The Pennsylvania State University

The Graduate School

Department of Agricultural Economics, Sociology, and Education

PARTICIPATION, PRICING AND PERCEPTION IN MARKETS WITH EXTERNALITIES

A Dissertation in

Agricultural, Environmental, and Regional Economics

by

Hernán Daniel Bejarano

Submitted in Partial Fulfillment
of the Requirements
for the Degree of

Doctor of Philosophy

May 2013

The dissertation of Hernán Daniel Bejarano was reviewed and approved* by the following:

James Shortle
Distinguished Professor of Agricultural and Environmental Economics
Dissertation Advisor
Chair of Committee

David Abler
Professor of Agricultural, Environmental, and Regional Economics and Demography

Edward Coulson
Professor of Economics , College of the Liberal Arts
Professor of Real Estate Economics, Smeal College of Business

Elena Katok
Ashbel Smith Professor-Management, School of Management University of Texas at Dallas

Richard Ready
Professor of Agricultural and Environmental Economics

Ann Tickamyer
Head Department of Agricultural Economics, Sociology, and Education

*Signatures are on file in the Graduate School

ABSTRACT

No one enjoys getting stuck in traffic or drinking water that has been contaminated by animal waste[1]. Aside from being pervasive and persistent nuisances, both traffic congestion and agricultural water pollution are the consequences of missing markets that result in negative externalities. Effective and politically acceptable solutions have been illusive for both. This dissertation presents three essays that address the design of policies for externalities using traffic congestion and agricultural water pollution as contexts.

The first essay initiates a lab experiment of a market entry game (MEG). MEG models create a setting where many individuals must simultaneously choose between two options. One of the options has a large potential but uncertain payoff. The other has a certain payoff that is independent of the others' choices. The first goal of this MEG is to test if simple policies, such as entry fees or subsidies, can be designed to induce optimal entry. To perform this test, the canonical MEG is revised by introducing uniform entry fees -- entry fees that are equal to all entrants. The second goal of the essay is to explore whether capacity uncertainty affects the choices. A new treatment in which market capacity is introduced as a random variable is used to achieve this goal. This essay presents to two main findings. On one hand, uniformity proved to be effective by decreasing entry, although entry was statistically different from that theoretically

[1] Anthony Downs start his book "Stuck in Traffic" (1992) citing several studies conducted in the late 80's and 90's where residents of U.S. suburban areas that regarded congestion as their most serious environmental problem. Estimations of the cost of congestion from the Texas Transportation Institute Urban Mobility report do not seem to indicate that this problem has been solved.

predicted for almost all the sub treatments. The second finding is that average number of entrants is not affected by the uncertainty of the market capacity.

The second essay presents an experimental test of a Pay-for-performance (PFP) mechanisms conducted with students and farmers. PFP are a class of policy instruments designed to increase (decrease) private voluntary provision of limited amounts of public goods (bads). This paper presents an artefactual field experiment conducted with farmers and students to examine the effects of strategic uncertainty on participation and efficiency of PFP mechanism. In this paper, we present an artefactual field experiment conducted with farmers and students. Subjects choose whether to participate in a 2-by-2 Bayesian game with private values (PVPG). Payoffs for those who choose to participate depend on the private value and others' participation choices, while the payoffs from nonparticipation are certain. Two PVPG experimental tasks with different feedback conditions and two treatments with High and Low participation payments were played by every subject. Participation was increased by High participation payments but less frequently than theoretical predictions. Subjects coordinated the efficient action profile at frequencies larger than those predicted by theory. Farmer and student groups presented similar participation levels but farmers with the same risk aversion profile as students chose to participate less frequently. This essay reveals the limits of generalizing the outcomes of the findings achieved in lab experiments with students to other populations of subjects.

Finally, the third essay describes a naturally occurring field experiment in Lima, Peru to assess if and how taxi drivers transfer congestion costs to customers. The experiment involved collaborators hailing taxis and negotiating fares at different times of day between specific locations with alternative route choices as treatments. A total of 1100 trips were conducted following the same bargaining protocol and the randomly assigned route treatments, from which taxi fares, travel times and routing decisions were collected. Results show that taxi drivers request fares that discriminate between routes that take longer travel times, but do not request enough to prevent earnings per minute from decreasing. Fares for congested trips are one third lower than metered fares constructed estimates. Insufficiency of fares increment during peak collaborators hours could be generated by either highly competitive market conditions, failure to perceive longer travel times or a combination of both. Customer waiting time and proportions of taxis over total traffic support the idea that drivers might perceive peak traffic hours as a competitive market therefore only partially transferring the cost of congestion into fares. These results highlight that unregulated taxi systems are successful at generating incentives for taxi drivers to make optimal routing decisions. However, they fail to improve traffic miscoordination because taxi driver misperceptions are left uncorrected. Real time routing and taxi market information technology could be used to improve the overall use of traffic network capacity.

Theoretical models of diverse problems, such as traffic congestion, use of common pool resources, and entry in newly created markets, share common characteristics. For example voluntary participation in new markets and traffic routing decisions are both essentially binary decision problems in which subjects can learn to coordinate by interacting but they might also fail to coordinate. Experimental economic research on binary decision choice settings has found that individuals usually behave in noisy ways, not predicted by theory. The theoretical models in this dissertation are used just to construct the framework guiding the experimental design. The experiments allow us to observe how subjects act when facing these problems. Finally, the econometric analysis allows us to test if theoretical implications are satisfied by the observed behavior.

The dissertation combines of three types of experiments, ranging from traditional laboratory experiments to naturally occurring field experiments, allowed me to observe how different experimental methods, with different subject samples and different degrees of control over external variables, could be used as tool to study different markets with externalities. This dissertation highlights how a combination of different methodologies, conducted over different pool of subjects, be it students, farmers or taxi drivers, should be used to better understand how individuals perceive and choose to act when the actions of other subjects affect their earnings.

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ACKNOWLEDGEMENTS

I've wanted to become an economist ever since I was twelve years old. It was 1990 then and hyperinflation was tearing through the Argentinean economy. The price of the newspaper I was selling had to be updated everyday. My mother, who owned a small clothing shop, changed her prices several times a day to avoid loosing money. Argentinean hyperinflation showed me how economic policy influences the private lives and decisions of citizens. By the time the next financial crisis hit the country in 2001, I was working as an economic advisor for the city of Buenos Aires.

My Ph.D trajectory resembles Marco Polo's quest in a way – I traveled deep within myself and discovered the American continent. I could never have completed the trip without the support of my parents, Jorge and Lidia. They supported my dream to become an experimental economist despite the fact it took me far away from Argentina. My brother Adrián, like my parents, offered me constant support over the years. The three of them have been my compasses: showing me the north but always marking the way south, back home.

Lissandra, my soul mate: your intelligence, honesty, and love gave me strength and belief in myself when I needed it most. At times, your support was the reason I didn't run away from my dream.

My two mentors and role models, Professors Jim Shortle and Steve Rassenti, helped me transition into the researcher I have become today. Professionally, Jim Shortle served as my advisor. When he agreed to work with me, I was unsure of where to go in my studies. Jim gave me the chance to work with him and to learn from him. He was an inspiration to me and we engaged in great projects together. Hopefully by now, some of Jim's relentless problem-solving capabilities, joy in working, and genuine interest in helping others has rubbed off on me. Steve Rassenti also showed me how to work with a smile on my face.

I would also like to express my gratitude to my committee members David Abler, Edward Coulson, Elena Katok, and Richard Ready. These four wonderful people went out of their way to make things work out for me.

Finally, I would like to thank my friends and doctoral colleagues from the Economics and the Agricultural Economics departments. In particular, I would like to thank those who were a part of my community and support network while in State College, namely Gaurab, Daniel-Xu, Tuan, Kerem, Florencia, Bernado, Milagro, David, Roberto, Rodrigo, and Veronica. These friends made State College my home far away from home.

Chapter 1

Applying Market Entry Games to Congestion Externalities

An important class of externalities involves congestion of common pool resources, ranging from roads, bridges, and airports to the Internet network (Arnott and Small, 1994; Mayer and Sinai 2003). Congestion externalities decrease a resource user's utility; examples of the cost externalities that congestion imposes on a user include longer commute times or slower data transferring speeds (in the case of the Internet). Additionally, each fisherman and cattle herder using a natural common pool of resources such as fisheries and common grasslands also generates a negative externality on the existing users.

Congestible resources are common resources with limited capacity. When access to use congestible resources is open, over-use creates congestion, creating a situation in which users are worse off than those who are not using the common resource[2]. Therefore, congestion can be viewed as a result of coordination failures. Congestion externalities exist because users do not internalize the social cost of their decisions. Congestible resources create competition among potential users. Optimal usage of congestible resources requires individuals to coordinate their use, meaning that not all potential users can use the resource at the same time.

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[2] I will use interchangeably *entry* and *use* and its related term *under-entry*, *under-use* as well as *over-use* and *over-entry* in this chapter.

Social and individual costs and benefits of using congestible resources are different. Therefore, social optimal and individually optimal uses of limited resources are usually different (Hardin, 1968). Pigou (1932) was the first one to analyze the differences between individual and social optimal levels of use of a congestible resource. Policies aiming to implement the social optimal use of a resource need to constrain access. In theory, a pigouvian tax equalizing the marginal individual's benefits to its social cost could attain the social optimal use. Economists have argued in favor of pigouvian taxes for environments with externalities (Mankiw, 2009).

Textbook pigouvian taxes rely on several simplifications, such as perfect knowledge of individual preferences and homogeneous individuals' value of use for the congestible resource. When individuals' value of use is heterogeneous, the optimal policy is a price scheme. A discriminatory price scheme, congestion pricing, can be imposed by charging more to individuals with the highest value of use (Vickrey, 1963). In theory, policy makers need to know the distribution of individual values for using the resource during each time period in order to design a policy that averts congestion. In the real world, an individual's value of use is private information that cannot easily be obtained. Congestion pricing policies have met considerable opposition for several reasons, including the potentially high cost of designing a pricing system aimed at inducing individual usage according to private values, as well as policy makers' aversion to implementing complex discriminatory policies. Policy makers aiming to regulate the use of a congestible resource have to choose between the bad, the worse, and the ugly.

No policy means congestion, simple policies are possibly suboptimal, and optimal policies might be too complex *to be implemented*.

How badly would simple policies do? Even though simple policies such as a uniform entry fee[3] seem to have a better chance of being implemented than more complex policies, to my knowledge, little research has been conducted to assess the effectiveness of this kind of policy. Theoretically, when all the potential users obtain the same value for using the common resource, then a uniform entry fee can be designed to induce individuals to coordinate in the use of the congestible resource (Anderson et al. 2008). The optimal uniform entry fee accounts by the negative externality that each new user generates making social and individual use equal. The theoretical instrument is argued not to work when individuals value for using the common resource are different. A uniform entry fee can potentially be effective if it generates heterogeneous changes individuals' decisions. Testing the effectiveness of entry fee policies to induce optimal social usage is an empirical endeavor.

Empirical analysis of congestible resources use present several difficulties. To begin, an individual's real world problem complexity is greater given that resource capacity, number of potential users, and the actions of users are usually uncertain and usually these actions are not publicly observed. Therefore, establishing whether an individual's actions are his or her best response is impossible, given a lack of information regarding an individual's information and uncertainty.

[3] Singapore's commuter pricing scheme is an example of how simplicity can improve the chance of a policy being implemented. Implemented in 1975, the scheme is simple: a uniform entry fee is charged to all cars entering into the central business district during the morning and afternoon peaks.

Researchers aiming to analyze observed use actions of congestible resources have limited information regarding individual's earnings and costs of using a congestible resource and outside options. An individual's characteristics are usually private information. Traditionally these characteristics can be estimated by surveys or via other econometric analysis (Small et al., 2005). Even when the data are available, estimation of an individual's payoff functions might be based on strong assumptions that are impossible to test.

In comparison to other approaches such as simulations or econometric analysis of naturally occurring data, the experimental method provides important advantages when it comes to testing policy effectiveness. A policy is effective if it attains the policy maker's desired results. Experiments are a reliable methodology to measure the success of groups of subjects at achieving an expected behavior, given that the experiment has the following characteristics. First, the experimental design provides control over a subject's payoff functions.[4] Second, traditionally unobserved subject's characteristics, such as risk aversion and time preferences, can be elicited through complementary experimental tasks. Moreover, experiments with more than one experimental task can estimate the relationship between unobserved characteristics and a subject's behavior in the main experimental task. Third, experimental treatments with different parameters can be a good and a feasible substitute to test hypotheses regarding the effects of parameter values and their association with monetary incentives to observed choices. Finally, genuine,

[4] Economic experiments can implement various utility functions through the use of experimental payoff functions. Experimental payoff functions merely transfer a subject's decisions to payments. The induced value theorem described by Smith (1976) shows how an experimental subject's preferences can be affected by income. Therefore, using the induced value theorem along with experiments a theory can be tested.

motivated human decisions can be observed. Therefore, relationships between payoff functions and outcomes can be easily identified. Experimental treatments can be used to test alternative policies of interest (Eckel and Lutz, 2003; Roth 2002).

This chapter uses modifications of the market entry game (MEG) experiment to test the effectiveness of a uniform entry fee to reduce entry into a congestible resource. In MEG, each subject must make a sequence of choices between two options: one with limited capacity, i.e., a congestible resource, and another with unlimited capacity (Rapoport 1995). Subjects receive feedback only on the number of entrants in the previous round before making a new choice. MEG is modified in two ways: entry fees and uncertainty regarding the capacity of the congestible resource are introduced in the experimental design. Modifications of the game reveal how choices to enter or not might be affected by the presence of uncertainty and entry fees.

The study focuses on the two following questions. First, are uniform entry fees effective at inducing the appropriate entry level? Second, does uncertainty capacity affect entry?

This paper reports the results of experiments on the ability of students to tacitly coordinate the use of a congestible good. Experimental treatments examine how uncertainty and entry fees influence the outcomes. Additionally, I study heterogeneous individuals' entry profiles.

1.1 Literature Review

This research is strongly related to the experimental economic literature on market entry games (MEGs). The experimental literature on congestion and congestible resources has been mostly influenced by the work of Amnon, Rapoport, and coauthors. Rapoport and coauthors focus their research agenda on understanding large groups' capabilities to coordinate entry in a market with limited capacity (Rapoport et al., 1998; 2002). The MEG theoretical model is closely related to the theoretical framework used in this research. The theoretical models are the same although the motivation of the present study is rooted in understanding the efficacy of simple policies, such as uniform entry fees and how capacity uncertainty affects the performance of subjects.

In Nobel prize-winning Daniel Kahneman's speech (Kahneman, 2002), he talks about the "magic" of the coordination that he observed in a MEG classroom experiment. Rapoport conducted an incentivized MEG; this canonical experiment presented subjects with homogenous payoff functions (Rapoport, 1995). Rapoport and coauthors found two common results during a sequence of different articles (Camerer, 2003). First, the average total entry is usually similar to that predicted by the Nash equilibrium solution of the game. Second, an individual's entry behavior cannot be described by Nash strategies. All of these articles additionally have in common two other characteristics. First, the payoff functions did not imply an explicit cost for choosing to enter. In the MEG, if the payoff function is such that entry does not imply an explicit cost, then the number of entrants under the Nash equilibrium is close to the congestible resource's capacity.

Second, the potential benefits from entering if fewer users choose to enter are an order of magnitude larger when compared with the payment for not entering.

Similar results highlighting groups' capacity to coordinate in MEG such as laboratory experiments have also been discussed in Selten et al. (2007). Motivated by the idea that lab experiments provide a controlled and reliable way of testing groups to tacitly coordinate, the authors conducted a two-market MEG inspired by traffic coordination. Two treatments were conducted; in treatment I, each subject knows his or her own payments only at the end of each round; in treatment II, every one payments for each option. The authors observed that changes were made more frequently when the subjects had *less* information. The working paper version of that article was the first to introduce MEG as a valid tool to study coordination and the use of congestible resources.

Following Selten's insights, Anderson et al. (2008) conducted another MEG to analyze congestion pricing and welfare effects. To my knowledge, this was the first and only additional MEG experiment with entry fees. This paper is in a similar spirit to my own. The authors recognize the problems of congestion pricing and the welfare losses generated by the asymmetries in payments from over-entry and under-entry. In games in which players have a binary decision space, they need to decide to enter or not to enter, and there is a congestible resource, such as the MEG, the social costs of over-entry will outweigh the benefits of under-entry. When over-entry occurs, larger numbers of users will be worse off than if they never entered; on the other hand, when there is under-entry, fewer users will obtain extraordinary benefits. After recognizing the importance of driving, drivers choose to coordinate in an effort to obtain equilibrium, i.e., those combinations of route choices that minimize travel time. Anderson et al. (2008) conducted experiments in which they attempt to understand how different policies can affect coordination. A single policy, an entry fee, is tested via two treatments with two different ways to determine the fees. In one treatment, the social optimal entry fee is implemented, and in the other users vote on entry fees. The authors' three main findings are as follows. First, the observed entry behavior was consistent with previous MEGs, i.e., aggregated entry was as described by the Nash equilibrium number of entrants; however, individual behavior was not consistent with Nash predictions. Second, entry fees shifted the number of entrants, showing that the imposition of these entry fees did not change the dynamic of the plays and that the agents were able to recognize the new equilibrium levels. Finally, when the subjects were able to choose the entry fees themselves, they chose entry fees close to the optimal ones.

Although Anderson et al. (2008) advanced research on MEG to analyze coordination and congestion but this paper has two major drawbacks. First, for the exogenously imposed entry fee treatments, only one treatment with one level of capacity was tested with no entry fee; optimal entry fee and non-optimal entry fee subtreatments were also conducted. Entry fees were low, allowing observation of average entry consistent with theoretical predictions even when only a few subjects modified their behavior. When congestion problems are severe, it is difficult to believe that policies motivating changes of 8% of the population might lead the system to a new equilibrium. Second, capacity remained known throughout all of the authors' experimental treatments.

More recently, Brandts and Yao (2010) took a step further in their research to understand the effects of uncertainty and ambiguity in a two-market MEG. The authors focused on understanding how different information can affect subjects' preferences for one market over another. They conducted two treatments, one risky and the other ambiguous. In the risky treatment, the subjects were informed that there were two possible market capacities, both known to occur with the probability of 1/2. In the ambiguous treatment, participants were told only that there is uncertainty about capacities, although the capacities really occur with the probability of 1/2. The authors found that average entry was higher under the ambiguous case than under the risky one.

Past research shows that MEG can be an appropriate instrument to study the research questions discussed in this chapter. The next two sections describe the theoretical framework and the experimental design. This experiment builds on a extensive literature regarding MEG but one in which experiments have been conducted with other motivations than the one for my research. I extend upon the research conducted by Anderson et al. (2008), which allows us to test whether the relevant observations of Brandts and Yao (2010) might be a key to shifting average entries via entry fees.

1.2 Theoretical Framework

The market entry game (MEG) is a simultaneous *N*-players one-shot game. Each player's strategy space includes two possible actions: enter or do not enter, or stay out. The payoff for staying out is certain and is independent of other players' choices. If an individual chooses to enter, the payoff is uncertain and depends on the number of other players who also choose to enter. An individual's payoff function is:

$$\pi(enter, stay\_out) = \begin{cases} v + r(c-x) - t - f & if \quad enter \\ v & if \quad stay\_out \end{cases} \tag{1}$$

The number of entrants is represented by *x*. The parameter *v* is the certain payoff for choosing to stay out. The parameters *v, r, c, t,* and *f* determine payoffs, given the number of entrants (*x*) and the resource capacity (*c*). The capacity (*c*) can be interpreted as the maximum number of users that can use the resource at a given time without making users' utility negative. The parameter *r* determines the amount by which previous users' utilities are reduced by one additional new user. The parameter *t* is the individual entry cost, the cost that each individual pays for taking the risk of greater utility that could be provided by the congestible resource. Different than *t, f* is the entry fee, a fee that is commonly charged to each one of the users of the congestible resource.

A set of N-choices is an equilibrium profile, when no player can do better by changing his choice in a unilateral way. If an equilibrium profile is directly related to a number of subjects choosing to enter and the remaining number of the subjects choosing to stay out, then the equilibrium profile is a single pure strategy Nash equilibrium. The number of players entering in a Nash equilibria (NE) is $x^{NE} < n$, then $n - x^{NE}$ players stay out. In equilibrium, each player should be unbiased toward the two options, entering and staying out. If one player could do better by changing his choice given the others' choices, then this profile of play would not be "equilibrium."

(2) $\pi(enter, x^{NE}-1)=v + r\,(c-x^{NE}) - t - f = \pi(stay\_out, x)$

When equation (2) holds, then no player can do better by changing his or her choice. Therefore, the MEG has $\binom{n}{x^{RNNE}}$ asymmetric equilibria in pure strategy Nash equilibrium profiles. Solving equation (2), the number of entrants for any equilibria profile is:

(3) $x^{NE}= (r\,c-\ t - f)/\,r$

There are a large number of mixed strategy equilibria in which individuals choose to enter or stay out with a given probability. From all the mix of strategy for Nash equilibria, there is a unique symmetric mixed strategy equilibrium, in which all of the individual agents enter with the same probability:

(4) $Probability(enter)=[r\,(c-2)- t - f\,]/\,[r\,(n-1)]$

In addition to the unique symmetric Nash equilibrium, there are multiple asymmetric mixed strategy equilibria in which a player or a subset of players decides to enter with a probability that is different from that expressed by equation (4). An example of an asymmetric mixed strategy equilibria profile is one in which one player always decides to enter, then this player plays $Pr(enter) = 1$. Given the behavior of this player, then the remaining players can think of the games as if they were facing a game with a capacity equal to $c - 1$. It is straightforward to observe that a profile of actions in which one player always enters and N – 1 players chooses to enter with a probability expressed by equation (4) but with $(c - 3)$ replacing $(c - 2)$ is an asymmetric mixed strategy equilibria.

The problem of the market designer (MD) is to design a fee that induces optimal entry. Optimal entry maximizes social welfare (*SW*) as given by

$$(5) \qquad SW_x = n\,v + x\,[r\,(c - x) - t - f] - I(x<c)\,Cost\,(c-x)$$

Where *Cost* is an arbitrary social cost that society has to afford when the capacity of the congestible resource is unused. This cost can be interpreted as an opportunity cost of not having the system in equilibrium, for example, the cost of maintaining a traffic network that is under-used. The non-achievement of this goal is expressed by the indicator function $I(x < c)$.

The socially optimal level of entry, x^{SO}, solves the first order conditions for maximizing *SW*. The optimal fee, f^*, makes the individual payoffs from entering equal to the value of the staying out option v at the socially optimal entry level. In order to do that, the optimal entry fee should equate the first order condition of the individual problem to zero at the social optimal level of entry. When this condition is satisfied, individuals deviating from the social optimum cannot improve payoffs. Accordingly, the optimal fees satisfy:

$$(6) \qquad \pi(enter, x^{SO}-1) = v + r\,(c - x^{SO}) - t - f^* = v = \pi(stay\_out, x)$$

Entry fees change payoffs for choosing *enter* independently of other actions. A positive entry fee, $f > 0$, decreases *enter*'s payoffs while $f < 0$ increases them. It is straightforward to notice that the equilibrium number of entrants change in the same sense that *enter*'s payoff. Therefore, x is smaller when $f > 0$ and larger when $f < 0$. Equation 3 showed that $f > 0$, implying that $x(f > 0) < x\ (f = 0)$. The first order condition for maximizing *SW* implies that $x^{SO} < x(f = 0) = x^*$; it is straightforward to notice that the pigouvian entry fee is positive.

1.3 Experimental Design

The payoff functions are given by equation (1) with specific parameterizations. Previous MEG experiments of Rapoport (1995) present symmetric players with $v = 1$, $r = 2$ and no intrinsic cost of entry $t = 0$ or entry fee $f = 0$. In each subtreatment, subjects are given the following description of their payoffs:

(7) If you choose Option A, your payoff will be: 17

If you choose Option B, your payoff will be determined by:

Individual Payoffs = $15 + 2\ \{c_t - (\#\ of\ participants\ choosing\ Option\ B\ at\ t)\} - fee_t$

For all the experimental treatments, the values of the outside and inside options *k, v*, individual cost of entry *t,* and the negative externality of an additional entrant *r* are always $k = v = 17$, and $t = 2$.

In Rapoport's experiments, the equilibrium number of entrants is either c or c – 1. Additionally, a subject choosing to enter obtains a payoff that triples what he or she gets for staying out. My experiment is different, given that choices of *v, k, r* reduce the difference between the potential utility of entering and staying out.

The experiment design is a two by six design, with two treatments and six subtreatments. In the first treatment of the MEG, the capacity of the congestible resource is deterministic and known by all the subjects. In this sense, our MEG subtreatments only differ from previous MEG experiments in that ours introduces entry fees. Using the MEG as a baseline, we introduce uncertainty about the capacity of the congestible resource in the expected market entry game (EMEG) treatment. The following subsections describe how introducing these modifications change the game's payoff functions.

1.3.1 Resource Capacity Uncertainty

The introduction of uncertainty in the EMEG subtreatments is achieved by changing c_t from a deterministic value, as it was in the MEG subtreatments, to a random variable with an expected value of *C*.

The payoff function of the EMEG can be described by the following equation

(8)

$$\pi(enter, stay\_out) = \begin{cases} v + r*(C_{st} - x) - t - f_{st} & if \quad enter \\ \\ v & if \quad stay\_out \end{cases}$$

where C_{st} is one of the possible values that the capacity can take. Capacity expected values $E(C_{st})$ are Low (4) or High (8). The distribution of C_{st} has the same probability for the expected value and 2 units above or below them. For each round of an EMEG subtreatment, a realization of C_{st} is drawn. The three possible capacity values (C_{st}, $C_{st} - 2$, $C_{st} + 2$) have the same probability independent of previous draws and what the players have played.

1.3.2 Entry Fees

The outside market cost is set at a value of 6; this value can be interpreted in two ways: as the opportunity cost of not using the congestible resource or as the cost of acquiring a unit of the resource through an outside source. Then, by fixing its value at 6, we focus on the cost of unused capacity interpretation, understanding that the cost of maintaining slack capacity is inefficient when the number of users is 2 less than the equilibrium number of subjects. Regulating a congestible resource makes sense if the cost of not using it at levels around equilibrium under utilization is larger than what entrants gain in the market at equilibrium levels.[5] Subjects are not informed of this cost.

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[5] Equilibria profiles of the game have either $c - 1$ or $c - 2$ subjects choosing to enter. When the number of entrants is $c - 1$, then the market is cleared. No additional earnings can be obtained by entering the market.

With cost at a value of 6 and a market capacity of 4, the optimal social entry level is at 2 and 3, subject to choosing the market option. For this level of capacity, the optimal entry fee is zero. For treatments with c = 8, a positive optimal entry fee exists that is equal to 4. The number of entrants that characterizes the Nash equilibria and mixed strategy probabilities of each subtreatment are expressed in Table I.1.

Treatment	**1**	**2**	**3**	**4**	**5**	**6**
Capacity (*c*)	4	4	4	8	8	8
Entry Fee (*f*)	–1	0	2	0	2	4
x^{NE}	3.5 & 2.5	2 & 3	1 & 2	6 & 7	5 & 6	4 & 5

Table 1-1 Experimental Design and Nash Entry

Both MEG and EMEG treatments can be analyzed as two by three experiments, where there are two possible levels of market capacity (four and eight), and three possible entry fee levels for each capacity level. Therefore, each treatment has six subtreatments, two without entry fees and four with different entry fees. These subtreatments aim to capture the effects of the entry fee as a policy tool for coordinating agent behavior around some equilibria for markets with different congestion externalities.

In this condition, each player entering obtains a market profit of just 2, making him or her indifferent between participating or not. The other possible equilibrium profile is when the number of entrants is $c - 2$. Here the market does not clear, but those who do not enter have no incentive to enter given that each potential entrant will obtain 17 if he enters, the same that he gets for not entering. In this condition, all the entrants obtain a profit of 4.

1.4 Experiment Implementation

The experiment entails 10 laboratory sessions, with 12 subjects in each session. The experimental sessions were conducted in the lab of the Interdisciplinary Center for Economic Science (ICES) at George Mason University (GMU). The International Foundation for Research on Experimental Economics (IFREE) provided the funding for the experiment via a dissertation grant.

For each session, GMU students were recruited through ICES's computerized recruitment software. Students did not have any previous experience as participants in another MEG experiment. In each session, 12 students participated either in a MEG or EMEG treatment. In each experimental session, subjects performed two tasks, the MEG experiment and the personality test.[6] The MEG task is performed as follows. First, students read a set of written instructions and then an experimenter describes the experiment and reads the instructions out loud. Second, a quiz is administered to test individuals to ensure correct understanding of the game. The experiment does not start before all the subjects answer the quiz correctly. Each student conducts the experiment at a computer terminal. Additionally, each student keeps a record of his decision for each round and the payoffs on record sheets. The experiment is programmed and conducted with the software z-Tree (Fischbacher, 2007). Communication between the subjects was prohibited once the experiment started.

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[6] In addition to the experiment, a personality test, (the IPIP-NEO test) was conducted by using a browser on the computer terminal in each session. The subjects did not receive additional payment for the personality test. We controlled for order effects. In some sessions, the order of tasks was experiment first then personality test, and in other sessions the order was reversed. No significant order effects were found. The analysis of data from the personality test and how this relates to the player profile are not part of this chapter.

The experimental part of the session proceeded as follows. The experiment consisted of 150 rounds of the MEG or EMEG binary decision environment. In each round the subjects choose to enter or stay out. The payoff functions that subjects face are those described by equation (1) for MEG sessions and equation (6) for EMEG sessions. The 150 rounds are divided into six blocks of 25 rounds. For each block, the market parameters remain constant and are those displayed in Table I. Sessions are conducted with two different orders of the subtreatment blocks. The experiment is implemented in this way to control for possible order effects.

During each round, information is presented in two parts. In the first part, a screen with the relevant information is displayed. The relevant information is the value of the entry fee and the market capacity or expected market capacity for that round. These values are displayed in the center of the screen with buttons for the participants to choose between entering or staying out. After all the subjects choose their preferred action, a new screen is presented. This new screen displays information regarding the individual's last decision, the number of entrants in the last round, and the payoff. Additionally, subjects are required to record their decisions and profits for each round on the provided decision sheets.

To reduce the burden of computation faced by the students, the provided record sheets display header tables that compute all the possible payoffs for all the different possible number of entrants, ranging between 0 and 12.

After all the 150 decisions were completed, the lab coordinator randomly selected a number between 1 and 150. The subjects were paid individually the earnings for the selected round at an exchange rate of $1 per experimental dollar so that subjects earned an average of $16.31 in addition to the $5 fee for participating. The experimental sessions lasted approximately two hours. Appendix A presents the written instructions and screen shots presented to the students.

1.5 Results

The experimental observations present three main findings. First, a uniform entry fee can reduce the number of entries. Second, uncertain capacity has no effect on entry. I describe and analyze these findings in the following sections. Third, subjects have heterogeneous entry decisions. The proportion of the round in which each subject chooses to enter varies among the various individuals within a group. Heterogeneity of behavior can be observed even when the subjects all have the same payment function and have similar backgrounds.

Result 1. Uniform entry fees reduce average entry but sustain over-entry (OE)

Uniform entry fees are effective if the observed entry mimics changes to the entry predicted by the Nash equilibrium. Figure 1 displays the average level of entry for each treatment, MEG and EMEG, and for each one of the six subtreatments.

Figure 1-1: MEG, EMEG, and Nash Entry

Figure 1.1 shows the most important findings of the experiment. First, the average entry always shifts in the direction that is predicted by the Nash equilibrium. The first row of graphs in Figure 1.1 shows all the subtreatments with the capacity of four, while the second row all those subtreatments with the capacity of eight. Additionally, moving from left to right, we increase the values of the uniform entry fees. Theory predicts that observed entry will decrease for all the subgraphs when we move from left to right. Therefore uniform-entry fees were effective on changing aggregated behavior. Second, except for subtreatment five, all the other subtreatments presented over-entry. In all the subgraphs, the observed entry for both, MEG and EMEG, treatments is always above the green line that describes the average number of entrants under the Nash equilibrium.

The explanation could be the differences between the payment functions of this experiment and previous experiments. Most of the previous experiments assigned payments for staying out that were equal to one (Sundali et al., 1995; Rapoport, 1995). Payments for entry were usually to an outside value of one plus the market gains or losses, which was a linear function of the number of entrants. When payment functions have these features, then entry seems to fluctuate around the Nash entry. The Nash entry is the number of entrants when subjects choices are those of the Nash equilibrium. Different from these experiments, are those in Erev and Rapoport (1998) and Rapoport et al. (2002), which present treatments in which payment for staying out is higher. Individual's entry behavior in previous MEG experiments is usually very noisy, i.e., subjects' pattern of play does not correspond with Nash predictions, but it can be explained with other theoretical models such as Quantal Response Equilibria (QRE) or Reinforcement Learning (RL) (McKelvey and Palfrey 1995, Sutton 1984). Although individuals' choices do not agree with theory, previous studies have found that average entry can be predicted by the Nash entry, with variation in entry usually just above and just below the Nash entry. Similar to the observations in my experiment, Sundali et al. (1995) and Rapport and Erev (1997) observed that over-entry increased when the payment for staying out increased.[7] The observed entry levels of Figure 1.1 are summarized in Table 1.2 below.

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[7] In experiments in which treatments changed the information conditions that players observed, the authors were able to explain a subject's distance to mixed strategy, Nash equilibrium play, and alternations in choices by fitting a reinforcement learning model.

Treatment Sub_treatment (Capacity and Entry fee)	Mean Entry	Mean x^{NE}	OE	UE	Kahneman
MEG					
Capacity =4					
1. Entry fee -1	4.21	3.00	39.20%	0.80%	60.00%
2. Entry fee =0	3.75	2.50	48.80%	4.80%	46.40%
3. Entry fee =2	2.47	1.50	48.00%	1.60%	50.40%
Capacity = 8					
4. Entry fee = 0	7.14	6.50	35.20%	10.40%	54.40%
5. Entry fee = 2	6.10	5.50	38.40%	9.60%	52.00%
6. Entry fee =4	5.34	4.50	40.80%	9.60%	49.60%
EMEG					
Capacity =4					
1. Entry fee -1	4.32	3.00	45.60%	6.40%	48.00%
2. Entry fee =0	4.08	2.50	62.40%	5.60%	32.00%
3. Entry fee =2	3.11	1.50	63.20%	1.60%	35.20%
Capacity = 8					
4. Entry fee = 0	6.89	6.50	30.40%	20.80%	48.80%
5. Entry fee = 2	5.92	5.50	33.63%	16.81%	49.56%
6. Entry fee =4	5.18	4.50	40.80%	16.00%	43.20%

Table 1-2: Average Entry and Entry classification

The columns in Table 1.2 help to put observed average entry into perspective. The first column describes the observed average number of entry decisions per treatment and subtreatment. The second column displays the average number for the Nash entry. From these two columns, we can see that for each level of capacity, the average number of entrants decreases as the entry fee increases. These changes in the number of entrants happen for both MEG and EMEG treatments. Additionally, we can observe that the average number of entrants is always higher than the Nash entry number.[8] The

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8 The average number of entrants (column 1) is larger than even the largest Nash entry number (column 2 + 0.5). I conducted various Chi-Square fit tests. For each subtreatment, I tested a number of alternative hypotheses. Every test compared the observed distributions of entry to a distribution function with positive

subsequent three rightmost columns are just the proportion of observed rounds per treatment and subtreatment that can be classified as under-entry (UE), over-entry (OE), or closer to equilibrium. When the observed entry is between the mean x^{NE} and plus or minus one, I classified that observation as Kahneman, given its relationship to Kahneman's argument. Therefore, each round of the experiment is classified as Kahneman if the observed entry is in either the lowest or the highest number of entrants under Nash equilibrium for that subtreatment. Table II seems to show that the proportions of the number of rounds falling into each classification, i.e., UE, OE or Kahneman, remain very similar across subtreatments. Although most of subtreatments with uniform entry fees—i.e., 1,3, 5,6—have larger proportions of rounds falling under the Kahneman classification.[9] Statistical non-parametric tests, such as the Kolmogorov-Smirnov test and Chi Square goodness of fit, cannot reject the hypotheses that proportions of either UE, OE, or Kahneman are generated from the same sampling distribution. Although mean and median tests reject the hypothesis that all the subtreatments with entry fees have the same mean and median that subtreatments with no entry fee, distributions of entry are only statistically significantly different for subtreatments with a capacity of eight (K – S = 1 & P-exact = 0.001 for MEG and K – S = 0.8000 p-exact = 0.019 for EMEG). For treatments with a capacity of four, to display a different distribution of entry, the subject

allocation of probability to the lowest number of entrants in the Nash equilibrium and to the highest number of entrants under the Nash equilibrium. I recursively ran series of 10 tests for each treatment and subtreatment. For each test, the probability assigned to the highest number of entrants under the Nash equilibrium decreased by 10. All treatments and subtreatments rejected all the 10 tests of hypotheses at a 1% significance level.

[9] This is true for all the MEG subtreatments and for three of the four EMEG subtreatments with entry fees. The only exception is EMEG subtreatment 6 in which subjects entered less often and, therefore, increased UE and decreased Kahneman proportions.

will have to be able to tacitly coordinate in a superb way. For each subtreatment with a capacity of four, at least eight of the twelve session participants have to abstain from entry at every round in order to obtain no over-entry. Small coordination mistakes for one subject in the sessions caused the distributions of entry to be similar.

Result 2. Uncertain capacity does not change entry behavior.

The differences between the EMEG and MEG treatments imply that for a subject choosing the same action, i.e., entry, if all the other subjects choose action in the same fashion, EMEG payments are more disperse than MEG payments. The EMEG treatment is riskier than MEG for all the subtreatments. EMEG is riskier because given a number of entrants, payments will then also depend on the random draw of the distribution, i.e., actual capacity can then be larger, or smaller, than the expected capacity. Therefore, if all the subjects have a similar attitude toward risk, we will expect the MEG and the EMEG entry to be different.[10] Figure 1.2 displays the observed entry for MEG and EMEG subtreatments.

10 Since the early work of Arrow (1965) and Pratt (1964), risk aversion and risk aversion attitudes have been a concept that is central to economic theory. A traditional economic assumption is that a subject's preferences present a certain degree of risk aversion. EMEG treatment mixes two kinds of uncertainties, one risk generated by the known distribution of capacity levels with the ambiguity generated by the unknown distribution of others' behavior. Therefore, the subjects are making choices in an ambiguous environment in the sense of Knight (1921).

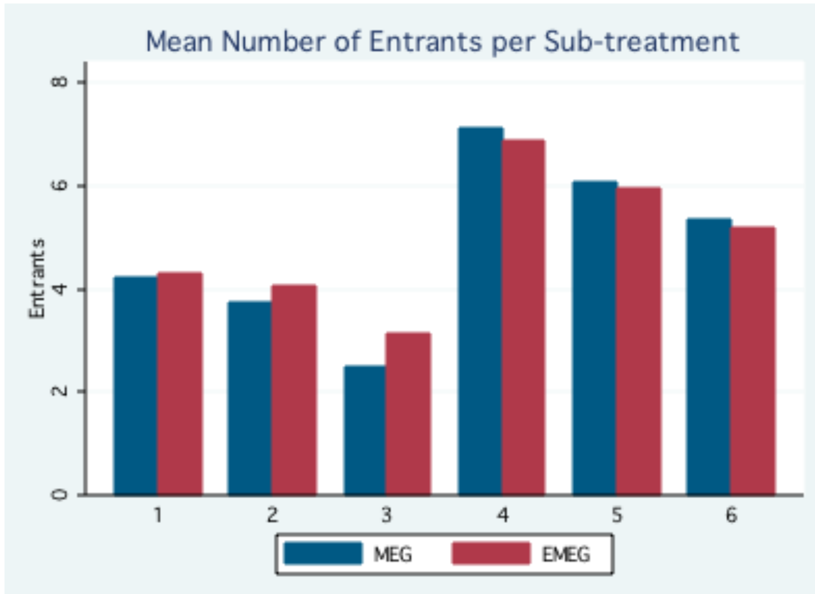

Figure 1-2 : MEG and EMEG Average Entry

It is straightforward to observe that there are non-significant differences in the observed average entry levels between the two treatments. Table 1-2 summarizes the mean and statistical tests comparing entry for both treatments over all subtreatments.

All subtreatments present a similar mean entry. Table 1-2's fourth column shows that there is no single subtreatment for which the null hypothesis is rejected by the Wilcoxon rank sum test. MEG and EMEG entry should be different under the assumption that all subjects are either risk averse or risk lovers. Even though the experiment did not include an additional task to elicit risk aversion, subjects' choices showed a large degree of heterogeneity, which could be interpreted as different attitudes toward risk.

Therefore, different subjects' choices could be attributed to certain unobservable characteristics. A potential unobserved characteristic of relevance is individuals' risk aversion attitude. Hence, the observed entry levels, which mimic risk neutral entry choices, emerged as a result of subjects' heterogeneous risk attitudes. The fact that risk-averse subjects will enter less often on EMEG but risk-seeker subjects enter more often implies that entry in both treatments is similar.

Result 3. Individuals' entry proportions are heterogeneous.

Similar to observations in previous research, I observed a large degree of heterogeneity in individuals' entry choices (Rapoport 1995, Rapoport et al. 2002, Camerer, 2003, Duffy and Hopkins, 2005). Each subject chose between enter or stay out options for each round of each subtreatment. A subject's entry profile is therefore composed of each decision as well as his or her percentage of entries for each subtreatment he or she plays. Figure 1-3 displays the histograms of entry profiles for each subtreatment .

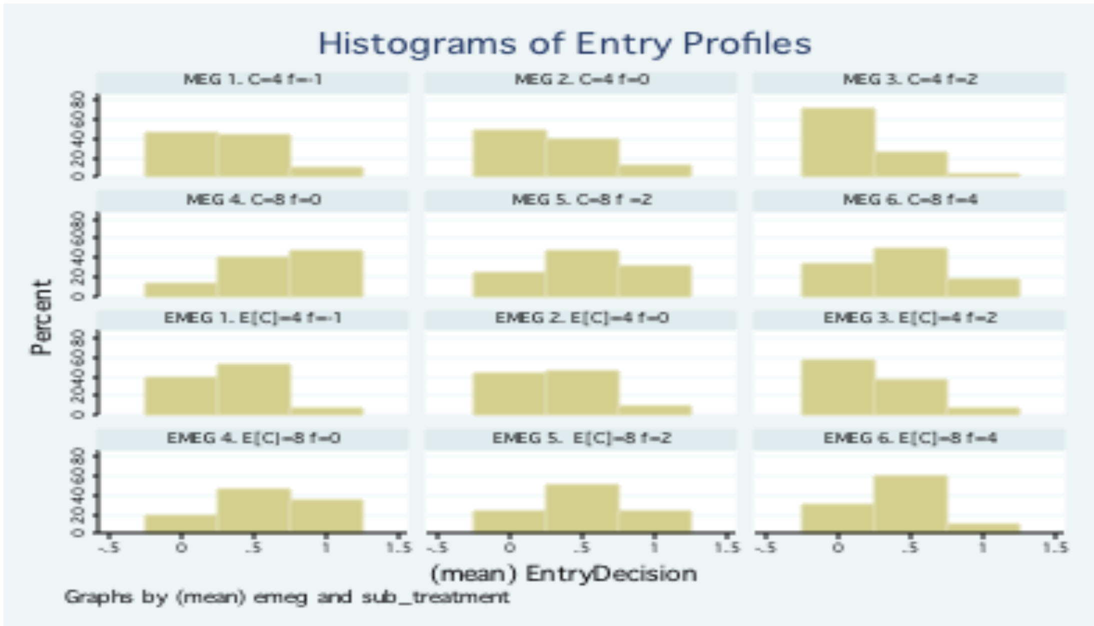

Figure 1-3: Histograms Entrants Types

Each histogram displays the proportions of subjects (1) choosing to stay out of all of the rounds or almost never entering, (2) entering approximately half of the time and (3) entering almost all or all of the rounds. Figure III has three main highlights. First, for every subtreatment, the proportion of individuals’ entry falling between one these three categories above is different than zero, therefore subjects classified in the three categories are present in all the experimental sessions and treatments. Second, the proportions of individuals choosing to almost always enter are lower for subtreatments with a capacity of four than for a capacity of eight. Finally, entry fees are more effective in decreasing the proportion of individuals who choose to almost always enter for subtreatments with a capacity of eight. Figure III’s second and fourth rows present MEG and EMEG subtreatments with capacity of eight. Moving from left to right, we find subtreatments with higher entry fees. It is straightforward to observe how the third bar of each graph decreases from left to right. These bars represent the proportion of subjects who chose to almost always enter. Therefore, entry fees are effective in that they increase the proportion of subjects who choose entry at a lower frequency.[11]

1.6 Discussion

In this chapter, we described that when groups of students played a MEG experiment, decreased use of a fictional congestible resource caused a uniform entry fee to be charged. Additionally, the experimental data revealed that aggregated entry did not change when the resource capacity was uncertain. Furthermore, changing a subject's entry profiles achieved entry fees effectiveness. Overall, uniform entry fee treatments proved to be an effective policy in the lab. Changes in entry varied between subtreatments without the distinction of the entry fee being theoretically optimal. The entry fees were shown to be robust in the face of uncertain capacity. Finding that aggregated entry in treatments with and without uncertainty capacity are statistically undistinguishable has important implications for policy design. If the goal of a policy is to reduce over-use or congestion, then designing policies based on the average individual will induce appropriate shifts in behavior on average.

However, effectiveness of the uniform entry fees does not support efficiency of them. Even though average entry changes in the direction predicted by theory, entry fees do not decrease the proportions of entry above the Nash entry. For each subtreatment, the number of subjects choosing to enter was larger than those defining the Kahneman

[11] Additional statistics of entry profiles are described in C, Table B.I.

equilibrium interval. Therefore, uniform entry fees are effective at reducing entry but fail to improve coordination. Different policies, such as discriminatory entry fees, might have a better chance of inducing coordination.

Individual's heterogeneous entry profiles could be the source of the other two results. If decreases in entry can be attributed to a limited number of subjects shifting behavior, then as long as these subjects switch between entering and staying out, coordination will not be achieved.

Understanding the sources of heterogeneity of individuals' entry profiles seems a necessary step in designing and testing whether discriminatory policies are needed in order to improve coordination.

An individual's coordination or adequate use of a congestible resource has to simultaneously choose between using the resource or not, which is an impossible task when subjects are competing for the use of the resource and its extraordinary benefit. The two findings of this research imply that simple policies can be effective and that modeling of homogenous players can be a good predictor of aggregated behavior in an experimental MEG. These findings are constrained by the limitations of the experiment, such as the laboratory scale, subject sample, and experimental implementation. Further research that replicates this experiment under different laboratory conditions, samples, and experimental design conditions is needed to test the robustness of the findings.

Chapter 2

Participation and Efficiency in Pay-for-Performance Mechanisms

Pay-for-performance (PFP) mechanisms are a class of policy instruments designed to increase (decrease) private voluntary provision of limited amounts of public goods (bads). They provide financial rewards to individuals for voluntarily undertaking qualifying activities. These mechanisms have appeal to policymakers when property rights, equity, or political considerations prevent the use of instruments that mandate compliance (Segerson and Miceli 1998). Payments for environmental services (PES) programs are considered part of the broader class of PFPs. Throughout the US as well as other countries, PES programs have been used to encourage landowners; typically farmers, to manage their lands in ways that increase wildlife habitat, sequester carbon, or reduce nutrient pollution.

PFP programs are voluntary, and thus are efficient only if induce those with highest gains (lower cost) to participate. One successful PFP application is the Conservation Reserve Program (CRP), which pays farmers to convert environmentally sensitive land highly erodible cropland or other environmentally sensitive acreage to vegetative cover, such as cultivated or native bunchgrasses and grasslands, wildlife and pollinators food and shelter plantings, windbreak and shade trees, filter and buffer strips, grassed waterways, and riparian buffers.[12] Despite the success of this program, however, farmers are often reluctant to participate in mechanisms that pay for adoption of environmental practices (Cooper and Keim 1996). An important contemporary example

[12] The Environmental Quality Incentives Program (EQIP) has been equally successful.

is Water Quality Trading (WQT).[13] In WQT programs, farmers participate in a trading market. Once they undertake the program's baseline participation requirements, they are able to sell water quality credits to municipal and/or industrial facilities, which in turn work towards reducing their own nutrient discharges. However, WQT programs implemented to date have garnered little participation, which characterized by their modest, if any, trading activity (Hoag and Hughes-poop, 1997; Breetz et al. ,2005; Ribaudo and Gottlieb, 2011).

Understanding the reasons for participation or lack of participation in such programs is difficult. Observations of successful programs are few, and this dearth prevents empirical analysis. Self-selection of participants into these programs. could be related to unobserved characteristics. Behavioral characteristics, such the opportunity cost of their participation, risk aversion, or distrust of the implementing institutions, remain unobservable. Unobserved characteristics are likely to influence candidates' participation. Therefore, even when empirical analysis is possible, identification of the reasons that motivate participation and the relationships between unobserved characteristics and participation are difficult to address through empirical analysis. PFP program designers and policy makers must rely on general assumptions regarding participant and non-participant preferences. In other words, program designers are prevented from deriving inferences from empirical data.

[13] Markets for WQT aim to reduce water pollution in an efficient way by inducing those individuals with the lowest cost of adoption of best management practices to participate in a program and into receiving permits that they can trade as a payment for their abatement. In a watershed those individuals for whom pollution cannot be efficiently controlled are usually called non-point sources (NPS). Non-point source pollution related to agriculture is now considered one of the largest remaining water quality problems in the U.S. (US EPA 1998, Ribaudo et al. 2001, Ribaudo 2003).

To date, there exists a large body of literature that estimates transaction cost and its effects on tradable permits (Stavins 1995; Gangadaran 2000) and other environmental programs (McCann et al. 2005). In such studies, characteristics of individuals are typically unobserved by the researcher; transaction costs and institutional factors are often more easily estimated and evaluated even under conditions of low participation, The impossibility of observing relevant individual characteristics can explain why individual's risk aversion have found to be crucial to explain late adoption of new beneficiary agricultural technologies (Feder 1980, Just and Zilberman 1983, Alpizar et al. 2011 and Barham et al. 2012). Little is known how risk aversion and aversion might affect individual's decision to participate in a PFP program. Given that PFP payments are uncertain, individuals' risk and uncertainty aversion are relevant to determine their participation even when gains can be obtained from this decision.

The goal of this research is to assess if different monetary payments in an experimental game based on PFP mechanisms affect participation and efficiency. Additionally, the experiment addresses a major void in the literature by attempting to measure how participant characteristics, such as risk aversion and payment preference, affect the decision to participate in a PFP program. This study seeks to answer three primary research questions. First, how do an individual's characteristics, such as risk aversion and cost, affect their participation and the efficacy of a PFP in which subjects compete for limited funding? Second and more generally, how can participant characteristics, such as risk aversion and cost, be brought to light so that PFP designers can create programs that garner better participation? Finally, are monetary payments a sufficient and effective way to induce PFP participation?

An experimental game provides a unique opportunity to observe farmers and students make choices as to participate or not in an experimental PFP program; further, the game sheds light on the distribution of risk aversion and cost considerations. The artefactual experiment allows us to observe if farmers' reluctance to participate in a simple PFP experimental game is different than students' choices (Harrison and List 2004). Specifically, a modification of 2- by-2 private value global games (PVGG) (Morris and Shin 2003) is used to design the experimental game. A PVGG is a game in which individuals receive a private signal of what their payoffs for each action profile could be. After receiving the signals, players play a simultaneous 2- by-2 game in which uncertain payoffs are implicit. The proposed experiment adds a policy variable to the PVGG; monetary prices may be paid to those pairs of players that coordinate in the social optimal equilibrium. In each round subjects observe the following information: a private potential earning for participation and a public knowledge of monetary prices. Subjects then decide if they participate or not. Because individuals don't know others' signals and actions, the game implies strategic risk. For each repetition of the game, individual and group measures are collected. I collected individual subject characteristics such as type (farmer or student), demographics, risk aversion, and decision (P or NP). At each round individual's choices can agree or not with the theoretically predicted choices. Therefore round efficiency levels are plausible of being estimated. Additionally, group's measures of participation and efficiency are collected. This data set therefore allows us to observe not only which farmers choose P more often but also when they do so.

The methodology used in this research is unique in several ways. First, to the best of my knowledge, this project is the first to use the PVPG in such a way that captures the essence of simple PFP. The PVPG maintains fundamental features of naturally occurring participation problems such as payoffs that depend on others' participation and heterogeneous gains for participation. Also, the experiment is the first implementation of the PVPG as an artefactual field experiment. Another unique aspect of this work concerns connecting risk aversion to participation profiles. This may also be the first time that this research approach has been used with American farmers.[14] Finally, this research is the first to conduct the same experimental game with American students and farmers. By doing this, I fill a gap of the external validity of lab experiments and contribute to the development of traditional agricultural economic research as a response to (Herberich et al. 2009).

A vacuum of knowledge exists between field and artefactual field experiments on one-hand and lab experiments on the other. For example, there is only a short list of choice experiments, artefactual and field experiments, conducted with American farmers (Barham et al. 2012, Peterson et al. 2007; Maile and Collins *forthcoming*) that are relevant in furthering the understanding of farmers' preferences and their decision-making processes. Alternatively, an extensive set of experimental economics literature

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[14] Bahram et al. 2012 methodology might seem similar but it is not. The authors conducted risk and ambiguity aversion elicitation tasks and then related the timing of farmer's choices of adopting a new technology. This second measure was obtained from a survey and not from an additional experiment.

has used the lab as a wind tunnel to testbed new mechanisms (Kahneman and Smith 2002). Even certain PFP programs, especially those related to emission and water quality trading, have been tested with students in the lab (Poe et al. 2004, Cason and Gangadhran 2005, Cason 2010).

To my knowledge, none of these has been used to inform policy makers. The lack of generalization of the results observed in both field experiments and lab experiment could be attributed to several causes. These include low levels of replication and little understanding as to how lab results translate to results in the field and vice versa. By conducting the same research with both kinds of subjects, I expect to start to fill this gap[15]. The external validity of the economic experiment to act as testbeds for new policy programs are of great relevance not only to economist but also to policy makers searching for the greater impact of their programs.

2.1 Literature Review

This chapter builds on four domains of economic research. One is the traditional literature on mechanism design. The second is the literature on 2-by-2 games, especially with those in which private information is present. Global gaming is an example of these (Morris and Shin 2002). The third domain is work on experimental testbeds of

[15] An important exception is Stoop et al. forthcoming. In this experiment both fishermen and students participated in traditional common pool resources lab experiments. Additionally, the researchers implemented a field experiments with professional fishermen in which they need to constrain from fishing. The authors founded striking differences between fishermen in the lab experiment and the field experiments. Although when deciding in the lab fishermen chose levels of fishing that were more cooperative than students, fishermen couldn't constrain from fishing in the field experiment.

environmental markets. The fourth is the literature that analyzes the effects of risk aversion and strategic risk aversion on individuals' patterns of play.

2.1.1 Mechanism Design

Theoretical literature on the provision and allocation of public goods emerged with the original work of Paul Samuelson (1954, 1955). Approximately around the same period, theoretical work on the existence of externalities and public bads was developed by the work of Coase (1960) and Hardin (1968) A good, in order to be considered public, is characterized by two qualities: non-rivalry and non-excludable. *Non-rivalry* suggests that an additional consumer at no additional cost can use the good, and *non-excludable* means that once the use has been created, any individual may have open access to the use of it. Open access and non-exclusion from public goods generates incentives for individuals to free ride on other's provision of the good. Therefore, even when the provision of the public good might be desirable from a societal point of view, individual's incentives and actions might oppose the provision of the public good. When there is a desire to provide public goods by private provisions and not by public ones, a mechanism to raise the cost of providing the public good (of reducing the public bad) should be implemented.

Different public policies and mechanism have usually been proposed to induce individual's contribution for public good provision. From the canonical work of Pigou

(1924) and Lindhal (1958) provided support to different taxes[16]. The problem with these mechanisms is that they require private information that is usually non-available. Recognition of the informational cost of these mechanism shifted economist interest to voluntary contribution mechanism.

The paradigm of voluntary contribution mechanism is the Vickrey-Clarke-Groves (VCG) auction in which *n* parties can achieve a socially optimal allocation of a good (bad) with multiple units. In equilibrium a VCG auction charges each individual the harm they cause to others. Additionally VCG ensures that the optimal strategy for a bidder is to bid the true valuations of the objects. Although VCG mechanisms decrease the informational cost of achieving social optimal outcomes, it still relies on the assumption that a given number of individuals are mandated to participate in the mechanism. All canonical papers assume that *n* parties are committed to participate. It has been only in the last two decades that the recognition of the effects of adding voluntary participation into the problem of providing (reducing) a public good (bad) was described. Saijo and Yamato (1999, 2010) described how it is impossible to design a mechanism in which all the individuals participate when participation is voluntary or provision of the public good is non-excludable. Additionally, Dixit and Olson (2000) describe how a negative externality is not robust to small changes in transaction costs when participation is voluntary.

[16] A pigouvian tax is a tax that equals the individual marginal cost of use, to the social marginal cost in a market with externalities. Therefore a pigouvian taxi should induce decrease in the creation of pubic bads. Similarly tax Lindhal taxation or pricing charges to each individual according to its marginal benefit of using the public good.

2.1.2 2-by-2 Games

The theoretical framework used for this experiment takes on the crucial characteristic of the participation problem by presenting a 2-by-2 game. The election of a 2-by - game is different from previous experimental testbeds of environmental markets that traditionally use N-players games. 2-by-2 games provide certain advantages to N player games. First, the strategic interactions (i.e how other's decisions affect once payments) are simpler to understand when a player is only related to a single partner. Second, 2-by-2 games have been used to model coordination, co-ordination situations. Especially, the type of 2-by-2 game used in this chapter, also known as anti-coordination game, has been used by game theorists who have modeled behavior under negative externalities where choosing the same action creates a cost rather than a benefit. The most well known 2-by-2 game of anti-coordination is the chicken or hawk-dove game first published by Smith and Price (1973).

This research is based on Bayesian 2-by-2 games, games in which given the private information each subject is of a type and has belief regarding other subject's types. Additionally, the experimental game requires subjects' possible actions to have special characteristics. One action has certain payoffs or a participative action with payoffs that are dependent upon others' actions. Binary environments, like the one presented in PVPG, have the potential presence of multiple equilibria. Strategic uncertainty, i.e. not knowing or being able to deduce what the other party will do, is greater in the presence of multiple equilibria.[17] On the other hand, multiple equilibria make the use of monetary incentives for different participation levels difficult. Focusing on the threshold strategy equilibrium approach used in global games theory solves these problems.

Global games have recently encouraged experimental economists to conduct new experiments (Cabrales et al. 2007, Heinemann et al. 2004 and 2009). Interpretation of global games suggests that although individuals are playing the same game, they may perceive public signals in different ways. Therefore, when signals regarding a common event, such as the state of an economy or a bank or the demand of a market, are private. If individuals react to signals in a common way, they can coordinate towards certain equilibrium.

2.1.3 Experimental Testbeds of Environmental Markets

Economists have been using experimental methods to test the design of PFP mechanisms in the last decade. Poe et al. (2004) has focused on testing the efficiency achieved by different institutions inspired by theory presented by Segerson 1988. This research has usually assumed that a fixed number of *n* is participants in a newly developed program such as WTQ or markets for emission permits. Experiments on markets for emission credits (Cason 2010; Cason and Gangadaran 2005), point and non-point water quality trading (Cason et al. 2003) and Payments for Ecosystem Services (Stoneham et al. 2003) were conducted in laboratories in which college students acted as

[17] In games with simultaneous moves, no communication and multiple equilibria individuals face strategic uncertainty even when they have certain and coherent beliefs regarding the others' degree of rationality and preferences. This does not happen in games with simultaneous moves, no communication but single equilibria, then if subjects are certain of the others' degree of rationality and preferences then there is no strategic uncertainty.

experimental subjects. The only exception is the experimental work of Cason, Saijo and Yamato (2002) in which participation was voluntary. The authors implemented a traditional public good experimental game

Experimental economics can provide a means of predicting behavior in environmental markets by considering explicitly the range of competing interests that all parties have in a policy, and how these interests affect desired and undesired outcomes. Recently some small field research has been conducted with farmers (Peterson et al. 2007; Maile and Collins *forthcoming*). Peterson and coauthors conducted a choice experiment elicit the "intangible costs" such as may include the disutility of the managerial effort required to maintain best management practices BMPs, and/or distaste for the WQT market procedures and rules might deter Great Plains farmers from participating in WQT. Authors surveyed 135 farmers, but a choice experiment differs from a field experiment; in this study farmers are not paid by their decisions and all the answers are hypothetical.

To the best of my knowledge, the only field experiments conducted with farmers in the United States is by Maile and Collins (*forthcoming)*. Here, the authors implemented the offer of voluntary contracts based on a theoretical model of ambient-based group approaches to no point source pollution (NPSP). The contracts were offered to farmers located in the Cullers Run watershed, West Virginia. The experiment, implemented over a three-year period, develops a payment formula between farmers and researchers. Farmers were able to resign the contract at any time. While adhering to the contract, they receive monthly payments according to the agreed payment scheme and their abatement. Compared to an artefactual field experiment, such as my work, implementing PFP programs present several a distinguishable advantage: a greater degree of external validity, i.e. farmers do sign a contract and are plausible of being monitored that they implement real BMP. In opposition, observing farmers behavior and adoption of the policies present several difficulties. The implementation periods that must be recorded can take multi-year periods, demand several meetings, and should note the naturally occurring features of the interaction between researchers, policy makers, and farmers or participants. Additionally, given that implementing real policies and contracts with farmers are more expensive than laboratory payments, the number of participants is significantly low; only 14 farmers participated in the Maille and Collins study. Low participation rates and no randomization of participants weaken the strength of field experiment results, impregnating the study with the same problems that real PFP have.

2.1.4. Artefactual field experiments, external validity and students versus non-students experiments

Artefactual field experiments are the same as conventional lab experiments but with a non-standard subject pool (i.e., non-students) (Harrison and List 20040. Artefactual field experiments present certain advantages, for example different from regular field experiments, artefactual field experiments allow researchers to abstract the results from all the potential different beliefs and interactions between researchers and, participants that could may exist in the long run. Additionally because they are run with a non-standard subject pool they can capture if certain characteristics of these non-standard pools influence choices in the experiment. To compare how pool characteristics influence choices in the experiment, two different pools are needed.

A number of recent papers have examined the soundness of subject pools in order to test the external validity of laboratory findings. For example, Belot and Duch (2010) compare student and non-student pools to understand how systematic differences between the experimental behaviors of the two groups. Frechette (2011) summarizes the analysis of 13 papers that have conducted experiments with students and professionals. The author concludes that in 9 of the 13 papers, professionals are neither closer or further from the theory in a way that would lead us to draw different conclusions. Of the remaining 4, only Palacios, Huerta, and Volij (2008) suggest professionals' choices were substantially closer to the predicted theory. The team finds that professional soccer players were able to transfer their skills and experience of kicking penalties in an unfamiliar laboratory experiment in which they played a zero-sum game. This result has important theoretical and methodological implications. Their work supported the Smith (2005) argument; that is, subjects in a competitive market might reach equilibrium through learning by experience even when they are unaware of being at equilibrium.

My research is related to Palacios-Huerta and Volij research in its goal. However, strategies in a naturally occurring market are more difficult to classify than strategies related to a penalty kick. For example, observed low participation in PFP could be explained as equilibrium if the market is conducted only once and subjects believe that everyone will participate with large probabilities. Because the market is only run once, players cannot change their choice after the market is conducted. Therefore, market skills are more difficult to quantify than skills that are naturally occurring. Defining experience and skills in markets settings is far less clearly defined that a penalty kick. It may be safe to assume that those with greater skills are able to survive longer and make business profitable. Of course, understanding how farmers' decisions in the experiment relate to their real decisions to participate or not in a PFP is an area needs further investigation.

2.2 Theoretical framework: Private Value Participation Games

I define a *Private Value Participation Game (PVPG)* as 2-by-2 private information game with some special characteristics. Possible player actions are either *non-participative* (NP) or *participative* (P) action. Individuals' payment for the NP action f *is* commonly known and independent of the choice of the other players. Individuals' payment for the P action are privately known, i.e., given an action profile where each individual participative action payment is *private* and a function *his* x_i signal, policy parameters g, and f and others actions x_i**.**

The three characteristics of these games are motivated by the voluntary participation problems. First, the presence of a *participative* P action, with interactive payment aims to represent a design characteristic of certain PFP. The characteristic of P implies that this action's payments present strategic uncertainty. Second, the *non-participative* NP action aims to mimic certain payment. Different values of the policy parameters g, and f change $t*$ modifying the proportion of individuals who should choose

P. These characteristics of PVPG allow us to test if changes in monetary payments induce those changes predicted by theory. Figure 2.1 presents the matrix of payoff of a PVPG.

		Player 2	
		p	NP
Player 1	P	(x_1, x_2)	(x_1+g, f)
	NP	(f, x_2+g)	(f, f)

Figure 2-1 PVPG Game

2.3 Experimental Design

Each experimental session consists of three experimental tasks. In this section, I start by describing the two experimental tasks are based on the game described on the PVPG. A PVPG with strategic substitutes incentives presented was implemented in two tasks.. Each PVPG task has two treatments, LOW and HIGH. In each treatment, parameters of the game are varied to induce different expected levels of voluntary participation. Table 2.1 summarizes the experimental design of each task in which subjects play PVPGs.

Treatment	G	f	t*
LOW	4	3.75	0.75
HIGH	3	1.00	0.25

g-co-ordination gain, **f**-outside options, and ***t****-participation thresholds values .

Figures 2.2 and 2.3 represent the two experimental game matrices of payoffs. They can be obtained by replacing Table II's ***f, g*** values multiplying them by 100 in the matrices of payoffs of the example games.

Player 2

Player 1	**P**	**NP**
P	(x_1, x_2)	$(x_1+\mathbf{400}, \mathbf{375})$
NP	$(\mathbf{375}, x_2+\mathbf{400})$	$(\mathbf{375}, \mathbf{375})$

Figure 2.2. PVPG LOW Treatment

Player 2

Player 1	**P**	**NP**
P	(x_1, x_2)	$(x_1+\mathbf{300}, \mathbf{100})$
NP	$(\mathbf{100}, x_2+\mathbf{300})$	$(\mathbf{100}, \mathbf{100})$

Figure 2.3. PVPG HIGH Treatment

Subjects play three tasks in each experimental session. The first experimental task is a simple risk preference elicitation experiment conducted previously in the lab by Eckel and Grossman (2002). Tasks II and III are different implementations of the games described by Figures 2.2 and 2.3.

For all treatments and sub-treatments, I fixed the distribution of private signals as uniform with support between 0 and 100. Those subjects that choose action P and are matched with another subject that chooses action NP only achieve the match dividend payment g.

Additionally, I conduct experimental sessions with two types of experimental subject: farmer or student. Six sessions were run with each type of experimental subjects. Table II presents the summary statistics of each type of experimental participant.

2.4 Experiments

A total of 13 sessions were conducted between March 20111 and June 2012. Six sessions where conducted with a total of 47 students. Students received a $5 dollar show-up payment. These sessions were conducted using a conference room at Penn State University Park. Seven farmer sessions were conducted in six Pennsylvania counties. Fifty-seven farmers participated in these sessions. Extension education offices or an appropriated meeting room were rented to conduct these meetings. Farmers received a $75 dollars show-up fee. Experimental exchange rate was the same for farmers and students. In addition to the show-up payment, participants gained an average of $57.5 dollars for incentives in a 2-hour experiment.

Each experimental session consists of at least 8 subjects. All the experimental rooms had a projector. Experimental instructions were projected and explained by the experimental coordinators. In Appendix B.2, I present the script used for the experimental session. This script has the slides presented and explained to the experimental subjects. Also Appendix B.2's script used to train the group coordinators. Group coordinators were Penn State Environmental Resource Management students explicitly trained for the task. Every student acting as experimental coordinator passed the human research-training course provided City training. In addition, a specific experimental script was prepared to explain the instructions. After given instruction, participants were provided with an oral quiz. The experiment only proceeds after the subjects answered the quiz .I supervised the how tasks were conducted for each session.

Each experimental session is composed of three tasks. Task I is the risk elicitation task and Tasks II and III are the PVPG games, which presented two sub-treatments, LOW and HIGH. Experimental sessions lasted between 1 hour and one hour and a half. The timeline of an experimental session is as follows:

Experimental Task I: Risk Elicitation Task

Experimental Task II: Experimental PVPG with NF condition

Experimental Task III: Experimental PVPG with F Condition

The experiment implements PVPG in two ways, and in both tasks, the same games are played in several rounds. For each round, each subject obtains different private values from the uniform distribution. Twenty rounds are played in Task II and 12 rounds in Task III. The difference between these two tasks provides information to parse the effects of information and feedback has on subjects' pattern of play. For each round of Task II and III, subjects are randomly and anonymously matched in pairs. In Task II, PVPG non-feedback **NF condition**, each subject chooses actions in repeated one-shot games, played without receiving any feedback information about the decision of his randomly matched partner. In Task III, feedback **F condition**, the subjects play the same PVPG experimental games as those in the NF condition. Different than in Task II is that in Task III, for each round each subject now observes the decision of his randomly matched partner.

Experimental earnings are determined at the end of each experimental session. At this moment, one task is chosen at random. The task that is selected is used to estimate participants' earnings. If Task II or Task III is selected, then one of the rounds is also chosen randomly. Subjects are paid according to the outcome that they obtained for that round of PVPG. I do not control for order between tasks, given that I wish the NF condition to be conducted before the subjects observe others' choices. I control for possibility of an endowment effect, given that subjects do not know their earnings before the entire session has been conducted, then no endowment effect should affect the experimental tasks.

Instructions are explained orally with the help of a PowerPoint presentation. The experimental sessions are conducted by a group of students especially trained for this purpose. Students run the sessions under the supervision of at least one of the researchers.

2.5 Results

The goal of this research is to assess how monetary payments and strategic risk features of the FP proposed PFP mechanism affect participation and efficiency of these political tools. The experimental implementation of a PFP mechanism by the *PVPG* allows me to analyze three relationships. First, I identify the relationship between payments and participation. Each treatment in task II and Task III, LOW and HIGH, implies that when a subject choose the action P, they are accepting to trade a greater strategic risk for greater expected earnings. The payments for P are strategically riskier than payments for NP. By changing the relationship between the gains of taking this risk *g* and the outside option *f,* each treatment should induce different proportion of subjects to choose P.

Comparing participation levels between treatments, we can assess the level at which each group is willing to participate for the different payments. Second, the relationship between feedback about other's decisions and individual actions was identified. Task II and Task III implement the same PVPG treatments but differ in the information that each individual knows after each decision. Comparing decisions between these two tasks, we can observe how individuals and groups react to knowing how others act. Knowing if repeated PFP leads to more participation and efficiency than one shot PFP is crucial for policy makers aiming to design good instruments to provide (decrease) public goods. Third, the relationship between individual's characteristics and pattern of play is explored. The experimental data set contains includes the gender, age, and the level of education achieved, while Task I provides a measure of individuals risk aversion.

The empirical strategy described in the previous paragraph allows me to answer the following research questions:

Question 1. Are observed participation levels predicted by theory?

Question 2. Do subjects attain theoretical efficiency levels?

Question 2. Do subjects play according to theoretical predictions?

Question 4. Do students and farmers play similarly?

2.5.1 Comparing Observed Choices to Theoretical Predictions

The theoretical model developed in Section 3 has implications for both individual choices and group choices. Individual choices should be consistent with the unique threshold equilibrium strategy; this means choices should be NP for all the private values x_i the subject observes below threshold t and P for those values above threshold. Subjects should switch their behavior only once. For groups, theoretical predictions said that we should observe that at each round a number of subjects Nt, equal to those with the subject observes below threshold t should choose P and the other subjects play NP. In the experiment, subjects could choose P or NP according to theory or not. It is interesting is that even when players could make individual mistakes, mistakes could cancel out and observed number of subjects choosing P could be closely predicted by theory. If individuals and groups play according to theory is a question that is deeply rooted in the methodological and scientific analysis of experimental economics[18].

Predictions regarding individual choices that satisfy unique threshold play and monotonic pattern of play are called point predictions. Theoretical predictions regarding the number of subjects in a group choosing to play P could and how this number depends on PVPG are group predictions. Point predictions face an unfair test when they are tested in the lab. Theoretical predictions are based on an assumption that the only thing that matters to experimental subjects is the payoff functions. Extensive literature in experimental economics and specially in artefactual lab experiments have shown that subjects bring to the lab more than just eagerness to earn some additional cash (Harisson 2005, Henrich 2000, Henrich et al 2001). The failure of point predictions have been documented in experimental economics findings that contradict game theory. Rejection of point predictions has been particularly relevant for simple games, i.e. games with a unique equilibrium and usually a dominant strategy for each player. Therefore, judging if the theory will fail or not in terms of the threshold strategies and values of the PVPG would be an unfair trial.

The first result of the experiment, that HIGH treatments induce higher proportion of P, only compares with the theoretically predicted *Nt* with the number of subjects who

[18] The relationship between economic theory and economic experiments has been analyzed in a number of articles (Smith 1989, Levine 2009, Schmidt 2009)

chose P. The second result compares if those who chose P were those that theory predicted they should choose P. Rejecting the theory because a non-significant proportion of subjects didn't play according to theory would have been an unfair trial. In this experiment, group behavior is classified as being consistent with the group implication of the theory if their choices agreed with theoretical predictions more than 50% of the time, we may consider them in line with theoretical implications This means for each round, we can count the number plays that agreed with theoretical implications.

Result 1. HIGH Treatment payments induced higher proportion of P choices.

HIGH treatments offer significant incentives for choosing P instead of NP. In HIGH treatment, subject's gains for choosing P when her match chooses NP are 200% to 300% more than by choosing NP. These incentives exist for everyone. Additionally, these gains are only realized if the matched subject chose NP. Therefore, if a subject knows that all the others have the same incentive and he does not want to bare the risk of an uncertain payoff, then he is better of by choosing NP. By choosing NP her payment is certain.

LOW treatments present subjects with a similar decision problem. In LOW treatments, incentives to choose P are more subtle. The largest gain she could achieve by choosing P is 33% more than by choosing NP. Therefore HIGH and LOW treatments represent how different payments structures of PFP embed subjects in different decision problems. By comparing participations in HIGH and LOW treatments, we are able to analyze if the potential gain of 200-300% of choosing P in HIGH treatments is sufficient to shift the number of subjects choosing P in comparison with the potential gains of 33% in the LOW treatments. Table 2.2 presents the average frequency of P choices over the thirteen experimental sessions.

	Observed % P	*Predicted % P*
PVPG No Feedback		
HIGH	50%	68%
LOW	34%	21%
Wilcoxon Rank sum test	z=2.85	z=4.19
PVPG Feedback		
HIGH	58%	0.82
LOW	34%	0.25
Wilcoxon Rank sum test	z=4.33	z=4.34

Table 2-2: Participation levels per treatment and condition

The second column of Table 2.2 displays the average proportion of P choices for each round of each treatment. This means the ratio of the number of subjects who chose P over the number of experimental participants, for each task, treatment and round. If subjects chose according to theory and all the possible private values were drawn in each round, the proportion should be 75 % for HIGH treatments and 25% for LOW ones. The third column shows the average number of P choices we should have observed if subjects playing according to theory given the private values they observed. It is apparent that HIGH treatments induce higher frequency P choices than the LOW treatments. This is consistent with the comparative statistics motivated by theory. The Wilcoxon rank-sum tests reject that hypothesis decisions are generated from the same distribution.[19] Information about the random partner's decision, i.e. feedback, does not seem to play an important role on subjects' choice. Changes in the frequency of P, as response to changes in the payments of the game, chosen are similar over the two (no feedback F in Task II and feedback F in Task III).[20]

While the HIGH treatments induce a greater frequency of P choices in both treatments, the proportion of P chosen between different treatments is smaller than predicted by theory. The second column in Table III shows the proportion of decisions that would have been P if subjects played exactly as the theoretical cutoff values indicate.[21] P was selected more often than theory would predict in for LOW treatments but less often than predicted by theory in the HIGH treatments. Over-entry occurred in 11 of the 13 sessions. In these sessions, subjects chose P more often that theory predicts for both tasks. The hypotheses testing equality of the proportion of P with the theoretical proportion are rejected (sign test=0.0112 for equality) and also the hypothesis that 0.9983 for over-entry). Under-entry occurred in 12 of the 13 sessions in task II and in all the sessions in task III in the HIGH treatments. (he hypotheses that the proportion of are

[19] Experimental sessions varied the order of LOW and HIGH treatments from session to session in order to control for possible order effect.

[20] Subjects choose P for high treatments in 10 of the 13 sessions for Task II and in all the sessions for Task III. Therefore the hypotheses that the choices of P in HIGH treatments are lower than the participation in Low treatments are rejected with probability 0.9888 and 0.999 for Task II and III respectively. Tables in Appendix B.
A present the percentages of P chosen for each session for both Task II and Task II.

[21] For all the sessions a set of random draws from a uniform distribution was taken. With this draw, the record sheets and booklets with private values for 12 potential subjects were printed. In each experimental session experimental Ids with its correspondent materials were randomly assigned. The observed private values for each session are just the result of the random allocation of the 12 experimental Ids.

equal to the theoretical proportion are rejected sign test=0.0034 for equality -entry task II and sign test=0.0002 for equality and 1 for under-entry task III).

These findings can be named as one finding: low sensitivity to monetary incentives could generate over-entry for LOW treatment and under-entry for HIGH treatment. If low sensitivity to monetary incentives or a conjunction of these and the fact that subjects might over update their belief about what others are going to play could explain why subjects choose P too frequently in those treatments in which they should not, over entry and choose P to infrequently when they should when they should. This result is consistent with previous findings for N-players entry games, and voting experiments (Goeree and Holt 2005).

One explanation for the deviation between theory and observation is offered by Goeree and Holt (2005) (GH), who argue that optimal choices can be difficult in problems with binary decisions (e.g., participation games, entry games, and certain collective action problems with a contribution threshold) This difficulty results from individual's best decision requiring correct beliefs about others' choices. The authors claim that under these conditions a relaxation of the extreme rationality of the Nash Equilibrium concept, the Quantal Response Equilibrium (QRE). Under QRE, subjects will assume that other players will make errors while choosing which action, P or NP, to play. In equilibrium, a subject's beliefs about other players are correct. It has been usually found on games with binary decisions, such as market entry games (MEG) or the PVPG, QRE explains most of the observed anomalies such as over-entry and under-entry Rapoport 1995).

Original development of QRE theory and its applications were designed for games of complete information in which the only unobserved characteristic of other players, was the rate at which they will do mistakes. Therefore QRE is not directly applicable to a game with private information such as the PVPG. GH proposition 2 (pp. 13), the authors describe the existence of a relationship between the parameters of the binary decision game such as the MEG, over entry, under entry and the QRE. if the mixed strategy Nash equilibrium has a probability of choosing P that is less than ½, the QRE predicts over-entry.

Alternatively, if the mixed strategy Nash equilibrium has a probability of choosing P that is greater than ½, the QRE predict under-entry. This relationship is reflected in the observed results of my two experimental treatments.[22] It is outside the scope of this paper to extend QRE applications to games with private information and estimate them for this experiment but this relationship suggests an interesting research agenda. Furthermore, if GH implications could be extended then the observed over-entry and under entry of the PVPG could be explained as a case of subjects playing with the belief that others will make mistakes. Result 2. Groups play according to theoretical implications.

[22] My experimental game is a game with incomplete information, subjects have private information about their private value xi, and the correct theoretical equilibrium concept is Bayesian Nash equilibrium. Although QRE was developed for Nash Equilibrium recent developments have extended the concept of QRE to Bayesian games.

For a subject to choose P or not P according to theory all the time means: that three things happen. First, she believes that everyone understands the experiment. Second, she believes that no one will make a mistake. Finally, she has to believe that no one will try to take any chance on inducing some deviation in any round. In addition, they have to believe that their understanding of others' rationality and preferences is common knowledge. It is easy to see that this assumption about behavior and beliefs will not hold in the PVPG experiment. however, certain heuristics might lead the subject to choose P or NP only based on her private values and a system of beliefs Table IV presents the average proportions of choices that agree with theoretical implications for each treatment

	Average proportion of choices that agreed with theoretical choices
PVPG No Feedback	
HIGH	56 %
LOW	71%
Total	63%
PVPG Feedback	
Task III	
HIGH	68%
LOW	71%
Total	69%

of the PVPG both with and without feedback (F and NF).

Table 2-3: Average percentage of theoretical play per round and treatment

Table 2.3 reveals how subjects' choices agreed with theory in more than 50% of the time. This agreement rate is overall for the pooled data. This means that for each round of the game, subjects agreed with the theoretical prediction more than not, no matter if they played without feedback NF about partner's choices (Task II), with feedback F (Task III), or if they were students or farmers. These agreement rates suggest that subjects do not play in a random fashion. Given that PVPG is a binary decision game, one may be tempted to think that these rates might occur no matter what game is played. Notice that in a game with only two possible actions, their probability of being right from a random selection is only 50%.

The hypotheses that individuals are not choosing randomly can be tested by a binomial test. The hypotheses of random play are rejected for three out of the four treatments. For Task II, the hypothesis is rejected for L treatment (Binomial test, N=2078, observed =705, Pr(k <= 705 or k >= 1373) = 0.000000 (two-sided test)). The same hypothesis of random play could not be rejected for the HIGH treatment (Binomial test N= 2082 , observed=1043 Pr(k <= 1039 or k >= 1043) = 0.947581 (two-sided test). For Task III, when subjects play with feedback F about partner's choices, both treatments reject the hypothesis of random play with equal probability. Low Feedback (Binomial test N= 1233, observed=496, Pr(k <= 496 or k >= 737) = 0.000000 (two-sided test) and High Feedback (Binomial test, N=1222, observed =712 Pr(k <= 510 or k >= 712) = 0.000000 (two-sided test)) Therefore, in three out of our four treatments, we rejected the hypothesis that players randomized between P and NP.

Individual's choices and the matching process that pair two choices randomly and anonymously have implications for the number of pairs of action profiles we should observe. In Section 3, the theoretical framework highlighted that the Nash equilibra of the PVPG with complete information game are the action profiles NP-P or P-NP. If subjects play symmetric threshold strategies, then the expected proportions of action profiles P-NP (co-ordination), P-P (over-participation) and NP-NP (under-participation) can be computed.[23] These proportions are described in Table V. Table V additionally displays the proportions of observed pairs of actions that subjects played in the experiment.

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Action Profile	**P-NP**	**P-P**	**NP-NP**
PVPG Feedback			
HIGH	47%	33.75%	18.25%
Theory	37.5%	56.25%	6.25%
LOW	45.25%	14.75%	40.00%
Theory	37.5%	6.25%	56.25%

Table 2.4: Distribution of Average Action Profiles

Table 2.4 illustrates two major findings. First, coordinated subjects played (P-NP) more often that any other outcome. Second, they achieved co-ordination by decreasing the frequency of miscoordination on those action profiles that theory predicted to occur most frequently. In this way, they played less over-participation (P-P) in the HIGH treatment and less under-participation (NP-NP) in the LOW treatment.

[23] I computed only the proportions of matched pairs for Task III with the drawn private values. Task II is the only one in which posterior realizations of the action profiles were observed by the subjects.

By increasing co-ordination, play of NP-P above the theoretically predicted percentage subjects produced two outcomes. First, they partially depart from the theoretical implication generating the overall observed under-participation in the HIGH treatment and over-participation in the LOW treatments. Second, by choosing to play P in this way, their expected payoffs of playing this action are greater than the payoffs of choosing NP. This premium in expected payoffs departs from the predicted risk neutral equilibrium play. Greater earnings for the riskier action could be interpret as a risk premium demanded for subjects to play P.

Result 3. Individual players do not play according to theoretical thresholds.

Theoretical solutions to 2-by-2 games with private information imply that there is a unique threshold value at which all individuals change from one action to the other, provided that the values are above or below the threshold value. This solution is a unique symmetric threshold equilibrium STE and has two implications on what behavior individual choices should present in order for that individual to behave as theory predicts. The implications are the following: First, to be consistent with theory, subjects' decisions should satisfy two properties. First, they should change from NP to P at most at one value Second, subject's play should be monotonic on private values. This means that each subject should play P for high values of x_i and NP for low values.

The first theoretical implication, play according to a unique threshold, is tested through examining the hypothesis that the number of mean observed switches is equal to one. The second implication can be tested by examining if on average subjects choose to P for higher private values than for lower ones. Table VI describes the average number of times that subjects chose to switch between P and NP actions and their average threshold. Given that most of subjects switched more than one time, an average threshold is just the mean value of that individual switching points.

	Mean # switches	Mean threshold value
PVPG No Feedback		
HIGH	7.80 t=29.82	49.28 t=12.59
LOW	8.59 t=19.61	44.62 t=-15.25
PVPG Feedback		
HIGH	4.78 t=17.47	60.22 t=-9.77
LOW	4.23 t=17.72	45.88 t=16.20

Table 2-5: Mean Switches and Individual Threshold

Table 2.5, second column, presents the average switches per subject for each treatment and feedback. It is easy to see that for every treatment and condition, subjects switched several times on average between P and NP. This finding is consistent with other studies related to simpler non-strategic risk elicitation tasks, such as the multiple switching behavior reported by Jacobson and Petrie (2009). Table 2.5 displays the t-values for tests that subjects switch exactly one time. The hypothesis that subjects switch only one time is strongly rejected for all treatments and conditions. Therefore, the theoretical prediction of unique threshold strategies is rejected. No one played with unique switching points in the non-feedback NF condition.

Experimental subjects switched from P to NP more than once. Does this imply that subjects choose between P and NP actions randomly? If subjects have additional variables that affect their utility such as attitudes toward risk or learning capabilities, then the theoretical prediction of unique threshold equilibria does not translate directly to the experiment. In the case of learning, for example, if the subject changes his beliefs regarding what other players will chose after receiving feedback of only one random partner, he might switch to the opposite action of what he played before even if his payoff function is still the same. The second column of Table 2.5 presents individual's cutoff values per treatment and condition. Although most of the subjects made multiple switches between P and NP, I estimate individual average switching behavior. Theory implies that the base payoffs at which an individual should switch from NP to P should be larger for the L than for the H treatment. The average cutoff values are similar for Task II but different for Task III. The hypothesis that the mean cutoff values are sampled from the same distribution is rejected in Task II (Mann-Whitney rank-sum z= -2.560, Median test Pcs=18.4808). While mean values are not different for the two treatments without feedback median values suggest that we cannot reject the hypothesis that they are sampled from the same distribution (Median test Pcs=1.5577). A different result is observed for Task III. In this case the hypothesis that means and median are similar are also rejected (Mann-Whitney rank-sum z= -5.368, Median test Pcs=18.4808).

The previous paragraph highlighted the difficulties of testing individual behavior. Even in artefactual field experiments, a large number of potential unobserved variables might explain the differences between subjects' choices and those predicted by theory. Analysis of mean and median differences could provide incomplete information about individual's rationality. For example, suppose that subjects divide in two very different groups of behavior: individuals with low values always enter and individuals with high values never enter. This would suggest that the average cutoff of this session is a private value of fifty. Alternatively, suppose that all the subjects in a session use a cutoff of 50. The average cutoff is again 50. Behavior in the second case is fully consistent with theory, but this is not so in the first case.. Thus group aggregates can mask the heterogeneity of individual choices.

The two theoretical implications, unique threshold and monotonic play on the private value, are quite strict given the influence that subjects' beliefs about others' comprehension of the task and beliefs. A simpler demand of rationality that we can request from subjects is to present their threshold values for the LOW treatment than for the HIGH treatment. Overall, subjects fail to satisfy this requirement, providing additional evidence of low sensitivity to monetary payments. Only 36% of the subjects presented higher average cutoff threshold for the HIGH treatment than for the LOW treatment under the NF condition, Task II. The result that the average threshold does not satisfy the order implied by a theoretical solution is similarly observed under feedback F condition. These results do not reject the rationality of the subjects; they just reject the use of the threshold concept. Given the large number of switches that individuals' choices displayed, the average threshold for each individual in a treatment is a really noisy signal of their strategy. A better measure should construct estimates in which the rationality of subjects' observed history is used to construct the probability that each subject will choose P at the different qualities of the private values. Results in which aggregated choices could be explained by the theoretical framework but fail to explain individual choices are consistent with previously observed behavior in experimental games with private information (Heinemann et al. 2004 and 2009; Duffy and Hopkins 2005).

To summarize, the experiment reveals a two interesting points. First, a significant number of experimental subjects fail to comply with theoretical implications. There are several reasons why this may be so. These include different degrees of rationality and comprehension of the game as well as different intrinsic characteristics of each person.

Second, subjects comply closely to theory for each round of the PVPG, resulting in changes in aggregated decisions that follow theoretical predictions. The significantly different participation levels for the different treatments found in the data suggest that the PVPG theoretical model is a good tool to use in predicting aggregated participation choices. Hellwig (2002) notes that it is not the only uncertainty about others' private values that may lead individuals to follow a cut-point strategy, subjects' beliefs about others' risk preferences may also induce such behavior. For each round, the decision of P or NP can not only be influenced by the subjects' analysis of the game but also but by other noises or perceptions he has regarding how other players will play. The experimental settings allowed individuals to visually search around for clues about other individuals' attitudes. Subjects' signals and perceptions are not perceived by the experimentalist and are a source of noise that can explain multiple switches.

Third, in addition to subjects' perceived signals, Task III explicitly includes a signal; in each round, each subject observes information about how one another player is choosing. This signal, the other subject's choice, can lead subjects to update their beliefs about others' preferences. Although I observe the signal that each individual observes as the other choices, the analysis of this updating process and its influence on subjects' patterns of play is outside the scope of this chapter. I argue that the increase in participation implied by the theory is supported by the observed subject's choices.

In the next section we focus on two specific personal characteristics: risk aversion and individual type, farmer or student. The focus on these two characteristics is of relevance to economist as well as to policy makers. The fact that students self selected in participating on lab experiments might behave different than other subjects question the external validity of certain lab experiments (Levitt and List 2007, Falk et al. 2011). The relevance of risk aversion as a determinant of farmers' decisions has a long tradition in economics (Feder 1980, Binswanger 1980). This experiments provides us the chance to observe if risk attitudes elicited with the same experimental task can inform the researcher about subject's choices in another task, the PVPG game.

2.5.2. Comparing Farmers to Students: the Role of Risk Aversion

Farmers and students differ according to their demographic characteristics. Table 2.6 suggests that the student sample population is on average younger than the farmer sample population and has a higher percentage of females.

Subject type	Percentage of Males	Mean Age	Mean Chosen Lottery
Students	60.42%	22	2.38
Farmers	89.29%	53	2.77

Table 2-6: Demographics and lottery choices of students and farmers

Table 2.6 shows the mean Lottery chosen by students and farmers. Figure 1 in Appendix B.3, presents the record sheet of Task I in the experimental session. As we can observe in Table 2.6, the average lotteries chosen by farmers and students are not different. A non-parametric test of means Wilcoxon rank-sum and Medians cannot reject the hypothesis that choices are generated by the same distribution (Wilcoxon rank sum z = 0.188, P >|z|= 0.8508, Pcs=0.0059 Pr = 0.939). The mean and medians levels of risk aversion of Pennsylvanian farmers in this sample are consistent with the modest risk aversion of Midwest farmers in a previous study (Barham et al. 2012). Although mean and median levels of risk aversion between farmers and students do not present significant differences, their distributions and the way that risk profiles relate to P choices are significantly different. These differences motivate my fifth finding.

Result 4. Farmers and students in the experiment have different risk aversion distributions and participation profiles.

Table 2.7 presents the number and proportion of students and farmers that chose the different lotteries and the proportions of P choices in the PVPG no feedback NF experimental task. The proportions of P chosen by each individual is a measure of how much strategic risk he is willing to accept in order to have a chance to gain the monetary incentives ***g.***

Lottery	Student			Farmer		
	# Subjects	**Proportion**	**P%**	**# Subjects**	**Proportion**	**P %**
1	7	14.58%	50.71%	21	37.50%	32.38%
2	22	45.83%	38.57%	11	19.64%	39.55%
3	14	29.17%	41.35%	8	14.29%	54.07%
4	4	8.33%	63.13%	4	7.14%	43.35%
5	1	2.08%	100.00%	2	3.57%	25.00%
6	0	0.00%		10	17.86%	46.75%
Total	48		44.48%	56		39.97%

Table 2-7: Lotteries Choices and Percentage P Chosen in PVPG No Feedback

The data in Table 2.7 displays the differences between the proportion of P chosen by farmers and students as well as the lottery they chose. Focusing on the proportion of P chosen in the PVPG without feedback NF we can understand better the relationship between risk aversion and strategic play (choice of P or NP). When the PVPG is played without feedback, then subjects could not learn or change their beliefs. Each choice between P and NP represents subjects' attitudes towards the strategic risk of choosing P based on their beliefs of what the rest of the group could choose. Therefore, even if the individual is uncertain about the other subjects' chances of choosing P, his beliefs should be the same between different rounds. In this way, the decision of P or NP in PVPG NF is an ambiguous decision task. Accordingly, the influence of risk preferences should be more apparent in the data without feedback.

Task I presents subjects with 6 lotteries (1-6) if we observe the selection of lotteries and we ask what is the average lottery chosen by farmers and students. The answer is similar; it is on average a lottery somewhere between the second and the third lottery. Moreover, their average choices of P of 44.48% versus 39.98% are not significantly different (Wilcoxon rank sum z= 1.402, Prob > |z| =0.1609). These results change when we focus on risk aversion types. However, when controlling for risk aversion types (subjects choosing the same lottery), participation decisions differ significantly. If risk aversion is a good indicator of subjects' willingness to choose P, the strategic risk, then we will expect hat students and farmers with similar risk aversion have similar proportion of P chosen.

Table 2.7 reveals some interesting aspects of how risk aversion and proportions of P chosen by farmers and students are different. First, although on average they choose similar lotteries, the distribution of lotteries chosen by farmers and students are different. . Student subjects expressed a high-to-moderate risk aversion, primarily choosing lotteries 2 and 3.[24] Most of the students do not choose those lotteries with higher expected values but also higher variance. Specifically, no student chose lottery 6, which would

[24] I followed Cardenas and Carpenter 2010, pp.5 considering a constant relative risk aversion utility function CRRA utility function u(x)= x1-r/(1-r) then we can classify subjects according to its coefficient r. The cutoffs, therefore, are the following: picking \$33|\$33 indicates extreme risk aversion, $r > 1.77$. Picking \$25|\$47 indicates $0.82 \leq r \leq 1.77$, \$18|\$62 indicates $0.48 \leq r \leq 0.82$, \$11|\$77 indicates $0.28 \leq r \leq 0.48$, \$4|\$91 indicates $0 \leq r \leq 0.28$, and picking \$0|\$95 indicates $r \leq 0$ or possible risk seeking.

indicate high risk taking behavior. Rather, 10 farmers did make this choice. Lottery 6 provides the same expected payoff as lottery 5, but with greater variance. Moreover, farmers' distribution of risk aversion is really different. Twenty-one farmers chose the extremely risk averse option, lottery 1, and at the opposite extreme, as mentioned, 10 farmers chose the risk-seeking lottery 6. Therefore, the similarity between the average and median lotteries chosen by farmers and student hides the fact that the two groups have really different risk preferences.

Second, for the subjects with same kind of risk aversion farmers usually choose lower proportions of P than students. Table 2.7 provides us with a picture of average P chosen by students and farmers through both HIGH and LOW treatments. The hypothesis that farmers and students mean decisions of P are generated from the same distribution can not be rejected. But farmers and students decisions are different in other ways. For example, as I describe in the next section, farmers and students choices of P can be similar in pooled data, but they can be different in the way that they choose P under different treatments and conditions.

Result 5. Farmers and students react to monetary incentives differently with and without feedback.

Experimental treatments were designed to induce different proportions of P (P%) to test whether farmers are more or less responsive to monetary incentives than students. Lab experiments conducted with a student population have been frequently used to inform the design of new PFP mechanisms. The results of Table 2.7 seem to support the argument that students in lab experiments behave similarly to farmers, in lab experiments. But Table 2.7 pooled the data of the two treatments of PVPG without feedback. Table 2.8 decomposes the first column of Table 2.2. Here it is displayed the proportion of P chosen by farmers and students separately.

	Observed % P	
PVPG No Feedback	LOW	HIGH
Farmers	26.70%	53.13%
Students	46.56%	42.40%
Wilcoxon Ranksum test	z=3.295 P > |z| = 0.0010	z=-1.174 P > |z| = 0.2402
PVPG Feedback		
Farmers	38.52%	57.00%
Students	41.61%	59.97%
Wilcoxon Ranksum test	z = -0.541 P > |z| = 0.5887	z = -0.861 P > |z| = 0.3893

Table 2.8: Percentage of P played by farmers and students

Farmers chose lower levels of P in the LOW treatment without feedback NF than students. This suggests that farmers may be more responsive to monetary incentives than students without the feedback condition NF. Specifically, we can observe that farmers are closer to the theoretically predicted proportions of P for the LOW treatment. The LOW treatment offers only a potential gain of 33% for choosing P, compared to the HIGH treatments. Farmers choose to participate less in LOW treatments than students, meaning that 33% is not enough for them to choose an action with strategic risk as P.

The findings described in Table 2.8 provide mixed support of the external validity of students' decisions as predictors of non-student subjects. On one hand, in three of the four possible cases, the Wilcoxon rank-sum test fails to reject the hypothesis that students and farmers P choices are generated from different distributions. This is true for both the HIGH and LOW treatments in the PVPG Feedback task. On the other hand, in the LOW treatment without feedback NF, the hypothesis that farmers and students P choices are generated from the same process was rejected. This means that farmers and students chose to participate differently in at least in one case where there was no feedback. Further, this implies that without feedback NF, monetary incentives have different effects on the participation levels of students and farmers. While students seem to be less sensitive to monetary incentives under no feedback, farmers appear to be highly sensitive.

2.7 Discussion

Voluntary participation is an important feature of some PFPs. PFP mechanisms have failed to induce voluntary participation of those called to increase public good provision or decrease the creation of public bads. Achievement of the appropriate levels and patterns of participation is crucial to performance. The CRP and EQIP have had significant levels of participation, but the patterns of participation do not lead to cost-effective outcomes. WQT programs implemented to date have been marked by low participation rates that prevent achievement of economic and ecological objectives (Breetz et. al 2005). The experiments conducted in Pennsylvania present more encouraging results. First, artefactual field experiments induced significant levels of participation and efficiency of subjects motivated by monetary payments. Second, farmers' performance and reaction to experimental treatments was at least as good as students and in fact outperformed them in several treatments.

Pennsylvanian farmers' choices revealed different aspects the distribution of risk preferences between farmers resulted more heterogeneous than students. This finding reveals one of the advantages of bringing experiments to the field. As highlighted by the Cardenas farmers' experiment (2010), the greater the variance in activities, wealth, education, and demographics, the greater the difficulty in designing a "one size fits all" PFP. Although differences in risk aversion did not relate to substantial differences of play in the PVPG, farmers with similar risk aversion to students' tended to participate less than them. Additionally, I observed a large proportion of risk-seeking farmers. This observation contradicts previous research with farmers in developing countries as well as in Minnesota and Wisconsin (Binswanger 1980, Barham et al. 2012). Differences with previous studies uncover the importance of replicating experiments across field sites. Replication can provide major gains to explain differences in choices.

Limitations of this work are generated mostly by the small sample of participants and participant selection process. Lack of substantial representative farmers of all counties and conditions of Pennsylvania dilutes the gains of external validity. Future extensions of this work should include a larger recruiting campaign and stratified survey design. Surveys or follow-up studies that allow researchers to link experimental choices with subjects' decisions in naturally occurring PFP markets will also provide additional external validity to the findings of artefactual experiments. Additional theory relating the relationship between risk, uncertainty and ambiguity aversion, and the existence of strategic risk aversion and its implications for PFP mechanism design is needed.

On a positive note, the willingness of farmers to participate and to engage in the experiment reveals that when the description of the research is done properly, farmers and other experimental subjects are willing to reveal their decision-making processes. This information can improve the design of PFP programs, and reduce the uncertainly surrounding PES effectiveness specifically.

Chapter 3

Do Cab Drivers Charge for Congestion? A Traffic Field Experiment in Lima, Perú

Traffic congestion plagues urban areas across the globe. With ground travel demand projected to rise, by all accounts, identifying innovative solutions to help maintain sustainable urban environments is capital (Downs, 1992). Although economists, engineers, and urban planners have suggested attenuating traffic congestion with more roads, public transportation, and congestion pricing, these options have either resulted in only modest improvements (Downs 2004). Moreover, road construction is often an unfeasible option and modifying city traffic pattern, or pricing road use encounter significant political resistance (Sorenson et al, 2008)[25].

While these common solutions to traffic congestion assume lack of sufficient traffic network capacity as a major causal factor, construction of new roads or expansion of current ones it is usually unfeasible in highly populated urban areas. Therefore, useful policies should address congestion as a coordination problem. Solutions are thus to be found in improving the use of existing resources. Identifying useful policies in this vein would require the identification of the nature of the congestion problem as well as a better understanding of drivers' and commuters' behavior. Identifying the causes of traffic congestion alone is a difficult task. Worse is the fact that any useful policy cannot be designed from the analysis of naturally occurring data, as, drivers' preferences and

[25] Some cities, such as Miraflores, Lima, Peru, is one of them do not legally allow the imposition of internal road tolls.

individual decisions are not usually observed. Comparing drivers' decisions to alternatives is, therefore, impossible with existing data.

Drivers create congestion by deciding to driver along the same route at the same time. Routing decisions of taxi drivers and private drivers have different implications. Unlike most private drivers, taxi drivers conduct multiple routing decisions per day. Each trip implies a routing decision. Therefore the experience gain and the implication that each routing decision has on taxi driver earnings are different than those of private drivers. Each routing decision affects a taxi driver's earnings, but he can usually compensate bad routing decisions with more frequent good routing decisions**.**

As highlighted by Tumer and coauthors (2009), traffic coordination problems are particularly interesting because individual actions, in these problems, are neither intrinsically good nor bad. As aggregations of individual choices lead to outcomes, individuals need to coordinate with others to achieve desirable ones, rather than learn a set of "good" actions. Understanding what actions subjects learn in these problems is crucial. Economics argues that incentives matter when it comes to prompting optimal choices. Different types of drivers, however, have different incentives to improve the optimality of their choices.

To identify the basic fundamentals of drivers' decisions on traffic congestion, I use field experiments that study taxi drivers, specifically how Lima's taxi drivers can bargain over expected congestion costs. By properly pricing congestion, taxi drivers could minimize the negative externalities imposed by others. Using real experts operating on-the-job allows us to observe their performance in estimating how an externality, congestion, may affect prices, as well as making routing decisions that effectively avoid negative effects. This field experiment was conducted to address two research questions: Do taxi drivers charge for longer expected travel times due to congestion? What are effects of congestion on requested fares?

Lima's unregulated taxi industry and considerable congestion problem provides a unique environment to examine if taxi drivers are experts at pricing congestion. Taxi drivers and commuters directly negotiate over how to split the cost of longer trips due to congestion. I therefore conducted a natural field experiment, in the sense of Harrison and List (2004), within the traffic network of the neighborhood Miraflores in Lima, Peru. Over the course of ten days, nineteen confederate taxi customers were employed to conduct 1100 taxi trips according to one out of three protocols[26]. The experiment allows me to study how the uncertain cost of congestion (a fundamental characteristic of the market) affects bargaining over trip fares.

To my knowledge, this traffic experiment is the first field experiment to use naturally occurring traffic conditions and street characteristics to create two treatment conditions, congested and non-congested environments. It is also the first field experiment to record all environmental conditions, such as traffic volume, number of taxis at bargaining point, and flow of taxis at each negotiation time and use them as variables for statistical and econometric analysis. The two existing field experiments

[26] In a naturally occurring field experiment In this type of experiment, the researcher does not control certain characteristics of the field. Different from lab experiments, in my research traffic conditions are not controlled by design; they occur naturally and the researcher aims to test if drivers identify these different naturally occurring conditions.

from Castillo et al. 2012 and Kensington 2012 studying bargaining in naturally occurring markets with taxis and rickshaws, respectively, completely ignore the relevance or influence of traffic conditions and expected times on fares. However, the availability of rich traffic data is necessary to parse how market, customer, and travel time expectations affect fares, earnings, and negotiations. As the data I collected includes fares and travel times of alternative routes at identical times of the day, values of alternative routes, distributions of travel times over different routes, and market conditions, my data set is the only one that can be used to observe how market conditions and alternatives routes affect fares.

Taxi drivers on average drivers requested higher fares for trips with longer travel times. Furthermore, taxi driver perception of reduced bargaining power when more taxis are available or failures to correctly estimate longer travel times seem to affect earnings. These limitations. in addition to a limited range of prices at which fares are negotiated, have a compounding effect on drivers' requested earnings per minute (*REPM)*. Comparing *REPMs* for congested and non-congested trips, I observed that at the worst congestion period's earnings per minute are 50% lower than when congestion is not present. Drivers are able to compensate decrease in their earnings through the morning. Additionally, drivers displayed superb skills at choosing routes optimally making average *REPM* for those Free-route trips higher on average than for pre-established routes trips. Taxi drivers' routing choices, between the two common departing and arriving points in the experiment, change according to traffic flows. By changing routes according to traffic, taxi drivers prevent trip travel times from increasing as much as they do on more popular routes. Taxi driver routing behavior, therefore, suggests that congestion might indeed be generated by the habitual routing choices of private drivers.

In this research, taxi drivers and customers bargain over a service, i.e. the trip, with a value and cost that are uncertain. Understanding how individuals bargain over goods with externalities is relevant to labor and environmental economists. Like taxi fare negotiations, non-unionized workers such as managers commonly negotiate their salaries (White 2008), while firm and division outcomes are uncertain and generated by the actions of all division members. In environmental economics, bargaining over pollution reduction can be interpreted along the same lines as taxi fare negotiations. Segerson and Miceli (1998) studied voluntary agreement contracts in which one party, the government, proposes a take-it-or-leave it contract to a firm. The contract exchanges actions, such abetment or emission reduction, for a payment. In the real world, voluntary agreed contracts mimic more of a bargaining process with haggling than a take-it-or-leave-it bargain. In this case again, parties participating in voluntarily agreements are uncertain about the value of environmental improvements and their costs. The lessons gleaned from this research regarding individuals' ability to correctly expect and price uncertain outcomes are also relevant to environmental and labor economists.

3.1 Literature Review

This work draws upon three branches of literature: theoretical papers that analyze the price discovery, psychological, cognitive and behavioral literature on time, traffic, and congestion perception, and recent research on naturally occurring bargaining markets. Each body of literature is described below.

3.1.1 Price Discovery Literature

Rubinstein and Wolinsky (1986) and Gale (1987) set the origins of price discovery literature, providing some guidelines of how a price will emerge in a market with sequential matching and bargaining. The problem I examine differs from theoretical work of Rubinstein and Wolisnky (1986) and Gale (1987) in several ways. First, in the theoretical work cited sellers typically know their cost and buyers distribution of good valuations. In Lima, taxi drivers have only estimations of trip's cost and customer valuations. Second, Lima taxi drivers work in an environment in which uncertainty is larger than in those described in theoretically related work. Travel times, opportunity costs of taking a trip, and the distribution of customer willingness to pay for a trip are all unknown and they can only be learned through experience.

3.1.2 Psychological, Cognitive and Behavioral Literature on Time, Traffic, and Congestion Perception

Cognitive and psychological research has focused on psychological tasks that are related to the work of Lima taxi drivers (Svenson et al. 2011, 2012 and Raghubir 2011). The first is the estimation of travel time and routing choices. A taxi driver should price a trip in some way that relates to his or her expectation of trip travel time. Their expectations depend on traffic volumes and on chosen routes. While taxi drivers appear to be good at routing decisions, little is known about their skills at travel time estimation. Psychological research on mean speed judgment has demonstrated that people usually overestimate travel time saving due to higher speed and underestimate travel time increases related lower speeds (Svenson and Sola 2010). Raghubir and coauthors find that students biased their estimation of their travel time depending on if they were traveling from home to work or vice-versa; these biases were consistently independent of their transportation method (Raghubir et al. 2011). In an experiment in Jerusalem, taxi drivers and students showed the same biased overestimation of time saved due to increase of average traveling speed. In this work, taxi drivers overestimations were smaller than those of private drivers (Peer and Solomon 2011).

Different from previous behavioral cognitive research, my experiment presents taxi drivers with the chance of revealing both their skills to negotiate over expect travel times as well as their skills to choose optimal routes. Taxi driver subjects in psychological research are usually requested to state their estimates of travel times or time savings from different mode choices. Traditionally, subjects are not additionally incentives to be accurate than just trying to remind or recall a requested task. Lima taxi drivers express their beliefs about travel time indirectly by way of the fare they request from customers for each trip.

3.1.3 Literature of Naturally Occurring Bargaining Markets.

Three recent papers, Castillo et al. 2012, Kensington 2012, and Balfoutas et al. 2011, conducted field experiments in taxi markets. The three studies focus on the characteristics of the bargaining process or parties and how these influence the final fares. To my knowledge, the work presented here is the first one to focus on the characteristics of the object that is bargained, the trip. Balfoutas analyzed routing decisions in a regulated taxi market, Greece. In this paper, only the authors acted as confederate customers, collecting all of the observations. Authors with different nationalities were used as a treatment variable to observe if Greek taxi drivers take longer routes when foreign customers request trips. Castillo and coauthors also conduct a naturally field experiment in Lima, Peru. The authors also focus on how gender characteristics of the confederated customers affect their initial prices and rejection rates under different protocols.

Keniston (2012) focuses on the welfare implications of bargaining systems. My methodology differs from Keniston's work. The experiment described here has a greater degree of control regarding time routes and negotiation protocol. Additionally, GPS track were collected to verify that each trip was conducted as it was planned. Keniston's methodological innovation relies on the estimation of a structural econometric model. The author uses data of a field experiment with rickshaws in Jaipur, India to estimate the equilibrium strategy functions from the data. The focus of his research is on the bargaining gain between taxi driver and consumer. Therefore his estimates maximize the probability that fares are equilibrium fares. Equilibrium fares are those that leave drivers and customers indifferent between accepting a fare or continuing to search for a new trip. I solve a theoretical model related to the theoretical framework of Keniston in the appendix, although my goal is to focus on the strategic behavior of the taxi driver. Specifically, my interest lies in understanding how system characteristics, such as traffic and market conditions, might affect taxi driver transfer of expected travel times into fares.

The experimental design, research questions, and the methodology improve upon lessons from previous experiments on bargaining in several ways. First, this is the first experiment with taxi drivers in which treatments with pre-established routes and non pre-established routes with common departing and arriving points are implemented. Although previous experiments used routes with predefined departing and arriving points, these did not control for driver route choices. Each time, knowing the best route demands that drivers distinguish travel times by alternative routes under the same traffic conditions. Second, previous experiments do not observe proxies to expectations of congestion or drivers' skills to forecast travel times and to choose optimal routes. Third, this is the only experiment in which two different negotiation protocols, one with and one without negotiation, are implemented. The differences between non-negotiation and negotiation to a pre-established fair price allow us to draw a baseline of what the outcomes can be if one side of the market does not bargain, as well as what are the distribution boundaries of a driver's willingness to accept for a trip fare. Finally, to my knowledge, this is the first experiment in which traffic volumes and trips are chronometrical and GPS recorded. This unique data of the traffic's physical characteristics and market characteristics allows me to decompose the effects that travel expectations and market conditions have on the fares. The physical characteristics of traffic should motivate driver's expectations of travel times, while the number of taxis around negotiation time should define the local market conditions and the temporary market power of the taxi driver.

3.2 Theoretical Framework

At any time of the day or night, taxis and customers search for a match. A number of idle taxis *St* drive around the traffic network searching for customers. At the same time, a number of customers *Dt* search for taxis. Then customers are matched to idle taxis with probability θ. Taxis are matched to customers with probability γ[27]. Customers have an explicit value for a trip *v* at time *t.* Customer's valuation is private information, but the distribution of valuation at each time is common knowledge to taxi drivers.

[27] Previous field experiments were based their analysis on understanding how theoretical models implication relate price to customer characteristics– Kensington 2012 presents a model with in which customers have a continuous distribution of trip's value. In opposition, in Castillo et al.(2012) customers only can have either high or low values for a trip. Additionally, both works do not depart of the older theoretical literature and therefore they assumed that the number of customers and drivers are fixed and know. This assumption, while simplifies the theoretical solutions have the drawback of hiding one of the main characteristics of the taxi or rickshaw markets. In these kinds of markets; the number of customers and idle vehicles changes during the day.

Once matched, customers and drivers bargain over the price of a trip. Bargaining processes outcomes are either agreements or rejections. Dynamics of a bargaining process typically follow a similar pattern. First, the customer requests a trip by telling the driver where he or she needs to go. After receiving the request the driver responds with an initial asking price. Proposals continue sequentially until either the parties agree on the transaction or they stop the bargaining process and start a new search.

Fares relate to congestion through the expected travel time *E(trip travel time)* but fare are a function of a process of search, matching and bargaining. To parse the relationships between fares and congestion, we need to decide what fare we need to use and what are the other variables influencing driver's request from a fare. Equation 1 presents a simplified model relating fares to all the relevant variables of this market. In the theoretical framework I chose one variable, *First Called Price (FCP)*, which is the drivers' answer to a trip's request, to describe how this measure should relate all the relevant variables of fare formation.

Previous theoretical and empirical research has three implications. First, depending on the bargaining procedure of each customer, several agreed fares can be of equilibrium (Fudenberg et al. 1987). Second, if customers have heterogeneous willingness to pay for a trip, taxi drivers know the distribution and both taxi drivers and customers play stationary strategies, it follows that there is a distribution of fares of equilibrium related to the distribution of willingness to pay (Gale 1987). As it turns out, bargaining process can introduce multiple equilibrium fares but under not signals regarding customer willingness to pay a unique distribution of fares/ Specially, the *FCP* should be related to fundamental variables and not to the bargaining process. Therefore, I do not derive the equilibria solutions of the bargaining stage of the game. I focus instead on the analysis of t The *FCP* and its relationship to the fundamentals of the model expressing these relationships as:

(1) FCP_t*=f (E(trip travel time), E(vt) , market characteristics at time t, taxi characteristics)*

Equation 1 right hand side includes all those variables that have been mentioned to affect fares in a unregulated taxi market. I include variables highlighted in theoretical customer willingness to pay for a trip at time *t vt* (Gale 1987, Fudenberg et al. 1987) . Given that driver's don't know *vt,* therefore *FCP* is based on the expected *E(vt)* t. Additionally The outside option of not agreeing in a bargain are waiting and keep searching. The cost of search and wait are functions of the market conditions. Interpreting Lauerman et al. (2012), a taxi driver who perceives changes in market condition, with its consequential change on outside options values, should change his FCP. Finally, a customer perceives taxi characteristics. Taxi characteristics are related to taxi's cost; therefore, a driver could request a different FCP given his induction hat customer perceives his differences in costs.

In identifying how congestion, which generates longer travel times, affects FCP, we need to parse for market conditions. In Appendix C.2, I extend Rubinstein and Wolinsky (1987) (RS for now on) to deal with two market states of the world: a non-competitive one and a competitive one. I show that if drivers and customers can identify at each period, which is the current state of the market, competitive or non-competitive. A non-competitive market is identical to the competitive market, except that there is a greater number of customers per taxi available. Although the RS model has homogeneous sellers and buyers, i.e. taxi drivers and customers, its implications regarding how market conditions affect fares in can be extended to the case of heterogeneous valuations and cost such as this. Additionally, RS model implies not haggling equilibrium and a unique price, the unique equilibrium fare of their model seems to have implications for *FCPs*. RS implies that fares should be higher when a taxi market is competitive. If customers and drivers recognize the state of the market, then they know that taxi drivers have higher bargaining power, or alternatively that customers have a worse outside option. Therefore under the same market condition *FCP* for routes with longer expected travel times should be higher than for routes with lower expected ones.

In addition to the RS extended model[28], walrasian theory also implies that FCP should be increasing with respect to expected travel times. Walrasian fares emerge when there are not implicit costs for searching a new match imply. In non-competitive markets, more customers than taxis, then taxi drivers recognize two things. First, they have bargaining power because there is an excess of demand. Second, because that there is not cost of searching for new customers taxi drivers try to obtain customers with higher willingness to pay. there are two cases, non-competitive and competitive markets. In a

[28] The Rubinstein and Wolinsky article emerged as a critic critique to walrasian theory, showing that even when the cost of searching converges to zero, prices in this market do not converge to the walrasian prices.

non-competitive market a taxi driver will always request higher *FCP* for routes with longer expected travel times. If he fails to do this, fares are not equilibrium ones. The driver cans search for a trip with lower cost and obtain more at no additional cost. In a competitive market, there is an excess of supply and customers using their bargaining power will push trips price to cost. Therefore because walrasian price equalizes cost and cost is higher for routes with longer expected travel times, FCP should also be higher for those routes. Therefore under walrasian theory, FCP for congested routes, those with longer expected travel times should be greater independently of the market condition.

This section described how different fundamentals of the problem such as fares, expected travel times, willingness to pay and market condition interact. Particularly, I simplify a model of price formation to one equation and describe how extension of two models RS and walrasian prices imply that FCP for congested routes should be responsive to longer travel times and therefore to expectation of congestions. The next sections describe how the experimental design took into consideration the characteristics of this market and problem in order to provides a data set with all the necessary variables to estimate Equation 1.

3.3 Experimental Design

3.3.1 Field Characteristics

The experiment was conducted in the neighborhood of Miraflores, in Lima, Peru. In addition to be included in the Lima taxi and traffic system, Miraflores has two major characteristics that constitute it as a suitable location to conduct the experiment. First, drivers are set to be on the decision problem in which two alternative routes between departing and arriving points exist. Alternative routes should have similar characteristics, for example, avenues compose both, not the number of traffic lights and general status of the streets. The connection between the departing point and arriving point should not be able to be reached straight by just choosing one street. The smaller network configuration that satisfies these characteristics is a triangular network. Miraflores' street grid is ideal for this study; the grid is composed of diagonals and circles, which makes it easy to design and test triangular traffic networks. With easily recognizable traffic patterns and a limited number of gridded roads capturing traffic, the problem of traffic coordination is clear in Miraflores .

Second, Miraflores contains a limited number of main roads, namely avenues, traveling north and south through the municipality. Additionally, Miraflores is a commercial and residential area located in between much more densely populated residential areas south of the metropolitan area (Chorrillos, San Juan de Miraflores) and the downtown Lima. This feature is ideal for the experimental design needed here. Large volumes of traffic fill the roads of Miraflores close to the beginning of the working day. Before that, traveling within Miraflores can be conducted with relatively non- congestion. Therefore, taxi drivers familiar with this area know how traffic fluctuates during the day. Additionally, because public transportation and taxis mostly transit through major arteries, Miraflores interior streets remain calm during the major part of the day. Non-congested interior streets offer detours to knowledgeable taxi drivers.[29]

3.3.2 Experimental Treatments and Conditions

The experiment has three treatments: Free Route (FR), Route 1, and Route 2 (called route treatments RR). Additionally, each trip could be conducted at congested (C) or non-congested (NC) intervals for the specific route it was assigned. Classification of the naturally occurring conditions according to different criteria is called "experimental conditions." Two different measures such as congestion perception and travel times are analyzed to route-interval treatments. Based on these measures naturally occurring traffic conditions are assigned to C or NC conditions. Given this, there are six possible types of observations. These are described in Table 3.1.

An experimental observation is one taxi trip. Collaborators, native Lima residents, conducted all trips with previous experience running surveys and bargaining with Lima taxi drivers. All RR trips require that taxi drivers to travel along the chosen routes and minimize protocol variance so that observations at different times of the day and prices are comparable. All confederate taxi passengers carry a chronometer, a booklet, and a GPS device[30].

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29 The presence of high traffic in the avenues but low traffic on interior street are not observed in Lima's downtown where congestion seem to invade all the street grids. The negative effects of congestion in downtown Lima have been a major concern of authorities (http://peru21.pe/2012/08/12/actualidad/miles-taxis-generan-caos-vehicular-calles-lima-2037209) A new plan of traffic rules is scheduled to be implemented in December 2013. A diagram showing the used GPS and chronometers is presented in the supplementary material.

30 Nonparametric test comparing travel times distributions of Routes 1 and Free routes during interval one can not reject the hypothesis of equal means (Mann-Whitney rank sum test z=-1.498 or equal distributions Kolmogorov-Smirnov K-S combined=0.354

Table 3.1 describes the experimental treatment design along with the main collected variables.

Route\Time	Non Congested Intervals	Congested Intervals
Route 1	$Fare_{NC1,}$ trip travel $time_{NC1}$	$Fare_{C1,,}$ trip travel $time_{C1}$
Route 2	$Fare_{NC2,}$ trip travel $time_{NC2}$	$Fare_{C2.,}$ trip travel $time_{C2}$
Free Route	$Fare_{NC0,,}$ trip travel $time_{NC0}$	$Fare_{C0,,}$ trip travel $time_{C0}$

Table 3-1: Experimental Design and Main Variables

Each confederate customer using a chronometer records trip duration. The confederate customer starts the chronometer once he sits on the back seat and stops once he steps out of the taxi. For each trip, each fare could be either the first requested price from the taxi driver if collaborators were instructed not to negotiate, or the negotiated price otherwise.

3.3.3 The Network

The treatment routes in Miraflores are implemented as described in Figure 3.1. All the trips requested are conducted between the departing-arriving point A and P. Trips could be either by Route 1 or 2, or by any other route connecting these points that the driver chooses in a Free Route (FR) treatment. Route 1 (violet) is made up of segments of Arequipa and Pardo Avenues. Meanwhile Route 2 (orange) is composed of segments of Santa Cruz and Pardo Avenues. Travel times from these two points are similar when there is no traffic congestion. More detail on network, routes, and the characteristics each route are presented in Appendix A. A pilot investigation conducted in October 2010 provided basic data on traffic patterns and road use in the municipality.

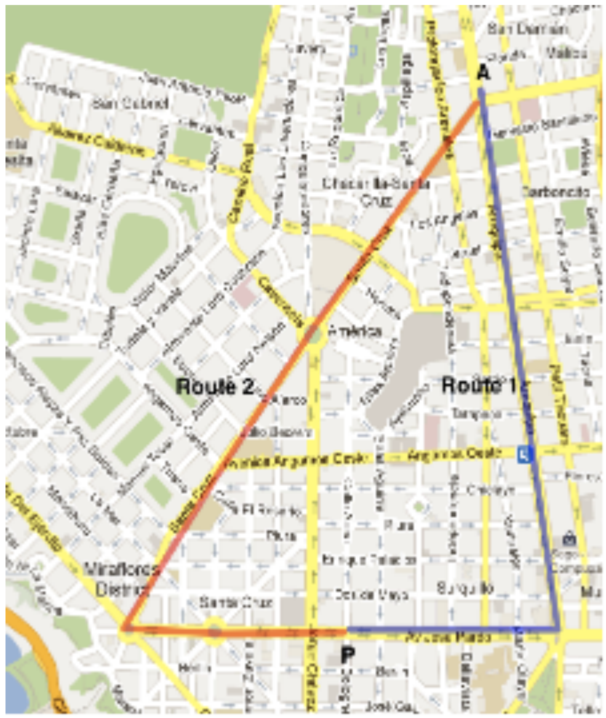

Figure 3-1: Network

Route 1 is 1.56 miles, which is shorter than Route 2 at 1.79 miles. Route 1 has more traffic lights (10) than Route 2 (6). Additionally, buses travel along Arequipa Avenue but not along Santa Cruz Avenue, the longest segment of Route 2. On average, Route 2 trips are slightly longer than those over Route 1, even under non-congestion conditions.[31]

3.3.4 Experimental Implementation

[31] Previous to the experiment, a pilot study in which protocols, routes and recording mechanisms were tested was conducted during the dates of 11-15th October 2010.

The experiment was conducted over twelve working days from June 18th to July 4th in June 2011.[32] Traffic flows varies in two senses: First, it varies with each day. This variation reflects the fact that most of the offices and business have common regular working hours. Additionally, traffic flows varying during the week. The experimental design was focus on finding traffic conditions that maximized within day traffic variation and minimized between day variations. By maximizing within day variation, I obtain a larger number of observations in a day share common weather and daily traffic conditions but differ on traffic volumes. By minimizing the variation between days, I obtained that observations of different days at the same time are relatively more comparable. It is straightforward to observe that given the differences between working days and weekend days between day variations between these two are of significance. Therefore, I eliminated weekends from my analysis. Additionally, I eliminated June 29th, which was a holiday. Although traffic flow varies between working days, pilot data did not present significant differences between average travel times of the different working days. Therefore, I the experiment was conducted during 10 working days.

A total of twenty-one collaborators conducted a total of 1100 taxi trips. These trips were conducted during three weeks in ten working days, with trips taken between 6:30 A.M. to 11:30 A.M.[33] We didn't experienced rain and the ten days had the usual Lima's June weather. Table I in C.1 describes the number of observations per day and

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[32] Additionally I collected data for a Friday afternoon, That afternoon we collected 96 trips. The distribution of travel times during afternoon periods differ from those observed during the morning.

[33] I called stated willingness to pay measure collaborators used to bargain during week 2, *Fair Fare.* The value of this variable changed every hour. The Fair Fare for hour *t* was estimated as follows*: FFt= (average travel time FR trips at t during week 1) * (FR earnings per minute week 1*). The rejections rates for each treatment and the analysis of the rejected trips are not included in this chapter.

weather conditions for each day.

Each trip was requested following the same protocol. However, during Week 1 collaborators *always* accepted the FCP with which taxi drivers responded to a request. Week 2 was different from week 1; after requesting the trip following the same protocol, collaborators stated their willingness to pay[34]. Therefore, some taxi drivers accepted and other rejected collaborators demand during week 2. This chapter analyzes only conducted trips. Table C.2 in Appendix C.1 Wilcoxon rank sum tests for the different demographics variables such as taxi drivers age, experience, ownership status for trips conducted trip in week 1 and week 2 can not reject the hypotheses that these measures are generated from the same distribution. Additionally, Kolmogorov-Smirnov function does not reject that their distributions are the same median and distributions of these variables. Therefore, being confident that the introductions of change didn't introduce a selection bias of different taxi drivers during week 2, FCP of all conducted trips can be analyzed together. Each trip represents one observation. Collaborators conducted each trip following an Experimental Protocol (EP) that was practiced and trained previous to collect data in the experimental the task for at least 4 hours. Data of each observation was recorded after the trip was conducted in booklets. The EP to conduct a trip was as follows:

1. Arrive at the departure point A (P) (a field coordinator will be waiting)

[34] Two days were allocated to collaborators training. During these two days I explained the protocols and dressing codes to the collaborators. We created a set of agreed expressions to name the arriving points and expressing desired route procedures in each observations that sound natural to drivers and that also prevented from signaling any kind of confederate income. Roll playing activities in which collaborators mimicked the procedures to collect an observation were practiced. In these, roll play was used to minimize the amount variance of natural over expressive body language presents. The ten remaining days were dedicated to running experimental activities in Miraflores.

2. Ask the experimenter for the assigned treatment (previously randomized by the experimenter)
3. Stop a taxi and ask for the price of a ride to point P (A) (mention route restriction, if applicable (Route's 1 and 2 treatments)
4. Observe number of taxis around the stopped one
5. Accept the price
6. Enter the taxi and start the chronometer.
7. Engage the driver in an informal conversation to collect taxi driver's information
8. Pay at arrival
9. Stop the chronometer
10. Complete the booklet
11. Report to the field instructor at P(A) for a new treatment assignment and re-start at 2.

There is only one difference between the FR and RR protocols. In RR treatments, collaborators request specific routes to drivers while in FR treatment clearly they do not. Each confederate was trained to announce routes during the trip request in a similar fashion. Training was crucial to homogenize trip request. Additionally, we emphasized the importance of assuring that taxi drivers understood the route description well enough to estimate travel time accurately and call his fare accordingly. [35] To implement specific

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[35] The pattern of traffic data collected showed quite consistency in 7 out of the 10 days. The remaining three days, changes in the individuals controlling the traffic counter devices seem to be affected its reliability. Based on the 7 days of traffic data with greater

route treatments, collaborators asked taxis to keep to a particular route to check something in passing. Collaborators carried a GPS, and tracking was used to check if RR treatments were conducted as predetermined. Additionally, GPS tracks reveal different routes used by taxi drivers on FR treatment.

During the taxi trip, collaborators engaged in an informal conversation with taxi drivers. These conversations allowed collaborators to collect measures of the driver's age, ownership, working hours, experience, and route preferences. Additionally, each confederate classifies the vehicle according to its type, sedan or wagon, and perceived status of the vehicle: new, average or bad. In addition to this task, collaborators collected data of how many taxis surrounded the taxi they choose. Additionally, for each trip, collaborators categorized its traffic conditions as Low Traffic, Regular, and Dense Traffic.

To control for traffic network characteristics, key descriptors such as length, number of traffic lights, number and width of lanes for each direction were recorded. Furthermore, flow and type traffic data was also collected during the June experiment. Two individuals were placed at A and two at P, to collect traffic data. Each Counter was equipped with a Jamar traffic counter (http://www.trafficcounter.com/). Using individuals to count traffic has advantages and disadvantages. One disadvantage is that data provided

degree of reliability currently I am working with traffic engineers at Penn State and University of South Wales to create a simulation program that mimics the observed patterns.

by individuals can be incorrect and noisy[36]. To control for measurement error, two Counters were therefore located in each position. By averaging their data, more reliable data was obtained. On the other hand, human counters are the only available method to discriminate traffic by type, such as taxi, bus, and private car traffic. Given that different types of vehicles generate different effects on traffic flows and fares to be negotiated by taxi drivers, recording vehicle type as well is essential. The Jamar traffic counters were thus programmed to record traffic flow data for taxis, buses, and private cars in 5- and 15- minute intervals for all streets and directions of arriving/departing points.

The trip is conducted after it is agreed upon. During the trip, the confederate informally asked questions aimed to record a number of important driver characteristics. After the trip ended, collaborators recorded this information in their record booklets.[37]

3.4 Empirical Model

The experimental design provides counterfactuals that can be used to identify the effects of congestion on fares. For each interval of time, the same population of confederate customers is randomly assigned to the different route-treatments. Trips are conducted from the same arriving and departing points following the same experimental

[36] A copy of the record booklet sheet can be found it in the additional material. Additional audio material with examples of the informal interview questions performed by the collaborators to taxi drivers can be provided upon request.

[37] Collaborators were trained during two days. The training included approximately 4 hours of practice in which collaborators roll played the experimental task. The training in this task was conducted to homogenize the way in which collaborators interact with taxi drivers. Additionally approximately 20 observations were conducted in which the researcher randomly choose when to join one of the collaborators to observe their performance.

Additional material describing the type of questions that collaborators asked drivers can be obtained by direct requested to the author via email protocol. Furthermore, within a given time interval, market and traffic conditions do not change substantially. Therefore, at a given time trips for different routes are only different on their correspondent travel times. If the only reason to create longer travel times is congestion. Furthermore, congestion is the only reason to explain different observed fares.

Travel time variations are more significant between different intervals. To parse how fares should change when market conditions are changing, we need to conduct a different kind of analysis. Non-parametric analysis is limited to within interval comparison. But for each interval, the number of observations in which two routes with the same arriving and departing points are conducted is limited by budget, logistic and experimental constraints. Regression analysis allows me to compare trips over different intervals. To better understand, how fares can change due to congestion I estimated different linear regression models of FCP using *OLS* with mixed effect models. Additionally, to understand how changes in travel times and its changes in requested fares affect taxi driver's income I model requested earnings per minute (*REPM*).

The *FCP,* driver's response to a requested trip is modeled as follows:

(2) $$FCP_{irt}=f(D_{i}, EWTP(C_{k}), E(TTT_{rt}), MK_{t})$$

where FCP_{irt} is the first price with which a driver i responded to a customer k request of a trip over the route-treatment T_r at time t. D_i are vehicle and driver characteristics. Drivers' characteristics are age, ownership, working hours, experience, and route preferences[38]. C_k customer characteristics are age, gender, and number of trips he/she has conducted on a given date. Finally, fares are a function of expected travel times *E(*TTT_{rt}*)* and market conditions MK_t.

Trip travel times on a route *r* at a time *t* are described as a function of route characteristics and traffic volumes at that given time *t*. *TTT=g(* Route traffic volume $_{rt,}$, *Route capacity).* The previous equation describes the traditional way in which a traffic engineer will describe travel time. Drivers observe only partial measures of traffic volumes and they might not known the capacity of each road. Therefore, expected travel time is not a deterministic function depending only on traffic flow and route capacity as it is described in the previous equation. Travel time expectations are influenced by driver's characteristics. For example, a driver's experience may enable him or her to estimate travel times more accurately. The number of hours the taxi driver has worked previous to the trip can influence in two ways. On one hand, longer hours of work on any given day provide the taxi driver with additional information about day and current traffic conditions what can help him to form more accurate expectation. On the other hand, longer hours increase tiredness what decrease driver's accuracy. Travel times expectations therefore is a function described by:

(4) $$E_i(TTT_{rt}) = y(\text{Route traffic volume}_{rt}, \text{Experience}, \text{hours of work}) + \varepsilon$$

[38]It is beyond the scope of this paper to explain how drivers generate expectations regarding consumer's willingness to pay for a requested trip, given some signals such as gender, body language, age, clothes and drivers' knowledge of the distribution of willingness to pay.
The experimental design controls for several of these characteristics, such as body language and clothing, then they are not included in equation (5). To Do: Include beauty and surveys on WTP for trips for different people

Where ε represents the error term. The error term represents two facts. First, there are several additional explanatory variables that can explain the formation of travel time expectations. Second, there are unobservable variables and error on the information collected by the collaborators and individuals counting traffic volume that will affect the estimation of the equation 4. Collaborators collected actual travel times, therefore assuming that expected travel times are a function of drivers' characteristics but that driver will have expectations correlated to the actual travel times. I estimate equation 4 as a linear function of the actual travel time and the collected driver's characteristics.

Drivers try to maximize income for each requested trip. Therefore, they take into consideration an expectation of customer willingness to pay for that trip. Taxi driver's request is based on this expectation. This expectation is modeled as. [39]

$$(5) \qquad EWTP(C_k)=z(Age, Gender)+ \xi$$

where age and gender are the confederate's age and gender for any given trip. It is outside the scope of this chapter to develop a structural estimation model regarding how one player, estimate the willingness to pay of the other player in a bargaining game. For the purpose of estimating equation 5, we will model driver's expectation of confederate willingness to pay as a linear function of his gender. Additionally, in the mixed effect

[39] As Lauerman et al. 2012 suggests if individuals have expectations about "future market conditions", also would affect *FCP*. If the number of sellers and buyer change over time, their offers and asks in the bargaining process are different that if this number is stationary. I take one step forward in the same direction that Lauerman and coauthors, recognizing the influence of different market states on fares in the Appendix C. It is outside of the scope of the paper recognize how the process of transition from different state of the market behaves as well as how individuals form expectations of the state of the market.

models estimated in next section, individual collaborators are introduced as variables. These variables can capture specific characteristics of each confederate.

The last argument of equation 2 we need to describe is market conditions MK_t . Several variables can represents market conditions, theoretical work will argue that the total number of taxis and customers at each time or average waiting times to find a new match could be the best measures (RS or Lauerman et al 2012). Obtaining these measures for Lima metropolitan area is unfeasible. Therefore MK_t are capture in two variables. The first is the number (#) of taxis surrounding the chosen one at negotiation time. This variable is recorded by the confederate and captures how competitive the local environment was at negotiation time. The second variable is Percentage (%) of taxis in traffic. This variable is aimed to capture how the taxi drivers perceive the supply of taxis at any given interval. Collected traffic volumes are used to construct this variable. Traffic recorders classified the traffic according the kind of vehicle such as taxi, buses, and private cars. The *% of taxis on traffic* is the ratio taxi and total traffic flows at each interval and day. Then each observation is matched with its correspondent *% of taxis on traffic* for its interval and day. It is outside the scope of this study to describe how existing market conditions may affect drivers' expectations of future market conditions and probabilities of finding a trip.[40]

Congestion can be defined and perceived in several ways. I am primarily interested in classifying each trip as congested or not according to its travel time length.

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[40] Interval 1 has lowest classification index, most of the collaborators classified as Low traffic with a mean index value 1.41 (Low_traffic_baseline) and its standard deviation is .2190551. Different that Interval 1, the other intervals mean is 2.05, that is the mean perception index for Interval 2. For a Regular_traffic_baseline this is 2.047 and standard deviation of .3685395.

A definition of congestion is based on travel times, statistical definition *SD*. The *SD* criterion tells that a route-interval is classified as congested if the interval's mean, median and distributions of travel times are significantly different from the distribution of travel times for non-congested trips. Appendix C.1.3 presents the classifications of the different inter-routes in Table A.C, II

Several non-parametric tests procedures were used to test the hypothesis that travel times for Free route and Route 1 trips are equal during 6:30 to 7:30 am. The mean time comparison test statistic, is z= -1.498 (Man-Whitney rank sum statistics) and the median statistics is Pcs= 0.0285 (corrected Pearson Chi). Therefore, the hypotheses of equalities of median and mean times cannot be rejected. Equality of distribution of travel times is tested by the Kolmogorov-Smirnov test K-S=0.1644 for each route-interval are conducted.

Section 3.1 reviewed the psychological, cognitive and behavioral literature on time, traffic, and congestion perception. One of the findings of this literature is that humans present bias at estimating travel times and travel time saving by switching modes or changing routes. . Therefore subjects could fail to perceive congestion and its relationship with travel times. For example, a driver could perceive a route as congested even when travel times on that route are not changing just because traffic in that route is composed by a truck instead of three cars (Reference). To parse the effects of congestion on fares, we need to analyze not only in how factual congestion, travel times affect fares but also those characteristics of perceived congestion that could be motivated by bias affect fares. A second definition of congestion is used. The declarative definition, *DD,* uses collaborators traffic classification to create a perceptual index. The difference between *SD* and *DD* classification is that while *SD* relies on observed travel times, *DD* relies on collaborators' categorization.

The relationships between collaborators' perception and DD classification can be explained as follows. For each trip, collaborators categorized trips traffic conditions as: Low Traffic, Regular, and Dense Traffic. Taking each day's categorizations and averaging them per interval route creates a *perception index*. Those average classifications that are closer to the values of Low Traffic (1) or Regular Traffic (2) are called index baselines for Low and regular traffic[41]. An interval-route is classified as congested if its mean perception index is statistically significantly different than the corresponding baseline index. Table 3.1 presents a classification when each interval-route perception index is compared with the low-traffic baseline and regular-traffic baseline, respectively. In the Appendix C, Table C.6 describes how interval-routes based_low and regular traffic_baseline are classified according to the declared definition (DD). Congestion classification criteria are used as a base to create dummy variables that have value 1 for those interval-routes classified as congested and 0 otherwise.

The empirical model described in equation (2) relates drivers, customers, and market characteristics to fares. This model relates experimental design and database of the theoretical framework (1). By replacing each one of the components of this model such as expected travel times and expected customer's willingness to pay (equations 3

[41] Although we cannot reject at 5% significance level the null hypothesis that Route 2 and Route 1 or Free Route treatments are different. Most of the Route 2's *REPM* for Interval 1 are higher than Route 1's mean but lower than Free Route's mean and median *REPM*

and 4) with its linear expressions and the variables measuring market conditions, we are able to estimate the first empirical model. In this empirical model, as a reflection of the congestion influence *FCP* only through $E_i(TTT_{rt})$. Therefore, there should be a continuous relationship. While travel times are continuous variables, congestion is usually defined as a discrete variable. Congestion is a threshold event. A route is congested when the volume of traffic is greater than that route capacity. Additionally, it is possible that commuters only recognize congestion when it implies a significative difference on travel times.

3.5 Implications of Equilibrium Behavior on Fares and Earnings

The theoretical framework imposes qualitative and quantitative conditions on the characteristics that the experimental measures should present. If drivers are able to recognize congestion, then their per-minute income for different routes should be similar. In section 3, I argued that RS model as well as walrasian theory implies that FCP should be increasing on expected travel time. Therefore *REPM* is just *FCP/TTT* should be similar for all the routes. Therefore, the main hypothesis is as follows:

Hypothesis I: at each interval REPM for each route-interval should be similar.

If drivers only care about their monetary earnings, then they should not discriminate over routes with the same road conditions and travel times. Failure to equalize REPM implies that drivers could obtain greater gains by either taking a different route or requesting a different price. Theoretical equilibrium implies the non-existence of arbitrage. No arbitrage conditions implies that if a route provides larger REPM then drivers will deviate increasing congestion until earnings per alternative routes equalize. In equilibrium, fares should only change to keep the same earnings per minute and drivers indifferent. By design, the experiment demand that trips for all treatments start and finish in the same departing and arriving point. If fares are different, this difference should be generated by longer travel times. Therefore changes in FCP should be proportional to changes in travel times making REPM of the different routes similar

3.6 Results

This work elicited three primary findings. First, drivers relate fares to travel times. Second, average fares change less than proportionally to travel times. As a result, earnings for congested interval-routes are lower than for non-congested ones. Third, routing decisions allowed FR to keep REPM constant. When drivers are able to choose their route average earnings minutes are not different for congested and non-congested periods. Finally, drivers compensate loses and gains for morning traffic conditions.

Two points should be noted from these findings. On one hand, drivers exhibit great capabilities to cancel the effects of congestion in their daily earnings. On the other hand, an unregulated market is insufficient to create incentives to change commuting behavior. Taxi drivers learn to choose routes optimally but they fail to request fares high enough when customers request trips over congested routes. This failure could be generated by failure to estimate longer travel times or by driver's belief of an overly competitive taxi market.

Drivers recognizing traffic congestion upon a trip request have two possible options. If the driver recognizes congestion while negotiating the trip, then the driver should reply with higher *FCP*. For those trips in which an explicit route is requested, taxi drivers could try to deviate if they perceive congestion ex-post. In opposition, for those trips in which drivers could chose routes freely, congested routes more than likely would not be selected. I focus my analysis on travel times *TTT*, *FCP*, *REPM.*

Result 1. Taxi drivers requested different fares for routes with different travel times.

Experimental treatment was designed to provide, at any period, trip routes that have similar expected travel times under conditions of no congestion. Thus when congestion is added into the equation, the only change between the two congested and non-congested trips is the creation of different travel times. Taxi drivers recognizing this phenomenon should change fares to compensate for congestion. Figure 3.2 shows a box-plot graph of the different observed trip travel times*, TTT,* for each route and interval.

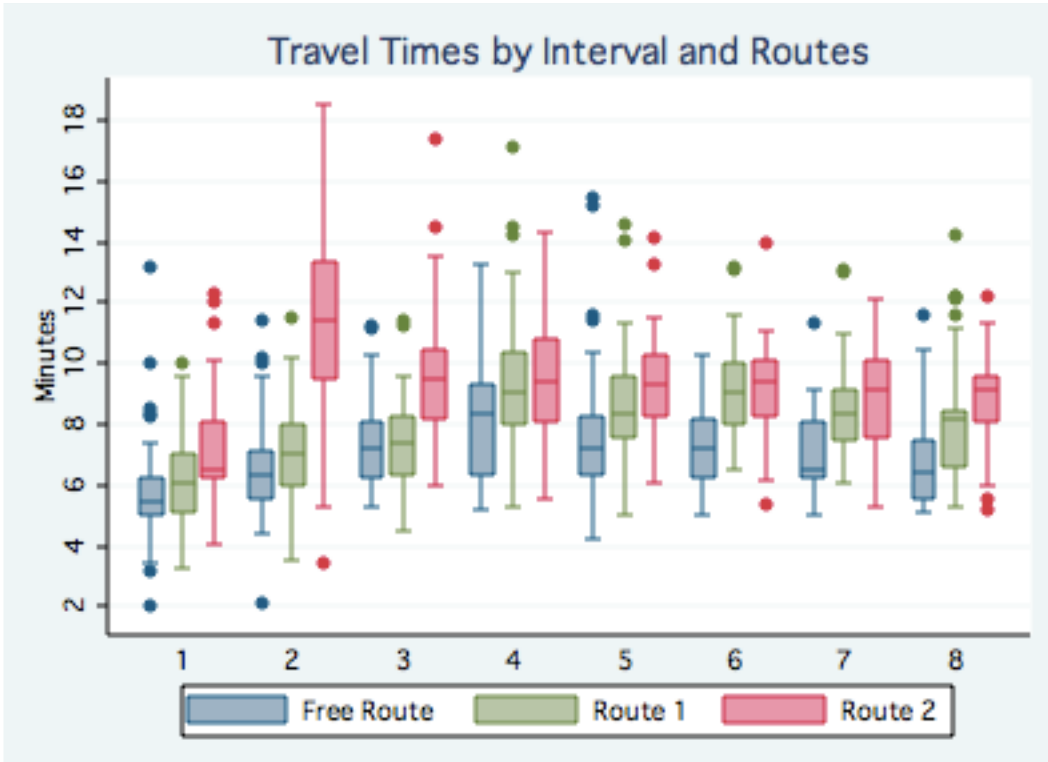

Figure 3-2 Box Plot Travel Times by Interval-Route Treatment

Figure 3.2 reveals that the goal of the experimental design was achieved. At intervals 1, 6:30-7:00 AM and 4 8:31-9:00, average travel times are similar. For these intervals, the null hypotheses that Free Route and Route 1 mean travel times are generated from the same distribution cannot be rejected (z=1.990, p=0.046 & z=-0.967, p=0.3337 respectively). For the remaining periods, there is always at least one route with greater average expected travel time. Additionally, four stylized facts characterize travel times of the experimental data. First, Route 2 presents usually longer travel times. For all intervals, Route 2 median travel times are longer than those for the other routes (z = -4.049, p=0.0001, ttr1-ttr2 t= -3.9985). Second, Free Routes are usually faster. No matter what interval the trip was conducted, Free Route travel times are the lowest for all of them (ttrr-ttfr t-test =6.8851). Third, travel times for at least two routes are similar under congestion or non-congestion. For each interval, two routes median travel and their distributions travel times are similar. Therefore fares and *REPM* for those two routes with similar travel times can be expected to be similar too. Additionally, we expect that fares for the remaining route treatment to be different. Four, I observe similar travel times with congestion and without congestion for alternative routes. Intervals 1 and 4 median travel times are similar for periods 1 and also during period 4. Although within a given time the three routes present similar travel times for intervals 1 and 4 are different. This means that the aggregated flow of traffic drives all trips to be longer during the middle of the morning, period 4. Median travel times at interval 1 is 6' 27", the lowest, median travel times during period 4 are 9' 6", the largest. Table

To satisfy the theoretical implication that REPM should be constant drivers transfer longer travel times within an interval into fares, then a box-plot of fares by routes (Figure 3.3) should follow a similar pattern to Figure 2. Figure 3 and Figure 4 reveal the limitations of an unregulated taxi system and also the surprising capabilities of drivers in Lima taxi network. I start by box-plotting the *FCP*

Figure 3-3: First Called Prices by Interval-route Treatment

Figure 3.3 describes two important features that characterize Lima's taxi fares. First, fares are usually negotiated in round Soles. Second, all the fares fall within small range of Soles; 1096 of our 1100 trips observed fares between S./4 and S./8. High requested fares, *FCP* of S./8 were rare with only 40 requests being observed. Round and bounded fares create drivers difficulties to charge for congestion in an unregulated taxi market.

If drivers can change fares to keep their REPM constant then the *FCPs'* pattern in Figure 3.3 should mimic TTTs' patterns of Figure 3.2. When drivers have mostly charge round fares within an small range of fares available, correct expectations of longer travel times might fail to be transferred into requested fares due to common developed social costumes. Drivers might constrain their behavior to ask only call fares within the range that common experience and learning has taught them. These fares have a positive probability of being acceptable ones. Requesting rounded fares could be a constraint on individual taxi fares. Mean, median and distribution of fares for interval-route-treatments do not necessarily need to be rounded. Therefore mean and median fares should reveal if taxi drivers were able to charge for longer travel times as a group to a group of customers. Figure 3.4 presents mean *FCP*.

Figure 3.4 Mean First Called Prices per Interval-route Treatments

It is apparent that mean *FCP* for the different route-treatments follows a path similar travel times in Figure 3.2. This means that the implications of fares being related to travel times are supported in the aggregated. I support this claim in three ways. First, Free

Route mean *FCPs* are the lowest between the three route-treatments for almost all the intervals. This fact corresponds with the understanding that Free Route travel times are the lowest travel times for all intervals. Second, Interval 4 *FCPs* are statistically indistinguishable. This finding would be also supported by the fact interval 4 travel times are also indistinguishable. Third, Route 2's *FCP* are the highest for almost all the intervals. This fact is coherent with the observation that Route 2 travel times are the longer between all the route-treatments for all the intervals. The only observation that contradicts this intuition is the fact that at interval 1, *FCPs* for all treatment-routes are different when their mean travel times are not. This factor could be potentially generated by a confounding of greater bargaining power that taxi drivers have when few drivers are in the road as it is the case during interval 1.

The patterns of fares as described seem to be route-idiosyncratic; overall, Route 3 trips receive a higher *FCP* than trips in the other route-treatments. It seems that taxi drivers recognize that trips over Route 2 takes usually longer. Second, that they can usually do better by choosing their own route. To obtain a better comparison of fares and earnings over different intervals, I analyze *REPM.* Also I analyze fares and requested earning per minutes as function of several variables that might affect fares:

Result 2. Requested earnings per minute are significantly affected by congestion.

The previous section described how three characteristics of the unregulated taxi market, rounded fares, market conditions and beliefs regarding customers' willingness to pay, might limit individual taxi drivers capability to increase fares enough to charge for congestion. Taxi drivers as groups where able to respond to the relationship between travel times and fares. Overall, the effects of not being able to change fares to charge for congestion can have an impact on drivers' income. The REPM values were used to study this. A trip REPM is just the ratio of trip's FCP over its observed travel time. Normalizing per minute, I search for a unit of measure that allows us to observe what a driver should expect to earn for trips conducted between different intervals.

Figure 5 graphs the observed *REPM* per interval-route. If changes in fares where linear with respect to travel times then we would expect to see straight lines for each route-treatment REPM. Additionally, if the linear relationship have a unitary slope, we expect to see a constant line within which earning per minutes do not vary across the mornings. Furthermore, if we assume that drivers do not discriminate between different routes and that they only charge differently because of their expected travel time, then the three route-treatment lines should be equal.

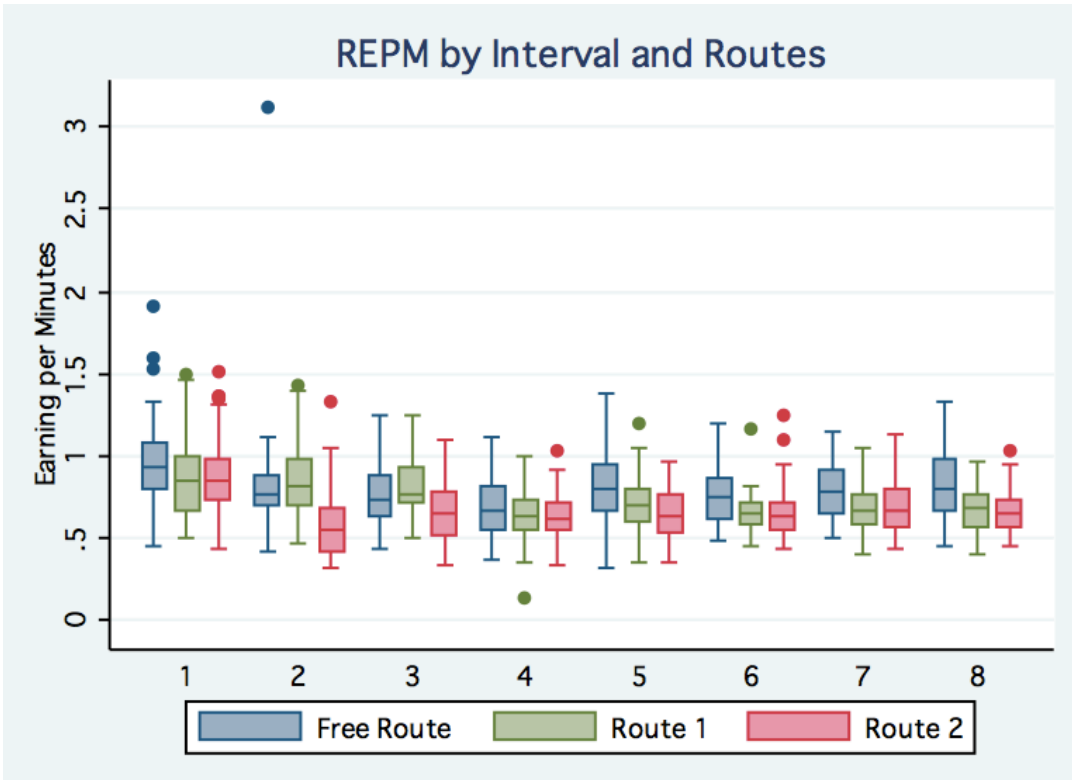

Figure 3-5: Requested Earning per minute (REPM) By Interval-Route Treatment

Two especially revealing findings are presented in Figure 5. First, *REPMs* between routes seem to be more similar than fares per routes. We should expect this pattern if fares are related to travel times. Notice that in Interval 1 mean *REPM* are really similar. If we recall that Interval 1 has the lowest travel times and is the only interval that was consistently classified as non-congested, under non-congestion condition *REPMs* are similar. The hypothesis that mean and median *REPMS* for *all* the treatments are equal at a significance level of 10% (chi-squared= 5.428 p=0.0663) cannot be rejected.

Additionally, we cannot reject the hypothesis that *REPM* means and median travel times for route-treatments with similar travel times. First, Free Route and Route 1 are equal (t=0.6605, z=0.772 & Pcs=0.2974).[42] Second, *REPM* decreased with congestion. Given the *FCP* lack of sensitivity to travel times, it seems that even when drivers might change the proportions of ***FCP*** requested above the mean, the changes are not sufficient to keep their earnings from falling during congested intervals. More importantly, *REPM* seems to fall dramatically for what we can consider unexpected congestion such as what was observed in Interval 2 on Route 2. Additionally, *REPMs* decrease during the intervals 4,5 and 6 the morning peak hour times. This observed feature seems to contradict the theoretical implication that if drivers are able to recognize that peak hours present a less competitive environment, then they should increase the fares they request at least as much to avoid *REPM* from falling. Therefore, even when drivers seem to be able to recognize route differentials and transfer them into their prices, they seem to fail to maintain characteristics that should be crucial for their earning. These characteristics include longer travel times due to congestion and market conditions.

Perhaps one reason why drivers failed to change fares so drastically is because travel times do not change drastically. Drivers seem to recognize differences in the travel times observed in the second interval. At Interval 2, drivers requested higher fares for Route 2 but these fares are not large enough to keep their *REPM* approximately constant (chi-squared= 39.418 p=0.0001). *FCP* sensitivity to longer travel times is low then requested earnings will fall during congested intervals. More important, *REPM* seems fall dramatically from being on average 0.84 S./minute for Free Route and 0.83 S./minute for

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[42] If we introduce a fix cost of an initial trip of S./2, S./ 3 or S./4 this does not change the results. The Kruskal Wallis test still rejects the hypothesis that now the net *REPM* are equal (chi-square 18.282 p=0.0001)

Route 1 trips to being 0.57 S./minute for Route 2 trips. The approximately difference of 0.27 S./minute in income represents what we can considered unexpected congestion as the one observed in Interval 2 on the Route 2[43].

Figure 4 suggests that the Free Route trips in the morning are the ones for which *REPM* varies the least. Reviewing Figures 2, 3, and 4, we can deduce that the Free Route REPM remain more constant through the morning times. This occurs not because taxi-drivers change their fares enough, but mostly because they find ways to change their travel times less. The Free Route fares almost never change, and then Free Route *REPMs* do not change as much; drivers that are able to choose routes freely can avoid congestion, even when congestion is unexpected. Drivers react to congestion by detouring, not by forecasting. Free Route mean earnings-per-minute during the whole morning are S./ 0.82 ($0.31). Route-treatments 1 and 2 are different. In these cases, drivers have only one way to prevent their *REPM* from falling, pricing the trip correctly.

Figure 4 shows how drivers have a hard time from preventing their *REPM* from falling. *REPMs* are S./0.75 for Route 1, and S.0.70 for Route 2 for the entire morning. While a difference of .06 and .11 cents may not seem economically significant, miscalculating congestion across an entire day could prove considerable. The economic relevance of these differences appears evident when we analyze them according to the definition of congestion. Table 3.2 presents the summary statics of REPM for Congested and Non-Congested trips over both SD and DD classifications.

[43] To explore if customer price discrimination is robust in different market conditions, we then ran independent regressions of Model 3 for each Interval. By analyzing Table VI route treatment coefficients, we can observe the consistency with the pricing statistics described in Figure 1 and Figure 2. While Route 2 coefficients are statistically and economically significant for most of the intervals, Route 1 coefficients are only significant for intervals 2, 4 and 6.

	Statistical Definition		Declared Definition	
	No Congested	Congested	No Congested	Congested
REPM Mean	0.79	0.64	0.89	0.72
Std. Dev.	(0.23)	(0.18)	(0.24)	(0.20)
Min	0.33	0.14	0.43	0.14
Max	0.75	0.62	0.87	0.70
Observations	865	235	244	856

Table 3-2: *REPM* for Congested and No Congested Trips

Table 3.2 describes how drivers' earnings per minute change under different congestion conditions and classifications. A trip conducted under a congested interval-route means that, on average, the driver will earn at least S./0.16 less per minute. Additionally, given that the average trip duration for congested trips is longer than for non-congested trips, we can observe that driver earnings are approximately S./1.54 and S./1.61 lower per trip for each congested trip, depending if we evaluate under the DD or SD of congestion. The lower potential earnings due to congestion are approximately a quarter of the average observed fares of S./ 5.92.

3.6.1 Regression Analysis

The data analysis in the previous section compares fares between routes but always at the same intervals. Regression analysis allows for the comparison of all trips. First, I run ordinary least squares (OLS) regressions to estimate how fares relate to the independent variables representing experimental treatments, market and traffic conditions and customer characteristics, I compare the sign and significance of the OLS coefficients the intuitions provided by the theoretical framework and the empirical model and the non-parametric test results.

Second, I estimate two random effect regressions by feasible generalized least square (FGLS). In the first regression the same variables used in the OLS regression are included. In the second regression the congestion dummies are added as explanatory variables. The choice of a random effect to control for confederate influence on *FCP* model instead of a fixed effect model is based in two reasons. The first reason is that the main research interest is to address the effects of congestion into *FCP*[44]. More specifically effects of congestion on interested in the whole population average *FCP*, not specific fares that a customer could obtain specific subject. The experimental design controlled for a number of factors that might create correlation between the repressors and the error. Collaborators take taxis as soon as they can after a trip and protocol has been assigned to them. Additional control was introduced by the random allocation of treatments and the fact that negotiation was conducted following EP. While these controls reduce the probability that unobserved characteristics affecting *FCP* other collaborators non-recorded features such as beauty, ethnicity, and voice tone could be correlated with the *FCP*.   The assumptions need to fit the random effect model are

[44] A supermarket is closer to the location P. Several supermarket customers are taxi drivers, this knowledge might lead drivers to thing is easier to find a customer close to P. Although the competition might be greater at P .

supported by the data. Results of the Hausmann test fail to reject the null hypothesis that the differences in the coefficients between the fixed effect and random effect model are systemic (Chi2(14) =7.26, Prob>chi2 = 0.9243).

More important, previous results described that *FCP* displayed low sensitivity to different time intervals and traffic conditions. Although FCP does not vary, given changes on travel time earnings do change. Therefore to estimate the effects of congestion and its consequent longer travel times. *REPM* are also regressed as a function of the same fundamental characteristics that generate the *FCP*. In this way the effects of congestion on earnings are estimated while controlling for all the other potential characteristics affecting fares and travel times.

Dependent Variable *FCP*	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Experimental Variables					
FR	-0.213***	-0.187***	-0.210***	-0.210***	-0.204***
R2	0.301***	0.249***	0.280***	0.280***	0.257***
Finish point	-0.210***	-0.183***	-0.355**	-0.355**	-0.309**
Trip minutes		0.0409***	0.0346***	0.0346***	0.0239*
Taxi driver characteristics					
Drivers age		-0.00467**	-0.00489**	-0.00489**	-0.00487**
Experience		0.000574*	0.000585*	0.000585*	0.000612*
rent		0.219**	0.218**	0.218**	0.210**
own		-0.0505	-0.0662	-0.0662	-0.0654
working_hours		-0.00842	-0.00952	-0.00952	-0.00840
gas		-0.112	-0.0929	-0.0929	-0.0826
diesel		0.00434	0.0310	0.0310	0.0258
wagon		-0.136***	-0.142***	-0.142***	-0.144***
Bad_car		-0.150*	-0.138	-0.138	-0.136
New_car		-0.0166	-0.0319	-0.0319	-0.0353
Market Conditions					
# taxis at negotiation point			-0.0119	-0.0119	-0.0143
% taxis in traffic	-		0.316	0.316	0.153
Congestion Dummies					
DD dummy					0.134**
SD dummy					0.00748
Constant	6.008***	5.923***	6.103***	6.103***	6.132***
Observations	1,100	1,097	1,010	1,010	1,010
R-squared	0.076	0.109	0.122	0.1222	0.1269
Number of id customer	19	Min obs	8	Max	19

All regressions estimated with robust standard errors. *** p<0.01, **p<0.05,*p<0.1

Table 3-3 *FCP* Regression Models

Table 3.3 presents the results of estimation of five regressions. Model 1 regresses OLS fares as a function of the experimental treatment variables and travel times. Model 2 adds taxi and driver characteristics. Model 3 adds variables that represents proxies of the market conditions. Finally, Model 4 estimates the FGLS random effect model with all the same variables. Finally, Model 5 adds congestion dummies to Model 4.

Regression results displayed in Table 3.3 support the theoretical framework. The effects of treatments FR and R2 as difference to R1 are captured by the dummy variables FR and R2. The sign of the coefficients of these two dummy variables are consistent with the analysis conducted in the previous section. FR trips are on average shorter that R1 trips and requested fares for them are lower. The opposite is true for R2 trips. Both coefficients are significative for all the models. Additional experimental design variables are also significant for all the models. Finish point a dummy variable that captures the effects of finishing the trip at P is negative. These coefficient might captures that despite travel times and routes distance been similar for trips in both directions, driver's preference for finishing at a point where they believe is easier to find a customer[45]. Travel times are significative for all the models except for the last model in which dummy variables capturing congestion are introduced. The observed results of these coefficients provide support to both the theoretical framework and the experimental design, given that signs and significance of the coefficients are consistent with their implications.

[45] It is only necessary to assume that the umber of taxi drivers at least does not increase at the same rate that the number of customers.

Driver characteristics influence requested fares. Driver's characteristics such as age and experience are statistically significative at %5 and 10% significance levels respectively but they are not economically significant. Different from that, ownership type are of relevance both statistically and economically. There are three ways in which a taxi driver can make himself able to have vehicle to use as taxi. Taxi drivers can own his taxi (own) (71.79% of the sample). Additionally a taxi driver can rent a vehicle it for long periods such as a week or a month used as my baseline(12.92 % of the sample) .Finally, that taxi driver can rent a vehicle for a turn of 8-12 hours (15.29% of the sample). Different ownership types imply different financial cost and most importantly differences on the flexibility that drivers have to choose their labor supply. A turn ownership type requires that the driver has daily rental obligations besides its fuel costs. The dummy capturing this ownership status, *turn,* is significant at 5% and with an economic magnitude of the order of the experimental variables. Most of the taxi characteristics such as the type of fuel, diesel, gas or oil or taxi status are not significative. The only vehicle characteristic that is significative is if a taxi is a wagon instead of a sedan. *Wagon* coefficient is significant at 1% and negative. This coefficient can capture the fact that usually wagons, which compose 41.73 % of the sample, are older than sedan.

Market conditions are represented by two variables, # *taxis at negotiation point* and *% of taxis in traffic.* The first one, # *taxis at negotiation point,* has a non-significant coefficient. The second variable representing perception of market conditions, *% of taxis on traffic,* has a significant and negative coefficient. These results support the implications of the theoretical framework, namely, that more competitive environments should observe lower *FCP*. In an informal survey, drivers recognized that they could more easily identify the number of taxis by the traffic that the demand at each time. Then when they observe large numbers of taxis in traffic, they perceive the market as more competitive. This decreases their *FCP.*

Model 5 introduces the Congestion dummy variables, to observe if drivers *FCP* under congested interval-routes are different from under the non-congested ones. This model reveals that only perceived congestion (DD_dummy) is positive and significant 5% level. Congestion dummy capturing larger than average travel times, SD dummy is not significant. These findings suggest two things: first, drivers only increase fares the congestion that they perceive. Second, congestion of perception is not only related to travel times. The conjunction of these two effects has implications for driver's earning. Congested trips turn to be longer and less profitable than non-congested. Table I3.4 regress *REPM* instead of *FCP* to have a better understanding of the effects of congestion on driver's earnings.

Dependent variable REPM	(1)	(2)	(3)	(4)	(5)
Experimental Variables					
FR	0.0581***	0.0594***	0.0577***	0.0600***	0.0377**
R2	0.0608***	-0.0594***	-0.0632***	-0.0636***	-0.00410
Finish point	0.0402***	0.0397***	0.122***	0.123***	0.0662*
Drivers, taxi characteristics					
Driver age		-0.00173***	-0.00190***	0.00181***	0.00172***
Experience		0.000310***	0.000312***	0.000285**	0.000265**
rent		0.0716***	0.0690***	0.0513**	0.0681***
own		0.00817	0.00443	-0.00294	-0.000296
working_hours		-0.0105***	-0.00833**	-0.00938**	-0.00931**
gas		0.0371	0.0352	0.0354	0.0166
diesel		-0.0156	-0.0145	-0.00880	-0.00790
wagon		-0.0209	-0.0160	-0.00953	-0.0104
Bad_car		-0.0389	-0.0374	-0.0332	-0.0342
New_car		-0.0213	-0.0234	-0.0154	-0.0157
Market Conditions					
# taxis at negotiation point			-0.0148***	-0.0153***	-0.0120**
% taxis in traffic			-0.297***	-0.299***	-0.122
Congestion Dummies					
DD dummy					-0.105***
SD dummy					-0.0797***
Constant	0.739***	0.809***	0.866***	0.861***	0.913***
Observations	1,100	1,097	1,010	1,010	1,010
R-squared	0.054	0.089	0.107	0.1055	0.1811
Number of id_customer	19	Min obs	8	Max	19

All regressions estimated with robust standard errors. *** p<0.01, **p<0.05,*p<0.1

Table 3.4 *REPM* Regressions

Table 3.4 present*s* three results. First, as expected*,* most of the variables significant for *FCP* also affect *REPM*. This is a natural result given that *REPM* is just a ratio of fares over travel times. Furthermore, *FCP* changes to different route-treatments show two important characteristics that were implied by the theoretical model. The first characteristic of relevance is that routes' *REPM* vary much less than routes *FCPs.* Hypothesis I implied that for each interval *REPMs* should be similar for all the routes. The route treatment coefficients in Table 3.5 highlight that although that coefficients are consistent with Hypothesis I. Although R2 is significant at 1% for models 1-4 leading us to believe that the fact that earnings for R2 are lower, even when R2's *FCP* are larger is generated by idiosyncratic route's effect. Model 5 shows that when congestion dummies are added then R2 coefficient is non significant anymore, meaning that there are no idiosyncratic differences between R1 trips and R2 trips. A different effect is observed concerning FR trips, Table 3.4 confirmed the observation that FCP for Fr was lower than those requested for R1. Table V, FR coefficients highlight than even when requesting lower fares, the fact that average travel times for FR trips are lowers have a significant implication on driver's earnings. *FR* coefficient is positive and significant even when we controlled for all the other covariates.

Second, driver's characteristic*s* matter for earnings. Table V displays the fact that all driver characteristics influencing *FCP*, also have an effect on earnings. Coefficients for driver's age experience and the ownership types, turn and own, are significant again significant as on the FCPS regressions but now they are significant at a higher level on the *REPM's* regressions*.* Along with these variables, working hour's coefficient is significant and negative. Therefore driver's characteristics affect *FCP* requested by drivers and changes on the *FCP* have effects have on earnings.

Finally, both congestion dummy coefficients are now significant and negative. These coefficients are significant at 1% level. Furthermore the magnitude of the effects of the congestion dummies on the *REPM* are larger than the effects of all the other significant variables. Therefore, when taxi drivers conduct congested trips, the presence of congestion diminish their *REPM* 2-3 times orders of magnitudes of what they could gain for being free to choose their routes *(FR)*. The results of the regression analysis are consistent with our non-parametric analysis at the end of the previous section[46]. Although, This support the intuition that the approximately lower S./1.20-1.50 earning per congested trip mean approximately 25% of the average fare during the morning (S./5.92). Given the frequency of congested trips that drivers need to conduct every day, it is relevant that they find ways to prevent their earnings from decreasing at during congested periods. The decrease on earnings per trip is S./1.5 for trips perceived as congested and S./1.7 for those whose travel times are statistically longer. These decreases in earnings are considerably more than increases in *FCPs*, observed average changes S./0.28 and S./0.33 respectively.

[46] The decrease on *REPMs* due to congestion S./ 0.18 are close to the S./0.14 and S./0.17 differences displayed on table II.

3.7 Discussion

Congestion is an externality that increases commuters' travel times and affects the income of those who drive for a living, taxi drivers. This research found that taxi drivers in Lima Peru's unregulated taxi system did not transfer the full cost of congestion to their fares during peak traffic hours. On average, taxi drivers increased fares for congested periods, but not enough to prevent earnings from decreasing. This is especially true when they are asked to take congested routes and not allowed to make their own routing decision.

Failure to increase *FCP* (first called price) enough to maintain earnings could be attributed to two factors, namely market conditions and congestion perception failure, or a combination of both. Market conditions and perceptions affect the fares drivers request. When drivers believe that customers have additional bargaining power in congested market conditions, they avoid increasing *FCP* that maintain income rate and thus decrease the chances of being rejected. Similarly, when drivers do not request significantly higher *FCP* for longer routes under market conditions similar to those found between 7:31 am and 8:00 am, then they fail to perceive idiosyncratic changes in congestion on certain routes. The interaction of changing market conditions and congestion perceptions decreases earnings over congested periods.

*FCP*s do not fully transferring congestion cost does not imply that agreed fares don't transfer different travel times. If this is the case, my finding emerged as a result of a negotiation habits and the experimental design. To test whether this is the case, the data set has also observations in which negotiated fare is collected. This data set from a second experimental task in the second week is not analyzed. The analysis of these trips and rejections in left for future research. Analyzing the negotiated fares data will allow us to observe how congestion costs are transferred to fares, when the latter are negotiated. If changes in the actual earning per minutes *AEPM* taxi drivers bargained for differ from the changes in requested earnings per minute *REPM* analyzed in this paper, taxi drivers may be much more successful at transferring congestion costs and maintaining earnings during congestion periods. Moreover, policy implications would change accordingly.

Failure to transfer full congestion costs to fares and perception errors have interesting implications. First, if taxi drivers as traffic experts fail to properly perceive travel times, then less experienced drivers might be more prone to this mistake and consequently to bad routing decisions. As a result, congestion due to misrouting will increase. Second, relying on individual incentives to choose optimal routes, such as income maximization for taxi drivers, might not be enough to decrease congestion because it does not resolve the perception problem. Taxi traffic in Lima, therefore, illustrates a situation described by Akerlof and Yellen (1985) in which small deviations from rationality has small effects on individual welfare but can have large effects on the aggregated outcome of an economic system. As individual net gains of improving travel times are small, individuals lack the incentives to improve perceptions and start adjusting departure and routing decisions.

Failure to perceive market conditions and their effects on bargaining strategies constitute important revelations about the empirical world that theoretical models need to incorporate and measure[47]. The fact that taxi drivers might fail to perceive market conditions as much as they fail to estimate longer travel times due to congestion is a call for new research on bargain in markets with changing market conditions such as taxi market, baby-sitting, and internet retail. There is currently no research that explains how perception of changing market conditions might affect price discovery and formation in markets where sellers and buyers search for each other sequentially and are bargaining over goods and services[48].

Designing policies that change and improve commuter-departing times, transportation modes and routing decisions must therefore focus on ways of correcting commonly identified perceptions errors. Metered taxi systems may resolve taxi perception errors and decrease congestion levels. Meters insure taxi drivers against congestion expectation failures and increase customer incentives to commute at non-congested periods. However, meters also decrease incentives to route optimally and create a moral hazard problem in which more informed taxi driver choose longer higher fare routes during periods at which the taxi market is non-competitive[49]. Meters can therefore also lead to more congestion. Given the ambiguous effects of metering on

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[47] Theoretical research such as RS always assume hat the number of players on the market is static and know. Lauerman et al. 2012 model a market with search and bargaining that the number of sellers and buyers might change over different periods but players always have the correct expectation of the numbers of sellers and buyers.

[48] In this research, informal surveys revealed that drivers perceive rush hour as a highly competitive market. Drivers might fail to perceive that peak hour demand increases higher than the supply of taxis, making peak hour a less competitive market. There are no empirical studies regarding how drivers perceive the competitiveness level of the markets at peak hour. The econometric analysis reveals that drivers might perceive the increasing number of taxis as a sign of a more competitive market. Therefore their perception of market conditions might prevent taxi drivers from increasing fares to compensate for the higher cost of longer and slower trips.

[49] Under a metered system, greek taxi drivers have shown to choose non-optimal routes when the customer seemed to a be a tourist Balafoutas et al. 2011

routing decisions and congestion, policies focusing on providing information drivers can use to update perceptions seem to be a more straightforward alternative. Information systems, using GPS data and smart phone applications, for instance, can tap into taxi driver knowledge of congestion to provide information for private drivers regarding real time optimal detours.

Taxi fares systems and fares potentially could affect commuting decisions. With exception of Arnott's plea to subsidized taxi fares in order to decrease private driving, little research has been done regarding how taxi fares can affect traffic decisions. This research shows that in addition to Arnott (1996) insights for regulated taxi systems, taxi fares and taxi routing information also can be used as tools in an unregulated taxi market. Taxi fares could be used to modify commuter's decisions, while taxi driver's routing decisions could inform private drivers about Additional research is needed to understand the interaction between fare systems and welfare.

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Appendix A

Material Supporting Chapter 1

A.1. MEG

Instructions: Second Task

Experiment and Experimental Rounds

There are **12** participants in today's experiment. Each of you will face the same decision problem. That problem entails a decision about whether or not to enter a market in which you can sell a commodity. If you choose not to participate, you will forgo money that you could earn by entering the market and selling the commodity. If you choose to enter the market, you can sell the product but you cannot know how much you can earn because the price of the commodity will be determined after you choose to participate. In this exercise all of you face the same cost function.

This decision problem will be repeated for several rounds. In each round you will be prompted by the computer to enter your choice about entering the market. The round will not proceed to the next round until each participant has entered his/her choice.

On your desk you should have a pen and several record sheets. Please now select the sheets marked with the header TASK 2.

Here you can see the information that will be displayed on the monitor in each round.

Figure A-1: Screen Shot of First Options

As you can see, in each round you have to choose between the **two possible options:**

(2) Enter

(3) Stay out

To make a decision, **CLICK** the button for the option you have selected with your mouse. After this, click the **OK** bottom in the lower right side of the screen.

The payoff from your choice is calculated as followed:

Choice: Stay Out, **Payoff** = **17**

Choice: Enter - Payoff=15+2*{Market Capacity-# of entrants} - your cost for entering – entry fee

The market revenues for choosing to enter are described by

Market revenues **MR= 2*{Market Capacity-# of entrants}**

As you can see these revenues can be

- **MR=0 if Market Capacity=# of entrants**
- **MR>0 if Market Capacity># of entrants**
- **MR<0 if Market Capacity <# of entrants**

Market profits=Market Capacity-- your cost for entering – entry fee

Therefore if you decide to enter the market the profits that you obtain from entering depends on everyone's decisions as well as on your possible entry costs and market's entry fee.

Market Capacity (MK)	4		Entry	Fee		0						
Number of Participants Entering	1	2	3	4	5	6	7	8	9	10	11	12
Payoff for Entering	21	19	17	15	13	11	9	7	5	3	1	-1

This Box provides estimation on how much you can earn depending on how many people in the experiment make the same decision as you.

Table A-1: Earnings Estimation

After *all of you* have entered your decision a new screen will be displayed with the results of the last round. This screen will display the following information:

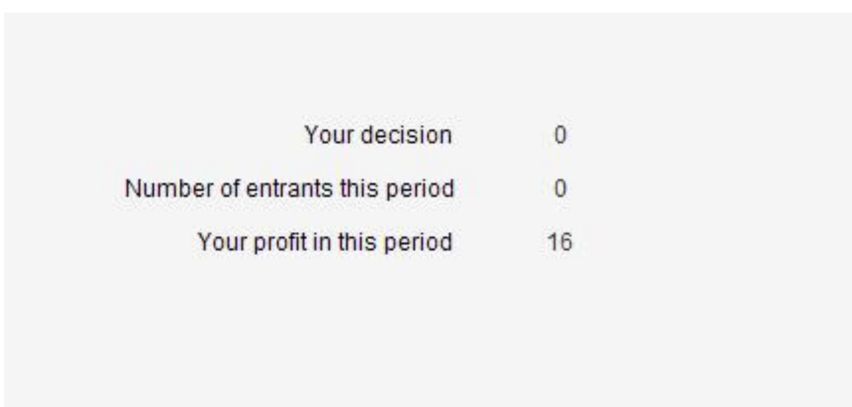


Figure A-2: Screen Shot B

You should record the information that is displayed in the sheets that you have in your desk. After recording the information you should click the CONTINUE button located in the lower right side of the screen. The record sheets to be filled will look as followed:

Market Capacity (MK)	4		Entry	Fee		0						
Number of Participants Entering	1	2	3	4	5	6	7	8	9	10	11	12
Payoff for Entering	21	19	17	15	13	11	9	7	5	3	1	-1

Table A-2: Task 2 Record Sheet

Decision

Task length

This task consists of several **JUST of 2 MARKETS. (1 round each)**

Total Task 2 Payoff

Your payoff after these 2 Markets will be the addition of what you have earned in each round. Your payoff will be translated to U$s Dollars at an Exchange rate of U$S 0.5 for each experimental dollar.

PLEASE MAINTAIN QUIET AND RAISE YOUR HAND IF YOU HAVE ANY QUESTIONS. WE WILL PROVIDE YOU A SHORT QUIZ TO CHECK YOUR KNOWLEDGE OF THE TASK. THANKS

A.2. Example Record Sheet

ID

Date , 2010

Task 1 Sheet 1

Market Capacity (MK)	**4**		**Entry**	**Fee**		0						
Number of Participants Entering	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Payoff for Entering	**21**	**19**	**17**	**15**	**13**	**11**	**9**	**7**	**5**	**3**	**1**	**-1**
Round	**MK**	**Fee**	**Enter**	**Payoff**								
1	4	0										
2	4	0										
3	4	0										
4	4	0										
5	4	0										
6	4	0										
7	4	0										
8	4	0										
9	4	0										
10	4	0										
11	4	0										
12	4	0										
13	4	0										
14	4	0										
15	4	0										
16	4	0										
17	4	0										
18	4	0										
19	4	0										
20	4	0										
21	4	0										
22	4	0										
23	4	0										
24	4	0										
25	4	0										

Table A-3: Task 1 Sheet 1 Example

A.3 EMEG

Instructions

You are about to participate in an experiment on decision-making. You will be paid \$5.00 for participating in the experiment to completion, plus an additional amount of money based on your performance in the decision making task. Your performance will depend in part on your understanding of the tasks, so please read the instructions carefully. If you have any questions at any time you are free to raise your hand and ask the lab supervisor. It is essential that you refrain from talking to other participants during the session.

You will be assigned with other participants to a work station where you will perform your tasks. Please stay at your station until the end of the experiment.

At the end of each task you will receive a payoff based on your performance in the task in *experimental dollar*s. Your performance in one task will not affect your payoff in the other. You are responsible for keeping *track* of your performance in *each* task using the record sheet that is provided at your workstation.

At the end of the experiment you will present your worksheet to the lab supervisor. The supervisor will pay your participation award plus the additional amount you have earned through your performance. The performance reward will not be equivalent to, but will be based on the experimental dollar payoffs.

Experiment and Experimental Rounds

There are **12** participants in today's experiment. Each of you will face the same decision problem. That problem entails a decision about whether or not to enter a market in which you can sell a commodity. If you choose not to participate, you will forgo money that you could earn by entering the market and selling the commodity. If you choose to enter the market, you can sell the product but you cannot know how much you can earn because the price of the commodity will be determined after you choose to participate. In this exercise all of you face the same cost function.

This decision problem will be repeated for several rounds. In each round you will be prompted by the computer to enter your choice about entering the market. The round will not proceed to the next round until each participant has entered his/her choice.

On your desk you should have a pen and several record sheets. Please now select the sheets marked with the header TASK 1.

Here you can see the information that will be displayed on the monitor in each round.

Figure A-2: Screen Shot of Task 1

As you can see, in each round you have to choose between the **two possible options:**

(4) Enter

(5) Stay out

To make a decision, **CLICK** the button for the option you have selected with your mouse. After this, click the **OK** bottom in the lower right side of the screen.

The payoff from your choice is calculated as followed:

Choice: Stay Out, **Payoff** = **17**

Choice: Enter - Payoff=15+2*{Market Capacity-# of entrants} - your cost for entering – entry fee

The market revenues for choosing to enter are described by

Market revenues **MR= 2*{Market Capacity-# of entrants}**

As you can see these revenues can be

- **MR=0 if Market Capacity=# of entrants**
- **MR>0 if Market Capacity># of entrants**
- **MR<0 if Market Capacity <# of entrants**

Market profits=Market Capacity-- your cost for entering – entry fee

The **Expected Market Capacity (EMK)** that you see in the Screen **is not going to be the Market Capacity.**

YOU WILL BE PAID (after choosing the round) for the results regarding the ACTUAL MARKET CAPACITY, as we explained before, that will be just one of the possible values of that the Market capacity can take.

Example

Expected Market Capacity 8

Values	Probability	Value*Probability
6	1/3	6/3
8	1/3	8/3
10	1/3	10/3
	Expected Value	24/3

Table A-4: Example

Therefore if you decide to enter the market the profits that you obtain from entering depends on:

- Everyone's decisions
- Your possible entry costs and market's entry fee
- Actual Market Capacity

This Box provides estimation on how much **you might expect to earn depending** on how many people in the experiment make the same decision as you.

Expected Market Capacity (MK)	4		Entry	Fee		0	Possible MK Values (Chance)		6 (1/3)	8 (1/3)	10 (1/3)	
Number of Participants Entering	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
Payoff for Entering	**21**	**19**	**17**	**15**	**13**	**11**	**9**	**7**	**5**	**3**	**1**	**-1**

Table A-5: Screen Box B

Remember: How much you earn depend on THE ACTUAL MK. Then for the same decisions what you might earn can also be, then you should consider the following values

Expected Market Capacity (MK)	4		Entry	Fee		0		AMK	2	4	6	
Number of Participants Entering	1	2	3	4	5	6	7	8	9	10	11	12
Payoff for Entering AMK=EMK=8	21	19	17	15	13	11	9	7	5	3	1	-1
Payoff for Entering AMK=4	17	15	13	11	9	7	5	3	1	-1	-3	-5
Payoff for Entering AMK=10	25	23	21	19	17	15	13	11	9	7	5	3

Table A-6: Screen Box C

After *all of you* have entered your decision a new screen will be displayed with the results of the last round. This screen will display the following information:

You should record the information that is displayed in the sheets that you have in your desk. After recording the information you should click the CONTINUE button located in the lower right side of the screen. The record sheets to be filled will look as followed:

Actual Market Capacity Last Period	4
Your decision	1
Number of entrants this period	1
Your profit in this period	22

Figure A-3: Screen Shot of Completed Record Sheet (example)

Expected Market Capacity (MK)	4		Entry	Fee		0		AMK	2	4	6
Number of Participants Entering	1	2	3	4	5	6	7	8	9	10	11	12
Payoff for Entering	21	19	17	15	13	11	9	7	5	3	1	-1

Round	EMK	Fee	AMK	Enter	Payoff
1	4	0			
2	4	0			
3	4	0			
4	4	0			
5	4	0			
6	4	0			
7	4	0			
8	4	0			
9	4	0			
10	4	0			
11	4	0			
12	4	0			
13	4	0			
14	4	0			
15	4	0			
16	4	0			
17	4	0			
18	4	0			
19	4	0			
20	4	0			
21	4	0			

Table A-7: Task 1 Record 1

Task length

This task consists of several *"Group of rounds."* For each group the values of **market, cost, and entry fees** are kept **constant**. After a group is completed, a new group will commence with new values of these variables. This change will be obvious to you because of the change in the numbers on the screen and also because you will have a different sheet

Total Task 1 Payoff

Your payoff after the completion of the task will be determined from your performance in one of the rounds. The round will be selected by chance. On the completion of the task, a random number between 1 and 150 will select the **number of the period** that will be used to determine payoffs. This round and this round ONLY will be YOUR PAYOFF for the TASK. Once the round is announced, review your record sheets and circle the payoff on that round. This sheet will be presented at the end of the experiment in order to get your payment.

PLEASE MAINTAIN QUIET AND RAISE YOUR HAND IF YOU HAVE ANY QUESTIONS. WE WILL PROVIDE YOU A SHORT QUIZ TO CHECK YOUR KNOWLEDGE OF THE TASK. THANKS

A.4. Additional Individual Entry Profiles Statistics

Subtreatment	Treatment	MEG	EMEG
1. Capacity =4 Entry fee= -1	Mean	33.35%	37.08%
	sd	26.71%	24.66%
	Maximum	96.00%	92.00%
	Median	32.00%	36.00%
	Minimum	0.00%	0.00%
2. Capacity =4 Entry fee=0	Mean	32.16%	33.92%
	sd	26.11%	24.64%
	Maximum	92.00%	84.00%
	Median	26.00%	28.00%
	Minimum	0.00%	0.00%
3. Capacity =4 Entry fee=2	Mean	18.41%	26.16%
	sd	23.41%	24.31%
	Maximum	92.00%	100.00%
	Median	8.00%	18.00%
	Minimum	0.00%	0.00%
4. Capacity =8 Entry fee=0	Mean	61.34%	56.96%
	sd	30.90%	29.93%
	Maximum	100.00%	100.00%
	Median	72.00%	60.00%
	Minimum	4.00%	0.00%
5. Capacity =8 Entry fee=2	Mean	50.68%	50.47%
	sd	33.90%	28.54%
	Maximum	100.00%	100.00%
	Median	52.00%	56.00%
	Minimum	0.00%	0.00%
6. Capacity =8 Entry fee=4	Mean	44.50%	43.24%
	sd	31.06%	23.73%
	Maximum	100.00%	84.00%
	Median	41.33%	47.00%
	Minimum	0.00%	0.00%

Table A-1.1. Entry Profiles Statistics

Appendix B

Material Supporting Chapter 2

B.1 Threshold Estimation

Solutions to global games rely on players playing and having coherent belief regarding other player playing threshold strategies. Given a cumulative probability function of the private signals F(t*) the policy parameters ***g, f*** the calculus of a Symmetric Threshold Equilibria Value **STEV** ***t**** follows the procedure described by Morris and Shin (2002). The calculus procedure includes several steps. First, the expected gains of playing *P* instead of *NP* for a player with a private value of *x* are estimated. The function ***U(x)=E(P|X=x)-f***, where ***E(P |X=x)*** is the expected payoff of playing *P*,.***E(P|X=x)*** is increasing in *x* therefore ***U(x)*** is also increasing. Second, ***t**** is defined as the value that makes the subjects indifferent between the two possible actions, satisfying the condition ***U(t*)=0.***[50] Following this procedure we can describe the ,STEP expression for 2 x 2 PVPG as:

$$t^*_{SS} = \frac{f}{1+g} \tag{2}$$

Table II describe how the experimental design by choosing different f***, g*** and ***p*** parameters values obtain different threshold values. These threshold values are related to group participation levels by *1-F(t*)*. The designed treatments expect to observe participation levels different from full participation and zero participation[51]

[50] It is straightforward to note that, if ***U(t*)=0*** and everyone is playing threshold strategies, then it is clear that **U(x| x< *t**)<0** and **U(x| x >*t**) >0,** making the threshold strategy best response to threshold strategies and, hence. Bayes Nash equilibrium of the game. Additionally, to satisfy uniqueness conditions of symmetric threshold equilibrium, I must have that *U'(x) >0* for all x and that $U(\underline{x}) < 0$ and *U(x) >0* where ($\underline{x}$,x) are the limits of the support of *x.* I satisfy all of these conditions in my experimental design.

[51] This is achieved because ***t**** belongs to the interior of the support of the distribution of private values

B.2 Experimental sections script

I. Introduction Greeting/Welcome/Thank-you

- Research Project/Goal
- Results confidential/ID # = identity/ name does not go on any form
- **QUESTIONS?**
- → **[Hand out: folders.]** ← (#2)
- **Highlight folders/Task** record sheets/MATCHING ID #s
  Session Overview: ("A brief overview of what today's entails.")

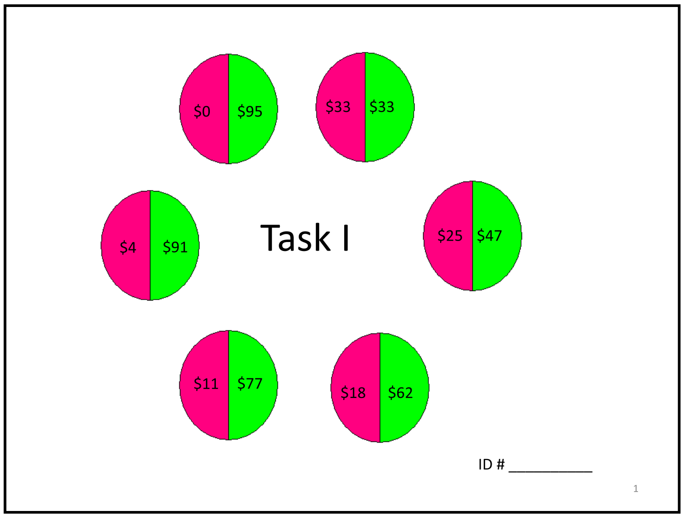
- 2-2.5 hours/3 tasks/decision making
- No right/wrong decisions
- Make choice best for you
- Payment is related to your choices , please take it serious- sake of the research.

- Reminder all info is confidential.
- **QUESTIONS?**

II. Task 1

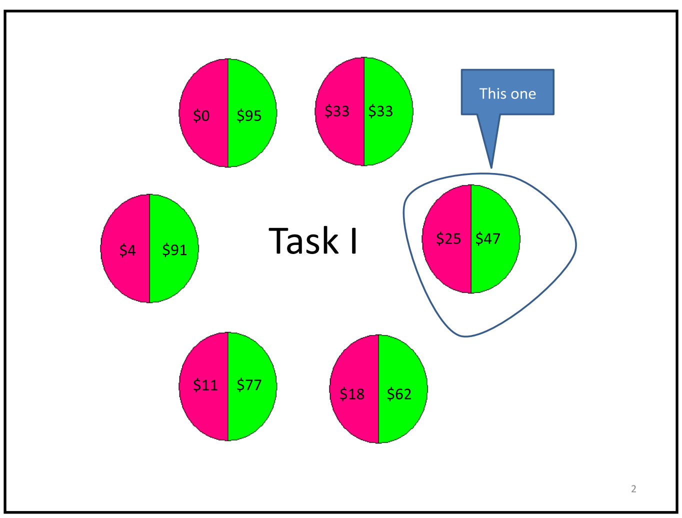
Easiest task

- Pick which option you favor above the rest. There are no good or bad options
- Intro: Slide 1- this is what task sheet will look like/
  [put up slide 1]

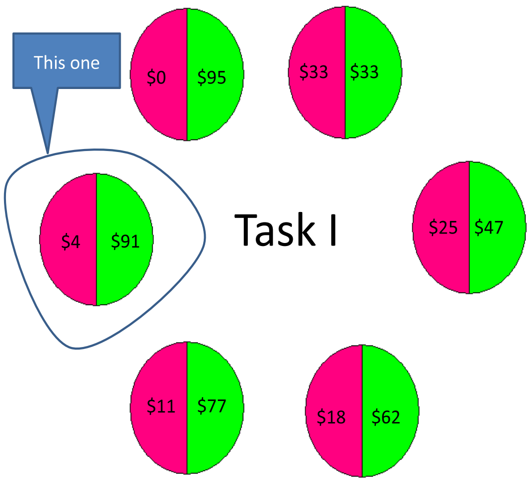


SLIDE 1

- [put up slide 2&3]



SLIDE 2



3

SLIDE 3

- Each option has 2 outcomes
- A high and a low payoff
- Each payoff is equally likely.

*** **<u>Discussion about Task 1 determining cash Prize</u>.*****

- Your choice in task 1 may determine your cash prize at the end
- After all 3 tasks are finished we will randomly select which task will determine your cash prize
- Each task will be equally likely
- 1 in 3 chance task 1 will be chosen.

- If task 1 is chosen this is how your prize will be selected
- (Reference to slide 3)
- Chose circle with 4 & 91- we will flip a coin and heads will be green- 91$ tails will be red- prize will be 4$
- ***QUESTIONS?***

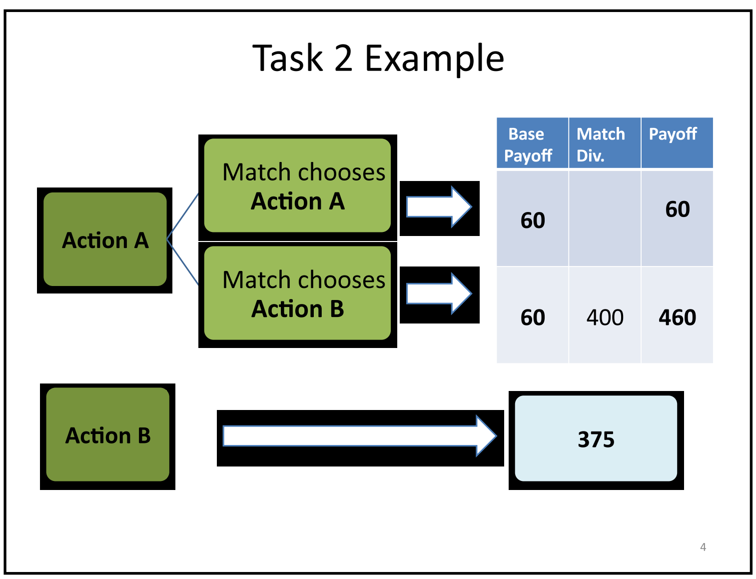
→[Hand out Task 1 Sheet]←

- **Write ID #** on sheet
- Finished: place completed task 1 sheet in **LEFT** hand pocket of folder.

III. Introduction to Tasks 2 and 3 ("We will go over a brief over view of tasks 2&3")

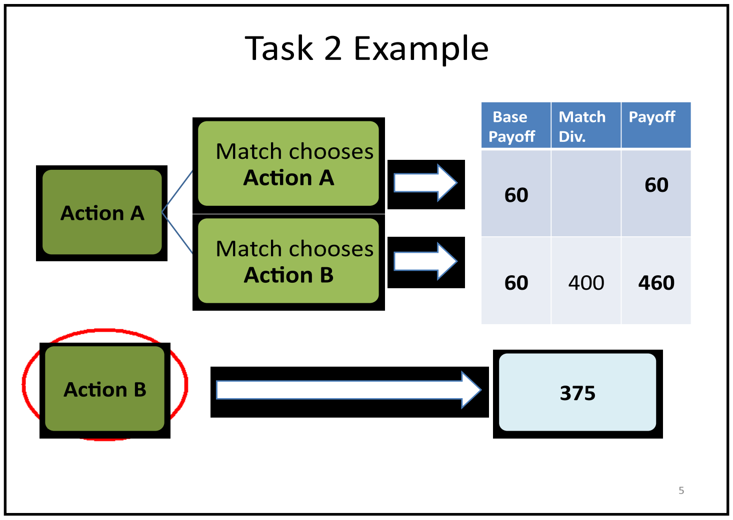
- Task 2 & 3 involve decision making in situation where your outcome depends on the decisions of others.
-

[Show Powerpoint Slide 4]



SLIDE 4

- Sheets from Tasks 2&3 will look like this
- Chose Action A or Action B

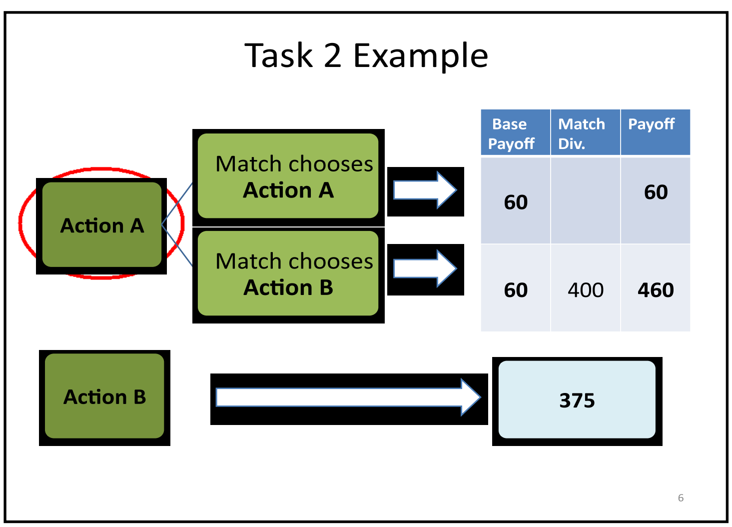


SLIDE 5

[Show slide 5]

- Pick Action B → certain payoff- $375
- Payoff does not depend on others decisions.

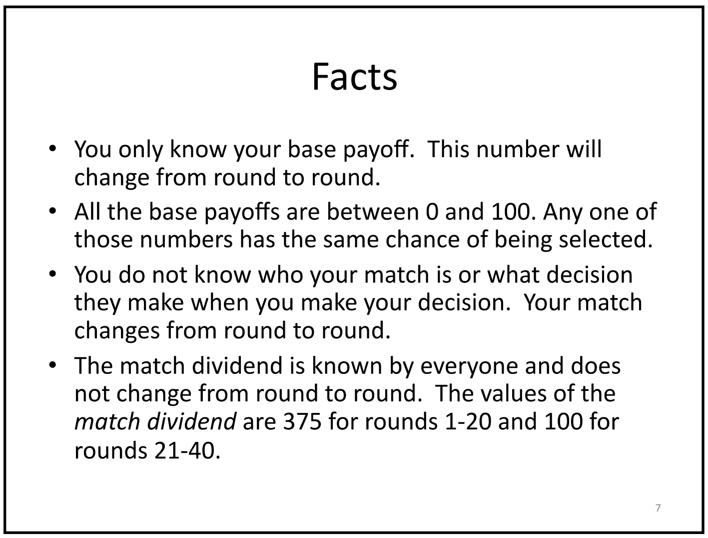
[Show SLIDE 6]



SLIDE 6

- Action A, payoff depends on matche's (sometimes partner) decision.
- Action A, match chose Action A, receive base payoff = $60
- Action A, match chose B, receive base + match dividend (400) total- 460
- When choosing action A, your payoff is always unknown, depends on match.

[Show SLIDE 7]

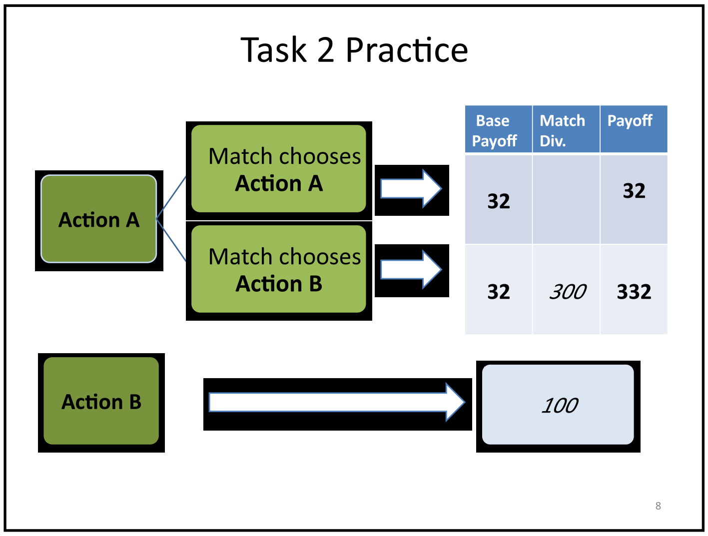


SLIDE 7

When completing tasks 2 & 3 here are a few facts to consider

- ***QUESTIONS?***
- ***→[Hand out practice sheets]←***
- Conduct a practice round using profector.
- Look over it for a few mins, then I will go over questions

[Show SLIDE 8]



SLIDE 8

[Go over practice round, ask for participation, use pointer.]

- **If you choose Action A and your partner choose A.**

1. **How much is your payoff for that round? (32)**
2. **How much is your base payoff? (32)**
3. **How much is your match's or partner's base payoff for that round? (Any value between 0 and 100 with same chance)**
4. **How much is his payoff? (I don't know, any value between 0 and 100 has the same chance)**

- **If you choose Action A and your partner choose B.**

1. **How much is your payoff for that round? (32)**
2. **How much is your partner's payoff for that round? (100, the payoffs for Action B are common and known for 15 rounds)**
3. **How much is your payoff if you choose B? (100, the payoffs for Action B are common and known for 15 rounds)**
4. **How much is your partner's payoff if you choose B? (It depends on if he has chosen Action A or Action B)**

Questions?

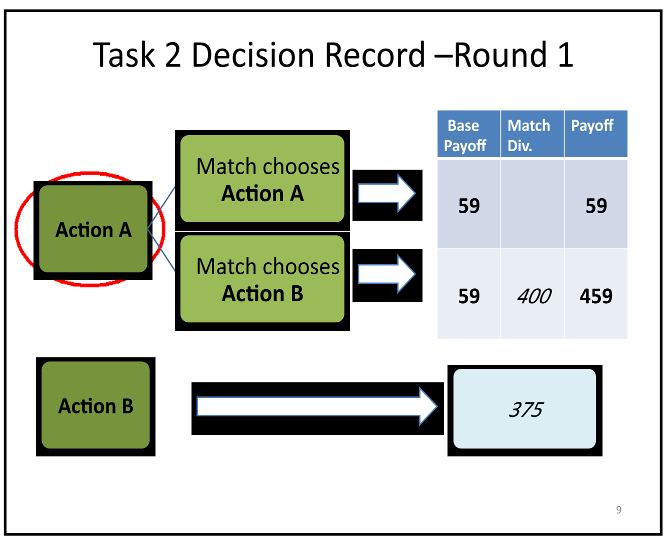
- Place practice round sheet in left pocket of folder
- **We'll start task 2**

IV. Task 2

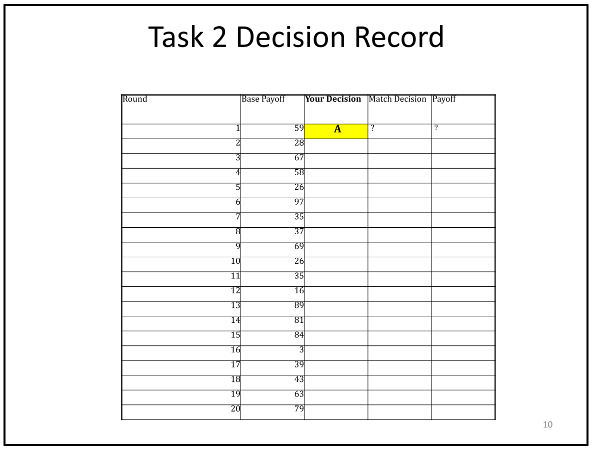
→[Hand out the <u>Task 2: Booklet 1</u> - Make sure booklet IDs match the participants]←

- 2 series of 20 rounds of decision making
- Chosing between Action A or B (SHOW ON BOOKLET IN HAND)
- Make sure your ID matched the ID on the booklet infront of you.
- Go through the booklet and make your decision for each round.

- To record your decision you will circle your action in the booklet & also write in on your task 2 record sheet.
- **[Show SLIDES 9, 10]**



SLIDE 9



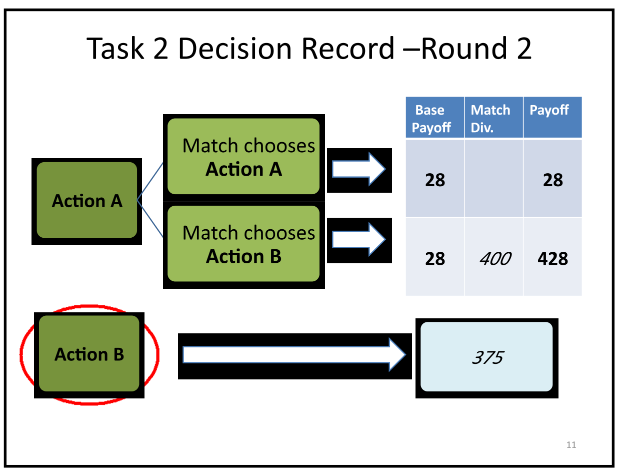
Task 2 Decision Record

Round	Base Payoff	**Your Decision**	Match Decision	Payoff
1	59	**A**	?	?
2	28			
3	67			
4	58			
5	26			
6	97			
7	35			
8	37			
9	69			
10	26			
11	35			
12	16			
13	89			
14	81			
15	84			
16	3			
17	39			
18	43			
19	63			
20	79			

10

SLIDE 10

- ACTION A- circle A, record A in your decision column
- Notice the ? in the match decisions column and payoff column. These are uncertain.
- **[Show SLIDES 11, 12]**



SLIDE 11

Task 2 Decision Record

Round	Base Payoff	**Your Decision**	Match Decision	Payoff
1	59	**A**		
2	28	**B**	**?**	**375**
3	67			
4	58			
5	26			
6	97			
7	35			
8	37			
9	69			
10	26			
11	35			
12	16			
13	89			
14	81			
15	84			
16	3			
17	39			
18	43			
19	63			
20	79			

12

SLIDE 12

- ACTION B- circle B, record B in decision column
- Record known payoff in payoff column.

- Before we begin- explanation if task 2 is selected a for the cash prize at end
- Reminder each task has an equally likely chance of being selected- 1/3.
- The task will be selected after all tasks are complete.
-
- If task 2 is selected- well select a round 1-40 at random.
- If decision is A, your payoff depends on your match.
- We will tell you which ID your match was at that point.
- In task 2 & 3 your cash prize will be 1/10 of your payoff.
- EX- Action B- payoff 375, your prize $37.5
- ***Questions?***

  - **W**ith your record sheet and booklet in front of you, start.
  - Complete this booklet, raise hand, we'll bring you next set of rounds.
  - You MAY talk, NO talking about your decision making or strategies.

- Done- place record sheet in left pocket.

  → [Collect bookelts]←

V. Determine the Cash Prizes ("we will now determine your cash prize")

→ [Select task by picking a pin-pong ball from a basket with A, B, C balls] ←

If TASK 1 is selected:

- **Pull out sheet for Task 1.**
  → [Flip coin. Heads = green; Tales = red] ←

If TASK 2 or TASK 3 are selected:

- **Pull out decision sheet for Task ____.**

  → [Select round using roller cage] ←

  → [Collect Folders]

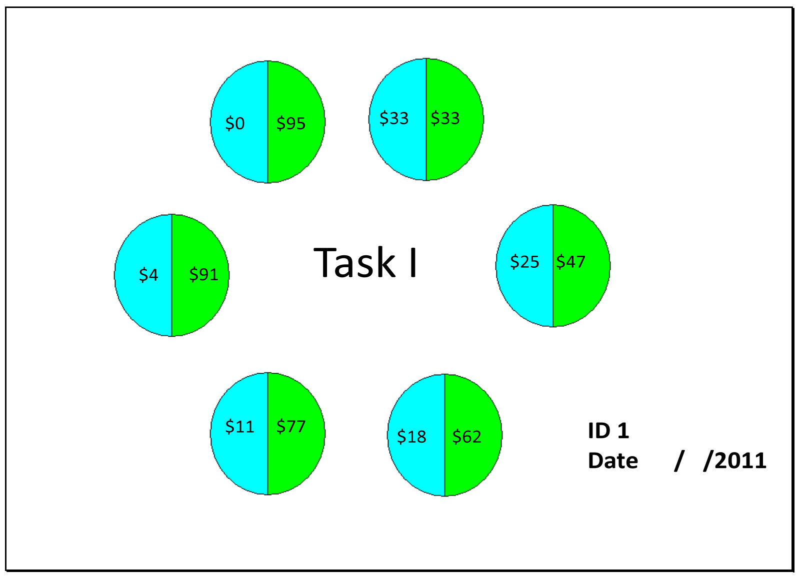
  → [Pass out survey]

  → [Distribute prize]

- **Conclusion/Thank you**

Appendix B3. Task 1 Slide Record Sheet

The record sheet for Task 1 is exactly the same that the Slide 1 of the script. Subjects just circle they preferred lottery



Appendix C

Material Supporting Chapter 3

C.1.1 Observations and Weather

Date	Day	FR	R1	R2	Avg. C°	Rain
6/21/10	1	36	35	34	16.48	No
6/22/10	2	30	26	33	16.05	No
6/23/10	3	37	32	34	17.13	No
6/24/10	4	35	33	33	15.93	No
6/25/10	5	33	25	36	15.76	No
6/28/10	6	54	46	45	15.90	No
6/30/10	7	44	42	38	15.55	No
7/1/10	8	40	38	52	15.08	No
7/2/10	9	34	35	43	15.00	No
7/5/10	10	31	34	32	15.28	No
Total	1100	374	346	380	Average:	No

Table C-I. Observations per day and treatment, weather

C.1.2 Taxi driver characteristics

	Week 1	Week 2	Wilcoxon Rank sum Ho: x(week 0) = x(week 1)
Working hours	2.65	2.53	z = 0.726 Prob > |z| = 0.4679
Fuel	3.40	3.48	z=-1.395 Prob > |z| = 0.1631
Ownership	2.58	2.56	z = 0.396 Prob > |z| = 0.6920
Route preferences	2.50	2.49	z = 0.055 Prob > |z| = 0.9560
Driver's age	40.60	41.12	z = -0.677 Prob > |z| = 0.4986
Experience (months)	88.32	89.49	z = -0.049 Prob > |z| = 0.9612

Table C.2. Mean of driver's characteristics categories

C.1.3. Network characteristics

#	Red	Green	Route Traffic Lights
Duration in Seconds			**Route 2 Traffic Light: Intersection**
2	25	25	Santa Cruz Avenue & Arenales Avenue
3	30	60	Santa Cruz Avenue & Santa Maria Avenue
4	68	36	Santa Cruz Avenue. & Angamos Oeste Avenue
5	53	49	Santa Cruz Avenue & La Mar Avenue
6	50	55	Santa Cruz Avenue & Espinar Avenue
7	40	60	Pardo Avenue & Arica Street
			Route 2 Traffic Light: Intersection
1	40	50	Arequipa Avenue & Los Angeles
2	40	50	Arequipa Avenue & Teruel Street
3	40	50	Arequipa Avenue & Cal. Garcia Calderon
4	40	50	Arequipa Avenue & Maria Parado de Bellido Avenue
5	40	50	Arequipa Avenue & Tarapaca Street
6	50	40	Arequipa Avenue & Angamos Oeste Avenue
7	40	50	Arequipa Avenue & Carril Street
8	40	50	Arequipa Avenue & 2 de Mayo Street
9	40	50	Arequipa Avenue & Pardo Avenue
10	30	60	Arequipa Avenue & Arica Street

Table C.3. Traffic lights locations and duration

C.2 Relationship between FCP and Congestion

In this appendix we show that in a sequential bargaining game with two states of the word, excess demand (ED) and excess supply (ES). We assumed that number of taxi drivers is fixed and greater than the demand of customers at non-congested states[52]. The number of customers at excess demand is strictly larger than at excess supply hours $C_{ED} > C_{ES}$.

I develop a price discovery game following Rubinstein and Wolisnky (1986) (RW for now on). If subjects, customers and taxi drivers, identify two different states of the world, ED and ES, then the solution for each states are the original RW equations. Solution to the sequential search and bargaining game that origins the emergence of fares has the same solution with different parameters. The equations represent the request that each party, customer or taxi driver, should do to split the gains of trade leaving the customer indifferent between accepting and keep searching. By analyzing taxi drivers equilibrium offer and its relationship with the parameters of the model, I show the relationship between *FCP* and taxi driver perception of customer probabilities of finding another idle taxi and his probability f finding a new customer.

Following RW, the market is conceived as a number of customers in state C_s and a number of taxi drivers T. Each taxi driver has only one unit available to sell, a trip at time t, for which we can assume it has a cost of zero. Each customer wants one trip and has a valuation $v_s>0$ for it. Therefore customers and drivers gains of trade are v_s . There are t=1,2,3.., discrete periods within a state of the world.

At each period t a bargaining process between a number of customers and taxi drivers continue in the following manner. Either taxi driver or customer is chosen randomly and proposes a fare x, this fare represents a division of the gains of trade. For the sake of simplicity, we follow RW and assume $v_s = 1$ for every state. If the fare is accepted, then customer obtains $(1-x)\delta^{t-1}$ and driver gets $x\delta^{t-1}$ where, $\delta<1$ is the common discount factor. If rejected then customers and taxi drivers keep their search in which case customers face a probability of finding a new taxi β_S and a taxi drivers find a new

[52] I follow closely Vega Redondo pp.166-170 description of RW model

customer with probability α_s. These probabilities are related to the number of taxis and customers hat are present in the market at each state of the world. We can assume that these probabilities are proportional to $1/C_s$ and $1/T_{s.}$ They reflect the market conditions. In the following paragraphs I solve the model for one state of the world. Then I show how the solution change when all the fundamentals of the model, *vs*, cost and negotiation strategies remain the same but market conditions change β_S,α_s .

Following RS, I focus my analysis on the semistationary strategies. Under these strategies players make their behavior only dependent on the current match. Customers and taxi drivers have continuation payoffs for each possible condition. Therefore they have continuation payoffs of I_c and I_T when they are idle and searching for a match. Additionally, they have M_c and M_T expected payoffs once they are matched but they haven't still negotiated. Semistationary strategies allow us to express us without the temporal index *t*. For each state of the world, ES or ED, continuation payoffs are related in the following way

(AB.1) $I_c = \delta[\beta M_c + (1-\beta) I_T]$

(AB.2) $I_T = \delta[\alpha M_T + (1-\alpha) I_T]$

Then if parties follow threshold strategies, in the following way:

A customer only accepts a fare x if and only if $x \leq x_c$

A taxi driver only accepts a fare x if and only if $x \geq x_t$

Then it is easy to derive the continuation payoffs of the two parties once they are matched

(AB.3) $M_C = 1-(x_c + x_t)/2$

(AB.4) $M_T = (x_c + x_t)/2$

Given that the first proposer is chosen randomly. Equations AB.3 and AB.4 just describe that with probability ½ either customer or taxi driver will make a proposal and the continuations value of accepting it is v_s minus the fare for the customer or just the fare for the taxi driver.

Customers and taxi drivers are at equilibrium when they offer a fare that leave the other player indifferent between accepting and keep searching. Therefore the equilibrium fares x_c* and x_T* should satisfy the following payoff indifference conditions

(AB.5) $x_c^* = (1-(1-\alpha)(1-\beta))I^*_T + (1-\alpha)(1-\beta)\delta M^*_T$

(AB.6) $x_T^* = (1-(1-\alpha)(1-\beta))I^*_c + (1-\alpha)(1-\beta)\delta M^*_{cT}$

The mode has six equations with six unknown, I^*_c , I^*_T, M^*_c , M^*_T, x_c* and x_T*. It is straightforward to show that this system has a unique solution. Furthermore we are only interested in the FCP which is represented as x_T* in this model. The solution to this system of equations provides us with an expression of FCP as a function of the discount factor and the probabilities of finding another taxi or customer.

(AI.7) $x_T^* = [2(1-\delta) + \delta\alpha - \delta(1-\delta)(1-\alpha)(1-\beta)]/[2(1-\delta) + \delta\alpha + \delta\beta]$

Two features of the solution to the model are worth noticing. First, we assumed cost equal to zero. Therefore, customers are drivers negotiate over the gains of trade. The fare x^*_T is a proportion of the gains of trade. If cost increases as long as there are gains of trade are positive, cost is less than value, and market conditions β_S and α_s remain the same. Then x^*_T should change with cost. Second, x^*_T depends on β_S and α_s. The partial derivatives of x^*_T with respect to the probability that customers find a new taxi is:

(AB.8) $$x^{*}_{T\beta}(\alpha,\beta) = \left\{ \frac{(1-\alpha)(1-\delta)\,\delta}{2(1-\delta) + \alpha\delta + \beta\delta} - \frac{\delta\big(2(1-\delta) + \alpha\delta - (1-\alpha)(1-\beta)(1-\delta)\,\delta\big)}{\big(2(1-\delta) + \alpha\delta + \beta\delta\big)^2} \right\}$$

Which for ceteris paribus values of α is negative. As the following graph displays the derivative for α_s=.99 and α_s=.01

The sign of the derivative is consistent with our economic intuition that taxi drivers bargaining power decrease when customers could find a taxi available with greater probability. On the other hand, when α increase the partial derivative is

$$x^{*}_{T\alpha}(\alpha,\beta)=\left\{\frac{\delta+(1-\beta)(1-\delta)\delta}{2(1-\delta)+\alpha\delta+\beta\delta}-\frac{\delta\left(2(1-\delta)+\alpha\delta-(1-\alpha)(1-\beta)(1-\delta)\delta\right)}{\left(2(1-\delta)+\alpha\delta+\beta\delta\right)^{2}}\right\} \tag{AB.9}$$

Therefore if taxi drivers have perfect recognition of their bargaining power FCP should increase. Additionally, if market conditions are kept constant FCP should increase with cost. If taxi drivers perceive an increase in the probability that customers find other idle taxi, then FCP should decrease.

Interval	Travel times Kruskal Wallis	
Article I.	Statistic	P
1. 6:31-7:30 am	5.428	0.0663
2. 7:31-8:00 am	39.418	0.0001
3. 8:01-8:30 am	19.260	0.0001
4. 8:31-9:00 am	0.975	0.6141
5. 9:01-9:30 am	9.349	0.0093
6. 9:31-10:00 am	15.429	0.0004
7. 10:01-10:30 am	12.457	0.0020
8. 10:31-11:30 am	11.841	0.0027

Table C. 4: Kruskal Wallis test of median travel times per interval-route treatments

Statistical Definition	Average Travel Time, SD in seconds, and Observations per Interval-Route		
Interval\Treatment	Free Route	Route 1	Route 2
1. 6:30-7:30 AM	368 (98) 61	390 (92) 67	442 (103) 81
2. 7:31-8:00 AM	422 (96) 53	446 (100) 48	721 (213) 47
3. 8:01-8:30 AM	462 (87) 56	471 (94) 45	604 (121) 60
4. 8:31-9:00 AM	515 (125) 33	591 (159) 35	587 (117) 28
5. 9:01-9:30 AM	485 (154) 34	551 (129) 33	578 (106) 35
6. 9:31-10:00 AM	461 (86) 47	560 (104) 35	576 (120) 30
7.10:01-10:30 AM	447 (88) 52	533 (101) 38	556 (98) 45
8. 10:31-11:30 AM	440 (108) 38	524 (113) 45	555 (95) 54

Table C.5 Statistical definition of interval-routes

Declared Definition	Perceived Congestion Index and SD per Interval-Route		
Interval\Treatment	Free Route	Route 1	Route 2
1. 6:30-7:30 AM	1.29	1.42	1.49
	(0.20)	(0.20)	(0.21)
	61	67	81
2. 7:31-8:00 AM	1.87	1.979167	2.319149
	(0.22)	(0.29)	(0.41)
	53	48	47
3. 8:01-8:30 AM	2.14	2.13	2.416667
	(0.20)	(0.26)	(0.23)
	56	45	60
4. 8:31-9:00 AM	2.27	2.34	2.32
	(0.33)	(0.35)	(0.42)
	33	35	28
5. 9:01-9:30 AM	2.26	2.45	2.46
	(0.42)	(0.27)	(0.24)
	34	33	45
6. 9:31-10:00 AM	2.17	2.37	2.33
	(0.20)	(0.31)	(0.27)
	47	35	30
7. 10:01-10:30 AM	1.98	2.32	2.24
	(0.22)	(0.22)	(0.31)
	52	38	45
8. 10:31-11:30 AM	1.97	2.09	2.17
	(0.15)	(0.40)	(0.34)
	38	45	54

Table C.6 Declare definition of interval-routes

CURRICULUM VITAE

Hernán Daniel Bejarano

1746 9th Street Apartment C	hbejainpenn@gmail.com
Santa Monica, CA 90404	hbejarano@psu.edu
Phone: (571) 232 7285	bejarano@chapman.edu

EDUCATION

Pennsylvania State University — September 2008 – 2013
Department of Agricultural Economics, Education and Sociology
Ph. D. Candidate: Agricultural, Environmental and Regional Economics

Pennsylvania State University — September 2004 – August 2007
Department of Economics
M.A. Economics

Universidad Torcuato Di Tella — March 2001- August 2004
Postgraduate Degree in Economics

Universidad Argentina de la Empresa — March 1996– January 2001
Licenciatura en Economia

PUBLICATIONS

H. Bejarano, Lance Cliffner Carl Johnson, Stephen Rassenti and Vernon Smith**.** Resource Adequacy: Should Regulators Worry? *Forthcoming* Berkley Electronic Journal Review of Network Economics

WORKING PAPERS

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