Column group's payoffs lead to a decrease of the probability of the Row group choosing In. Here, the effect becomes more pronounced as the value of the shock increases. We find qualitatively similar effects for Column group. Specifically, the probability of Column group choosing In is increasing in the shocks to the Column group's payoff (u_2) and decreasing in the shocks to the Row group's payoffs (u_1) with the effect becoming more pronounced as the size of the shock increases.

[11] We can statistically reject that the coefficients are equal at the 5% significance level for all but one of the comparisons.

$x = 50$ & $\Delta = 75$		
	Row (In)	Column (In)
u_1 (base $= -75$)		
-30	0.290	-0.205
	(0.0336)	(0.0249)
10	0.642	-0.318
	(0.0378)	(0.0250)
35	0.972	-0.415
	(0.0186)	(0.0316)
u_2 (base $= -75$)		
-30	-0.187	0.239
	(0.0233)	(0.0258)
10	-0.239	0.574
	(0.0282)	(0.0322)
35	-0.352	0.977
	(0.0411)	(0.0110)
Constant	0.212	0.240
	(0.0262)	(0.0174)
Observations	704	704

$x = 50$ & $\Delta = 125$		
	Row (In)	Column (In)
u_1 (base $= -60$)		
-5	0.330	-0.227
	(0.0314)	(0.0281)
30	0.551	-0.358
	(0.0332)	(0.0250)
85	0.966	-0.426
	(0.0155)	(0.0301)
u_2 (base $= -60$)		
-5	-0.250	0.307
	(0.0245)	(0.0335)
30	-0.324	0.494
	(0.0290)	(0.0341)
85	-0.398	0.983
	(0.0340)	(0.00965)
Constant	0.254	0.259
	(0.0184)	(0.0177)
Observations	704	704

$x = 100$ & $\Delta = 75$		
	Row (In)	Column (In)
u_1 (base $= -110$)		
-75	0.239	-0.165
	(0.0316)	(0.0326)
-50	0.568	-0.290
	(0.0457)	(0.0326)
-20	0.938	-0.375
	(0.0247)	(0.0360)
u_2 (base $= -110$)		
-75	-0.136	0.278
	(0.0404)	(0.0308)
-50	-0.193	0.517
	(0.0390)	(0.0411)
-20	-0.290	0.966
	(0.0382)	(0.0155)
Constant	0.189	0.207
	(0.0239)	(0.0227)
Observations	704	704

$x = 100$ & $\Delta = 125$		
	Row (In)	Column (In)
u_1 (base $= -125$)		
-50	0.295	-0.233
	(0.0262)	(0.0320)
-25	0.523	-0.318
	(0.0354)	(0.0309)
30	0.955	-0.426
	(0.0235)	(0.0312)
u_2 (base $= -125$)		
-50	-0.239	0.295
	(0.0336)	(0.0319)
-25	-0.227	0.500
	(0.0363)	(0.0400)
30	-0.330	0.955
	(0.0445)	(0.0187)
Constant	0.233	0.250
	(0.0292)	(0.0228)
Observations	704	704

Table 10: OLS Regressions: Non-Linear effects

E.3 Logit Regression with Linear Effects

In this subsection we estimate logit regressions with linear effects using the same covariate structure as the regression in Section 4.3. The results for estimating a linear effect using logit regression are given below in Table 11. We also estimate the same

$x = 50$ & $\Delta = 75$		
	Row (In)	Column (In)
u_1	0.0739	-0.0535
	(0.00829)	(0.00946)
u_2	-0.0337	0.100
	(0.00631)	(0.0134)
Constant	0.292	-0.319
	(0.158)	(0.201)
Observations	704	704

$x = 50$ & $\Delta = 125$		
	Row (In)	Column (In)
u_1	0.0604	-0.0375
	(0.00654)	(0.00640)
u_2	-0.0287	0.0718
	(0.00492)	(0.00791)
Constant	-0.695	-1.075
	(0.196)	(0.255)
Observations	704	704

$x = 100$ & $\Delta = 75$		
	Row (In)	Column (In)
u_1	0.0806	-0.0475
	(0.0100)	(0.00690)
u_2	-0.0290	0.100
	(0.00581)	(0.00806)
Constant	2.948	2.594
	(0.343)	(0.290)
Observations	704	704

$x = 100$ & $\Delta = 125$		
	Row (In)	Column (In)
u_1	0.0538	-0.0310
	(0.00785)	(0.00412)
u_2	-0.0189	0.0680
	(0.00391)	(0.00701)
Constant	1.075	0.656
	(0.168)	(0.244)
Observations	704	704

Table 11: Logit Regression: Linear Effects

specification using subject fixed effects. The results are in Table 12.

E.4 Non-Linear Effects

In this subsection we estimate logit regressions with non-linear effects using the same covariate structure as the regression in Appendix 10. The results for the non-linear effects logit specification are shown in Table 13 below.[12]

[12]For $x = 100$ and $\delta = 75$, some of the observations for the column group were perfectly determined leading to Stata to drop these observations when estimating the regression.

$x = 50$ & $\Delta = 75$		
	Row (In)	Column (In)
u_1	0.0951	-0.0702
	(0.0100)	(0.0137)
u_2	-0.0431	0.132
	(0.00805)	(0.0204)
Observations	704	704

$x = 50$ & $\Delta = 125$		
	Row (In)	Column (In)
u_1	0.0759	-0.0561
	(0.0101)	(0.0126)
u_2	-0.0365	0.107
	(0.00687)	(0.0185)
Observations	704	704

$x = 100$ & $\Delta = 75$		
	Row (In)	Column (In)
u_1	0.0919	-0.0627
	(0.0144)	(0.00856)
u_2	-0.0380	0.116
	(0.00755)	(0.0161)
Observations	704	704

$x = 100$ & $\Delta = 125$		
	Row (In)	Column (In)
u_1	0.0639	-0.0460
	(0.0103)	(0.00666)
u_2	-0.0228	0.0973
	(0.00517)	(0.0140)
Observations	704	704

Table 12: Logit Regression: Linear Effects with Subject fixed effects

$x = 50$ & $\Delta = 75$		
	Row (In)	Column (In)
u_1 (base $= -75$)		
-30	3.873	-2.686
	(1.148)	(0.495)
10	5.947	-4.095
	(1.230)	(0.619)
35	10.17	-5.713
	(1.420)	(1.012)
u_2 (base $= -75$)		
-30	-2.078	4.948
	(0.429)	(1.118)
10	-2.595	7.706
	(0.482)	(1.286)
35	-3.883	12.43
	(0.729)	(1.537)
Constant	-2.837	-3.849
	(1.014)	(1.010)
Observations	704	704

$x = 50$ & $\Delta = 125$		
	Row (In)	Column (In)
u_1 (base $= -60$)		
-5	4.975	-2.586
	(0.816)	(0.459)
30	6.389	-3.934
	(0.956)	(0.547)
85	10.35	-5.131
	(1.264)	(0.868)
u_2 (base $= -60$)		
-5	-2.818	5.527
	(0.436)	(1.162)
30	-3.504	6.959
	(0.545)	(1.214)
85	-4.333	12.38
	(0.737)	(1.388)
Constant	-3.151	-3.861
	(0.712)	(1.008)
Observations	704	704

$x = 100$ & $\Delta = 75$		
	Row (In)	Column (In)
u_1 (base $= -110$)		
-75	2.581	-1.674
	(0.630)	(0.411)
-50	4.264	-2.897
	(0.793)	(0.452)
-20	7.666	-4.054
	(1.005)	(0.612)
u_2 (base $= -110$)		
-75	-1.183	0
	(0.434)	(.)
-50	-1.684	1.539
	(0.445)	(0.286)
-20	-2.643	5.555
	(0.523)	(0.619)
Constant	-2.375	0.769
	(0.499)	(0.343)
Observations	704	528

$x = 100$ & $\Delta = 125$		
	Row (In)	Column (In)
u_1 (base $= -125$)		
-50	3.092	-2.429
	(0.603)	(0.449)
-25	4.291	-3.247
	(0.696)	(0.491)
30	8.838	-4.684
	(1.359)	(0.649)
u_2 (base $= -125$)		
-50	-2.074	5.228
	(0.395)	(1.038)
-25	-1.975	6.642
	(0.425)	(1.100)
30	-2.984	10.62
	(0.622)	(1.188)
Constant	-2.183	-3.894
	(0.516)	(1.029)
Observations	704	704

Table 13: Logistic Regressions: Non-Linear effects