Abstract

Title of dissertation: Essays in Behavioral and Experimental Economics

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My dissertation consists of three essays on behavioral and experimental economics. In Chapter 1, I introduce an integrated model of risk attitudes and other-regarding preferences that extends the standard notion of inequity discount to lotteries. In this model, a decision maker perceives inequity partly by comparing the marginal risks she and others face. It predicts that fairness considerations will alter risk attitudes, in particular, a higher tolerance to positively correlated (fair) risks compared to negatively correlated (unfair) risks. It is also capable of explaining the behavior by which people help others probabilistically (known as ex ante fairness). Furthermore, in contrast with the existing view of ex ante fairness based on expected outcomes, my model does not imply that stronger ex ante fairness behavior is associated with less risk sensitivity. I study these predictions with evidence from an experiment. I find that subjects take more risks when outcomes are ex post fair compared to when they are ex post unfair. I confirm ex ante fairness behavior is a common choice pattern and document how, according to the model, it responds to its relative price. Finally, I reject the implication of existing models that stronger ex ante fairness behavior correlates with less risk sensitivity.

Chapter 2 is a joint work with Professor Brit Grosskopf (University of Exeter, UK).

People communicate in economic interactions either aiming to alter material outcomes or because they derive direct satisfaction from expressing. In our study, we focus on the latter, the non-instrumental motivates, and find that this less researched aspect of expression has important economic implications. In particular, we experimentally study ex-post verbal expression in a modified Power-to-Take game and document people's willingness to pay for this kind of expression possibility. Our experiment contributes to previous studies discussing the role of mood-emotional states. We find that purely expressive as well as reciprocal motives are both non-trivial components of the valuation for non-instrumental expression. We demonstrate that expression possibilities have important impacts on welfare beyond what our standard economic view predicts.

In Chapter 3, Emel Filiz-Ozbay, Erkut Ozbay and I study multi-object auctions in the presence of post-auction trade opportunities among bidders who have either single- or multi-object demand. We focus on two formats: Vickrey auctions where package bidding is possible and simultaneous second-price auctions. We show that, under complementarities, the Vickrey format has an equilibrium where the objects are allocated efficiently at the auction stage whether resale markets are present or not. The simultaneous second-price, on the other hand, leads to inefficiency with or without resale possibility. Our experimental findings show that the possibility of resale in second-price auctions decreases the efficiency rate at the auction stage compared to the no resale case. However, after resale, the efficiency rate in second-price is as high as that of Vickrey auction without resale outcomes in the experiment. Preventing resale neither benefits nor hurts auction revenues in a second-price format. This last chapter has been recently published in Games and Economic Behavior, Volume 89, Pages 1-16, January 2015.

Essays in Behavioral and Experimental Economics

by

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A mi madre, Luz Cielo

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Contents

List of Figures

List of Tables

Chapter 1

Risk Attitudes and Fairness: Theory and Experiment

1.1 Introduction

Many decisions we make have consequences not only for ourselves but for other agents we care about – or with whom we compare ourselves – and such consequences are uncertain at the moment we make the decision. Similarly, risk taking choices often occur in environments where comparisons with respect to others are unavoidable. Financial officers decide on risks borne by others; entrepreneurs make decisions that imply different risks for themselves and for their partners; climate change policies aim to increase the odds of positive outcomes for future generations; and colleagues competing for a promotion (or a prize) face uncertainty but also might exhibit concerns about unfair opportunities and unfair final outcomes. All these are examples where *risks* and *others* are both essential considerations in the decision.

In this paper, I research on two relevant aspects of the interplay between risk attitudes and other-regarding preferences. First, I ask to what extent the regard for the welfare of others affects risk attitudes. Second, I ask how the behavior in which people help others probabilistically (known as ex ante fairness) arises. To motivate these two questions, I start discussing two simple examples.

Suppose there are two people, you and a partner, and two coin-flip risks A and B. Both risks pay to you either 5 dollars or 20 dollars. Further, in each risk your partner's luck is determined by the same coin and involving the same amounts. But risks A and B differ in one thing: in risk A you two receive the same amount always, and in risk B you two are always paid unequally. Formally, $A : \frac{1}{2}(5, 5) \oplus \frac{1}{2}(20, 20)$ and $B : \frac{1}{2}(5, 20) \oplus \frac{1}{2}(20, 5)$. If you dislike both unequal outcomes and risks, then your desire to avoid risks will be higher for risk B than for risk A. Equivalently, you will optimally take more *fair risks* (like A) than *unfair risks* (like B), disregarding the fact they both expose you to the same marginal uncertainty.[1] You will behave differently facing the same personal risk.

This behavior – known as *ex post fairness* seeking – is a relevant pattern to study because, on one hand, it is predicted by standard extension of models with inequity aversion (Fudenberg and Levine, 2012), and, on the other hand, previous experimental research has claimed there is no link between social preferences and risk attitudes (Brennan et al., 2008; Bolton and Ockenfels, 2010) or that people prefer independent risks over correlated ones (Rohde and Rohde, 2011). As will be detailed below, my model predicts people will tolerate more risks that are ex post fair than risks that are ex post unfair, and my experimental evidence backs such prediction.[2]

Consider now this example related to my second question. As before, you and some partner that you care about are affected by your decisions. This time you have two mutually exclusive outcomes: one comparatively advantageous to you (outcome A) and one comparatively advantageous to your partner (outcome B). Suppose despite caring about him/her, you still prefer alternative A over B. However, even if you can decide the chances of these two outcomes, you might choose to give B some chance of occurrence rather than no possibility at all. If so, you will *share* with the other person *the chance* that something "good" will happen at the expense of your own prospects. In fact, while doing so, you are also taking on more risk. This type of behavior is known as *ex ante fairness* seeking, and experimental evidence shows it is a common behavioral pattern (Krawczyk and Le Lec, 2010; Brock et al., 2013). This raises the second main question of this paper: how ex ante fairness behavior arises. As pointed in previous literature (Krawczyk and Le Lec, 2010; Brock et al., 2013; Saito, 2013), while this is a common behavior it cannot be explained by theories purely based on

[1]Notice I use the term "fair risk" to denote uncertainty that guarantees *ex post egalitarian outcomes* across agents. This should not be confused with the term "*actuarially* fair gambles" that in part of the literature denotes lotteries with zero expected value.

[2]In section 1.2, I offer an explanation regarding why previous experimental research either did not look into the right question or presented some design deficiencies.

the assessment of ex post outcomes such as our standard expected utility theory.[3] But it is not obvious how to extend the standard theory to incorporate ex ante fairness. One possible answer is that individuals with this kind of behavior present pro-social preferences but care little about risks and so for them, *sharing in chances* and in sure dollars look the same. An alternative view is that these people do care about risks but their sense of *equal opportunity* consists of comparing the possibilities or prospects to which each person gets access. In this view, an individual shares in chances because – to some extent – she wants both sides to have the *possibility* of favorable outcomes. The model I introduce in this paper corresponds to this latter view, while main existing theory of ex ante fairness (Saito, 2013) conforms to the former. Due to the strong implications about risk attitudes the existing view presents, I will argue in this paper that my model has conceptual and empirical relative advantages.

More specifically, in terms of theory, I propose a model that takes the following form:

$$U(L) = \mathbb{E}\,[\,W(\,g(x,y)\,,\,D(F_x,F_y)\,)\,] \tag{1.1}$$

where L is a lottery over two-people social outcomes (*decider*, *other*), W is increasing in g and decreasing in D. g captures the main features of deterministic preferences and ex post fairness. D captures the *ex ante fairness penalty* by being sensitive only to differences in marginal risks. Although this model might look too general –it is after all defined over distributions– and therefore capable of organizing data better just by being more flexible, I show that, provided with the proper structure, it incorporates ex ante motives at the modeling cost of one single additional parameter. In that regard, it is comparable to the most utilized model (Fudenberg and Levine, 2012; Saito, 2013). In the new model, the conditions imposed on D are crucial. The most important and intuitive of these conditions is that D must extend the notion of *inequality discount* to the lottery space, in a way $U(L)$ behaves as a standard social preferences model in risk-free situations.

Let me show one example of how my model operates. Consider the following utility

[3] As we will discuss in the theory section, ex ante fairness behavior does not conform to the Expected Utility Theory because the *independence axiom* behind this theory implies option A will be strictly preferred to any non-degenerate lottery. This behavior is the same nature of *Machina's Mom* famous example in which a planner (aka mother) with two equally valued citizens and, sadly, only one indivisible good, might strictly prefer to randomize over who gets it instead of giving the item to one of the citizens with certainty (Machina, 1989).

for lottery L: $U(L) = \mathbb{E}[x - (1-\delta)d(x,y) - \delta D(F_x, F_y)]$, where F_x and F_y denote the corresponding marginal risks, $D(F_x, F_y) = \int \frac{1}{2}|F_x - F_y|^2 dt$ and $d(x,y) = \frac{1}{2}|y - x|$. This extends the Fehr and Schmidt (1999) model to the uncertainty domain, while incorporating ex ante fairness motives when $\delta > 0$.[4] Importantly, in full certainty, $D = d$; which means ex ante fairness motives merge with the ex post fairness motives, and the whole utility simplifies to $U(x,y) = x - \frac{1}{2}|y - x|$. That is, this instance of my model simply becomes an instance of the standard Fehr and Schmidt (1999) model (hereafter F&S).[5] Although this example gives a flavor of how my theory operates, it still lacks some important elements. First, because the F&S utility is piece-wise linear, it predicts that individuals are not responsive to the price of helping others. Second, it does not incorporate reasonable risk attitudes. For example, it predicts attitudes towards perfectly fair risks will be neutral. A full instance of my model will incorporate both: reasonable risk attitudes and convex deterministic preferences.

I contrast my model with the *expected inequality aversion* (EIA) model, introduced in Fudenberg and Levine (2012) and axiomatized in Saito (2013). In the EIA model, the decision utility of lottery L is given by $U(L) = \delta u(\mathbb{E}x, \mathbb{E}y) + (1-\delta)\mathbb{E}u(x,y)$, where $u(x,y)$ represents deterministic social preferences and δ the strength of ex ante motives.[6] I show that a core implication of this theory is that, holding other motives constant, more ex ante driven individuals will do more risk taking compared to less ex ante driven decision makers. In that sense, the former are supposed to exhibit higher risk tolerance than the latter individuals.

In the empirical section, I present evidence from a laboratory experiment that allowed me to study the main questions of the paper with observed behavior. Individuals in the study performed decisions in four different types of tasks. There were eleven decision rounds for each type of task. Task type 1 (the *sharing chance*s task) is the decision environment that elicits ex ante motives. Here each decision problem gives the *decider* two fixed, mutually exclusive (undominated) outcomes as in my first example above. Subjects are then asked to decide on the probabilities of these

[4]For example, if $A = (1,0)$ and $B = (1,2)$, then a 50-50 lottery over A and B is strictly preferred to either A or B.

[5]In this particular instance of the F&S model, I assume $\alpha = \beta = \frac{1}{2}$. But an asymmetric measure inside terms D and d replacing the absolute values will fully generalize F&S model for arbitrary α and β.

[6]In all mentioned papers, except Gaudeul (2013), $u(x,y)$ is the standard Fehr and Schmidt (1999) utility.

two outcomes. Task type 2 (the *taking fair-risks* task) elicits risk attitudes free of fairness concerns. In this task, subjects decide how much risk to bear in a two-state contingent commodity environment with the feature that either state of the world pays the same amount of money to the decider and her counterpart. Task type 3 (the *taking unfair-risks* task) elicits risk attitudes that also contain fairness concerns. In this task, subjects face the same environment as in task type 2, except in this task risks are perfectly negatively correlated; and each *state* pays unequally unless no risk is taken. Still, both subjects in each pair face the same marginal risks. Task type 4 is the standard *deterministic giving* decision environment where other-regarding preferences are elicited in a standard deterministic dictator-like game varying the budget and the price of giving.[7]

The experimental results are as follow. First, as predicted by my theory, I find that social considerations impact risk attitudes in the ex post fairness seeking direction: subjects exhibited higher tolerance to fair risks (choices of type 2) than to unfair risks (choices of type 3). I also confirm ex ante fairness behavior is a rather common choice pattern and, building upon previous literature, I document how it responds to changes in its relative price and how agents trade off this motive with other. Importantly, I empirically study the property of expected-outcomes-based models by which a stronger ex ante fairness behavior implies less risk sensitivity. The experimental evidence is not consistent with such behavioral pattern. To the best of my knowledge, mine is the only model consistent with the full set of evidence my experiment presents.

The rest of the paper is organized as follows: In Section 1.2, I discuss the previous theoretical and experimental literature. In Section 1.3 I present my model and discuss the main existing model. Section 1.4 describes the experimental design and procedures. Section 1.5 present the empirical results. Section 1.6 provides the main concluding remarks and discusses future research agenda.

[7] An attractive feature of my experiment is that the graphical interface utilized allowed me to elicit a larger set of choices compared to previous experiments.

1.2 Related Literature

The study of decision making incorporating uncertainty along with the consideration for others is relatively recent. Although attitudes towards risks are among the most studied matters in economics, for the most part they have been regarded as invariant or determined only by demographic characteristics.[8,9] Similarly, other-regarding preferences have been mostly studied in riskless environments (see e.g. Camerer, 2003; Fehr and Schmidt, 2006; and Meier, 2006).[10]

In recent years, the question about how other-regarding behavior operates under uncertainty has received more attention. Karni and Safra (2002) present a model of individual preferences over procedures that randomly allocate one indivisible item among N individuals. The decision maker in such a model has one *fair/moral self* that cares about others getting chances to get the prize, and one *egoistic self*. Balancing her preferences for equalized chances with her standard self-centered attitudes, the resulting combined preferences are capable of explaining ex ante fairness seeking behavior. Interestingly, the authors require these preferences to conform to expected utility theory when restricted to the set of fair procedures.[11] Though Karni and Safra's work is restricted to the specific case of one indivisible good, random procedures, and it does not discuss the role of risk attitudes, it can be thought of as a precursor of my model. Other models that are defined over distributions include Borah (2013). His model, presented axiomatically, has a representation that is linear with respect to two components: an individual's expected utility over social outcomes and a (ex ante) component that depends only on the risks faced by the *other* agent. One undesired feature of this model is that its departure from the expected utility theory remains even within perfectly fair uncertainty.

The majority of the remaining theories of fairness or altruism in probabilistic environments have a common property: they are based on the idea that people, in different degrees and manners, look at and compare expected outcomes. Bolton et

[8] The first formal study of risk attitudes is almost three centuries old: Bernoulli (1954/1738).

[9] See Dohmen et al. (2011) for a study of demographic determinants of risk attitudes.

[10] Connections between decision theory under uncertainty and *social choice* theory have been studied for longer; see Gajdos (2005) for a short survey and Grant et al. (2012) for an example of a model of an impartial planner with ex post inequality aversion.

[11] As we shall see in the next section, this intuitive criterion is not met by some of the main models of a more general environment.

al. (2005), for example, extend the ERC model (Bolton and Ockenfels, 2000) assuming, as in the original model, that people care about relative payoffs except these are replaced by *relative expected values*. Similarly, Trautmann (2009) extends Fehr and Schmidt (1999) to the uncertainty case by simply making the F&S inequality discount to depend on expected outcomes. In the same spirit, Krawczyk and Le Lec (2010) propose a formulation that linearly combines an egoistic expected utility component and a fairness component that depends, in turn, on the (subjective) expected outcomes of the decider and the other agent. An issue with this last model is that it lacks of ex post fairness concerns.

A model that stands out is the *Expected Inequality Aversion* (EIA) model. Introduced in Fudenberg and Levine (2012) and axiomatized in Saito (2013), it has also been used to organize experimental data in Brock et al. (2013) and Gaudeul (2013). In this model, decision utility takes the form of a linear combination between the utility of expected outcomes $u(\mathbb{E}[x, y])$ and the expected utility $\mathbb{E}[u(x, y)]$. $u(x, y)$ is the standard Fehr and Schmidt (1999) utility in all articles mentioned, except in Gaudeul (2013), where each individual outcome is replaced by a power function of the corresponding outcome. Since this model presents interesting features and has received the most attention of all theories based on expected outcomes, I discuss it further in the theory section and study it empirically along with the model I propose in the paper.

Experimental research has been active on this topic as well. Two bodies of research are the most relevant for the purposes of this paper: the experimental research on ex ante fairness and the studies of attitudes towards risks over social outcomes. In the case of ex ante fairness, Krawczyk and Le Lec (2010) and Brock et al. (2013) both document evidence from probabilistic Dictator-Game decisions like the one described in the first introductory example. In these tasks, subjects decide the chances of two fixed, mutually exclusive and undominated outcomes. In both papers, authors find *sharing in chances* (exhibiting ex ante fairness) to be a common behavior; at least one third of subjects assigned positive probabilities to unfavorable outcomes. However, only the first paper finds that subjects share less in chances than in deterministic terms (comparing the corresponding expected values).[12] Importantly, none of these

[12]My experimental evidence shows the same pattern.

papers discuss in depth the role of risk attitudes in these situations.[13]

In the case of attitudes towards risks over social outcomes, interestingly –and surprisingly– there is not a clear answer to the question whether individuals avoid risks with negative correlation (between their outcomes and others') more than risks with positive correlation. A central implication of ex post fairness is that people will strictly prefer positively correlated (more fair) lotteries over negatively correlated ones, so risk taking must be affected by social considerations. Nonetheless, Brennan et al. (2008) and Bolton and Ockenfels (2010) both claim there is no empirical link between fairness concerns and risk taking. There are, however, important design and analysis features in both works suggesting this conclusion needs to be re-examined. In the case of Brennan et al. (2008), their design does not allow them to directly test this hypothesis because outcome correlation, a key feature to elicit ex post fairness, is absent from all risky options in their design. My reading of their finding is that it only shows that the regard for others' risks is a very weak motive (which *per se* is an interesting finding). Bolton and Ockenfels (2010), on the other hand, do have alternatives where risks are perfectly correlated (positively and negatively) but in the pure comparison between each of these lotteries against a safe-fair option, their experiment only has 25 individual choices. This gives the authors insufficient statistical power. To gain power, they combine data from the correct comparisons (a perfectly correlated risk vs a safe-fair option) with other tasks where the safe option was unfair. Doing so, however, confounds risk attitudes with inequity concerns: if the safe options already have inequality built-in, the impact of fairness concerns in the attempted comparison is weakened. As expected by their low power and confounded statistical exercise, they find no significant difference in risk taking between fair-risks and unfair-risks. Rohde and Rohde (2011) report on an experiment testing whether "risk attitudes are affected by the risks others face". They find own-risk attitudes to be only marginally affected by others' risks. More importantly, subjects in their

[13] Although not the same environment as my paper, Cappelen et al. (2013) research on a related aspect. They ask what are people's typical fairness views regarding risk-taking behavior. Fairness views are cleverly associated with whether or not an external observer redistributes post uncertainty payoffs in a society where subjects can choose different degrees of risk. Because an ex post *loser* comes in two flavors: he might have taken *too much risk* or he might have been just *too unlucky,* different redistribution to these two loser-types indicate different fairness views. They find great heterogeneity in people's fairness views. It must be noted that in this paper, however, the notion of ex ante fairness is defined over subject types (risk-takers and risk-avoiders) not only over social lotteries as is in my paper.

experiment strictly preferred imposing the same lottery uniformly on other subjects (for example where each other person receives an independent lottery yielding 20 euro with 30% probability and 10 euro with 70%) over an unequal allocation with the same average value (i.e. paying 20 euro to 30% of these other subjects and 10 euro to the rest). They incorrectly used this finding (which is an ex ante fairness driven pattern) to claim that "people prefer risks to be independent across individuals in society rather than correlated". Although it is true there is correlation in the most chosen option, this correlation is rather weak even for small societies (laboratories for that matter). Therefore, it is not an appropriate design to study the role of risk correlation on risk attitudes.

Experiments in Gaudeul (2013) also include tasks with positively and negatively correlated risks. Although this paper reports individuals being "slightly more risk averse if outcomes are negatively correlated", there are two important shortcomings with the experimental design. First, the elicitation of preferences occurs via the BDM mechanism (Becker et al., 1964), which adds a layer of uncertainty to each choice problem. Second, the "safe alternatives" are never perfectly fair because by design their exact position is jittered randomly to make subjects "think" more carefully about the choice they face. In my view, this adds even another layer of decision processing that is problematic. In a context where inequality aversion is likely to be a central force shaping behavior, including options that are already (slightly) unequal might weaken the power of these motives. [14]

1.3 The Model

Setup: I focus on a two-person environment where each agent faces uncertain prospects over a single resource (money). Behavior is modeled via preferences for lotteries over social outcomes. Each ordered pair (x, y) indicates the resource allocated to the decision maker (DM) and her counterpart, respectively. The full set of outcomes

[14] Other less related, but still relevant papers are the following. Karni et al. (2008) study empirically the predictions of Karni and Safra (2002). Chakravarty et al. (2011) find that individuals making decisions for an anonymous stranger exhibit less aversion towards risks faced by the stranger than towards own risks. Van Koten et al. (2013) study risk attitudes restricted to uncertain pie-sizes in bargaining games. Finally, Harrison et al. (2012) study how risk attitudes towards social outcomes vary with information regarding risk preferences of the *other* agent, finding that learning others' risk preferences makes individuals more risk averse.

$X \subset \Re^2_+$ is assumed to be convex. For the model to be meaningful, I assume at least some risks are *fairness-irreducible* in that ex post transfers –i.e. reallocations after uncertainty is resolved– are not possible. I assume preferences $\succcurlyeq$ are rational, continuous and represented by a continuous utility function $U(L)$ of lotteries over outcomes in X. It is also assumed that, when restricted to degenerate lotteries, DM's preference relation $\succcurlyeq$ is strictly monotonic along the set $\{(x, y) : x = y\}$ and smooth *almost everywhere*. When it is not ambiguous, I use $U(F)$ as interchangeable with $U(L)$, if F is the CDF associated with lottery L.

In this environment, the following motives may potentially coexist: First, DM's regards for her own payoffs and risks. Second, DM's considerations for her counterpart's payoffs and risks. And, finally, DM could present fairness concerns in the *ex post* sense (i.e., preferences for risks that are positively correlated among agents over risks with negative correlation, Fudenberg and Levine, 2012) and in the *ex ante* sense (i.e., preferences for helping others probabilistically – *giving chances*).

The novel element of my theory is that it incorporates a notion of ex ante fairness based on *how balanced (marginal) possibilities are* distributed between DM and her counterpart. In this model, *ex ante forces* arise from a comparison of marginal risks, regardless the correlation of personal outcomes the joint risk implies. Every lottery where the two agents do not face the exact same marginal risk will be interpreted by DM as if they are not getting access to the same *opportunities* and therefore a utility discount will apply. This discount need not be symmetric: it can be lopsided towards discounting advantageous positions less than disadvantageous. Outside this ex ante discount, the rest of motives are modeled in standard fashion. The general formulation of my model is given in equation 1.2:

$$U(L) = \mathbb{E}W(\, g(x, y)\, ,\, D(F_x, F_y)\,) \tag{1.2}$$

where W is increasing in g and decreasing in D. g, is the main component capturing standard deterministic social preferences and ex post fairness. It is assumed g is concave and increasing in its first argument and also along the 45 degree line. D is the penalty for ex ante unfairness. W's main role is to balance the relative strength of ex ante forces with respect to the rest of standard motives. A simple formulation for W that will accommodate most interesting and tractable instances is:

$$U(L) = \mathbb{E}W\left(g(x,y) - \delta\, D(F_x, F_y)\right) \tag{1.3}$$

I now discuss in more detail the ex ante fairness discount term, D. I describe first the properties we want D to exhibit and then provide an intuitive formulation that satisfies such properties. First, we want D to be well defined and bounded for arbitrary marginal risks F_x and F_y. Second, and more importantly, we want D to extend the notion of *inequality discount* that already exist in deterministic models to the lottery space. In particular, we want D to be minimized if and only if $F_x = F_y$. We can achieve this by defining D in relation to a notion of distance in the function space where F_x and F_y are defined. These basic criteria can be achieved by defining D as:

$$D(F_x, F_y) = \int |F_x(t) - F_y(t)|^p\, d\mu(t) \tag{1.4}$$

In this formulation, D is the Riemann-Stieltjes integral, with respect to function μ, of the absolute difference between the marginal CDFs, and where this difference is raised to the power p (it is assumed that $p \geq 1$). This is a notion of distance between the involved marginal risks. Notice also D is a positive transformation of the distance between these CDF functions based on the familiar L^p norm. For that reason, it is immediate to see D is minimized if and only if $F_x = F_y$ (with $D = 0$).

Three elements characterize ex ante motives in this formulation: the absolute value inside the integration sign, the exponent p, and the function μ. The absolute value in this equation assumes a symmetric discount for inequality. By changing this absolute value for a redirected or asymmetric absolute value we achieve a lopsided inequality discount. This generalizes the notion of asymmetric inequality discount proposed in Fehr and Schmidt (1999). The exponent p captures a more subtle component of ex ante motives related to how much one values giving *at least some* chance to the other side. For example, by setting $p = 1$, the ex ante discount associated with these two lotteries $\frac{1}{2}(1,0) \oplus \frac{1}{2}(1,2)$ and $1(1,0) \oplus 0(1,2)$ is the same. When $p > 1$, instead, the former exhibits a smaller ex ante discount than the l.[15] The function μ allows for the incorporation of *decreasing marginal utility*. For example, when $\mu(t) = t$, displacing the same pair of unequal marginal risks to the right will maintain the

[15] This assumes $\mu(t) = t$, for simplicity.

same ex ante discount D. But this will be unreasonable if the ex post component $g(x, y)$ exhibits decreasing marginal utility because the displacement will make ex ante forces unreasonably larger relative to the ex post ones. By setting the $\mu(t) \neq t$ and making it compatible with the curvature of g, we can guarantee risk displacements will not exacerbate ex ante motives unreasonably. In the next subsection, by means of two examples, I show how the asymmetric discount (example 1) and the function μ (example 2) operate.[16]

Importantly, D generalizes familiar measures of inequality discount. Take for example $p = 2$ and $\mu(t) = t$. If L is a degenerate lottery at $(\bar{x}, \bar{y})$, D becomes simply the absolute distance between x and y: $D = |\bar{x} - \bar{y}|$. That is, D becomes a simple measure of inequality that shows up in standard models of inequity aversion. In particular, assuming the formulation in equation (1.3), deterministic preferences are fully given by some $u(x, y) = g(x, y) - \delta D(x, y)$, since W in such case will be an order-preserving transformation.

The function $g(x, y)$ also determines whether these preferences present ex post fairness or not. As will be formally stated in subsection 1.3.2, when g presents a form of supermodularity (a formal expression of *inequality aversion*) the model yields ex post fairness behavior the model.

To summarize, when the model consists of equations (1.3), (1.4) and a standard concave function g, it presents the following relevant properties: First, it behaves as a standard social preferences model in absence of risks. Second, if $\delta > 0$ and large enough, there always exist two outcomes A and B such that the decision maker prefers a non-trivial lottery between these two outcomes rather than either outcome for sure. In other words, the model presents ex ante fairness, as desired. Further, this model is able to introduce ex ante motives at the modeling cost of one single additional parameter (δ), although it could also accommodate more flexibility from the exponent p. Third, attitudes towards fair-risks can be independent from deterministic preferences for giving as well as from ex ante fairness motives. Fourth, if g presents inequity aversion, the model exhibits ex post fairness behavior. Finally, this model satisfies the corresponding extension of Karni and Safra (2002) axiom of *fairness independence* that requires behavior to conform to the *expected utility theory* within the set of fairness procedures (in our environment, the set of lotteries that

[16] I use $p = 2$ in all examples.

make $F_X = F_Y$).

Because of the familiarity of the proposed D (in equation 1.4) with the $L^p - norm$, I call my model the *LP model*.

Examples

These two examples show how model extends previous deterministic other-regarding preferences to risky environments while incorporating ex ante motives (and, in the second example, risk attitudes as well).

Example 1: Extending Fehr and Schmidt (1999) with ex ante fairness.– Consider the following utility:

$$U(L) = \mathbb{E}\left[x - (1-\delta)d(x,y) - \delta D(F_x, F_y)\right] \tag{1.5}$$

where

$$D(F_x, F_y) = \int \alpha(F_x - F_y)_+^2 + \beta(F_y - F_x)_+^2 dt \tag{1.6}$$

and

$$d(x,y) = \alpha(y-x)_+^2 + \beta(x-y)_+^2 \tag{1.7}$$

To economize, I use: $(z)_+ = \max\{0, z\}$. In this formulation, we have set $W = g - \delta D$, $g = x - (1-\delta)\, d(x,y)$ with respect to equation (1.2), and $d\mu = dt$. The relative strength of ex ante motives is captured by δ. The functional D in this example is a lopsided norm with the same parameters as the regular F&S model. In absence of risks $D(x,y)$ becomes simply $d(x,y)$ and the whole model collapses to the standard Fehr and Schmidt (1999) utility. This model exhibits ex ante behavior as desired: For example, assuming $\alpha = \beta = \frac{1}{2}$, and setting $A = (1,0)$ and $B = (1,2)$, we have that a 50-50 lottery over A and B is strictly preferred to either A or B. Figure 1.1 shows how D extends the F&S inequality discount d to the lottery space. Depicted in red, we have the DM's marginal CDF and, in blue, the counterpart's. The left panel, the case with no risk, shows how standard deterministic inequality discount works as in the F&S model. The right panel shows how D extends this inequality aversion to the lottery space.[17]

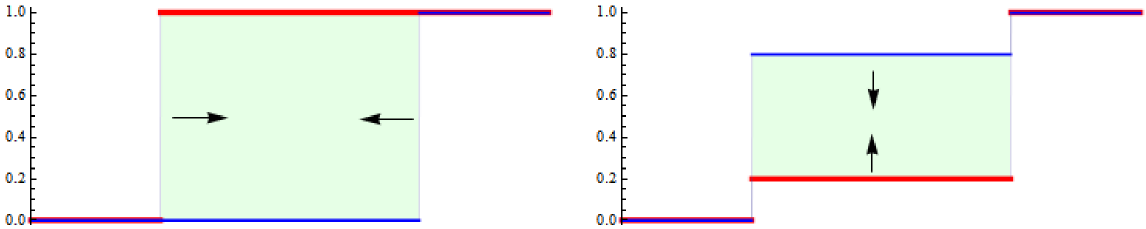

Figure 1.1: Deterministic Fairness Concerns (left) - Ex ante Fairness Concerns (right). In red, the DM's marginal CDF; in blue counterpart's marginal CDF. The arrows indicate the direction of inequality concerns that operate in the current deterministic models (left) and in the model I introdude (right).

Example 2: *Extending Andreoni and Miller (2002) with inequality aversion, ex ante fairness and risk attitudes.*– Consider the following utility:

$$U(L) = \gamma^{-1}\mathbb{E}\left[ax^\rho + (1-a)y^\rho - \theta\left((1-\delta)\,d\,+\,\delta\,D\right)\right]^{\frac{\gamma}{\rho}} \tag{1.8}$$

where

$$D(F_x, F_y) = \int |F_{x^\rho} - F_{y^\rho}|^2 dt \tag{1.9}$$

and

$$d(x,y) = |x^\rho - y^\rho| \tag{1.10}$$

Here, F_x is the marginal CDF of x within lottery L, and F_{x^ρ} is the marginal CDF of x^ρ (similarly for y). Notice that another way to express the ex ante discount is this: $D = \int |F_x(t) - F_y(t)|^2 d\mu(t)$, with $\mu = t^\rho$. This shows how function μ operates in equation (1.4).

Parameters a, ρ and θ fully describe deterministic preferences among which θ is the weight given to *all* inequality concerns. Within these inequality concerns, d captures the discount for ex post inequality and D captures the discount for ex ante inequality. δ gives the relative weight of the latter. γ shapes attitudes towards perfectly fair-risks. For simplicity, I assume symmetric inequity aversion in this example. It can be seen

[17]In this particular case, the graph represents ex ante motives in the particular case in which the two fixed outcomes are symmetric: A=(x, y) and B=(y, x) where $x \neq y$.

that if lottery L guarantees perfect equality (i.e. there is risk but $Pr[X = Y] = 1$), then $d = D = 0$ and this function $U(L) = \mathbb{E}(\frac{x^\gamma}{\gamma})$ fully determines preferences towards fair-risks. On the other hand, in risk-free situations, we have that $D(F_x, F_y) = \int (F_{x^\rho} - F_{y^\rho})^2 dt = |\bar{x}^\rho - \bar{y}^\rho| = d(\bar{x}, \bar{y})$. Therefore, the deterministic instance of this model are given by:

$$U(x, y) = \min \left\{(a - \theta)x^\rho + (1 - a + \theta)y^\rho \, , \, (a + \theta)x^\rho + (1 - a - \theta)y^\rho\right\}^{1/\rho} \tag{1.11}$$

This utility models preferences with altruism that is responsive to the price of giving, as documented in Andreoni and Miller (2002) and in Fisman et al. (2007), and also with inequality aversion when $\theta > 0$ which generates the corresponding kink along the 45 degree line. The deterministic case where there is no inequality aversion (i.e. $\theta = 0$) makes this utility simplify to the original Andreoni and Miller (2002) model of altruism with *constant elasticity of substitution* (CES).

1.3.1 The Expected Inequality Aversion Model

In this subsection, I briefly discuss the Expected Inequality Aversion (EIA) model (aFudenberg and Levine 2012; Saito 2013) and a more general version that I refer to as the Generalized EIA (GEIA) model. The utility function in the EIA model is given by:

$$U(L) = \delta_s u(\mathbb{E}[x, y]) + (1 - \delta_s)\mathbb{E}[u(x, y)] \tag{1.12}$$

where u is the classic F&S utility: $u = x - \alpha(y - x)_+ - \beta(x - y)_+$. Fudenberg and Levine (2012) and Saito (2013) argue that the first term of the RHS of this equation captures the ex ante motives and the second term the ex post motives. In this model δ_s indicates the relative strength of ex ante fairness concerns. What I refer to as the *Generalized Expected Inequity Aversion* (GEIA) model, has the same formulation of equation (1.12) except the F&S utility is replaced by a generic social preference utility $u(.)$, with the condition that $u(.)$ must be concave in each argument and along the 45 degree line. The concavity condition rules out both: risk loving behavior and non-convex deterministic preferences for giving. The concavity along the 45 degree line captures the aversion to risks that are egalitarian in ex post sense. One important virtue of the GEIA model is that it extends existing other-regarding models to incorporate ex ante motives using only the first moment, the expectation. Furthermore, it does so at the modeling cost of one single additional parameter. The reason why I want to focus on the GEIA formulation and not on its simpler EIA version is because the latter yields some unreasonable predictions that can be easily corrected precisely by replacing the F&S utility with a concave utility. For example, in the EIA model, the piece-wise linearity of the F&S utility implies that in riskless situations the DM is (a.e.) unresponsive to the price of giving, and that attitudes towards perfectly fair risks are neutral.[18] The GEIA solves those minor issues but keeps its core tenet: that *people exhibit ex ante fairness behavior because they partly assess and compare their expected outcomes with others'*. This postulate directly implies these two testable predictions: (i) tolerance to risks increases with ex ante fairness motives, and (ii) highly ex ante fairness oriented individuals disregard differences in risk correlation. Additionally, also testable, the GEIA model does not conform to the expected utility theory even regarding perfectly fair risks. That is, it does not satisfy Karni and Safra's axiom of *fairness independence*.

Because my model differs from the GEIA in all these predictions, one of the objectives of the experimental exercise is to test such implications. In subsection 1.3.2, I present these implications formally.

1.3.2 Empirical Predictions

In this section, I present the propositions that describe the main behavioral patterns predicted by the LP model. I also present some propositions with predictions that are exclusive to the GEIA model. Later, in the empirical part of the paper (sections 1.4 and 1.5), I test these behavioral implications.

In what follows, for simplicity, I assume $X = \Re_+^2$ and the formulation of the model that is given in equation (1.3) with W linear, $\mu(t) = t$, and $p > 1$. Also, I assume that deterministic preferences are positively monotonic in both x and y.

Let me first state the predictions about ex post fairness behavior. Consider lotteries L^{fair} and L^{unfair} to depend on a choice variable α:

1. $L^{fair}(\alpha) = \frac{1}{2}\left(\alpha\bar{Z}\,,\,\alpha\bar{Z}\right) \oplus \frac{1}{2}\left((1-\alpha)\,\underline{Z}\,,\,(1-\alpha)\,\underline{Z}\right)$ and,

[18] See López-Vargas (2014) for a detailed comment o n the EIA model.

2. $L^{unfair}(\alpha) = \frac{1}{2}\left(\alpha\bar{Z}\,,\,(1-\alpha)\,\underline{Z}\right) \oplus \frac{1}{2}\left((1-\alpha)\,\underline{Z}\,,\,\alpha\bar{Z}\right)$

where $\bar{Z} > \underline{Z}$. Notice that both lotteries make outcomes for the DM and her counterpart perfectly correlated. In L^{fair} this correlation is positive and in L^{unfair} it is negative. Consider also the following choice problem:

$$\max_{\alpha\in[0,1]} U(L(\alpha)) \tag{1.13}$$

When this choice problem is over fair risks ($L^{fair}(\alpha)$), the decision consists of balancing risks and returns according to DM's preferences. When, instead, this problem is over unfair risks ($L^{unfair}(\alpha)$), the decision necessarily incorporates DM's fairness considerations as well, because ex post outcomes are always unfair in such a decision problem. Notice that in this context α is a measure of risk tolerance. The *personal* expected value in either lottery is $\mathbb{E}x = \mathbb{E}y = 0.5\left(\alpha\bar{Z} + (1-\alpha)\,\underline{Z}\right) = 0.5\left(\underline{Z} + \alpha(\bar{Z} - \underline{Z})\right)$. Therefore, if the DM tolerates risk perfectly she will choose $\alpha = 1$. If, instead, she behaves with extreme risk aversion, she will choose making sure this equality holds $\alpha\bar{Z} = (1-\alpha)\,\underline{Z}$ by choosing $\alpha = \alpha^{safe} \equiv (1 + \underline{Z}/\bar{Z})^{-1} < 1$.[19] I define α^{fair*} as the solution to problem (1.13) when $L(\alpha) = L^{fair}(\alpha)$, and $\alpha^{unfair*}$ as the solution when $L(\alpha) = L^{unfair}(\alpha)$.

For Proposition 1, I also need to define the property of supermodularity.

Definition $g : X \to \Re$ is (*strictly*) *supermodular* with respect to $z, z' \in X$, if $g(z \uparrow z') + g(z \downarrow z') \geq (>)\, g(z) + g(z')$ where $z \uparrow z'$ denotes the component wise maximum and $z \downarrow z'$ the componentwise minimum of z and z'. We say g is *globally* supermodular if it is supermodular with respect to any z, $z' \in X$.

The supermodularity assumption that will be imposed on g is a formal expression of inequality aversion.[20] Intuitively, it states that the incremental utility associated to an positive change in DM's resources (x) is bigger if such a change in x improves equality compared to when it hurts equality. Proposition 1, formally states that this weak form of inequality aversion implies ex post fairness behavior.

Proposition 1 (ex post fairness) In the LP model, if g is (i) globally supermodular, and (ii) strictly supermodular with respect to any two outcomes $A =$

[19] Any choice below α^{safe} is irrational.

[20] All standard models of inequity aversion satisfy this property.

(x_A, y_A) and $B = (x_B, y_B)$ with $y_A > x_A$ and $x_B > y_B$, then the optimal risk tolerance to fair lotteries is higher than to unfair lotteries: $\alpha^{fair*} > \alpha^{unfair*}$.

Proof in Appendix A.

Notice that α is directly observable from choice problems like the one in expression (1.13), so this proposition can be empirically tested.

Next, I state the predictions about ex ante fairness behavior. Let $L(p, A, B)$ denote a lottery over outcomes A and B where p is the probability of A:

$$L(p, A, B) = p\,(x_A, y_A) \,\oplus\, (1-p)\,\,(x_B, y_B) \tag{1.14}$$

Without loss of generality, I will assume for the rest of this subsection that A and B satisfy $y_A > y_B$ and $x_B > x_A$. That is, A and B are undominated and A is disadvantageous relative to B in terms of the DM's resource. Consider now this choice problem:

$$\max_{p\in[0,1]} U(L(p, A, B)). \tag{1.15}$$

Define p^* to be the solution to this problem. This is the choice problem where DM chooses or not to *share chances* with others and, if $p*$ is a non-trivial probability, we say DM exhibits ex ante fairness seeking behavior.

Proposition 2 (ex ante fairness) In the LP model, if $\delta > 0$, then there exist two outcomes A and B in X such that the corresponding optimal $p*$ satisfies: (i) $p^* \in (0, 1)$, and (ii) for low enough δ, p^* is increasing in x_A, y_A and decreasing in x_B, y_B.

Proof in Appendix A.

Proposition 2 states formally that the LP model exhibits ex ante fairness behavior that manifests in DM's preferences for *sharing chances* with her counterpart. Furthermore, the proposition states that when ex ante forces are present but are not predominant (δ is positive but low enough) DM will react to the attractiveness of (the relatively disadvantageous) outcome A.

Next, I state propositions describing the behavioral predictions of the GEIA model. The core implications of the GEIA model are: (i) risk tolerance correlates positively with ex ante fairness behavior, and (ii) ex post and ex ante fairness concerns trade-off in behavior. Propositions 3 and 4 state these implications formally, and the following discussion provides their intuition and the kind of test we can implement about them with observed behavior.

Proposition 3: In the GEIA model, the optimal tolerance to fair risks, α^{fair*} in problem in expression (1.13), is increasing in the ex ante motives δ_s.

Proof in Appendix A.

Proposition 4: In the GEIA model, the ex post fairness observable measure, $\alpha^{fair*} - \alpha^{unfair*}$, converges to 0 as δ_s goes to 1.

Proof in Appendix A.[21]

These propositions describe how, in the GEIA model, risk taking behavior is affected by the ex ante fairness parameter δ_s. Intuitively, Proposition 3 simply says that the higher is the weight (δ_s) of $u(\mathbb{E}x, \mathbb{E}y)$ in the GEIA utility, the less responsive to risks the DM becomes.

Importantly, while risk attitudes are observable through chosen$\alpha' s$ in decisions like the one problem (1.13), δ_s is not directly observable. For this reason, in Proposition 5, I establish how the parameter δ_s of the GEIA model can be approximated from observed behavior. To see how Proposition 5 operates, I need to define a new choice problem. As in problem (1.15), consider two outcomes A and B, and, without loss of generality, let me assume $B \succ A$. Next, I define the following *deterministic* choice problem:

$$\max_{s \in [0,1]} U(sx_A + (1-s)x_B \, , \, sy_A + (1-s)y_B) \tag{1.16}$$

where s is the weight given to outcome A in the convex combination between A and B. Let s^* be the solution to such problem. Notice that problem (1.16) is a general way to express the standard deterministic Dictator Game. To

see how I use choice problems like the ones in expressions (1.15) and (1.16) to approximate δ_s, consider the simple case where $A = (0, a)$, $B = (b, 0)$. Notice that in the GEIA model, a perfectly ex-ante motivated decision maker ($\delta_s = 1$) will assess

[21]It is important to note that if u satisfies inequity aversion, captured by the same supermodularity property I previously imposed on g, we have that $\alpha^{fair*} > \alpha^{unfair*}$, as in the LP model. Therefore, in such case, $\alpha^{fair*} - \alpha^{unfair*}$ is on average decreasing in δ_s.

any lottery $L(p, A, B)$ only by its expected values – i.e. by looking at $U(L(p, A, B))$= $u(\mathbb{E}x, \mathbb{E}y)$=$u(px_A + (1-p)x_B\,, py_A + (1-p)y_B)$. Therefore, for such a decision maker choosing p in problem (1.15) and choosing s in problem (1.16) are actually the same decision, and so they have the same solution: $p* = s*$. Suppose instead the decision maker is perfectly ex post driven in the GEIA model ($\delta_s = 0$). In such case, $U(L(p, A, B))$= $\mathbb{E}u(x, y)$=$pu(x_A, y_A) + (1-p)u(x_B, y_B)$ and therefore $p* = 0$ as I assumed $B \succ A$. In the in between case ($0 < \delta_s < 1$), and for A and B such that $s* > 0$, we have that $p* < s*$ and that $p*$ increases with δ_s. For that reason, the observable measure $\hat{\delta}_s = p*/s*$ is a good proxy of δ_s that I use to test empirically propositions 3 and 4. Proposition 5 states this formally.

Proposition 5: In the GEIA model, $p*$, the solution to problem in expression (1.15), satisfies:

(i) $p*$ is weakly increasing in δ_s, and

(ii) $p* \in [0,\, s*]$.

Proof in Appendix A.

With the proxy $\hat{\delta}_s$, I can test Proposition 3, the core implication of the GEIA model regarding how risk attitudes are affected by ex ante motives (δ_s). To see how this test works intuitively, consider again the simple case of $\delta_s = 1$. Such a decision maker will always choose $p* = s*$, and, because her utility is $U(L) = u(\mathbb{E}x, \mathbb{E}y)$, she will also choose always $\alpha^{*fair} = 1$. Therefore, individuals that behave as strongly or perfectly ex ante fairness driven ($p*$=$s*$), but at the same time avoid risks to some degree ($\alpha^{fair*} < 1$), are inconsistent with the GEIA model. Furthermore, this test of the GEIA model does not restrict to individuals that exhibit $p* = s*$. Suppose two individuals have the same deterministic preferences u (that can be elicited via decisions in deterministic Dictator Games) and so they both choose the same $s*$, always. Suppose also that, compared to individual 2, individual 1 chooses $p*$ (in problem 1.15) closer to $s*$. This can only mean that he has a higher δ_s and so, by the utility of the GEIA model (equation 1.12), he must tolerate fair risks more than individual 2: $\alpha_1^{fair*} > \alpha_2^{fair*}$. The empirical analogue of Proposition 3 is then that α^{fair*}must correlate with $\hat{\delta}_s$ once we control for deterministic choices. This will be one of the hypotheses I test with experimental data.

1.4 Experiment

In this section, I present evidence from a laboratory experiment designed to jointly study other-regarding preferences (ex ante and ex post fairness concerns, in particular) and attitudes towards risks in a social setup. I focus on studying the empirical correlate of the propositions in Section 1.3.2 that described the choice pattern of ex post and ex ante fairness in the LP model, as well as how risk attitudes interact with fairness motives in the GEIA model.

1.4.1 Design

Individuals in the experiment performed decisions in four different types of tasks. There were eleven decision rounds for each task type. The experimental protocol and the interface in which subjects made all decisions are described in the *procedures* subsection.

Task type 1 – sharing in chances.- This decision environment elicits ex ante motives. Each decision problem of this type gives *decider* two fixed, mutually exclusive (undominated) outcomes e.g. $A = (0, 90)$ and $B = (90, 0)$. Subjects are then asked to allocate probabilities between the two outcomes. Formally, for two given outcomes (x_A, y_A) and (x_B, y_B), each decider was asked to choose $p \in [0, 1]$ to form his preferred lottery $L(p*)$ from this set $\{p\,(x_A, y_A) \oplus (1-p)\,(x_B, y_B) \,:\, p \in [0, 1]\}$. Each decision round had a different pair of fixed outcomes A and B. The graphical interface that was presented to subjects can be seen in Figure 1.2. The full list of specific choices presented to subjects is reported in the first column of table 1.1.

Task type 2 – taking fair-risks.- This task elicit risk attitudes free from fairness concerns. In each choice of this task, subjects decide how much risk to bear in a two-state contingent commodity environment, with the feature that either state of the world (A or B) pays the same amount of money to decider and her counterpart (i.e. marginal risks are perfectly positively correlated). The probability of each state is given and subjects are informed about it. Formally, given p_A, each subject was asked to choose a lottery $L(\alpha)$ from this set: $\{p_A\left(\alpha\bar{Z}\,,\, \alpha\bar{Z}\right) \oplus$

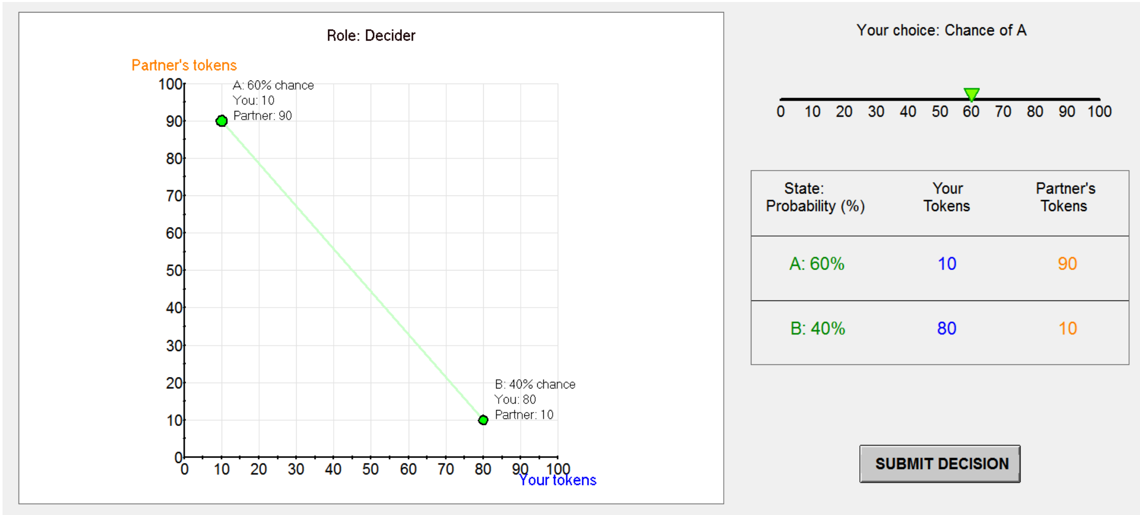

Figure 1.2: Interface of Tasks Type 1: Sharing Chances

$(1-p_A)\ ((1-\alpha)\,\underline{Z}\,,\,(1-\alpha)\,\underline{Z})\}_{\alpha\in[0,1]}$, where $\bar{Z}$ and $\underline{Z}$ denote the maximum total payoff that each agent could potentially obtain in State A and State B, respectively. I am assuming here that state A has always the highest return. In the actual experiment, across choices, the higher return varied from A to B randomly. Each of the eleven decision rounds had a different pair of fixed $\bar{Z}$ and $\underline{Z}$. Six decisions used $p_A = 0.5$, $\bar{Z} \neq \underline{Z}$, three decisions used $p_A \neq 0.5$, $\bar{Z} = \underline{Z}$, and two decisions used $p_A = 0.5$, $\bar{Z} = \underline{Z}$. The graphical interface that was presented to subjects can be seen in Figure 1.3. The full list of specific choices presented to subjects is reported in the first column of table 1.2.

Notice that this choice problem can be interpreted as a two-state environment with two securities or claims (one for each state). Each security pays one token to each agent if the corresponding state is realized. Furthermore, each subject is given a budget and face potentially different relative prices for securities A and B (or *state prices*). If, for example, the given budget is $\bar{Z}$, and price of B-security is 1, then the price of A-security is $\underline{Z}/\bar{Z}$, and the quantities of A-securities and B-securities that is aquired are $\alpha\bar{Z}$ and $(1-\alpha)\,\underline{Z}$, respectively.

Task type 3 – taking unfair-risks.- This task elicits attitudes towards risks with unfair outcomes. Similar to task 2, subjects decide how much risk to bear in a two-state contingent commodity environment. However, in this task, either

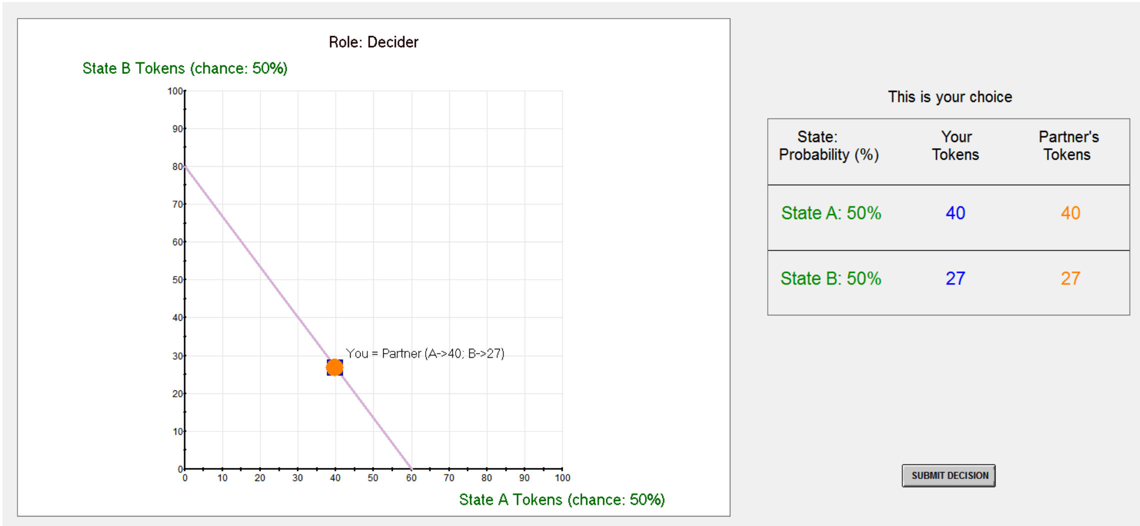

Figure 1.3: Interface of Tasks Type 2: Taking Fair-Risks

state of the world (A or B) pays are unequally to decider and counterpart, unless no risk is chosen to be borne. In fact, marginal risks are perfectly negatively correlated. The probability of each state is given and subjects are informed about it. Formally, given p_A, each subject was asked to choose a lottery $L(\alpha)$ from this set: $\{p_A\left(\alpha\bar{Z}\,,\,(1-\alpha)\,\underline{Z}\right)\oplus(1-p_A)\left((1-\alpha)\,\underline{Z}\,,\,\alpha\bar{Z}\right)\}_{\alpha\in[0,1]}$, where $\bar{Z}$ and $\underline{Z}$ denote the maximum total payoff that the decider (partner) could potentially obtain in State A (B) and State B (A), respectively. Each of the eleven decision rounds had a different pair of fixed $\bar{Z}$ and $\underline{Z}$. Six decisions used $p_A = 0.5$, $\bar{Z} \neq \underline{Z}$, three decisions used $p_A \neq 0.5$, $\bar{Z} = \underline{Z}$, and two decisions used $p_A = 0.5$, $\bar{Z} = \underline{Z}$. As in task type 2, marginal risks are the same between decider and her counterpart. The graphical interface that was presented to subjects can be seen in Figure 1.4. The full list of specific choices presented to subjects is reported in the first column of table 1.2.

Task type 4 – deterministic giving.- It is the standard *riskless giving* decision environment where deterministic other-regarding preferences are elicited in a standard dictator-like game varying the budget and the price of *giving*. Formally, a subject was asked to choose y to form an allocation (x, y) from those satisfying the constraint: $q\,y + x = M$. Across rounds, the price of giving q and the size of the budget M varied. The graphical interface that was presented to subjects can be seen in Figure 1.5. The full list of specific choices presented to subjects is reported in the first column of table

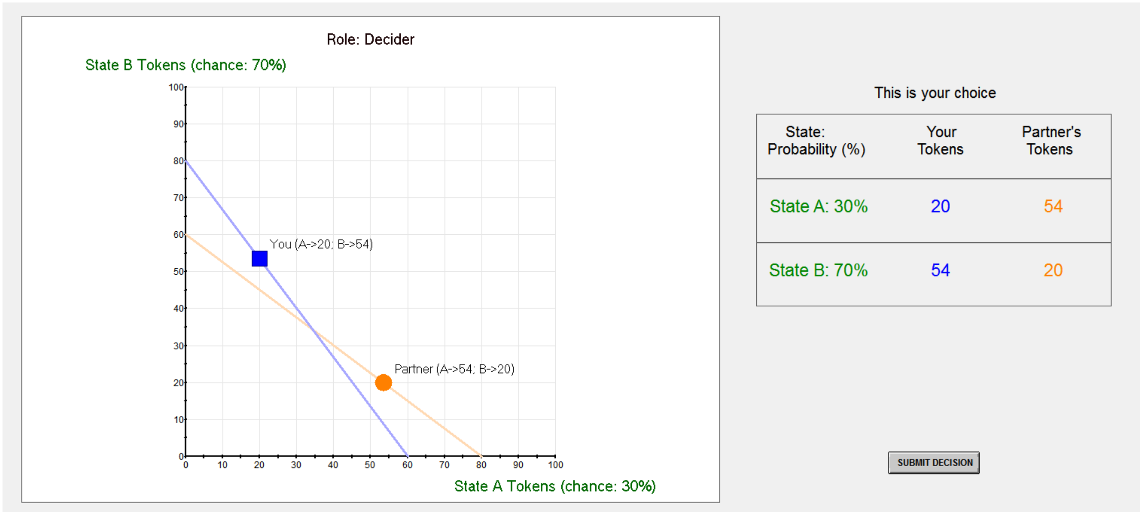

Figure 1.4: Interface of Tasks Type 3: Taking Unfair-Risks

1.3.

1.4.2 Hypotheses

Hypothesis 1 (Ex post fairness): Tolerance to fair-risks (α^{fair}'s from tasks 2) is higher than tolerance to unfair-risks (α^{unfair}'s from tasks 3).

This hypothesis states the prediction of Proposition 1.

Hypothesis 2A (Ex ante fairness): Subjects exhibit ex ante fairness behavior: they commonly choose non trivial probabilities, $p \in (0, 1)$, in tasks of type 1.

Hypothesis 2B (Ex ante fairness): Ex ante fairness behavior (probabilities p chosen in tasks of type 1) respond positively to the relative benefits of helping a partner. That is, p is increasing in $\frac{y_A - y_B}{x_B - x_A}$.

Together, these two hypotheses state the predictions of Proposition 2. While existing evidence already indicates ex ante fairness is a common behavior, and so Hypothesis 2A is backed by evidence, further characterization of how individuals trade-off this motive with other motives – like the one stated in Hypothesis 2B – has not been studied in detail.

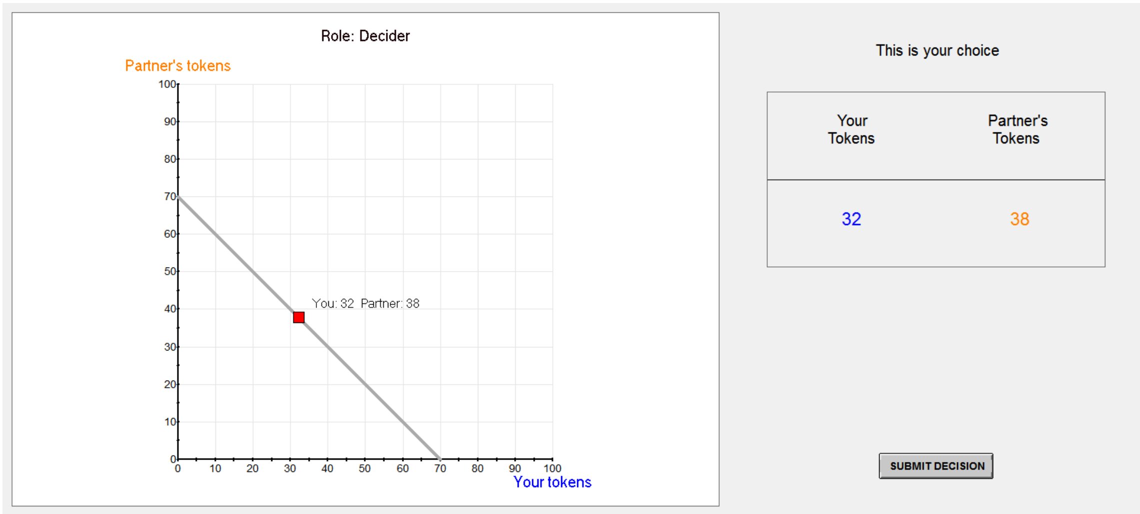

Figure 1.5: Interface of Tasks Type 4 - Deterministic Giving

Table 1.1: Statistics - Task Type 1 - Sharing Chances

Decision Rounds Outcomes A, B	$-\frac{y_A - y_B}{x_B - x_A}$	$Pr[A]$	$s.e.$
A:(10,60); B:(80,30)	-0.43	11.09	2.61
A:(10,45); B:(80,10)	-0.50	19.65	4.09
A:(0,90); B:(90,0)	-1.00	17.55	3.76
A:(10,80); B:(80,10)	-1.00	19.62	4.12
A:(10,50); B:(50,10)	-1.00	21.75	4.07
A:(30,60); B:(60,30)	-1.00	22.85	3.71
A:(10,80); B:(45,10)	-2.00	30.29	4.57
A:(30,80); B:(60,10)	-2.33	28.02	4.39
A:(10,80); B:(45,45)	-1.00	10.33	3.09
A:(45,45); B:(80,10)	-1.00	36.78	5.43
A:(30,30); B:(60,60)	1.00	8.96	2.82

Table 1.2: Statistics - Tasks 2, 3 - Taking Fair and Unfair Risks

Decision Rounds	$R = \frac{Pr[B]\, I_B}{Pr[A]\, I_A}$	z_A Task 2	z_A Task 3	Safe Choice
Pr[A]=50%; I_A=100; I_B=25	0.25	51.6	47.1	20.0
Pr[A]=50%; I_A=75; I_B=37.5	0.50	39.5	33.4	25.0
Pr[A]=50%; I_A=90; I_B=66	0.73	48.8	44.7	38.1
Pr[A]=50%; I_A=50; I_B=50	1.00	25.5	25.9	25.0
Pr[A]=50%; I_A=76; I_B=76	1.00	38.9	38.6	38.0
Pr[A]=50%; I_A=66; I_B=90	1.36	30.5	35.2	38.1
Pr[A]=50%; I_A=37.5; I_B=75	2.00	18.6	21.2	25.0
Pr[A]=50%; I_A=25; I_B=100	4.00	10.4	13.1	20.0
Pr[A]=70%; I_A=60; I_B=60	0.43	39.5	38.9	30.0
Pr[A]=30%; I_A=60; I_B=60	2.33	18.5	21.3	30.0
Pr[A]=90%; I_A=60; I_B=60	0.11	52.4	47.5	30.0

Notes:

Table 1.3: Statistics - Tasks 4 - Deterministic Giving

Budgets	$\frac{P_y}{P_x}$	Decider $\bar{x}$	Decider s.e. x	Partner $\bar{y}$	Partner s.e. y	$\frac{\bar{x}}{\bar{y}}$
Max X=25; Max Y=100	0.25	17.12	1.06	31.32	4.26	1.83
Max X=37.5; Max Y=75	0.50	26.41	1.35	22.23	2.7	0.84
Max X=65; Max Y=100	0.65	46.96	2.32	27.72	3.58	0.59
Max X=66; Max Y=90	0.73	46.17	2.36	27.08	3.22	0.59
Max X=50; Max Y=50	1.00	33.65	1.61	16.43	1.61	0.49
Max X=76; Max Y=76	1.00	54.73	2.21	21.3	2.21	0.39
Max X=90; Max Y=90	1.00	65.32	2.89	24.72	2.9	0.38
Max X=100; Max Y=65	1.54	70.5	3.63	19.26	2.36	0.27
Max X=90; Max Y=66	1.36	67.39	2.89	16.62	2.13	0.25
Max X=75; Max Y=37.5	2.00	53.16	2.86	11.03	1.43	0.21
Max X=100; Max Y=25	4.00	72.3	4.15	7.03	1.04	0.10

Hypothesis 3 (GEIA - ex ante vs risk tolerance): Tolerance to fair risks (α from tasks 2) correlates positively with ex ante fairness seeking behavior (choices from task 1 and the proxy of δ_s).

This hypothesis provides the empirical test of Proposition 3, where δ_s is approximated following the result in Proposition 5.

Hypothesis 4 (GEIA - ex post vs ex ante): The measure of ex post fairness, $\alpha^{fair} - \alpha^{unfair}$ (from tasks 2 and 3) decreases with stronger ex ante fairness seeking behavior (choices from task 1 and the proxy of δ_s).

This hypothesis provides the empirical test of Proposition 4, where δ_s is approximated following the result in Proposition 5.

1.4.3 Procedures

Interface:

The experiment used a graphical interface for all decisions. Tasks of type 1 were presented as shown in Figure 1.2. In such a screen, deciders are informed about the two outcomes (in tokens) by means of a graph and a table. They were then asked to use a *slider tool* to choose the probability of allocation (x_A, y_A). Tasks of types 2 and 3 were presented as shown in Figures 1.3 and 1.4. In such screens, deciders are informed about the odds of each state (in percentage terms). They were then asked to drag with the mouse the shapes that determine the lottery for herself (blue square) and for her counterpart (orange circle). Tasks of type 4 are the standard Dictator Game, shown in Figure 1.5. Interface design for tasks 1 is novel. Interface design for tasks 2-4 are similar to those used in Choi et al. (2007) and Fisman et al. (2007).

Sessions and Protocol:

The experiment was run at the Experimental Economics Laboratory at the University of Maryland (EEL-UMD). The program was coded in z-Tree (Fischbacher, 2007). For a total of 7 sessions, 110 undergraduate students were recruited via EEL-UMD's online recruitment system. A session took about 60 minutes, in which every subject was asked to make choices in a series of decision rounds. At the start of a session, pairs were formed by anonymous matching. In a pair, one subject was assigned to the role of *decider* and the other subject was assigned to the role of *partner*. Both pairing and role assignment were done randomly, and they remained fixed for the entire session. Subjects were informed of their role at the start of the interaction, before any decision was made. For each pair, both the decider and partner were posed the same decision problems, however, only the choices made by the decider determined the payoffs.

The order in which tasks were presented within a session was randomized to eliminate order effects. Also, for each task, subjects were posed eleven decision problems ("decision rounds"). The order in which each round appeared was also randomized. At the end of the session, subjects were paid according to one randomly selected decision made by the decider plus a fixed participation fee of 5 USD. Exchange rate was 1 USD for every 5 experimental tokens. The experimental instructions can be found in Appendix A, Section A.2.

1.5 Results and Discussion

Result 1 (Ex post fairness): Ex post fairness considerations affect risk taking behavior. In particular, tolerance to fair-risks is higher than tolerance to unfair-risks.

To build a measure of risk tolerance in each choice of the contingent commodity settings (tasks of types 2 and 3), I use the proportion of a given budget that is allocated to the high return security normalized by the perfectly safe choice. Formally, if I_A and I_B represent the intercepts of the budget line with the axes for State A and B, respectively, then our risk tolerance measure is:

$$\hat{\alpha} = \frac{z_{high} - Safe}{\bar{Z} - Safe} \tag{1.17}$$

where z_{high} is the amount of high-return security chosen by the decider, $\bar{Z} = \max\{I_A, I_B\}$ and:

$$Safe = \left(\frac{1}{I_A} + \frac{1}{I_B}\right)^{-1} \tag{1.18}$$

If $I_A \neq I_B$, it can be seen that $\hat{\alpha} = 0$ when DM is perfectly risk averse; and $\hat{\alpha}$=1 when she is (highly) risk neutral. I use this measure to compute two different Indices of risk tolerance. Consider this example to see how $\hat{\alpha}$ is a measure of tolerance to uncertainty. Suppose $I_A = 6$ and $I_B = 3$. By equation (1.18), $safe = 2$. If, for example, DM takes a big risk and chooses 5 units for state A and only 0.5 units for State B (i.e. $z_{high} = 5$). Then $\hat{\alpha} = \frac{5-2}{6-2} = 0.75$. If, instead, DM chooses a more conservative $z_{high} = 2.1$, then $\hat{\alpha} = 0.025$.

In Risk Tolerance Index 1 (RTI_1), I averaged at individual level all $\hat{\alpha}$'s from choices that induced tension between risks and returns (i.e. $I_A \neq I_B$). There were 9 of such choice problems see Table 1.2. In the second index, Risk Tolerance Index 2 (RTI_2) I used only $\hat{\alpha}$ from the choices that implied the highest tension between risks and returns ($\bar{Z}/\underline{Z} = 4$). This occurred in two choice problems of task 2. I follow the same procedure for tasks of type 3 (unfair risks).

I compare RTI_1 obtained from behavior facing fair risks (tasks of type 2) and behavior facing unfair risks (tasks of type 3). I find $RTI_1^{unfair} = 20.23$ (s.e. 3.67) and $RTI_1^{fair} = 30.45$ (s.e. 3.99). That is according to this index, tolerance to fair risks is nearly 50% higher than to unfair risks. The difference is statistically different in simple one-sided mean tests (p=0.0023) as well as in sign-rank test (p=0.0007). This result is robust to alternative formulations of risk tolerance, such as RTI_2. Figure 1.6 shows that the comparison of histograms between RTI_1 in tasks of type 2 vs tasks of type 3. It can be seen that when risks are ex post unfair, more subjects decide to avoid risks almost completely, as my model predicts.

Result 2 (Ex ante fairness): Helping partners probabilistically – i.e. exhibiting ex ante fairness behavior – is a common behavioral pattern (Hypothesis 2A). Furthermore, this conduct responds to the relative benefits of helping a partner. This is, if A is Decider's comparatively disadvantageous outcome, chosen p_A^* is increasing in the relative benefits of A over B: $\frac{y_A - y_B}{x_B - x_A}$ (Hypothesis 2B).

This result utilizes only choices from tasks of type 1 (*sharing chances*). Choices from these tasks confirm that ex ante fairness concerns are an important force in these environments. Considering only choices involving undominated outcomes (first 10 rows of Table 1.1), subjects assigned a positive probability to the disadvantageous

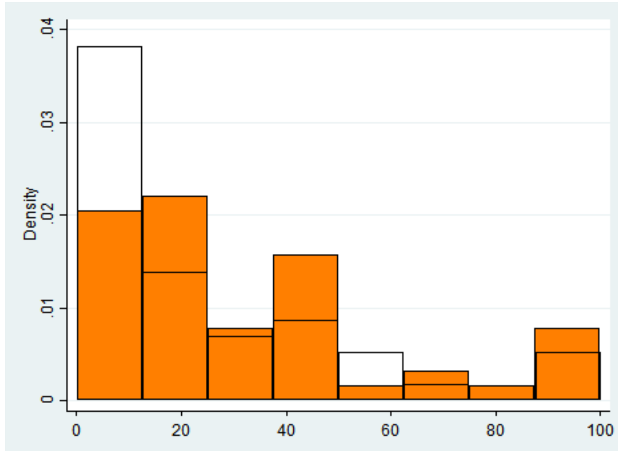

Figure 1.6: Tolerance to fair risks (orange) and unfair risks (white)

outcome in 46% of all choices. Further, 40 out of 55 deciding subjects (72%) gave a positive probability to the disadvantageous outcome in at least one choice of this task.

The second part of Result 2, is fully reported in Table 1.1. The first column of this table describes each choice by stating the two outcomes A and B.[22] The second column indicates the substitution rate of expected values, $\frac{y_A - y_B}{x_B - x_A}$. That is, *how much partner's expected dollars increase when decider gives up one expected dollar*; which is a broad measure of the benefits achieved by each (expected) dollar decider sacrifices to help the other. The third column indicates the average probability deciders gave to outcome A. In this table that outcome A is always the more advantageous to partner side.[23] Also, all up to row 8, this table is sorted by the substitution rate.

With this information, we can see that subjects, on average, responded strongly to the relative benefit of sharing in probabilities. When giving up one expected dollar implied only a 0.43 increase in partner's expected dollars, deciders gave to outcome A a probability of only 11.1% (1st row). When instead the relative benefit was 2.33, the probability of outcome A went up to 28%, on average (8th row of the table). This difference is statistically significant (p-value<0.01). Rows 3-6 of this table shows choices where the relative incentive to share chances (in column 2) is constant and always 1. Instead, across these choices, the experimental design varied the degree of

[22] E.g. "A:(10,60); B:(80,30)" means: if outcome A realizes, Decider gets 10 tokens and Partner gets 60. And if outcome B realizes Decider gets 80 tokens and Partner gets 30.

[23] In the experiment outcomes labels were allocated randomly.

risk. Data shows subjects shared more chances when the was less risk involved. For this choice A:(0,90); B:(90,0) subjects shared on average only 17.5% (row 3). However, when facing these outcomes A:(30,60) and B:(60,30) they shared 22.9% (row 6). The latter being statistically higher (p-value<0.05). Interestingly as well, comparing rows 9 and 10 of the same table, we observe subjects shared substantially more chances if helping others also involved increasing the odds of a perfectly fair outcome (row 10 – 32.8%) as opposed to when it involved moving away from it (row 9 – 10.33%).

The last choice reported in this table is a rationality check. Outcomes for this choice are A:(30,30) and B:(60,60) implying that rational subjects can only choose Prob[A]=0. We instead find that 11 subjects assigned a positive probability. Although on average this probability is 8.9%, it is mostly driven by five subjects that gave 50%. This result is somewhat striking given how consistent and well behaved results are on average. One possible explanation is that because all ten of the other choices presented undominated outcomes, some strongly ex ante fairness oriented subjects might have mixed this choice with the one involving outcomes A:(30,60) and B:(60,30). Four of these five subjects gave 50% in both of these choice problems.

Result 3 (GEIA - ex ante vs risk tolerance): Tolerance to fair-risks does not relate positively to ex ante fairness seeking behavior as the GEIA model predicts.

To test Hypothesis 3, I estimate a series of regressions where the dependent variable is a measure of tolerance to fair risks, and the main regressors is a measure of the strength of ex ante fairness behavior, a proxy of delta. The GEIA model, as a core implication, prescribes that individuals with stronger sense of ex ante fairness will necessarily become less sensitive to risks, my model predicts they do not relate. I use the same measures of risk tolerance utilized and described in Result 1, the Risk Tolerance Indices 1 and 2 (RTI_1 and RTI_2).

As independent variables, where I need a proxy of ex ante fairness motives, I use the following regressors. According to Proposition 5, I built a proxy of δ_s based on the comparison between what is *given* deterministically (s*) and what is given probabilistically (p*) in a task with the same pie size and relative prices. I use the deterministic task with the constraint $x + y = 90$; and the probabilistic task with outcomes $A : (0, 90)$ $B : (90, 0)$. The proxy for δ_s is then $\hat{\delta_s} = Pr[A] * 90 - y$.

I also run specifications where I directly use as regressors choices from the tasks of type 2 (ex ante fairness), using as controls choices from tasks 4 (deterministic giving). These variables are reported in the regression Tables 1.4 and 1.5 as "ex ante fairness Indices" and "deterministic giving". [24]

Results from Tobit regressions are reported in Tables 1.4 and 1.5. In the first table, dependent variable is RTI1 and in the second table is RTI2. In both cases, the first five rows contain ex ante fairness variables (our variable of interest). In all these regressions, there is no statistical indication of a positive relation between stronger ex ante fairness behavior (giving more chances) and tolerating risks more. Hypothesis 3 is rejected.

Result 4 (GEIA - ex post vs ex ante): Ex post fairness behavior does not correlate negatively with ex ante fairness behavior, regardless we control or not for deterministic preferences.

To test hypothesis 4, I run a regression where the dependent variable is $RTI_1^{fair} - RTI_1^{unfair}$ and the independent variable is the proxy of δ_s constructed for Result 3. Testing the hypothesis that the sign of the corresponding coefficient in this regression is negative is rejected ($p<0.05$).

From results 3 and 4, I conclude the following about the GEIA model. Although the GEIA model predicts ex ante fairness behavior, its core implications regarding how risk attitudes relate to fairness behavior do not hold in observe behavior. I interpret this as evidence favoring my model since these results imply that a formulation of ex ante fairness solely based on first moments do not match the data. And therefore we need a model the considers further moments, like mine.

[24] In these regressions, "Ex ante fairness index 1" equates to chosen p* when A=(0,90); B=(90,0); "Ex ante fairness index 2" equates to average chosen p* among choice problems where relative expected benefit of A over B equals 1; "Ex ante fairness index 3" equates to average chosen p* among choice problems where relative expected benefit of A over B is below 1; and "Ex ante fairness index 4" equates to average chosen p* among all choice problems where neither A or B dominate the other outcome in first order stochastic sense. "Deterministic Giving 1 - 4" in those regressions, correspond to the analogous choices except for tasks of type 4.

Table 1.4: Tobit Regr. - Attitudes Towards Fair Risks - RTI_1

	(1)	(2)	(3)	(4)	(5)	(6)
Delta Proxy	0.089					
	(0.141)					
Ex-ante fairness index 1		-0.153				
		(0.162)				
Ex-ante fairness index 2			-0.068			-0.279
			(0.300)			(0.298)
Ex-ante fairness index 3				-0.012		0.275
				(0.288)		(0.297)
Ex-ante fairness index 4					-0.053	
					(0.342)	
Det. Giving 1		-0.036				
		(0.217)				
Det. Giving 2			-0.205			-1.366***
			(0.424)			(0.408)
Det. Giving 3				0.326		0.923*
				(0.400)		(0.502)
Det. Giving 4					-0.020	
					(0.486)	
Constant	29.706***	33.826***	36.005***	21.959***	31.885***	31.668***
	(4.589)	(6.086)	(6.981)	(7.140)	(7.378)	(6.664)
Pseudo R2	7.0e-04	1.9e-03	1.8e-03	4.9e-03	1.7e-04	.033
N	55	55	55	55	55	55

Notes: See text for detailed construction of depvar. All Tobit regressions used LL=0 and UL=100. Standard errors in parentheses. Significance: * 0.10; ** 0.05; *** 0.01.

Table 1.5: Tobit Regr. - Attitudes Towards Fair Risks - RTI_2 (Robustness)

	(1)	(2)	(3)	(4)	(5)	(6)
Delta Proxy	0.073					
	(0.182)					
Ex-ante fairness index 1		-0.363*				
		(0.194)				
Ex-ante fairness index 2			-0.117			-0.294
			(0.366)			(0.372)
Ex-ante fairness index 3				-0.226		0.200
				(0.356)		(0.347)
Ex-ante fairness index 4					-0.258	
					(0.438)	
Ex-post fairness index 1		-0.524*				
		(0.309)				
Ex-post fairness index 2			-0.921			-2.496***
			(0.563)			(0.616)
Ex-post fairness index 3				0.285		1.342**
				(0.455)		(0.602)
Ex-post fairness index 4					-0.440	
					(0.607)	
Constant	44.979***	64.586***	67.127***	44.394***	60.100***	61.547***
	(6.933)	(10.749)	(12.089)	(10.969)	(12.219)	(10.931)
Pseudo R2	2.5e-04	.015	.013	1.4e-03	5.9e-03	.042
N	55	55	55	55	55	55

Notes: See text for detailed construction of depvar and regressors. All Tobit regressions used LL=0 and UL=100. Standard errors in parentheses. Significance: * 0.10; ** 0.05; *** 0.01.

Further Descriptive Results

Taking fair and unfair risks (task types 2 and 3)

Table 1.2 reports summary statistics from choices in tasks 2 and 3. The first column details the choice problem. For example, the first choice: "Pr[A]=50%; Max A=100; Max B=25" represents the choice problem where State A occurred with 50% probability and paid a maximum of 100 tokens and where State B pays a maximum of 25 tokens.[25] The second column shows the probability adjusted price of a State A security relative to a State B security. In the first row of the table, for example, the price of A-security is 1/4 of the price of B security. The third and fourth columns show how many State A securities decider bough in choice problems of Tasks 2 and 3, respectively. The fifth column in this table shows what a perfectly risk averse agent would choose in each choice problem. Table 1.2 is sorted by the relative price (column 2) all up to the 9th row which includes choices with 50-50 States. We see in the behavior of all these 9 choice problems two stylized conducts. First, that subjects responded to the risk / return tension as standard theory predicts: when securities were priced the same, on average, no risk was taken. When one security offered a higher return than the other by having lower relative price, some risk was taken towards the high return security.

More importantly, exactly as Result 1 states, we can observed that every time there was a risk/return tension (all choices except choices in rows 5 and 6) deciders took more risk in Task 2 than in Task 3. We can observe that by realizing that in all such cases, the quantity of State A-securities of Task 3 is closer to the the perfectly risk averse (*safe*) choice of column 5.

Deterministic Giving (Task Type 4)

Table 1.3 the results of the deterministic giving task. The first column details the budget intercepts at Decider's axis (X) and at partner's (Y). The second column shows the relative price of giving: Py/Px. Columns 3 and 5 report the average amount in tokens deciders allocated to themselves ($\bar{X}$) and to partners ($\bar{Y}$), respectively. Column 7, reports the ratio $\bar{Y}/\bar{X}$. Again, on average, behavior in this tasks strongly conforms

[25] In notation from our propositions: $\bar{Z} = 100$ and $\underline{Z} = 25$ in this example.

to standard consumer theory. When *giving sure dollars* is very cheap relative to *keeping* them, Py/Px=0.25, subjects give partners about 1.8 times what they keep for themselves. On the other side of the price range, if the price of giving relative to keeping is 4, subjects pass one tenth of what they keep (see last row of Table 1.3).

1.6 Conclusions and Research Agenda

My paper studies two important questions involving risk attitudes and other-regarding preferences. First, I asked whether or not risk attitudes are affected by the regard for others – and if so, how. Second, I asked how fairness concerns operate under uncertainty. In particular, what drives ex ante fairness. To answer these questions, I propose an integrated model of risk attitudes and social preferences. This model, which I name the LP model, extends the standard notion of inequality discount to lotteries assuming an individual makes a comparative assessment of the marginal risks she and others face. Following the intuition of ex post fairness, the LP model predicts a higher tolerance to risks with positively correlated outcomes compared to tolerance to risks with negatively correlated outcomes. Importantly, my model is capable of explaining ex ante fairness behavior manifested in people's preferences for helping others probabilistically. I also briefly present and study the core implications of the *expected inequality aversion (EIA)* model (Saito, 2013) that are at odds with my model.

I report on an experimental study of my model's predictions as well as of the distinctive implications of the EIA model. I find that social considerations impact risk attitudes: subjects take substantially more risks when outcomes were ex post fair compared to when they were ex post unfair. To the best of my knowledge, mine is the first lab experiment that precisely measures the impact on risk taking behavior of ex post fairness considerations. This result is important because previous experimental literature (Brennan et al., 2008; Bolton and Ockenfels, 2010; Rohde and Rohde, 2011) had claimed the impact of social considerations on risk attitudes was virtually null.

I also confirm ex ante fairness behavior is a common choice pattern and document how, according to the model, this motive responds to the attractiveness of the outcomes involved. Finally, I also studied the core implications of the EIA model concluding that, although this model is capable of explaining ex ante fairness behavior its predicted positive link between risk tolerance and ex ante fairness does not hold in observed behavior.

There are several directions in which the literature on this topic can expand. My model and experimental findings have important implications for our theoretical understanding of economic interactions that involve risks and that are prompt to social comparisons, calling for an extension of our current modeling approaches in such contexts. Think of a tournament, for example, where risk attitudes and fairness concerns have been studied separately and found to be important forces for behavior and achieved efficiency. My model offers a framework to study those two forces jointly, accounting for their interaction.

At a more aggregate level, my model sheds some light on how risk taking behavior might vary across the income distribution. In particular, it predicts that, other things constant, higher risk taking behavior will be observed among individuals at the tails of the distribution compared to individuals in the middle.

Chapter 2

On the Demand for Expressing Emotions[1]

2.1 Introduction

There is a simple but important puzzle regarding the communication that occurs in many face-to-face economic interactions: the amount of communication we see in real life far exceeds the amount of content flow our standard economic theories predict. If we pay attention to a negotiation process between two strangers in a flea market, we would probably observe a lot of back and forth—sometimes even of seemingly unrelated topics—while our models predict mostly no communication in such environments.

This gap in our understanding mainly emerges because current economic models leave out some fundamental purposes that communication has in reality. Our standard approach sees communication as fundamentally instrumental in the sense that it is capable of altering material outcomes. In particular, the most standard models predict that communication will transmit effective content only when parties' interests are at least partially aligned (Crawford and Sobel (1982) and Farrell and Rabin (1996)). In conflict situations (such as bargaining) there will be no meaningful content

[1]This paper is coauthored with Brit Grosskopf (University of Exeter, UK). The authors would like to thank James Konow, Erkut Ozbay, Elke Renner and John Shea for valuable comments, and seminar participants at the Universite de Cergy–Pontoise, George Mason University, Loyola Marymount University, University of Nottingham, University of Zurich and the audience at the North–American ESA Meeting, 2013 in Santa Cruz. Financial support from the NSF under grant SES 1321 1025034 is gratefully acknowledged.

flow. However, this view clearly contrasts with our human intuition that commonly utilizes communication with broader strategic purposes than those contemplated in this orthodox view and that often perceives communication as being a good or a bad in and of itself.

Previous experimental literature has already presented evidence of broader strategic uses of communication in bargaining environments. Galinsky and Mussweiler (2001) and Andreoni and Rao (2011) all document instances in which communication commonly favors the speaker in the material allocation. These studies further imply that people are somewhat aware of some behavioral reactions to communication and are able to exploit those biases to achieve better material positions. Persuadability, over-reaction to information, and empathy sensitivity are some of the mechanisms in play.

Economic studies of the type of communication that has no further material implications (for example, because it takes place after the allocation is determined) has been minimal. Existing studies document that this kind of expression in bargaining environments is a likely behavior and its anticipation does in fact change material outcomes. However, there is no systematic study of its full economic value: how much is this type of expression possibility worth? To the best of our knowledge ours is the first study to answer this question. In particular, we study a type of expression and environment that have been linked to mood and emotional states in previous studies: unidirectional, ex-post verbal expression in bargaining-like settings. Brain scans, self–reports as well as physiological measures of emotional arousal support the idea that bargaining environments are indeed charged with emotional states.[2] Xiao and Houser (2005) and Xiao and Houser (2007) document that verbal expression in ultimatum and dictator games is likely to emerge as an expression of emotions. Importantly, while the existing research relates emotion and mood to communication observed in bargaining interactions, it has not yet been established what motives drive such expressions or how exactly they affect traditional measures of welfare as well as subjective well–being. Our research tries to address these questions as well.

We implement in the laboratory a modified version of the Power–to–Take game

[2]E.g. Pillutla and Murnighan (1996); Bosman and Van Winden (2002); Sanfey et al. (2003); De Quervain et al. (2004); Reuben and Van Winden (2005); Ben-Shakhar et al. (2007). Note that we often use 'emotional state' to refer what psychologists more accurately call 'feeling state'. That is, the situation where a subject experiences a 'feeling of' a certain emotion.

(PTT, hereafter). This is an asymmetric bargaining environment where previous research has identified strong emotional–mood changes experienced by the vulnerable side (e.g., Bosman and Van Winden (2002)). In our experiment, each subject first earns money in a real effort task. Then, subjects are randomly matched to one another and assigned roles, T and R. Role T (the *taker*) is given the authority to withdraw a percentage of the counterpart's labor income, while role R (the *responder*) is only asked to guess what percentage that will be. All treatments share this interaction, but differ in what comes afterwards. To study the broad value of expression, we elicit in our main treatment R's valuation of sending an ex–post verbal message to the taker. To isolate the purely expressive motives from the reciprocal ones, we implement a treatment where a third party – not the taker – is the recipient of the message. We also implement some additional treatments to check the robustness of our findings.

Our evidence confirms that people value the ability to express and are willing to pay significant amounts of money for it. Purely expressive and reciprocal motives are both nontrivial components of this valuation. We show that when expression is allowed the vulnerable side experiences a smaller decrease in subjective well–being. This suggests that beyond the instrumental purposes expression can have a real impact on well–being in economic interactions. This can be useful for further theoretical modeling, in particular, the design of institutions.

The chapter is organized as follows: Section 2.2 discusses the related literature on the topic as well as some theoretical considerations. Section 2.3 details the experimental design and Section 2.4 presents and discusses our results. We conclude with some final remarks in Section 2.6.

2.2 Conceptual Framework and Literature

This section presents the predominant conceptual framework of communication and expression in economics. It summarizes the literature that studies the presence of mood and emotional elements in economic interactions and discusses the previous studies of expression in bargaining setups.

2.2.1 Communication and Expression in Economics

Communication in economic interactions has been long studied for its instrumental purposes, that is, for how it can alter play and therefore impact material outcomes. Within this approach, the most standard view states that agents in strategic interactions with material interests will use communication in an attempt to coordinate actions or to shape the opponent's beliefs about his/her own private information. For communication that is costless and occurs before and during play, i.e. *cheap talk*, it has been shown that the more incentives are aligned and the bigger the coordination surplus, the more informative and welfare improving communication becomes. Although these theories predict a multiplicity of equilibria, reasonable refinements predict informative equilibria to be among the most likely (e.g. Crawford and Sobel (1982); Farrell and Rabin (1996) and Charness (2000)).

This view, however, predicts that in environments where agents' interests are perfectly opposed to one another – such as in fixed–pie bargaining situations – communication will convey virtually no information and will not have an impact on material allocations. Experimental evidence shows otherwise and suggests that communication can have instrumental purposes even in such situations. Allowing expression can sway opponents' motivations through different channels often bringing benefits to the "speaking" side. For example, in an experimental bargaining setup, Croson et al. (2003) find that under imperfect information, lies and threats do have an impact on the material surplus distribution. In a similar setup, Galinsky and Mussweiler (2001) find that, by stating a high initial price, a party at a negotiation might *anchor* the range of counter offers at a higher level than otherwise possible. They refer to the same type of anchoring effect first discussed by Tversky and Kahneman (1974). Another relevant instance is provided by Andreoni and Rao (2011) who document that even in a Dictator Game, the party that is able to issue a pre–play message gets a higher material payoff. The authors point out that from the perspective of the receivers, communication is a social cue capable of activating altruistic behavior by heightening empathy.

Less research exists within economics regarding types of communication that have direct welfare implications without necessarily affecting the distribution of resources. We use the term noninstrumental for this type of communication and the verbal expression we study in this paper mostly lies in this category.[3] Two potentially relevant sources of noninstrumental communication are mood and emotion. Although these are in effect partially incorporated in any utility–based theory, some essential features of their functioning inform further extensions of our more standard models. In particular, they could explain part of the observed noninstrumental communication and give reasons why noninstrumental communication can be important for welfare outcomes. In fact, as we shall see later in this section, the evidence for the presence of mood and emotions (and their expression) in bargaining environments is growing. Therefore, a more precise look into how they affect welfare is needed. The rest of this section briefly discusses the approaches and evidence related to mood, emotion and noninstrumental expression in economics.

2.2.2 Emotions and Mood

Although there is still debate on the definition and approaches to emotions, most psychologists would agree that emotions are mechanisms that involve reactions in brain, mind and body. The degree to which cognition (the subjective appraisal of the situation), other neurological activity or bodily changes are regarded as the essential part of these processes, is the main difference between different theories of emotion. In most approaches, however, we find the following main features or components: emotions have *aboutness* (or *intentionality*) and *valence. Aboutness* means that an emotion occurs in reference to an event or some stimulus, and *valence* that emotions are not typically experienced as neutral; instead, they take a position on a pleasure–pain scale. They also present *action tendencies* in that they make certain behaviors more likely to occur during the emotional episode. This highlights another important feature: emotions are temporary processes where the mechanism involved is active for a finite, often short span of time.[4] Mood, on the other hand, is intimately linked

[3] Although it is a broader term that encompasses many ways in which internal and subjective states are reflected in behavior, we use *expression* mainly as interchangeable with *noninstrumental communication*.

[4] For a discussion on definitions and essential features of emotions see Frijda (1986); Ekman (1994); Oatley et al. (2006). Another important dimension that has long received attention in the definition and characterization of emotions is the degree to which they are more innate and less cognition-based mechanisms. What the literature has termed as *basic emotions* (e.g., Plutchik (1980); Ekman (1992)) commonly refers to these more automatic mechanisms that emerged earlier in human evolution.

to the feeling of emotions for it is a signed mental state. However, it has received less detailed study because it is less traceable to specific mechanisms, stimuli, and behavior. Mood, in general, involves more awareness and lower arousal levels than a typical emotional episode. As a mostly conscious state, moods are active for longer spans of time. Similar to emotion, moods have *valence* and *tendencies*: they have a sign as they are most commonly perceived nonneutral, and they make certain behavior more likely while they last. Finally, they operate more as a background state where past or anticipated stimuli or thoughts are all combined or synthesized (Dingman (2008)).

In the economics literature, progress has been made in extending the standard model to incorporate emotions and mood. Elster (1998); Loewenstein (2000); Rick and Loewenstein (2007) and Manzini and Mariotti (2011) are examples of this advance. Given that the incorporation of these elements in our modeling implies abandoning the idea that motives are invariant, a big challenge this literature faces is separating the actual influence of mood and emotion on decision–making from other sources of indeed inconsistent behavior. Rick and Loewenstein (2007), for example, categorize emotions according to how they operate on decision making. Their first category, *expected emotions*, refers to the expected collateral psychic value of each alternative, the emotional states that an outcome provides along with those benefits directly caused by the realization (consumption) of the outcome. This is already assumed in the standard model. A second category, and new to the standard model, comprises of emotions experienced at the moment of the decision–making and occurring only in relation to it. These are called *integral immediate emotions*. Finally, there are emotional states whose origin is unrelated to the choice but happen to occur at the same moment of decision–making and affect it. Rick and Loewenstein (2007) call these *incidental immediate emotions*. Manzini and Mariotti (2011) incorporate this last category into their model of *moody choice*. They propose a formal extension of the revealed preference approach to incorporate mood–influenced decision making into the standard model. Their main contribution is giving content to the broad idea that, unlike indecisiveness or plain randomness, mood must have a signature pattern when it shapes decisions, and choice data should reflect that. They narrow down the type of data and tests that help identify this influence.

2.2.3 Previous Research on Emotions and Bargaining

This subsection presents in more detail the previous experimental research on emotions and expression in bargaining environments. A series of studies have documented mood and emotion reactions in such environments, especially among the disadvantaged party. Pillutla and Murnighan (1996) document that feelings of anger and spite are common among responders in ultimatum games. Sanfey et al. (2003), using fMRI scans, find that responders who reject unfair offers presented higher activity in the anterior insula, a brain area associated with disgust. De Quervain et al. (2004) observe that effective punishment in the ultimatum game activates a brain area implicated in processing rewards, indicating that punishment gives actual satisfaction.

Bosman and Van Winden (2002) study behavior and emotions in a two–player Power–to–Take game. In their design players earn income in an individual effort task preceding the game. Then, one player can claim any proportion of the other's income. The second player can respond by destroying a percentage of his/her own income in order to reduce the amount actually transferred. They find that a higher *take rate* by the first player increases (decreases) the intensity of negative (positive) emotions experienced by the second player, and that negative emotions drive destruction. At high emotional intensities, responders have the tendency to destroy everything. In the same environment, Reuben and Van Winden (2005) report feelings of shame and guilt among takers. The authors also find an important asymmetry: responders that punished others who treated them badly do not always treat others nicely when they switch positions in later rounds. Pure social preference motives are inconsistent with this, since such motives would predict a certain symmetry in the behavior of the same subject across roles. Their evidence is not compatible with self–serving biases as the cause of this asymmetry. Therefore, this behavior might be induced by immediate emotions that are specific to the type of choice that proposers and responders make.

Ben-Shakhar et al. (2007) use physiological as well as self–reported measures of emotional states in the PTT game. To measure physiological changes they apply skin conductance response (SCR) measures, widely used in scientific research of emotional arousal. They find a strong correlation between the responder's resource–destruction behavior and both measures of emotional arousal, with more negative states predicting higher chances of destroying all resources. It is important to notice that the observed strong correlation between physiological measures of (actual) arousal and the self–reported ones supports the use of self–reports to measure emotional changes, as we do in our experiment.

In relation to ex–post verbal expression, previous research has studied bargaining setups where the disadvantaged party can send free written messages to counterparts. It is found that messages are likely being driven by emotional states. Xiao and Houser (2005), in particular, conduct an experiment in which an ultimatum game (UG) is augmented to allow responders to send an ex–post free written message to the proposer. They find that rejections of small offers (i.e., 20 percent of the pie) went down from 60 percent to 32 percent compared to the ordinary UG. The authors leave open the question of the underlying cause of this behavior, that is, whether expression gives relief or whether it is seen as an alternative punishment. Xiao and Houser (2007) observe that very unfair donations (i.e., 10 percent percent of the pie in the dictator game DG) decrease from about half to one fourth when the receiver can send an ex–post free written message to the dictator. Finally, Ellingsen and Johannesson (2008) find that when verbal feedback is allowed, the fraction of zero donations decreases from about 40 percent to about 20 percent, and there is a corresponding increase in the incidence of equal splits from about 30 percent to about 50 percent. Recipients who receive no money almost always express disapproval of the dictator, sometimes very strongly. Following an equal split, almost all recipients praise the dictator. In all cases, low donations or offers are associated with messages entailing negative emotions. Fairer donations from dictators facing possible verbal responses are interpreted by Xiao and Houser (2007) as being cognitively dissonant (Festinger (1962)). In a no expression environment, dictators take advantage of the ambiguity (the self–serving biased thought that it is fair to be selfish, Babcock and Loewenstein (1997)) but under expression possibilities they cannot avoid recognizing the conflict between their convenient beliefs and reality. This implies dictators or proposers would prefer a no expression environment, but this has not been established yet. It could also be the case that dictators might want to buy and feel positive expressions.

2.3 The Experiment

Our experiment is designed to measure valuations for expression in an economic setup where, as discussed previously, it has been shown that the motivation for expression is substantially emotional. We use a modified version of the Power–to–Take game. This game is a somewhat extreme bargaining environment where only one side's resources are vulnerable. It is also seen as a tax–authority/citizen relationship or a very asymmetric negotiation.

In order to restrict our analysis to expressions that are largely originated in mood and feelings of emotions or aim to induce emotional states in others (i.e., to eliminate instrumental cheap talk type of motives) we focus on a type of expression that has no material consequence; this expression occurs after material resources of the interaction are settled. To properly elicit valuations, our design innovates with respect to previous experiments in two aspects. First, we separate the *size of the stimulus* from the *opportunity cost of responses*. This is in contrast to the usual UG or PTT, where the *size of the stimulus* (money offered and taken, respectively) is deterministically related to the cost of responding (one gives up what is offered or destroys the money left, respectively) and where in consequence valuations cannot be studied independently from the size of the stimulus. Second, we implement a BDM mechanism to induce sincere revelation of the corresponding material value of expression (Becker et al. (1964)).[5]

The second main question of the research is regarding the purpose of the emotion expression. As discussed previously, the purpose can be either *intrinsic,* stopping the negative feeling of anger for example, or *extrinsic*, such as harming the opponent. As Xiao and Houser (2005) point out, lower rejections when expression is possible can be interpreted as a relief effect, but such behavior is also consistent with an attempt to harm. Their research did not disentangle the two. In the case of physical health, for example, emotional expression seems to follow the *venting hypothesis* that is associated with taking–it–out/relief motivations. However for the type of feelings occurring during bargaining and with a clearer defined intentional object, the opponent, it seems very plausible for us that the main motive might be actually harming. In order to

[5]We argue this elicitation method does not seem to be taxing cognition excessively in our environment.

disentangle emotion expression goals we run different treatments that differ in the recipient of the message. While under the *venting/relief emotions hypothesis* some valuation will be assigned even if the message is not directed at the source of the stimulus, but at a third party; under the *extrinsic purpose hypothesis*, most value will be assigned to messages that are directed at the origin of the stimulus.

2.3.1 Experimental Design

Our design modifies the Power–to–Take Game (Bosman and Van Winden (2002)) as follows. Each player receives \$3.00 as an endowment and earns additional income by completing a number of search tasks.[6] These search tasks are real effort tasks where each individual has to search for the top of a mountain in a two–dimensional grid using the mouse of the computer. The search tasks are calibrated so that all participants roughly earn the same amount of money (about \$10) in order not to introduce any differences in initial income. After the search tasks are over, participants are randomly matched in pairs and roles are assigned. Each pair consists of a taker (T) and a responder (R). Each T player then decides what percentage of R's task income (excluding the \$3 of initial endowment) to transfer into his/her own account. T's strategic move is referred to as *the stimulus* since this move is the cause of R's emotional arousal. Likewise, T is referred to as the *source of the stimulus* and the amount subtracted is referred to as the *size of the stimulus* as it is reasonably conjectured that higher transfers from R's account will trigger a stronger arousal. Another simple way to think of the stimulus is by defining it as the difference between the expected and the actual take rate, also referred to as the *surprise gap*.

Then, R is informed about T's action and asked about his/her maximum willingness to pay to send a written message. As explained previously, the willingness to pay is elicited in an incentive compatible way using a *BDM* mechanism (Becker et al. (1964)). This is an important feature of our design. In previous research, the cost of an action, for example rejecting in the Ultimatum Game, was perfectly tied to the *size of the stimulus* (i.e., the amount offered). An offer of \$1 implied an opportunity cost of rejection of \$1 too. This makes proper assessment of the valuation for rejection/destruction impossible as we can only observe one price of the

[6] The small size and symmetry of this initial endowment are expected not to change the perception of fairness by either player.

Table 2.1: Summary of the Experimental Design: Main Treatments

	Recipient/Cost of the message
OFU	Costly message read by T player
SLTM	Costly message read by a third party
FM	Free message to T player
NM	No message

action for each size of stimulus. In our design, the cost of an action (the price of sending a message) will be independent of the size of the stimulus (the amount taken by T). After each R has stated his/her value, he/she is informed about the actual price which is randomly drawn from a uniform distribution between \$0 to \$3. If the stated willingness to pay is higher than the random price, the participant pays the actual (randomly generated) price and can take the action. If the stated willingness to pay is lower than the random price, the participant will not be able to take any action and will not have to pay anything. Some expression desires might be left unfulfilled as the random price turns out higher than the stated willingness to pay.[7]

The initial endowment of \$3 is given to ensure that even somebody whose entire task income has been taken by T can respond if she/he really wants to. Table 2.1 summarizes the main four treatments that differ with respect to who will be the recipient of the message. *OFU* – Only for You – allows for messages to be sent to the source of the stimulus, i.e. the T player with whom the R player is paired. *SLTM* – Somebody Listen to Me – allows for messages to be sent to a third party that is not involved in the decision making and whose payoff is unaffected by the decision. We recruited one extra participant for every 5 pairs and assigned him/her the sole purpose of reading messages that are sent. All participants know at the very beginning of the experiment what kind of expression can potentially be used. Senders of messages receive acknowledgement of when the designated party has read the message. We also study behavior in two polar control treatments. One in which no message can be sent, *NM* (no message) and one in which a free message can be sent to T, *FM* (free message) (see Table 2.1).

Besides eliciting the willingness to pay for writing a message (and following Charness and Grosskopf (2001); Bosman and Van Winden (2002) and Konow and Earley

[7]The BDM mechanism was explained in detail at the beginning of the experiment, before subjects knew their roles or any emotional arousal occurred.

(2008)), we also collect self–reports of subjective well–being, emotions currently experienced and mood states at the very beginning of the experiment. We repeat the corresponding questionnaires at the end of the experiment. The self–report of a variety of emotions experienced at that moment will also help us to control for some incidental background feelings/states of participants. An important issue with the self–report is the discrepancy between what is actually felt in the emotional episode and the beliefs people form about it. This gap is exacerbated by the quick fading out of the episodic memory; so it can bias the self–report (Robinson and Clore (2002)). Some of these considerations are taken into account for our design. For example, we embedded the application of the questionnaires into the same computer interface as the game, so we keep participants in a *hot* state, minimizing the perception that the interaction had finished.

2.3.2 Hypotheses

Our design allows us to properly elicit the valuation for a certain type of response conditional on the size of the stimulus and other covariates. This allows us to formulate our first hypotheses.

Hypothesis 1: Takers are responsive to the possibility of expression by their counterparts (instrumental effect of expression).

Hypothesis 2: People are willing to pay for expressing, i.e., there is a demand for expressing emotions.

Hypothesis 3: The stimulus size does affect the valuation, i.e., the stimulus does shift the demand: the more money is taken the higher is the valuation.

Hypothesis 4: The valuation (the demand) is higher when the expression is directed at the *source* of the stimulus.

Hypothesis 5: Material outcomes as well as expression possibilities affect mood emotional states and self–reported well–being (noninstrumental effect of expression).

2.3.3 Sessions

Experimental sessions were conducted at the Economic Research Laboratory at Texas A&M University and at the Experimental Economics Lab at University of Maryland. Our participants were undergraduate students with a non-economics major. All sessions were computerized, using a computer interface programmed in zTree (Fischbacher (2007a)). Instructions were read aloud and questions answered in private. After reading the instructions and having questions answered, all participants had to answer a set of questions that were meant to test whether the instructions had been understood. All answers were checked and corrected by the experimenters and remaining questions answered. Throughout the sessions the subjects were not allowed to communicate with one another and dividers separated the individual computer terminals.

2.4 Results and Discussion

In this section we present the results of the experimental study. We implemented our four main treatments in 34 sessions recruiting a total of 472 subjects (236 pairs).[8] It is important to highlight that we obtained a different number of observations in each treatment across the two campuses, and although the main behavioral patterns were equivalent, some measures present nonnegligible differences between the two universities. To correctly account for this fact, we regard the data of each treatment as coming from a stratified sample, where each campus represents a stratum. We then assumed that both campuses have same–size populations. Also, we needed more observations to conduct statistical analysis focused on the *OFU* treatment. Therefore, we collected more pairs (71) for this treatment compared to the rest of treatments. Table 2.2 shows the distribution across treatments of the most relevant variables in the experiment, summarized by their means, as well as the number of pairs studied in each treatment.[9]

Notice that, as our design dictated, the task income is virtually the same ($10.3) for all treatments and both types of participants with negligible dispersion (a coeffi-

[8] Additionally, the *SLTM* treatment combined had seven third–party receivers/readers of the messages, which were not studied for obvious reasons.

[9] Reports in Table 2.2 broken down by university can be found in the Appendix B.

Table 2.2: Summary Statistics

	FM	*OFU*	*SLTM*	*NM*
Number of pairs	57	71	44	64
Task Income T ($)	10.34	10.32	10.32	10.34
Task Income R ($)	10.34	10.34	10.35	10.33
Take ratio (percent)	47.91	63.83	64.86	67.88
Expected take ratio (percent)	53.55	56.28	55.66	54.94
WTP>0 (percent)	82.6*	68.3	48.0	N/A
WTP for msg. ($)		0.78	0.33	
Final Earnings T ($)	18.3	19.92	20.03	20.36
Final Earnings R ($)	8.38	6.58	6.54	6.32

All statisticss are sample means, except for the number of pairs.
* This refers to the percentage of people who write a message when writing is free.

cient of variation of approximately 1 percent). All tests either across treatments and participant roles within treatments do not reject the null hypothesis that task incomes come from the same distributions and have the same central tendency measures.[10] The discussion of the take rate, the willingness to pay and the self–reported measures of emotions require further analysis presented in separate subsections.

2.4.1 The Take Rate Behavior

The take rate is the percentage of the responder's labor income that is appropriated by the taker. Each taker decides how much to take from his/her counterpart after learning how much both players have made in task income. We find that the take rate is statistically equivalent across all treatments except in the free message treatment where the take rate is lower. While the mean take rate was 67.8 percent in *NM*, 63.8 percent in *OFU* and 64.8 percent in *SLTM*; this rate was only 47.8 percent in *FM* (see Table 2.2 and Figure 2.1). We run a regression, reported in Appendix 2.4, of the take rates over treatment dummies, considering the stratified structure of the data. We tested if the mean take rates differ across treatments; and only the tests of *FM* against *OFU*, *SLTM* and *NM*, were significant. The null hypotheses of same mean are rejected in all cases in favor of typical *FM* take rates being lower (one–sided p–values $= 0.007$, 0.007 and 0.001, respectively for *OFU*, *SLTM* and *NM*). We also

[10]Reports are omitted but available form the authors upon request.

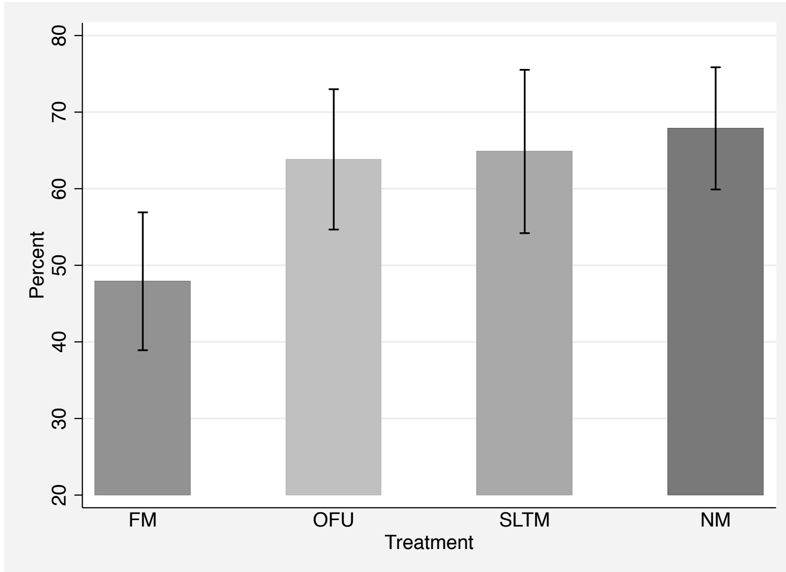

Figure 2.1: Take Rate and 95 percent C.I.

implemented Hodges–Lehmann tests for median differences (Hodges and Lehman, 1963). This nonparametric test gave the same results: all comparisons against *FM* resulted in positive median differences at 95 percent level of confidence; and no other contrast rejects the null of zero difference.

Confirming Hypothesis 1, the contrast between *FM* and *NM* establishes that takers do care about the message they might receive as a response when deciding how much to take. The 16 percent lower take rate under *FM* compared to *NM* (which amounts to about $1.60) is an approximate measure of how much takers value modifying their counterparts' behavior regarding sending a message. This can be either because the taker believes that a lower take rate will reduce the probability of receiving a negative message or increase the probability of receiving a positive one. The similarity of takers' behavior between *NM* and the rest of treatments (*OFU* and *SLTM*) is less immediate. Intuitively, these results suggests that takers possibly perceive *FM* as the only environment where they could get a response with high chances. This might be because *FM* is the only treatment where responders are able to express freely and costlessly. Also, takers might underestimate responders' valuations for writing messages in the same way individuals tend to mispredict reactions driven by emotions in themselves and in others. Therefore their extraction behavior is qualitatively distinct only in the *FM* environment.

While takers are asked about their take rate decision, responders are asked to guess how much that take rate will be. We find responders believe that takers' behavior is roughly independent of the message features of the environment and expect the take rate to be around 55 percent in all treatments (see Table 2.2 and Figure 2.2). That is, expected take rates do not vary significantly across treatments. We tested two measures: means, via a regression as for the actual take rate, and median difference, via a Hodges–Lehmann test. We do not find the self–reported beliefs about the take rate to be statistically different between treatments. Every test based on the regression that compares the expected take rates of any two treatments fails to reject the null of equal conditional mean and every median difference test did not reject the null of a zero median difference.

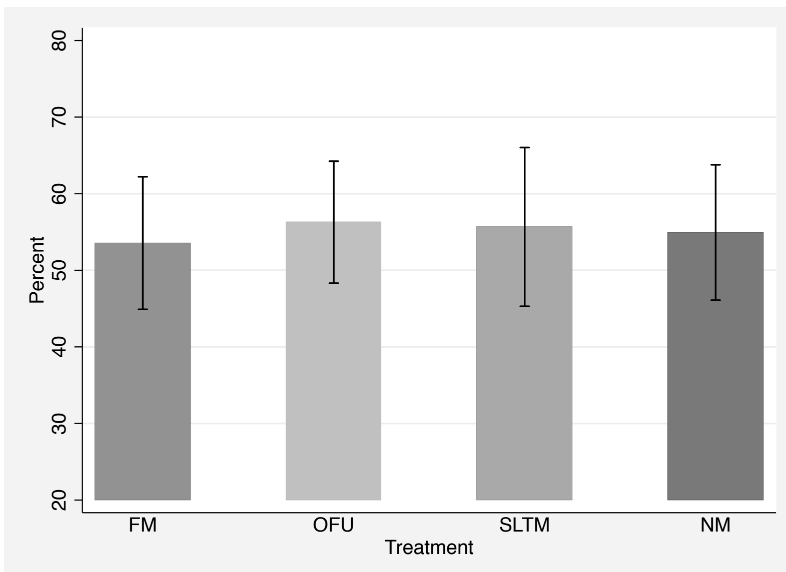

Figure 2.2: Expected Take Ratio and 95 percent C.I.

This result is consistent with the idea that a typical responder cannot predict the impact of expression possibilities on the taker's behavior; therefore, they see the situations the taker faces as equivalent across treatments. There could be several reasons why this happens. For example, responders failing to anticipate takers' feelings regarding different chances of getting a message, or responders, when guessing counterparts' behavior, mostly focusing on the material dimension of the environments. Though these are interesting questions, adressing them lies outside the scope of the current paper.

2.4.2 Message Valuation

As explained in the design section, in the message–enabled treatments, responders are asked about their valuation to write a message after they learn the take rate (*OFU* and *SLTM*) or whether or not they want to write a message (*FM*). A first basic question is then whether or not responders value using messages at all in this context. The relevant environment to answer this question is our free message setting (*FM*) where we found that 82.6 percent of responders did send messages. Given that there is a small yet positive cost of doing so, it is reasonable to conclude that responders value the possibility of writing messages to the takers. The second basic question is whether or not this tendency to write a message depends on the take ratio that responders faced. It could be that higher take rates would cause a bigger tendency to respond verbally. We found, however, that the propensity to send a message does not have the take rate as a significant explanatory variable.[11] So, we know that writing a message in this environment is valued in that most people do it when the material cost is zero. Our main focus here, however, is finding out what part of this valuation can be materialized (i.e. can be substituted with money). While the *FM* data suggested that, broadly speaking, most people found sending messages worthwhile, the *OFU* data informs us about the monetary equivalent of this valuation. Our evidence suggests, first, that the majority of people do translate this valuation into the monetary dimension, as we find that 68.3 percent of responders in *OFU* have a strictly positive willingness to pay and second, that the probability of having a strictly positive material valuation (WTP>0) does indeed depend on the size of the stimulus: the take rate. In our probability regressions with the *OFU* data, the take rate did in fact explain the probability of having a strictly positive valuation for sending a message in the *OFU* treatment.[12] But not only did people have a strictly positive valuation for expressing, confirming Hypothesis 2, we also find that this material valuation is sizable relative to the resources the responder has

[11]We run probit regressions with the *FM* data testing if the probability of sending a message is affected by the take rate (with and without its squared term, to allow for simple nonlinearity). We do not reject the null hypothesis of the whole model having no explanatory power over deciding to write a message. We repeat this exercise with the *surprise* term (actual take rate minus expected take rate), finding that the probability of sending a message is not explained by *surprise* either.

[12]We also found that the index underlying this relation is nonlinear in the take rate. The surprise, on the other hand, is not explanatory for having a strictly positive WTP. The regressions are reported in Appendix B.

available after the material interaction. This means that the possibilities of expression in this type of economic setting are important determinants of the final well–being. In particular, we find that, on average, a responder in the *OFU* treatment is willing to pay \$0.78 to write a message to the taker, which corresponds to 11.6 percent of his/her disposable income that amounted to \$6.73 after the taker withdraws money from his/her account.

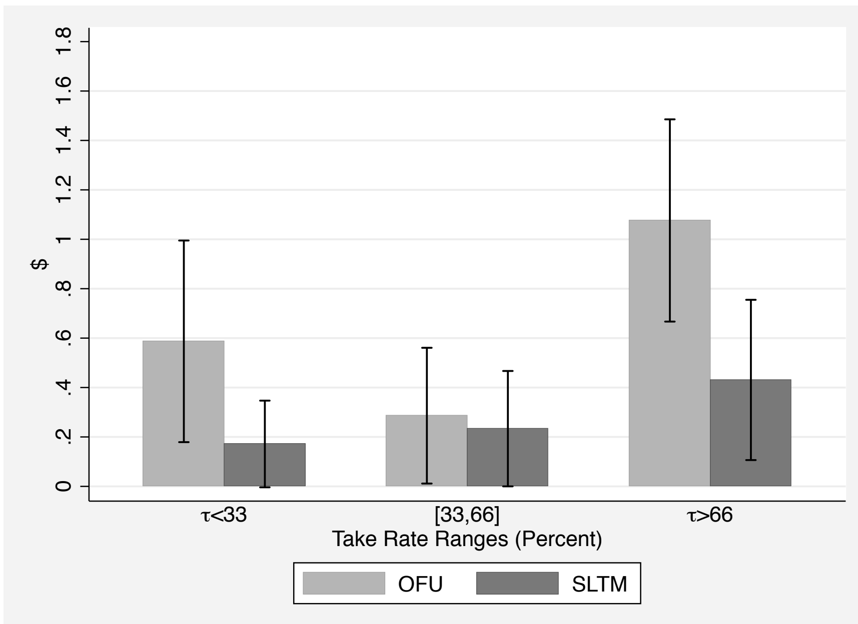

Figure 2.3: Mean Willingness to Pay with 95 percent C.I.

Now that we have established that the typical WTP represents an important amount in relation to the resources available, we might ask whether or not this valuation varies with different take rates. As detailed in Section 2.3, one of the contributions of our design is that, unlike the original PTT game and other bargaining games used in experiments, we can study this valuation conditional on different sizes of *stimuli*. Put simply, we can see how the WTP varies with different take rates.

We find that the take rate influences the monetary valuation of ex–post verbal expression and, in fact, there exists a nonlinear relationship between the take rate (the stimulus) and the WTP. This means that responders' valuation for being able to reply is stronger when facing very low (pro–social/nice) take rates or very high (self–interested/harming) ones. In particular, in *OFU*, for take rates up to 33 percent the average willingness to pay is \$0.59, for take rates above 33 percent and below 66 percent the average WTP is only \$0.29, and for high take rates (above 66 percent) the average WTP is \$1.07 (see Figure 2.3). The comparison of the take rates over these three groups is not very precise as the number of observations in the categories is not very large (the upper category gets 37 observations, 52 percent of all cases). However, it gives enough information to show: (i) that the WTP is positive over all take rate ranges (one–side test for zero mean WTP had p—values of 0.002, 0.021 and < 0.000 for the bottom, middle and upper ranges of the take rate, respectively) and (ii) that there is a nonlinear u–shaped relationship between the WTP and the take rate. This confirms Hypothesis 3 as very high take rates induce higher valuations. However, this hypothesis did not consider the nonlinear nature of this relationship.

Table 2.3: Regression WTP in *OFU*

	(Model 1)	(Model 2)	(Model 3)	(Model 4)	(Model 5)
Take Rate	-0.030**				-0.032**
	(0.012)				(0.015)
Take Rate (Squared / 100)	0.034**				0.033**
	(0.011)				(0.012)
Surprise		0.006**			0.003
		(0.003)			(0.004)
Surprise (Squared / 100)		0.002			-0.000
		(0.006)			(0.006)
Surprise (Abs Value)			0.003		
			(0.018)		
Surprise (Abs Val. Sqrd / 100)			0.000		
			(0.000)		
Good Surprise (tk≤Etk)				0.004	
				(0.004)	
Bad Surprise (tk>Etk)				0.008	
				(0.007)	
Constant	0.846**	0.684**	0.677**	0.661**	1.013**
	(0.319)	(0.169)	(0.325)	(0.226)	(0.488)
Observations	71	71	71	71	71
R2	0.18	0.09	0.01	0.09	0.20

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parenthesis.

We test this nonlinearity by running a regression of the WTP against the different polynomial expressions of the take rate. We find that a quadratic equation is appropriate to describe this u–shaped relationship.[13] One alternative conjecture

[13] We provide the Figures associated to these regressions in Appendix B. We also run a fractional polynomial regression. While it mildly improved the regression's explanatory power, its predicted WTP correlate near perfectly with those of the simpler regression with a quadratic term. We keep the quadratic specification for the rest of our analysis.

about the relationship between WTP and the take rate is that responders react to the difference between the expected and the actual take rate, the *surprise*, as opposed to the take rate itself. It is intuitive to think that highly positive or highly negative surprises will result in a stronger desire to submit a message. If surprise is the actual (or just a better proxy of the perceived) stimulus, we should observe that this variable explains the WTP behavior better than the raw take rate. However, we found that the surprise does not explain the observed WTP as well as the raw take rate. Table 2.3 report various specifications for regressions of the WTP against either the raw take rates and/or the surprise (allowing for nonlinearities via quadratic terms). We found that the raw take rate performs better than any specification that includes the surprise term. The evidence indicates that the raw take rate is what causes variation in the material valuations for expressing.

2.4.2.1 Directed Expression Vs. Being Listened to

We have established that the majority of subjects in the responder position attaches a monetary value to being able to respond verbally, and also that this valuation comprises a nonnegligible percentage of the resources available to him/her. Further we have shown that the desire to reply is bigger if the taker's behavior is highly pro–social or highly egoistic. Now we need to unbundle further the value of the message to characterize better the motivations involved. Under *OFU*, the two main components of a message are *(i)* the expression possibility itself (being listened to by anyone) and *(ii)* the response/reciprocal possibility (taking an action directed at the source of the harm/good itself). The *SLTM* treatment gives us only the first component for in this treatment the responder is able to write a message as in *OFU* but now the recipient of the messages is a third party, not the taker. Since the reader remains anonymous to takers, we claim that the willingness to pay to send a message in *SLTM* fundamentally pins down the value of being–listened–to, what we had earlier called the *purely expressive motive.*

Our experimental findings confirm that typical responders do value positively this pure expression possibility (48 percent of participants presented a strictly positive WTP_{SLTM}, and we reject the null of zero mean WTP_{SLTM} in favor of the alternative of mean $WTP_{SLTM} > 0$, $p < 0.001$). On average, responders' value of being listened to is \$0.33, which accounts for 42 percent of the \$0.78 that was the total value of directing a message to the taker. Further, we found that this difference is statistically significant, and that the value of pure expression is lower than the value of directed expression ($WTP_{SLTM} < WTP_{OFU}$, one–sided $p = 0.002$).[14] This means that both the value of pure expression as well as the value of taking it back and directing a message to the source of the harm (*the reciprocal motive*) are important components of the material valuation of expressing in this setting. This favors Hypothesis 4 that stated simply that $WTP_{SLTM} < WTP_{OFU}$.

Our evidence also indicates that the value associated with pure expression motives (WTP_{SLTM}) does not depend on the take rate as the total value of directed expression (WTP_{OFU}) did.[15] In particular, in relation to the three categories of take rates we discussed previously, the mean WTP_{SLTM} is significantly greater than zero in all of them. Differences in WTP_{SLTM} across categories were insignificant. Finally, we need to point out that the importance of the purely expressive motive relative to the total value of the directed expression varies with the take rate. The stylized fact is that at very high and very low take rates, addressing the taker becomes more important and the purely expressive motive is less important. In fact, only for the bottom and the top categories do we reject the null that mean WTP_{SLTM} is equal to mean WTP_{OFU} in favor of being lower ($p = 0.031$ and $p = 0.006$, respectively). Intuitively, this is in line with the conjecture that an important part of these material valuations for expression is mediated via changes in the emotional or mood states of responders. Presumably, extreme take rates (low or high) trigger mood and emotional changes that relate more to reciprocal forces increasing the value of addressing the source of stimulus.

[14] The reason why we use a direct comparison of the WTP across treatments is because previously we have established that *OFU* and *SLTM* have statistically equivalent take rates.

[15] Regressions of WTP_{SLTM} against the take rate with and without a quadratic term rejected the null of the take rate explaining the WTP in this environment.

2.4.3 Robustness

We run some additional treatments as robustness checks. Although the comparison with these treatments is imperfect for they were run only at one of the two campuses were this study was conducted (University of Maryland), they are useful and confirm our findings. The first treatment is a modified *OFU* which reverses the order in which the willingness to pay and the mood–emotional reports were elicited. In the main treatment we elicited the WTP right after the interaction as its measure is the main interest of this paper; in the robustness treatment instead, the subjective states were elicited before the valuation. If reporting emotions acts as a close substitute for expression or if the time passed after the interaction until being asked about the WTP is so long that subjects' desires to express get colder, we would expect the WTP to decrease significantly. However, we find the WTP is still strictly positive and although it is slightly lower than in *OFU* (mean=0.54, s.e.=0.17, n=24), this difference is not significant.

A second robustness treatment isolates alternative explanations for our finding of positive WTP for expression. We run a treatment where we elicit subjects' willingness to pay for just writing something on the computer even though it will go nowhere, not even the experimenter. This is an extreme version of studying purely expressive motives as there is no receiver of the expression. Although this should receive more attention in future research, our results suggest that this kind of expression has either very little or no material value at all. The valuation of this expression is not statistically different from zero (p=0.1) and statistically lower than WTP_{SLTM} or WTP_{OFU} (p=0.000 and p=0.038, respectively).

2.4.4 The Role and Change of Mood and Emotional States

We now study the relationship between the take rate (the stimulus), the mood–emotional states and the material valuation of expression. As indicated before, we collected responses to self–reported well–being, mood and emotional questions before and after the economic interaction. These measures have been previously used in Batson et al. (1988); Charness and Grosskopf (2001); Bosman and Van Winden (2002) and Konow and Earley (2008), and they contain information about general well–being, momentary well–being, feelings of the most basic emotions (intensity of feeling anger, fear, irritation, etc.), mood related states (opposite scales for: bad mood - good mood; sad - happy; gloomy - cheerful, etc.) and some other fillers (see Appendix B for details).

Although the analysis for specific items is informative, different groups of emotions and mood dimensions are closely related and comove as different shocks and mental states occur. From the perspective of the modeler, this comovement of feelings and states suggests that a substantial part of the activity boils down to a few main mechanisms (or factors) that the stimulus acts on. Therefore, it makes sense to focus on the few factors whose sign and/or intensity changed significantly over the course of the interaction. Along those lines, we identified one main group of eight mood and emotion items that behave exactly in this way: across different factor analyses we conducted, with ex–ante reports, with ex–post reports or with their difference, this set of variables behaves as if associated with an underlying factor. There were eight variables included 7–valued scales for feelings of happiness and joy, opposite 9–valued scales for bad mood – good mood, sad – happy, depressed – elated, gloomy – cheerful, displeased – pleased, and sorrowful – joyful. We study a normalized before–after difference of this index. To generate this measure we first built the ex–ante index with a factor analysis that includes these variables. We then used the same coefficients and the ex–post reports to compute the ex–post index. Finally we compute the change in this index normalized to the ex–ante standard deviation, σ. We study the ex–ante/ex–post change of this index.

As measured by this mood–emotion index, henceforth *MEI*, our results show that the environment generates very different experiences for the two roles. When we pool all treatments, responders' *MEI* changes are on average negative and dispersed ($mean = -1.05\sigma$, $sd = 1.4\sigma$). Takers, on the other hand, experience a positive and less volatile change ($mean = 0.67\sigma$, $sd = \sigma$; see Figure 2.4). Similar patterns are observed in all treatments: takers improve their state and responders deteriorate around twice as much (see Table 2.4). Interestingly, when expression is completely free, responders experience a substantially milder shock compared to any other treatment where expression is either costly, impossible or directed at a third party. More precisely, comparing the two polar treatments *FM* and *NM* we find expression does not impact the takers' *MEI* (they show a mean change of 0.68 in *FM* and 0.58 in *NM*, which is statistically not significantly different from oneanother) but it does have a

Table 2.4: Ex–ante and Ex–post emotional–mood states by roles and treatment

	Taker			Responder		
	Before	After	Diff	Before	After	Diff
FM	-0.09	0.60	0.68***	-0.11	-0.56	-0.44**
OFU	-0.15	0.51	0.66***	0.08	-1.26	-1.34***
SLTM	0.06	0.85	0.79***	0.29	-0.86	-1.15***
NM	0.08	0.66	0.58***	0.03	-1.26	-1.29***

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, for null Diff $\neq 0$.

significant impact on responders as their mood-emotional state deteriorates much less compared to the completely silent treatment (responders *MEI* change is -0.44 in *FM*, and -1.29 in *NM*; p=0.00. Table 2.4). This difference in our measure of subjective well–being for responders that amounts to 0.85σ and goes in favor of the expressive environment (*FM*) can be conjectured to have two sources. First, it can be related to the fact that responders under *FM* do receive on average higher final payoffs as the take rates are lower and, second, to the fact that under *FM* they fulfill their expression desires. Using data from FM and NM, we conduct the simple test whether or not expression possibilities have a positive impact on subjective well–being by regressing the ΔMEI against the total monetary payoff and the indicator of expression possibilities (a dummy that takes 1 for *FM* treatment and 0 for *NM* treatment). We find that expression possibilities account for aproximately 0.4σ after controlling for the effect of the material payoff (p=0.03).

Another central question to our research is how the emotional states are affected by the stimulus and how they relate to the material valuation of expression. First, we find that the take rate has a strong negative effect on the mood–emotional states. The regression analysis shows that a ten percent increase in the take rate decreases the mood and emotional index by 0.25σ. This implies, as expected, that events in the material dimension cause strong mood emotional reactions. This impact of the stimulus on the self–reported emotional states is remarkably stable across treatments. We find that mood–emotional reactions are associated with higher valuation for expression. The more negative or the more positive these reactions are, the higher the willingness to pay.[16] These results suggest, as conjectured, that the relationship between the WTP and the MEI mirrors the relationship between the WTP and the

[16] Figure B.1 of Appendix B illustrates these relationships.

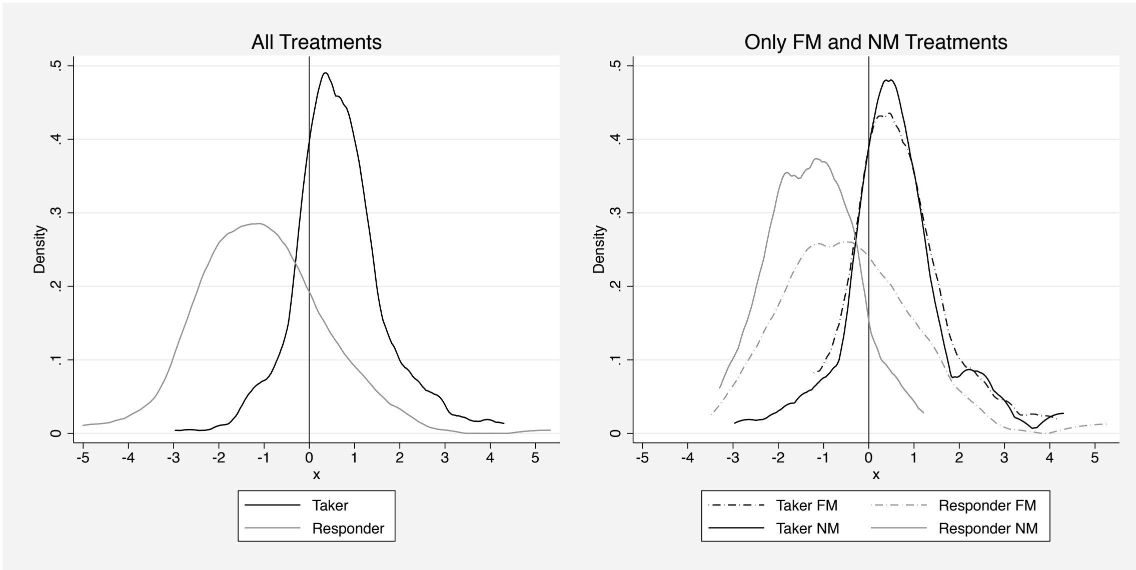

Figure 2.4: Change in Mood-Emotion Index

take rate.

The relationship between the take rate, the emotional states and the willingness to pay can be put in a shock–mediator–outcome framework if the material valuation is seen as the final outcome and the change in MEI as the mediator. By means of conducting a seemingly unrelated regression comprising of the following equations:

$$\Delta MEI = \alpha + \underset{-.024\,(.003)}{\beta} \tau + \epsilon_M \tag{2.1}$$

$$WTP = \delta + \underset{.293\,(.142)}{\delta_1} \Delta MEI + \underset{.138\,(.044)}{\delta_2} \Delta MEI^2 + \delta_3 \tau + \delta_4 \tau^2 + \epsilon_W \tag{2.2}$$

we implement a standard mediation analysis, except for a customized nonlinear relationship. The results indicate that the mediated impact of the take rate on the expression valuation through ΔMEI:

$$\frac{d\Delta MEI}{d\tau} \times \frac{\partial WTP}{\partial \Delta MEI} = \beta(\delta_1 + 2\delta_2 \Delta MEI) \tag{2.3}$$

is statistically different from zero when ΔMEI is below -2 or above 0.[17] These

[17]Detailed results are available upon request.

results suggests that emotional and mood states mediate the impact of the take rate only (or more strongly) when the reaction in such states is strong enough. Now, although the results are appealing, there are also reasons to be skeptical with respect to a mediation interpretation in this context. As it is pointed out in the recent literature, estimation biases might potentially emerge from the fact that our design did not randomize the mood emotional state (the mediator) with another shock (see Imai et al. (2010) and Bullock et al. (2010)). We acknowledge this shortcoming but believe that using the change in the emotional state – as opposed to the ex–post level – partially takes care of this problem; that is, the omitted unobservable factors that might simultaneously impact the levels of MEI and the WTP are less likely to show up in the ΔMEI equation. Again, these results favor Hypothesis 5: expression possibilities as well as material outcomes do affect peoples' mood–emotional states, pointing to the non–instrumental effect of expression.

2.5 Well–Being

Incorporating expression while not increasing the pie–size, does shift substantial gains toward the disadvantaged side of the bargaining. This can be seen by conducting a nonstandard well–being analysis based on the self–reports. We use two measures for this purposes, the change in *MEI*, discussed previously, and a simpler measure of current happiness, a 1–9 scaled question on how subjects describe how they feel at that very moment from *extremely unhappy* to *extremely happy*. With both measures we find the combined effect of the interaction on both roles to be negative for all treatments except the free message treatment (*FM*). This is because while in all treatments takers increase their perceived well–being roughly the same, responders do experience the free message treatment differently. Responders decrease their well–being in all treatments approximately twice as much as taker increase theirs, except in *FM* where responders well–being falls only one third compared to the other treatments. In particular, combined ΔMEI is 0.12 (s.e. = 0.137) in *FM* and is -0.34 (s.e. = 0.13) in *NM*. For the change in the 1–9 scaled momentary well–being measure, the combined effect in *FM* is -0.17 (s.e.=0.19) and -1.02 (s.e.=0.25) for *NM*.

2.6 Conclusions

Departing from the traditional approach to communication in economics that emphasizes its instrumental purpose – i.e. how it affects play and outcomes in the material interaction – we focus on the noninstrumental aspect of communication. We study the value and purpose of ex–post (written) verbal expression in a modified Power–to–Take game, where previous research suggests expression is likely to be driven by mood–emotional episodes. We measure the value of directed verbal expression and isolate purely expressive motives from the reciprocal ones by varying the recipient of the messages across treatments. In order to conduct a welfare analysis of incorporating expression, we run polar treatments where expression is totally costless and where expression is not possible.

Our evidence confirms that this type of expression has a nonnegligible material value, and, moreover, that purely expressive and reciprocal motives are both nontrivial components of this valuation. We show that (self–reported) mood and emotional states are associated with a higher material desire to express. Our evidence suggests that, beyond the classical purposes (such as *cheap talk*), whether or not verbal expression is possible has a real well–being impact in usual economic interactions as, on average, the disadvantaged side experiences less of a reduction in self–reported well–being when expressions are allowed. We further document that the anticipation of expression possibilities alters the behavior of the taker in a pro–social direction.

Our findings are useful for the design of institutions. In fact, a recent change in the way court rulings are conducted in England and Wales seems to acknowledge the value of expressions. Victims of crime will get a chance to speak in court. The new Victim's Code will entitle victims to personally address offenders to explain how a crime has impacted them by reading a statement in court.[18] This new code is seen to give victims the choice to explain to a court and the offender(s) in their own words the personal and emotional impacts a crime has had on them and their families, a process that is known to help victims cope and recover from crime. This ruling acknowledges the intrinsic motivation behind the noninstrumental effect of emotion expression as currently, judges read such statements in private with only parts being read alloud by the prosecutors. This new ruling is not meant to change verdicts but is predicted

[18] `http://www.bbc.co.uk/news/uk-24710184` accessed November 10, 2013.

to increase the subjective well–being of the disadvantaged side. Whether this change also has instrumental effects remains to be seen as a decrease in crime rates might take time to manifest itself.

Participatory democraties clearly go a step further in asking for expressions before decisions are made. Interestingly enough, citizens report to be happier in such circumstances (see e.g. Frey and Stutzer (2002)). Human beings seem to value the ability to express themselves, whether it being ex–ante or ex–post of any outcome allocation.

Chapter 3

Multi-object auctions with resale: Theory and experiment[1]

3.1 Introduction

The large scale of privatization of assets, such as spectrum licenses, and gas and electricity supply, attracts attention to multi-object auctions (see e.g. Krishna and Perry, 2000; Ausubel, 2004). Unlike the auctioning of non-government owned assets, the efficiency of the allocation, rather than revenue maximization, is the main objective of these auctions (see McMillan, 1994; Ausubel and Cramton, 1999; Cramton, 2002). This objective may be achieved at the auction stage or by allowing post-auction trade among bidders.

As a means of allocating objects efficiently, Vickrey auctions are often considered. The attractiveness of a Vickrey auction is that it extracts the true value of the bidders via simple strategies that are independent of the underlying distribution of values (see Ausubel and Milgrom, 2006). On the other hand, conducting a Vickrey auction, explaining its pricing rule and its transparency to the bidders, can be quite complex, especially when there are large packages of objects and many bidders. Due to these complexities, most spectrum auctions in the US do not allow for package bidding and, in rare cases, such as a 700 MHz auction, allow bids on only a limited number

[1] This is a coauthored work with Emel Filiz-Ozbay and Erkut Y. Ozbay. We thank Lawrence Ausubel, Peter Cramton, Jacob Goeree, Isa Hafalir, Dan Levin, Thayer Morrill, Dan Vincent and seminar participants at Duke University, Johns Hopkins University, North Carolina State University and Sabanci University for fruitful discussions. Emel Filiz-Ozbay and Erkut Y. Ozbay thank NSF SES-0924773 for research support.

of packages (Cramton, 2002). Running simultaneous second-price auctions may be more practical but may lead to inefficient allocations when complementarities exist (see De Vries and Vohra, 2003; Cramton et al., 2006). In that case, bidders are naturally interested in resale at the conclusion of the auction.

Post-auction trades among bidders are observed in various settings, such as auctions of antiques, real estate, art, emission allowances, or spectrum licenses. In government auctions, where one would expect the government to be able to forbid resale, it is hard to prevent companies from merging (as was the case after the UK spectrum auctions in 2000 and 2003).[2]Therefore, it is important to understand both theoretically and empirically how auction outcomes are affected by the existence of resale markets. Various studies have shown that, typically, auction behavior is affected by the possibility of resale and therefore the efficiency and revenue of the auction may change depending on the existence of resale markets (see e.g. Haile 1999; 2000; 2001; 2003; Gupta and Lebrun, 1999; Hafalir and Krishna, 2008; Zhoucheng Zheng, 2002; Garratt and Tröger, 2006).

When multi-objects are auctioned, bidders' demands may differ depending on how large or small they are. For example, in FCC auctions, some bidders are smaller than others because of geographical restrictions or financial constraints, or because they have different uses for the objects. Therefore, they prefer to bid on only a small number of licenses. Moreover, in spectrum auctions (as well as in many other settings), large companies might value multiple licenses to serve large geographical locations more than the sum of the values of each license because the marginal cost of serving a larger area can be lower. In our model, we consider one large bidder (the global bidder) and N small bidders (the local bidders). There are N units to be sold. The global bidder is interested in all units, and each local bidder is interested in a single unit (see Krishna and Rosenthal, 1996, and Chernomaz and Levin, 2012 for similar settings[3]). The valuations of the bidders are independent and private. This setup resembles the situation of telecommunications firms interested in radio-

[2]Hutchison, a telecommunications company, bought TIW, a Canadian firm which won the most valuable license, just after the spectrum auctions in 2000. Pacific Century Cyberworks, a large Hong Kong company, took over Red Spectrum and Public Hub, two small firms, less than a year after the UK spectrum auctions in 2003.

[3]Krishna and Rosenthal (1996) develop this model in order to study the FCC auctions of licenses for the radio-frequency spectrum. Chernomaz and Levin (2012) study theoretically and experimentally first-price auctions in this setting. Neither of these models allows for post-auction resale.

frequencies in different areas, which might have independent valuations due to the varying demands in different geographical regions.

We study both Vickrey auctions where package bidding is allowed and simultaneous second-price auctions where an auction is conducted for each unit. We consider the case where resale among bidders is allowed and the case where it is not. The resale markets, when they are allowed, are designed so that the winners of the auction can make a take-it-or-leave-it offer to the unsuccessful bidders as in Hafalir and Krishna (2008).

We show that the Vickrey auction with package bidding has an equilibrium that allocates objects efficiently at the auction stage with or without resale possibility. Particularly, truthful value bidding is equilibrium when resale is allowed. Hence, resale trade will not occur after a Vickrey auction in that equilibrium. On the other hand, simultaneous second-price auctions do not allocate the objects efficiently at the auction stage when resale is possible or prohibited in any equilibrium. Moreover, in any equilibrium of these auctions, full efficiency cannot be achieved by resale.

Based on these theoretical findings, it is important to investigate experimentally the tradeoff between running a complex but efficient Vickrey auction, and a simple but inefficient simultaneous second-price auction. First, our Vickrey auction experiments with or without resale do not achieve efficiency. The complexity of this pricing rule makes it hard for the subjects to discover that simple efficient equilibrium. Additionally, our experiments compare simultaneous second-price auctions when resale is allowed and not allowed in terms of efficiency. We show that the presence of resale markets diminishes the efficiency rates at the auction stage of the second-price format compared to the no-resale case. However, in this format, after resale, efficiency rates improve to the level of the outcome of our Vickrey auctions without resale experiments.

Although revenue may not be the main concern of government auctions, resale activity is typically considered a loss of the seller from the gains of trade. Contrary to this intuition, our experiments show that the resale possibility does not affect seller's revenue significantly in second-price auctions.

The existing models of auctions with resale in the literature mainly consider single object problems. The literature on auctions with resale provides six main reasons for resale: (i) new information regarding the values of objects arrives after the auctions (see Haile 1999; 2000; 2001; 2003 and Gupta and Lebrun, 1999), (ii) new buyers arrive after the auction is over (Haile et al., 1999), (iii) asymmetry in the auction may lead to inefficient allocation (Zhoucheng Zheng, 2002; Hafalir and Krishna, 2008), (iv) presence of speculators in the auction (Garratt and Tröger, 2006; Pagnozzi, 2007; 2009; 2010), (v) coordination on collusive outcome (Garratt et al., 2009), and (vi) misperception of resale markets (Georganas, 2011). Our setup is closest to the third type because a multi-object auction setting with complementarities provides a natural asymmetry in terms of demand of bidders and therefore may lead to inefficient allocation under different formats.

The experimental literature on auctions with resale is limited, probably because the theoretical developments on this topic are relatively recent. Lange et al. (2011) experimentally study symmetric first-price auctions where bidders' valuations are initially noisy and there is room for resale. Georganas and Kagel (2011) test Hafalir and Krishna (2008). Georganas (2011) experimentally studies symmetric English auctions with resale and shows deviations from equilibrium that he interprets as misperception of resale. The only other paper, to the best of our knowledge, studying a multi-object setting with resale possibility is Pagnozzi and Saral (2013). Their paper complements ours as they analyze different bargaining mechanisms at resale stage following a uniform price auction without complementarities.

The rest of the paper is organized as follows. Section 3.2 presents our theoretical model and states the theoretical results that motivate the experiments. Section 3.3 summarizes the experimental design and findings. Section 3.4 concludes. The proofs of the statements presented in the theoretical section, the instructions used in the experiments and the auxiliary empirical results discussed in the text can all be found in the Appendix C.

3.2 Model

Our setup is similar to the model introduced by Krishna and Rosenthal (1996) (see also Chernomaz and Levin, 2009, and Goeree and Lien, 2014). There are $N > 1$ markets, each containing one object for sale. Markets are indexed by $i \in \{1, ..., N\}$. There are N *local bidders* and local $i \in \{1, ..., N\}$ is denoted by l_i. Local i is present only in market i. There is a *global bidder* (denoted by g), who is present in all markets.[4] All bidders are risk-neutral.

Before the auction, each bidder privately observes a signal. Each bidder's signal is drawn from a commonly known distribution function F defined on a support $[0, \bar{s}]$ with $\bar{s} > 0$. Signals are independently and identically distributed.

The value of the objects for the seller is zero. For each local bidder, her signal is her private value for the object that she is interested in. Also, for a given signal of the global bidder, any two packages of the same size are valued the same.[5] Formally, $v^n(s)$ is the value of obtaining $n \geq 1$ objects when the signal of the global bidder is s. There are complementarities for the global bidder: $v^n(s) > v^{n-k}(s) + v^k(s)$ for any $0 < k < n \leq N$ and $s > 0$. For each n, $v^n(s)$ is strictly increasing and differentiable in s, and the derivative is strictly increasing in n, i.e. $v^{n'}(s) > v^{n-1'}$for any s. As a normalization, $v^1(s) = s$. Also, $v^n(0) = 0$ for any n. For example, when $N = 2, v^2(s) = 2s + \alpha$ with $\alpha > 0$ (as in Krishna and Rosenthal, 1996) and $v^2(s) = 2\beta s$ with $\beta > 1$ (as in Chernomaz and Levin, 2012) satisfy all the aforementioned assumptions.

The objects are first auctioned to the bidders and then the bidders may trade the objects with each other at a post- auction resale stage when it is allowed (we will study auctions with and without resale possibility).

Auction stage

We study two types of auction formats:

- Simultaneous second-price auctions: N simultaneous auctions are run, one for each market. In market i, local i and global submit their bids. The highest bidder receives object i and pays the losing bid (the second highest bid) of that market.

- Vickrey auction[6]: N objects are sold in one auction. Local i submits a bid

[4] For example, a local broadcaster is interested only in the license to serve its region, while a national broadcaster is present in markets for all regions. This is in line with the motivation of Krishna and Rosenthal (1996). Nevertheless, the local bidders may want to bid in other markets when there is resale possibility. Allowing this kind of speculative bidding may lead to having many buyers at the resale stage and hence complicate the post auction trading. Additionally, in reality, some restrictions, such as geographical or legal, may prevent such speculative bidding. Therefore, we rule out this possibility.

[5] Given the auction formats that we analyze, this assumption is made to simplify the notation.

[6] This is equivalent to the second-price auction when a single object is auctioned. It is considered

for object$i$; the global submits bids for each possible package of objects. The objects are allocated to those bidders who have the highest total bids for all the auctioned objects. Each winner pays a price that is equivalent to the externality she exerts on other bidders.

Independent of the auction format, all bids are disclosed after the auctions.[7]

Resale stage

After the auction stage is completed, each winner may offer a price at which to sell the object to the losing bidder of the corresponding market (as in, e.g. Hafalir and Krishna, 2008). These take-it-or-leave-it offers cannot be negotiated. If an offer is accepted, the trade takes place at the offered price. If it is rejected, the winner of the auction keeps the object. The timing of the offers is as follows: If the global wins all the objects, she makes Nsimultaneous offers to the losing locals. If the locals win n objects and the global wins $N-n$ objects, first the n winning locals make offers to the global, sequentially.[8]

The order of the locals' offers is randomly determined, and every local observes each offer as it occurs. After the global sees n offers that are made to her, and before deciding whether to accept them, the global makes simultaneous offers to $N-n$ losing locals. After all the offers are made, first the losing locals decide whether to accept or reject, then the global observes these decisions and decides whether to accept or reject the offers that are made to her.[9]

the appropriate generalization of the second-price auction for multi-object settings (see e.g. Krishna, 2009).

[7]In these auctions the losing bids are, naturally, disclosed to the winners because the losing bids determine the prices that the winner pays. When the global wins all the objects or none of the objects, announcing the winning bids reveals redundant information since the winner sets the price in the resale stage (see the description of the resale stage). Although observing all winning bids may potentially affect a local's offer in the resale stage when global wins in other markets, in Table 3.8 we see that this information is not a significant variable affecting the resale price of the local.

[8]This sequential take-it-or-leave-it offer protocol generalizes to the standard bilateral case in the sense that under complete information the trade is efficient and the unique equilibrium price gives the full surplus to the offering party. This unique equilibrium property wouldn't hold with some other generalizations such as simultaneous offers.

[9]Although we commit to this resale protocol in the theoretical model and the experimental design, our results on auctions with resale, Propositions 2 and 3, hold if instead losing bidders make the resale offers or the proposer of the resale offer is randomly determined at the resale stage. Moreover, even if the global bidder is allowed to make conditional offers in the resale stage, the theoretical results still hold. Although it is experimentally possible that global bidder who wins both objects

Throughout the paper, we study Perfect Bayesian Nash Equilibrium. It is common knowledge among bidders whether or not a resale stage will follow the auction.

Simultaneous second-price auctions with and without resale

When there are no complementarities between objects and resale is not allowed, it is well known that sincere signal bidding is an efficient equilibrium in weakly dominant strategies. Our first observation states that when complementarities exist, there is no equilibrium in which goods are allocated efficiently at the auction stage. This is true regardless of whether resale is allowed or not.

The equilibrium bid strategies are denoted by $\{b_i(s_i), b_{gi}(s_g)\}_{i\in\{1,\ldots,N\}}$ where $b_i(s_i)$ is the bid of local i with signal s_i , and $b_{gi}(s_g)$ is the bid of global in market i when she has signal s_g.

Proposition 1. *The simultaneous second-price auctions do not have any equilibrium where the auction stage allocates objects efficiently. This is true whether resale is allowed or not.*

The intuition behind this proposition is as follows. Without complementarities, efficient allocation depends only on the ranking of values within each market. Consequently, any equilibrium that is monotone and symmetric will be efficient (in particular, sincere bidding). Under complementarities, however, the efficiency of the whole game is entangled. Although the bidding strategies must depend only on the bidders' own signals, the efficient allocation in market i might depend on the realization of signals in other markets.

This result indicates that the auction stage is inefficient, but it is not clear whether or not allowing for resale will lead to efficient allocation eventually. Next, we show that any equilibrium of the SP auctions with resale will be inefficient in the final outcome (after the resale stage).

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may end up selling only one object at a low price while expecting to sell both at a profitable level, such an exposure problem is observed very rarely (only 1.57% in SPR and 1.62% in VR). Nevertheless, it is important to note that such global bidders might have set a price anticipating this exposure problem in the resale stage. One may investigate whether the bidders take into account the potential exposure problem in the resale stage by running a treatment by allowing for conditional offers.

Proposition 2. *The simultaneous second-price auction with resale has no efficient equilibria.*

The idea of the proof of Proposition 2 is that if a small downward deviation by a bidder who loses inefficiently for some realization of signals was not beneficial, then her upward deviations would be beneficial. This means that the bid strategy of a bidder cannot be strictly monotone for signal ranges where she may lose inefficiently. Hence, whenever a bidder loses the auction inefficiently, the winner could not infer the loser's value from her bid. Such a "ratchet effect" as studied by Laffont and Tirole (1988) has been applied to auctions by Lebrun (2010) and Xu et al. (2012). The techniques used in the literature are not applicable to our setting because we have multiple auctions at the same time. Our proof uses a vector calculus technique extensively used in physics (Flanders, 1973). This technique is novel in auction theory and might be found useful in other applications.

Proposition 2 implies that this game does not have a separating equilibrium. As can be seen from the proof, this means that the equilibrium bid functions should have some pooling portion. Moreover, this result is robust to the resale protocols where losing bidders make the resale offer, the proposer is randomly determined, the global makes the first offers when she wins only some of the objects, or the global is allowed to make contingent resale offers. The exact nature of the resale protocol is irrelevant for this result because it is a proof by contradiction where we assume that the auction bids reveal the signals of the bidders whenever the auction outcome is inefficient. This implies that the bidders know the nature of the efficient trade and which prices are acceptable or not at the resale stage of such equilibrium. Those different resale protocols affect the resale price but not the post trade allocation of objects (because in the proof by contradiction the final allocation is always assumed to be the efficient one). Since the proof does not particularly rely on the resale price, the arguments still hold under these alternative protocols.

Remark 1. The simultaneous second-price auction with resale has a pooling equilibrium where locals bid zero and the global bids $v^N(\bar{s})$ in each market for any realization of signals. In this equilibrium, the global always wins the auctions, and no information regarding the signals will be revealed in the resale stage. The global offers the price vector that maximizes her expected payoff given her signal.

It is also a pooling equilibrium for the global to bid zero in each market, and the locals bid $v^N(\bar{s})$ independent of their signals. The resale stage prices are set optimally. In both of these equilibria, the after resale allocation will be inefficient with positive probability.

The two equilibria characterized in Remark 1 are completely uninformative at the auction stage, and they are "collusive" in the sense that the bidders should somehow coordinate on who bids zero. Since the theory predicts impossibility of a separating equilibrium or any other equilibrium with a stronger solution concept (such as dominant strategy), coordination on one of the pooling or partially pooling equilibria will be unrealistic to expect from the subjects in our experiments. Nevertheless, the theory predicts inefficiency, and experiments can help us understand the severity of this inefficiency.

Vickrey auction with and without resale

In the auction stage, a single auction is run to sell all the objects. Each bidder submits bids for all possible packages of the objects that she is interested in. In our setup, this means that each local submits a bid for object i and the global bidder submits bids for each package. The auction allocates the objects to the bidders who have the highest combined bids for all objects. Each winner pays a price that is equivalent to the externality she exerts on other competing bidders (Vickrey, 1961). This means that each winner pays the difference between what the highest total bid would have been if she did not participate in the auction (and the others bid the same) and what the highest total bid excluding her bid is in the current situation.

If resale is not allowed after the auction, it is known that a Vickrey auction has an efficient equilibrium (Vickrey, 1961). In this equilibrium, value bidding is a weakly dominant strategy.[10] In Proposition 3, we show that when there is resale possibility, a Vickrey auction still has an efficient equilibrium. Although bidding true valuation

[10] A Vickrey auction has other equilibria as shown in the literature (see Blume et al., 2009). Similarly, when resale is allowed, there are implausible equilibria. As noted in Blume et al. (2009), in any equilibrium, except the value bidding equilibrium, the bidders need to coordinate on who bid zero similar to the equilibria of SPR discussed in Remark 1.

for each package remains an equilibrium strategy for the auction stage, it is no longer a weakly dominant one.

Proposition 3. *The Vickrey auction with resale has an equilibrium that allocates the objects efficiently in the auction stage.*

The proof of Proposition 3 constructs this efficient equilibrium where local i bids $b_i^*(s_i) = s_i$ and the global bids $b_{g_I}(s_g) = v^{|I|}(s_g)$ for a package $I \subseteq \{1, ..., N\}$. Hence, the auction outcome is efficient, and no resale will occur. It is important to notethat this result is robust to aforementioned alternative resale protocols.

3.3 Experiment

In the previous section, we saw that a Vickrey auction has an efficient equilibrium with and without resale. On the other hand, simultaneous second-price auctions may allocate the objects inefficiently at the auction stage whether there is a resale possibility or not. Furthermore, the existence of resale markets does not guarantee the efficiency of the final outcome. Our experiment is designed to study the following: (1) comparisons of the efficiency rates in SP and Vickrey auctions with and without resale; (2) sources of efficiency losses when there are any; (3) rankings of formats by the bidders and the seller.

3.3.1 Design of the experiment

The experiments were run at the Experimental Economics Lab at the University of Maryland (EEL-UMD). All participantswere undergraduate students. The experiment involved four treatments: simultaneous second-price auctions without resale (SPNR), simultaneous second-price auctions with resale (SPR), Vickrey auctions without resale (VNR), and Vickrey auctions with resale (VR). We conducted six sessions for each auction format. In each session, there were 15 subjects. No subject participated in more than one session. Therefore, we had 360 subjects. The random draws were balanced in the sense that we used the same sequence of random number "seed" signals for all auction formats, so that the random draws matched across treatments. A new set of random draws was used for each session in each format.

Participants were seated in isolated booths. Each session lasted less than two hours. The experimental instructions are provided in the Appendix C. To test the subjects' understanding of the instructions, they had to answer a quiz before the experiment started. The auctions did not begin until each subject answered all of the questions correctly.

In each session, each subject participated in 30 auctions. Each subject was assigned a role, global or local, and the roles remained fixed throughout the session. Each auction had one global and two locals who were randomly matched. Two objects were auctioned. The global bidder was interested in both objects and each local was interested in a single object. More specifically, local 1 was interested in the object sold in Market 1 and local 2 was interested in the object in Market 2. Bidders were randomly re-matched after each auction. All bidding was anonymous. Bids were entered via computer. The experiment was programmed in z-Tree (Fischbacher, 2007b). At the conclusion of each auction, the bidders learned the outcome of the auction (i.e. whether the global or a local won in each market and the submitted bids).

At the beginning of an auction, each bidder received a private signal from uniform distribution on $[0, 100]$, independently. The signal of a local was her valuation for the object that she was interested in. The signal of a global was her valuation of the single object. A global's valuation for the package of two objects was 3×(her signal).

In treatments without resale possibility, the payoff of a subject in a round was the difference between the value of the object(s) that she received in the auction and the auction price. In treatments with resale possibility, a subject earned.

Payoff=(Value of the object(s) owned after resale)+(any amound received in a resale trade)-(any amound paid in auction or resale stage)

All the amounts in the experiment were in Experimental Currency Units (ECU). Subjects received \$7 as participation fee and \$3 initial endowment to cover any possible losses in the experiment. No subject lost all of the initial endowment. The final earnings of a subject were the sum of her payoffs in 20 randomly selected rounds in addition to the participation fee and the initial endowment. The payoffs in the experiment were converted to US dollars at the conversion rate of 50 ECU = \$1. Cash payments were made at the conclusion of the experiment. The average subject payment was \$19.85.

Simultaneous second-price auctions without resale (SPNR): Each local bidder submitted a bid only for the object in her market. The global bidder submitted bids for each object. Bids could be any integer number from $\{0, 1, 2, ..., 300\}$. The computer allocated each object to the bidder who submitted the highest bid for that object. A winner's payment was what the losing bidder bid for the object.

It is immediate to show that, when resale is not allowed, truthful value bidding is the local bidders' weakly dominant strategy. Only the global bidder has a non-trivial problem. Proposition 4 shows how the equilibrium can be constructed in this case for the parameters used in the experiment.

Proposition 4. *In the simultaneous second-price auctions without resale when* $N = 2, v^2(s) = 3s$, *and the signals are independently and uniformly distributed on* $[0, 100]$*, truthful value bidding is the locals' weakly dominant strategy and global's equilibrium bidding strategy in market* $i \in \{1, 2\}$*is* $b^*_{g_i}(s) = b^*_g(s) = min\left\{\frac{100s}{100-s}, 100\right\}$.

Vickrey auction (VNR): Each local bidder submitted a bid only for the object in her market. The global bidder submitted a bid for each object and a bid for the package containing both objects. Therefore, the global submitted three bids. Bids could be any integer number from $\{0, 1, 2, ..., 300\}$. The computer allocated the objects to the set of bidders who submitted the highest combined bids for the two objects. A local winner's payment was calculated by the following formula:

Price = (the highest total bid if that winner were NOT present) − (the other winner's bid in the current highest total bid).

For each object she wins, the global pays the local bidder's bid in that market.

Simultaneous second-price auctions and Vickrey auctions with resale (SPR and VR): The auction stages of SPR and VR were the same as SPNR and VNR, respectively. After the auction stage was over, the bidders learned all the bids in each market and the resale stage started. Non-negotiable resale offers were made by the winners of the auction stage. In the experiment, in order to decrease the number of decisions to be made, all the winners of the auction stage were asked to make resale offers. Note that a winner who did not want to sell could always ask for an unacceptable resale price.[11] If a resale trade took place, then the object was transferred to the buyer, the buyer paid, and the seller received the resale price. The timing of the resale offers was as follows:

- If the global won in both markets, then she made simultaneous offers to the locals. Upon observing the resale offers, the locals simultaneously decided whether to accept or reject the corresponding offer.

- If the two locals won the auctions, then one randomly determined local made the first resale offer; after observing this, the other local made an offer. After observing both locals' offers, the global decided whether to buy any object(s) in the resale stage.

- If local i won the auction in market i, and the global won the auction in market j, then first local i made a resale offer. After observing this, the global made a resale offer to local j. Then local j decided whether to accept the global's offer. Upon observing this, the global bidder decided whether to accept the local i's offer. All the moves in the sequential resale game described above were observable by the players.

3.3.2 Experimental Results

We start our analysis by considering the efficiency of the allocation in each treatment. We use the efficiency measure that is also used in Chen and Takeuchi (2005). In this definition, the efficiency of an auction is measured as the ratio of the total surplus of the allocation to the highest possible surplus among all possible allocations, where total surplus is the sum of bidder profit and auctioneer revenue. Then, for each auction, the ratio is normalized by the average surplus of all possible allocations as

[11] Although subjects were not explicitly told what an unacceptable resale price was, the subjects made unacceptable offers when they did not want to sell. 300 ECU was the highest unacceptable offer for our parameters and subjects offered that price a few times (we observed resale price of 300 in 48 and 32 out of 900 auctions in SPR and VR, respectively).

follows:

$$Efficiency = \frac{the\ total\ actual\ surplus\ -\ average\ surplus}{the\ highest\ possible\ surplus\ -\ average\ surplus}$$

Table 3.1 presents the efficiency rates for each auction format for all periods as well as the first and second halves of the experiment. For the pairwise comparisons of the efficiencies we run Mann–Whitney rank tests. Based on all periods' data, at the auction stage, SPR achieves significantly lower efficiency rates than VNR and SPNR (z=−9.067; p =0.0000and z=−6.990; p =0.0000, respectively). However, after the resale stage, the efficiency rate of SPR is significantly higher than that of SPNR (z = 3.706; p = 0.0002) and is not significantly different from that of VNR (z = 1.031; p = 0.3024). Note that in SPR, VNR and SPNR, the efficiency rates improve in the second half of the experiments; nevertheless, these efficiency comparisons are preserved. The difference between the efficiencies of VNR and SPNR is significant in the overall data (z = 2.585; p = 0.0098). However, due to learning in SPNR, this difference becomes insignificant when we look at the last 15 periods (z = 1.004; p = 0.3154).

VR achieves lower efficiency rates than other formats. We believe this is due to the difficulty of understanding both the Vickrey pricing rule and the resale protocol. Note that the efficiency rate after resale of VR is lower than its auction stage efficiency, and this is due to inefficient resale activities in the first half of the experiment. However, there is a learning effect, i.e. the inefficient resale was corrected in the second half of the experiment. But still the efficiency rate after resale is not significantly different from the one in the auction stage (z = 0.481; p = 0.6303). Due to the subjects' apparent difficulty understanding the VR format, the detailed analysis of VR for Periods 16–30 is presented in online Appendix C.[12]

Recall that the equilibrium of VNR is efficient. However, the efficiency rate in the experiment is significantly less than 1 (p = 0.0000, one-sided t-test). This lack of efficiency is actually not surprising in Vickrey auction experiments (see Kagel and Levin, 2010 for a detailed survey). Particularly, overbidding in single-object Vickrey auctions (see e.g. Kagel and Levin, 1993) and underbidding or truthful value bidding

[12] Appendix C also includes all the analysis restricted to the second half of the experiment for all the formats. As can be seen, the main results of the paper are not affected qualitatively.

Table 3.1: Average Efficiency Rates

Auction Format	Periods 1-15	Periods 16-30	All Periods
Vickrey - No Resale	0.769	0.788	0.779
	(0.044)	(0.027)	(0.030)
Vickrey - Resale			
Auction Stage	0.771	0.701	0.736
	(0.026)	(0.024)	(0.008)
Resale Stage	0.616	0.715	0.666
	(0.045)	(0.039)	(0.041)
SP - No Resale	0.708	0.783	0.745
	(0.024)	(0.014)	(0.012)
SP - Resale			
Auction Stage	0.560	0.570	0.565
	(0.056)	(0.051)	(0.051)
Resale Stage	0.796	0.827	0.811
	(0.039)	(0.027)	(0.025)

Notes: Session-clustered standard errors are in parentheses.

in multi-object Vickrey auctions (see Chen and Takeuchi, 2005) have been reported. Although the demand of each bidder is symmetric in the corresponding literature, our results extend these findings such that local bidders who are interested in only a single object overbid, while global bidders who are interested in two objects bid truthfully or underbid. For the draws used in the experiment, the equilibrium efficiency rate of SPNR stated in Proposition 4 is 0.95, but the efficiency rate in the experiment is significantly less ($p = 0.0000$, one-sided t-test). For SPR, we calculate the expected efficiency rate for the pooling equilibrium characterized in Remark 1 by the following simulation exercise. We assume that locals bid zero and the global with any signal s always wins the auctions and sets the rational resale price of given that the auction stage is uninformative. Then, we calculate the expected efficiency rate based on five million signal draws by using the parameters of the experiment. Such a pooling equilibrium leads to an efficiency rate of 0.77, which is significantly less than what we observed in the experiments ($p = 0.0061$, two-sided t-test).[13] Next we investigate

[13]Given the complementarities, the equilibrium where the global wins the auction all the time will lead to higher efficiency than the equilibrium where the locals win the auction since the resale stage

Table 3.2: Efficiency Leaks in VNR Format

	Efficient Outcomes						
Observed	Count			%			
Outcomes	L-L	L-G, G-L	G-G	L-L	L-G, G-L	G-G	Total
Local-Local	234	28	89	**89.7**	44.4	15.5	39.0
LG, GL	16	31	72	6.1	**49.2**	12.5	13.2
Global-Global	11	4	415	4.2	6.3	**72.0**	47.8
Total	261	63	576	100.0	100.0	100.0	100.0

Notes: Local-Local or LL denotes outcomes where each local bidder obtains the object in the corresponding market; LG (GL) denotes outcomes where local bidder A (B) obtains object A and Global bidder obtains B (A); Global-Global or GG denotes outcomes where Global bidder obtains both objects.

the sources of the inefficiencies. The first three columns of Tables 3.2-3.4 present the number of auctions where the efficient outcome allocates both objects to the locals (column 1), one object to a local and one object to the global (column 2), and both objects to the global (column 3). The rows of Tables 3.2-3.4 classify actual allocations based on the type of winning bidders: both locals receive an object in the experiment per treatment (row 1), one local and the global receive one object each (row 2), and the global receives both objects (row 3). The 4th, 5th, and 6th columns show for each type of efficient allocation, how actual allocations distributed in percentage terms. For example, out of 900 VNR auctions, in 576 auctions the global should have received both objects in the efficient allocation, but this happens in only 415 (72%) auctions. In 72 (12.5%) auctions one object is inefficiently allocated to a local, and in 89 (15.5%) of them both objects are inefficiently allocated to the locals. Note that, in Table 3.4, we classify the efficiency rates at the auction stage and at the resale stage separately. The percentages of efficient allocations at the auction stage are 40.6% when the globals do not win any auction, 31.2% when the globals win only one auction, and 28.2% when the globals win both of the auctions. Similarly after the resale, those percentages are 32.9%, 18.1% and 49%, respectively.

Tables 3.2-3.4 demonstrate that the major source of inefficiency in all the formats arises from allocating an object to a local bidder inefficiently. For example, in VNR, when one local and the global should receive one object each, in 44.4% of the auctions

takes place with no information regarding the signals in both cases.

Table 3.3: Efficiency Leaks in SPNR Format

	Efficient Outcomes						
Observed	Count			%			
Outcomes	L-L	L-G, G-L	G-G	L-L	L-G, G-L	G-G	Total
Local-Local	218	17	40	**83.5**	27.0	6.9	83.5
LG, GL	30	39	170	11.5	**61.9**	29.5	11.5
Global-Global	13	7	366	5.0	11.1	**63.5**	5.0
Total	261	63	576	100.0	100.0	100.0	100.0

Notes: Local-Local or LL denotes outcomes where each local bidder obtains the object in the corresponding market; LG (GL) denotes outcomes where local bidder A (B) obtains object A and Global bidder obtains B (A); Global-Global or GG denotes outcomes where Global bidder obtains both objects.

Table 3.4: Efficiency Leaks in SPR Format

	Efficient Outcomes						
Observed	Count			%			
Outcomes	L-L	L-G, G-L	G-G	L-L	L-G, G-L	G-G	Total
Local-Local							
Auction Stage	219	22	124	**83.9**	34.9	21.5	40.6
Resale Stage	222	19	55	**85.1**	30.2	9.5	32.9
LG, GL							
Auction Stage	33	40	208	12.6	**63.5**	36.1	31.2
Resale Stage	33	41	89	12.6	**65.1**	15.5	18.1
Global-Global							
Auction Stage	9	1	244	3.4	1.6	**42.4**	28.2
Resale Stage	6	3	432	2.3	4.8	**75.0**	49.0
Total	261	63	576	100.0	100.0	100.0	100.0

Notes: Local-Local or L-L denotes outcomes where each local bidder obtains the object in the corresponding market; L-G (G-L) denotes outcomes where local bidder A (B) obtains object A and Global bidder obtains B (A); Global-Global or G-G denotes outcomes where Global bidder obtains both objects.

both locals receive the objects inefficiently. Similarly, when both of the objects need to be allocated to the global, in 28% (12.5% +15.5%) of the auctions at least one local receives an object inefficiently. However, when locals should receive both objects efficiently, this happens 89.7% of the time. The main reason for the local bidders to win inefficiently is due to their aggressive bidding strategy. In the next subsection, we analyze the bidding behavior of the local and global bidders in detail and show that while locals overbid, the globals do not. The lowest efficiency rate is observed in the auction stage of the SPR. This is mainly due to the observed inefficiencies when the global should have received both objects for the outcome to be efficient. In only 42.4% of these auctions does the global win both auctions. Given that under the complementarities the global should receive the package efficiently for most of the draws (in 576 out of 900 auctions), the loss of efficiency in this case affects the overall efficiency rate of SPR at the auction stage. At the resale stage of SPR, the locals who win the auction inefficiently sell the objects to the global, and the efficiency rate of SPR improves to VNR's rate.

Bidding behavior

The globals' bids for single objects are mostly symmetric in all formats. The percentages of auctions where globals' bids in different markets are the same are 56.8%, 76.6%, and 71.2% for VNR, SPNR, and SPR, respectively. Furthermore, the percentages of auctions where globals' bids in different markets differ from each other by at most 5 ECUs are 79%, 87.6%, and 86.1%, respectively for VNR, SPNR, and SPR. The average absolute difference between the two single-object bids of a global is 5.1, 3.1 and 3.9, respectively for VNR, SPNR, and SPR.

In all formats, the median bids as well as the frequencies of winning are non-decreasing with signals. This is in line with the monotone strategy of VNR and SPNR; however, it also indicates that neither the locals nor the global are using the pooling equilibrium strategies described in Remark 1 in SPR. In Figs. 1–3, we plot the raw data, the linear regression as well as the mean and median of bids conditional on signals for each format.

In VNR, although value bidding is the weakly dominant strategy for both the global and the locals, the global is in-different among bids in a range for certain

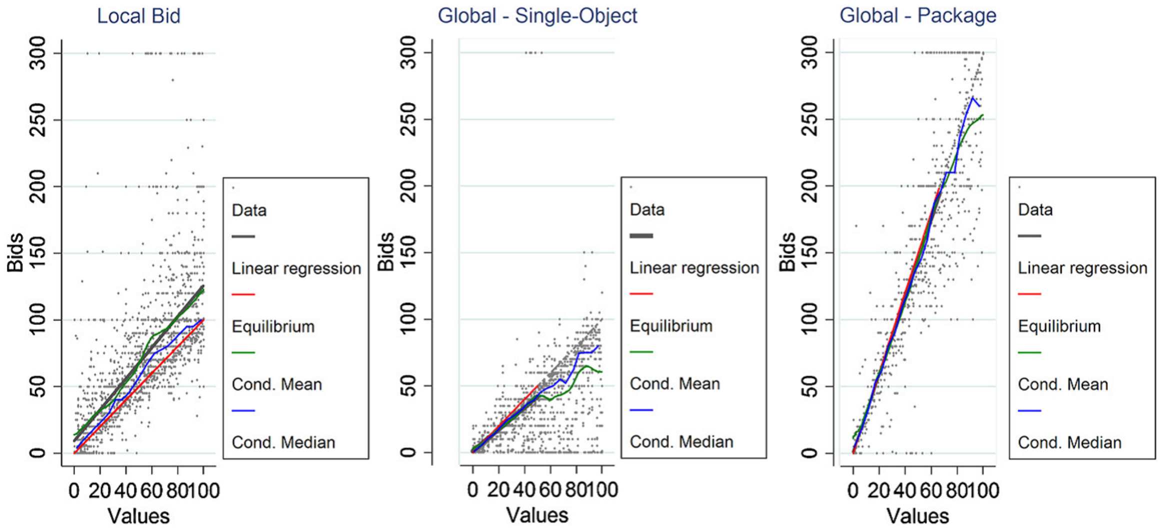

Figure 3.1: Bidding behavior in VNR

realization of signals provided that the locals bid their signal. In Figure 3.1, the equilibrium is not drawn for those signals. In particular, for signals above 50, the global is indifferent among any bids less than her signal for single-object. In the data, 80.5% of the global's single bids are below her signal when the global's signal is above 50. Similarly, for signals above 66, she is indifferent among any bids more than 200 for the two-object package. Of the globals with signals higher than 66, 77.1% bid more than 200 for two-object packages. Note also that both mean and median curves are almost linear up to signal 50 in single-object bids of the global in Figure 3.1, and they are non-linear and below the 45 degree line for signals above 50. Similarly, the mean and median in the package bids of the global are almost linear up to signal 66, and they are above 200 after signal 66.

The bid regressions for VNR are presented in Table 3.5. The global's two-object package bids are in line with the theoretical prediction. In the regression analysis restricted to signals less than 67, the test of the constant being zero and the coefficient of the signal being equal to 3 is not rejected (p =0.170). The global's single-object bids are mostly less than the value of the single object. We reject the hypothesis that the coefficient of the signal is significant and equal to 1 and the rest is zero in the regression for the globals' single-object bids (p =0.000). On the other hand, locals tend to bid more than the equilibrium prediction. In Table 3.5, the coefficient of the signal is more than 1 for the local (p =0.000). This can be explained by joy of

Table 3.5: Bid Regressions for VNR

	Depvar: Locals' Bids	Depvar: Global's Single-Object Bids (for Signal < 50)	Package Bids (for Signal <67)
Signal	1.174***	0.830***	2.885***
	(0.029)	(0.050)	(0.073)
Constant	4.041	1.267	3.048
	(5.701)	(1.909)	(3.977)
N	1800	882	616

Notes: The standard errors are in parentheses. These are regressions with random effect at individual level and fixed effect at session level. * <0.10, ** < 0.05, and *** <0.01.

winning (see e.g. Cooper and Fang, 2008).

The joy of winning has an interesting implication for the global bidders in VNR. For example, say the global's signal is 30, and the locals bid 10 and 70. If the global bids truthfully, she wins only one item, but by underbidding for the single items, she will win two items. Assuming that she enjoys winning two items more than winning one item, she may want to underbid on single item and not do so on the package. This is what we see in our VNR data. Nevertheless, while joy of winning explanation would predict overbidding for the packages as well, as in Chen and Takeuchi (2005), we do not observe overbidding in the package bids.

Figure 3.2 shows the behavior in SPNR. The locals bid more aggressively than theory predicts. For local bidders, the coefficient of the signal is significantly higher than 1 in the regressions in Table 3.6 (p =0.00). This is also consistent with the joy of winning explanation.

By Proposition 4, for the parameters used in the experiment, the equilibrium strategy of the global is as follows: for signals higher than 50, any bid on the interval [100, 300] is equally good; for signals less than 50, $b_g(s) = \frac{100s}{100-s}$. By log-transforming this equation, we get a linear equation $y = \alpha + \beta\tilde{s}$ where $y = ln\, b_g(s)$, $\alpha = ln(100) = 4.605$, $\beta = -1$, and $\tilde{s} = ln(\frac{100}{s} - 1)$. In the second column of Table 3.6, for the realized signals less than 50, we estimated the coefficients of this linear model with random effect at individual level and fixed effect at session level. We find that the coefficient and the constant are significantly different from the theoretical prediction

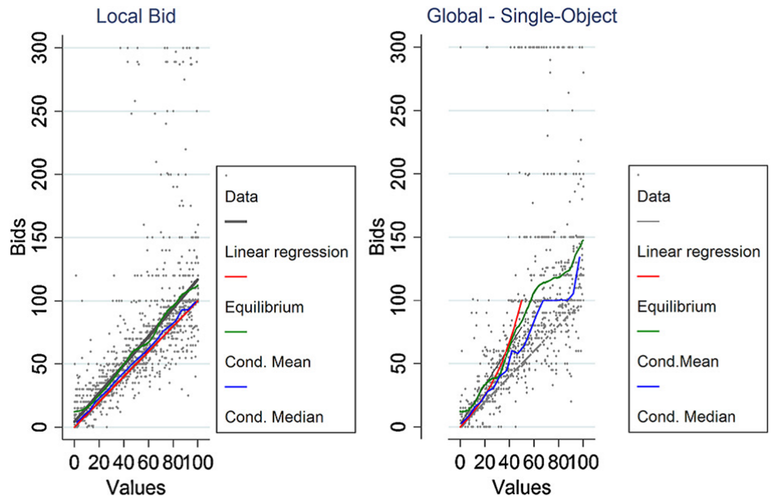

Figure 3.2: Bidding Behavior in SPNR.

Table 3.6: Bid Regressions for SPNR

	Depvar: b_l	Depvar: $ln(b_g)$ (for Signal $\leq$ 50)
Signal	1.115***	
	(0.021)	
$ln(\frac{100}{s_g} - 1)$		-0.755***
		(0.018)
Constant	11.118	4.369***
	(6.813)	(0.054)
N	1800	850

Notes: The standard errors are in parentheses. These are regressions with random effect at individual level and fixed effect at session level. * <0.10, ** < 0.05, and *** <0.01.

(p =0.000); hence, the globals' bids are less than what the theory predicts except for very low signals. Also, for globals' signals higher than 50, only 40.4% of bids are above 100. To sum up, as in Vickrey auction, here the global bidders who are interested in more than one object tend not to overbid except for very low signals. This is also observed in Figure 3.2. Due to complementarities, the global bidders face an exposure problem in SPNR. Although joy of winning motivation may imply overbidding for the globals in SPNR, the exposure problem is more severe since the locals are overbidding. The observed underbidding of the globals in this format can be explained by the globals' fear of paying too much for single item. Moreover, the globals with low signals are unlikely to experience exposure problem and for them the joy of winning may dominate exposure problem effect. Hence, by this explanation those globals may tend to overbid. This is indeed what we see in the data.

Figure 3.3 illustrates the bidding behavior of the locals and the globals in SPR. This figure shows that the bidders are not playing a pooling equilibrium where only one type of bidder always wins (see Remark1). Only 9 out of 1800 local bids were zero, and 15 out of 1800 global bids were 300.[14] We observe that the locals bid more than their value. Additionally, bidding more than one's value is more pronounced in the SPR format compared to the SPNR (p =0.000by Kolmogorov–Smirnov test). On the other hand, the bids of the global in SPR are less than those in SPNR (p =0.000by Kolmogorov–Smirnov test). One reason for this might be that, given the aggressive behavior of the locals in SPR, the global wants to lower her bid to make the locals think that her value is not much and hence get a lower resale prices from them.[15]

The literature considers nonzero bids of bidders with zero values as speculation since zero valued bidders are the only bidders who are bidding solely to benefit from the resale activity (see e.g. Garratt and Tröger, 2006). In SPR, 87.5% of the zero valued local bidders submit positive bids. Nevertheless, zero valued bidders may be submitting positive bids without strategically considering the resale activity. For example, even in SPNR, where there is no resale possibility, 68.8% of the zero valued local bidders submit positive bids. Furthermore, 58.3% of the zero valued globals

[14] Also less than 1% of the global bids for signals less than 50 were higher than 150.

[15] This explanation is supported by the price regressions in Table 3.8 where a local's resale price offer increases with the bid of global when the global needs to buy the second object in the resale stage.

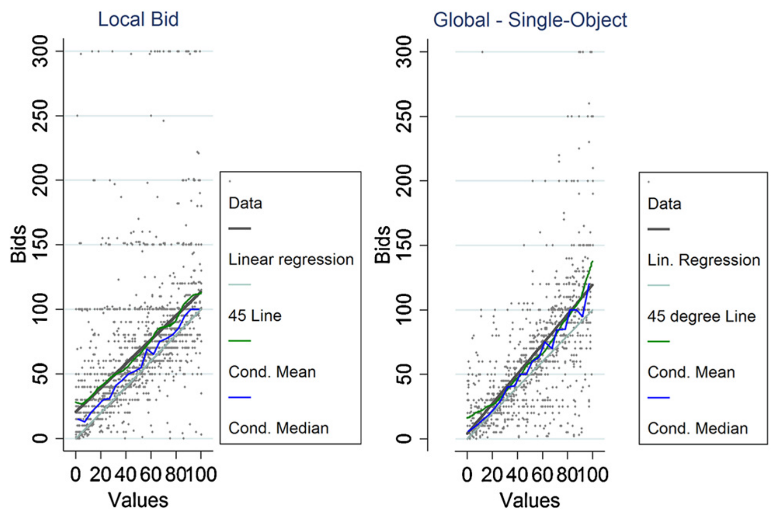

Figure 3.3: Bidding behavior in SPR.

submit positive bids in SPR and 50% in SPNR. We conclude that locals speculate more than the globals when we allow for resale.

Figures 3.4 and 3.5 compare, respectively, the bids of locals and globals for different signal bins in SPR and SPNR.[16] Especially for low signal bins, locals bid more aggressively in SPR than in SPNR. In fact, for all signal ranges up to 70 (except for the range [41, 50]), the median bid of SPR is significantly above the median bid in the SPNR format. On the other hand, the globals' median bids for any signal bin above 20 are significantly lower in SPR than in SPNR.

Resale stage in SPR

In the resale stage of SPR, the percentage of locals posting profitable offers (i.e. those who asked for resale prices above their own valuation) is 91.7%, and the percentage of rational acceptance (i.e. acceptance of resale terms if and only if doing so was profitable) among all losing bidders is 95.5%. The high rate of rational acceptance of resale offers has been also reported in a context where the seller offers a take-it-or-leave-it price to the losing bidder for the sale of a second unit (see Wilson and Salmon, 2008).[17]

[16] The box plots are created using standard techniques. The box represents the interquartile range (IQR); the whiskers extend to the furthest point within 1.5 $\times$IQR; the horizontal line in a box represents the median.

[17] However, in VR, only 77.5% of local offers were profitable, while the rational acceptance of resale offers was 90.4%. This result indicates that the major source of the inefficient sales is due to locals

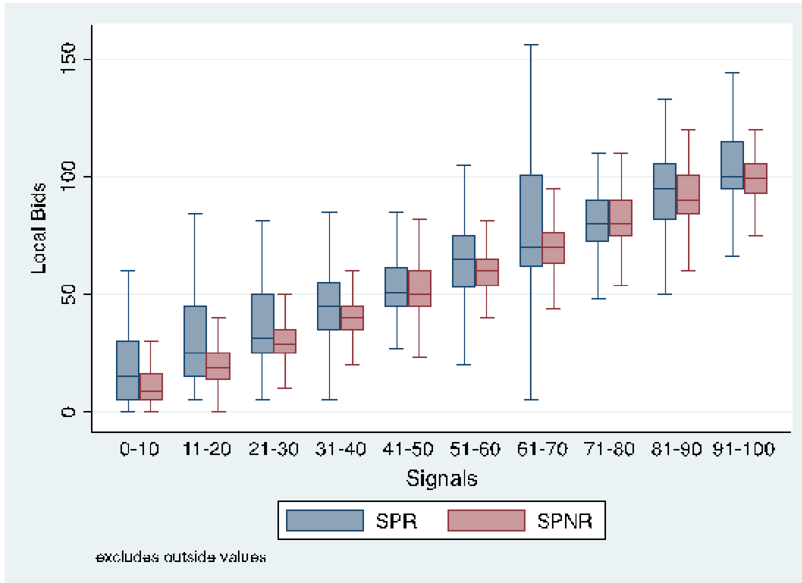

Figure 3.4: Locals' bids box-plots for SPR and SPNR.

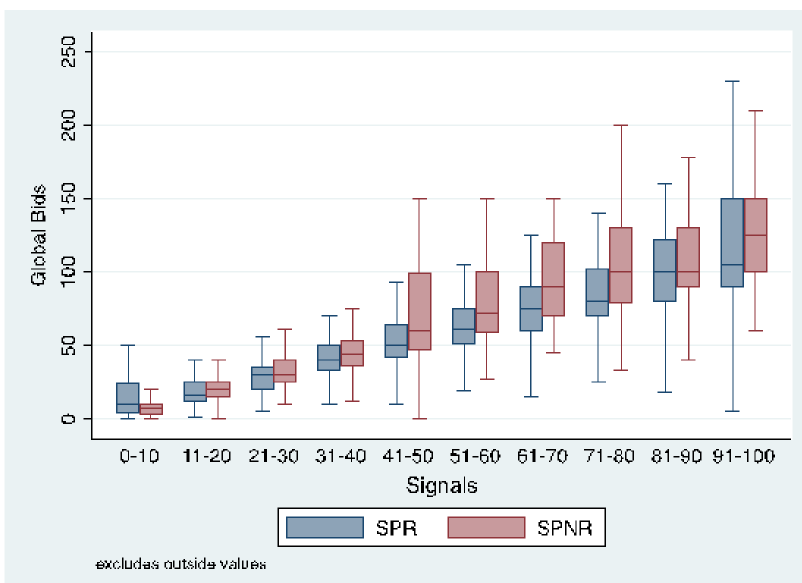

Figure 3.5: Globals' bids box-plots for SPR and SPNR.

Table 3.7: Average Resale Prices in SPR

Auction Outcome	Resale Prices Paid by Global	Locals
Local-Local	70.1	
	(4.178)	
LG, GL	84	42
	(3.145)	(5.411)
Global-Global		63.5
		(7.904)

Notes: LG (GL) denotes outcomes where local bidder A (B) obtains object A and Global bidder obtains B (A).

Table 3.7 reports that higher resale prices are paid by the global when she buys the second object in the post-auction trade than when she goes to resale after losing both objects in the auction. The difference is significant (p=0.000 in the comparison of 70.1 and 84). This finding is intuitive because the locals know that the marginal utility of the second object to the global is higher than the value of single object due to complementarities and they try to extract the additional surplus generated when the global receives the second object. As another implication of the complementarities, after the auctions where only one object is received by the global, the resale price is higher when the global buys than when she sells (p =0.000 in the comparison of 84 and 42). Similarly, when the global offers resale price for both objects, she charges a higher price than that when she sells only one object (p =0.023 in the comparison of 42 and 63.5). This is due to the additional value to the global of keeping an object when she has two versus one object.

Table 3.8 reports the results of the regressions for the locals' resale offers. When the locals win both objects in the auctions, their offers are affected only by their own signals. However, when the locals win only one auction, the offer of the winning local depends not only on her own signal but also on the global's bid in the same market (how much this local paid in the auction) and the bid of the other local (how much the global paid in the other auction that she won). These results suggest that when the global gets only one object in the auction, the local who has the other object is aware that the global must buy it to enjoy the extra payoff of the complementary object. Hence, when setting the price, this power gives an additional motive to the

offers.

Table 3.8: Regressions for Locals' Resale Offers in SPR

	LL		LG, GL
	First Offer	Second Offer	Local's Offer
Signal	0.876***	0.932***	0.647***
	(0.060)	(0.072)	(0.079)
Global Bid (same object)	0.15	-0.042	0.453***
	(0.148)	(0.190)	(0.129)
Global Bid (other object)	-0.127	-0.034	0.158
	(0.154)	(0.185)	(0.138)
Other Local Bid	-0.034	0.021	-0.195**
	(0.034)	(0.048)	(0.096)
First (local) Offer		0.044	
		(0.056)	
Constant	28.014***	16.391**	20.652***
	(6.639)	(7.968)	(6.143)
N	365	365	281

Notes: L-L denotes the auction outcome where locals win both objects. LG or GL denote the auction outcome where one local wins an objects and Global wins the other object. The standard errors are in parentheses. These are regressions with random effect at individual level and fixed effect at session level. $* < 0.10$, $** < 0.05$, and $*** < 0.01$.

local to take into account all the relevant information. For example, if the global's bid is high, she sets a high price to extract more from the global's payoff from the complementary objects; when the global's bid is low, she thinks that the global may sell it to the other local or be unwilling to pay a high price for the complementary object. The negative and significant coefficient of the other local's bid (i.e. how much the global paid in the market she won) in the third regression of Table 3.8 may be interpreted as follows: The higher bid by the other local may indicate a high value by that local and therefore the high probability of the global selling to that local rather than buying one more object. As a response, the offering local should lower her price in the resale if she wants the global to buy from her rather than sell to the other local. On the other hand, in the auction stage, if the global does not get any of the objects, a local is no longer the sole seller to the global, and the other local's price plays a role in the decision of the global as well. In this case, the locals just set a profitable price.

Table 3.9: Regressions for Globals' Resale Offers in SPR

	Global wins one object	Global wins both objects (Both offers)
Signal	0.569***	0.569***
	(0.074)	(0.061)
Local Bid (same object)	0.354***	-0.014
	(0.081)	(0.054)
Local Bid (other object)	0.014	-0.038
	(0.033)	(0.044)
Other Offer	-0.080*	
	(0.042)	
Constant	27.655***	48.863***
	(5.609)	(4.879)
N	194	197

Notes: The games where the offers are less than or equal to 100. The standard errors are in parentheses. These are regressions with random effect at individual level and fixed effect at session level. $* < 0.10$, $** < 0.05$, and $*** < 0.01$.

Table 3.9 reports the regression results for globals' resale offers for the offers not higher than 100. This is because we assume that any resale offer exceeding a price of 100 can only be made with the intent not to sell. In the regressions, the locals' bid is significant only when the global wins a single object. If a global offers a price less than 100 to sell the single object she has, she wants to extract as much as she believes she can from the losing local based on the information received from the auction stage. When the global wins both auctions and considers selling the objects, only her own signal is significant. In this case, there is room for an exposure problem because the global who aims to sell both objects may end up selling only one. To avoid this, the global sets profitable prices and increases the chance that both locals buy when she wants that.

Auction revenue

Table 3.10 reports the average observed auction revenue in each treatment as well as the average revenue predicted by the equilibrium for the Vickrey auction and for SPNR, for the draws used in the experiment. Using the 6 independent sessions per treatment, the Mann–Whitney test is used to compare the revenues. There is no significant difference between actual auction revenues in the different formats (for

Table 3.10: Average Revenues

Treatment	Theoretical Revenue	Observed Revenue
Vickrey	76.8	83.3
	(2.150)	(3.160)
SPNR	78.1	81.9
	(2.320)	(2.020)
SPR		80.3
		(4.670)

Notes: Session-clustered S.E. reported in parentheses.

Vickrey vs. SPNR, z=0.320 and p =0.749; for Vickrey vs. SPR, z=0.801 and p =0.423; for SPNR vs. SPR: z=−0.961 and p =0.337). There is also no significant difference between the actual and predicted revenues of SPNR (z=1.363 and p =0.173). However, the actual revenue in Vickrey auctions is significantly higher than that predicted by the theory (z=1.992 and p =0.046).

The Vickrey format generates more revenue than its equilibrium prediction because the locals bid aggressively in the experiment, as argued earlier. Also, in SPR auctions, locals bid more aggressively, but globals bid less aggressively than they do in SPNR. Those behaviors have opposite effects on revenue and thus cancel each other out. Hence, these two formats generated similar revenues in the experiment.

Bidder's payoff

Next we compare the formats from the bidders' perspective in Table 3.11. Using independent session averages, Mann–Whitney tests demonstrate that the payoff of the local is the highest in the SPR format. On the other hand, the payoff of the global is not significantly different across auction formats (i.e. globals have statistically equivalent mean and median payoffs in all formats, for all signal ranges, see also Figure 3.6). Figure 3.7 highlights that the mean and median payoffs of local bidders with signals above 70 are statistically higher in SPR than those in the other two formats.

3.4 Conclusion

We have studied multi-object auctions when post-auction resale among bidders is possible. Theoretically, Vickrey auc-tions (both with and without resale) have

Table 3.11: Bidders' Average Profits

Treatment	Locals' Profits		Global's Profits	
	Theoretical	Observed	Theoretical	Observed
Vickrey	12.28 (0.972)	12.7 (1.218)	67.8 (1.704)	49.99 (1.922)
SPNR	11.66 (0.981)	12.23 (0.705)	67 (1.737)	51.19 (2.472)
SPR		15.89 (1.800)		48.59 (1.119)

Notes: Session-clustered S.E. reported in parentheses.

Mean Median

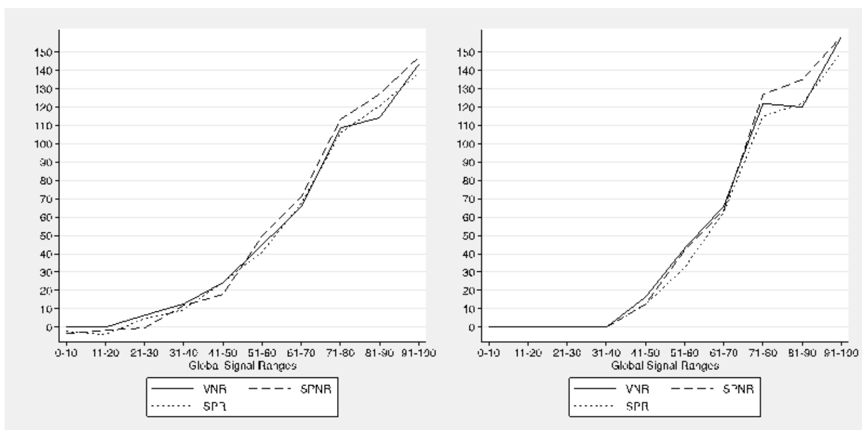

Figure 3.6: Globals' mean and median profits.

Mean Median

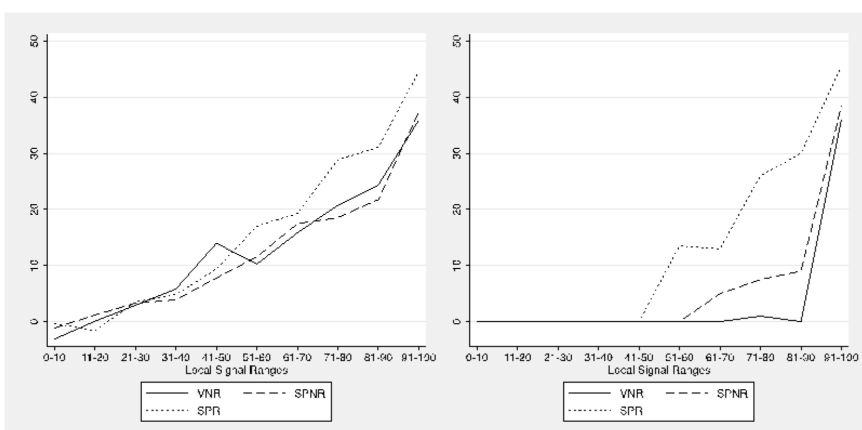

Figure 3.7: Locals' mean and median profits.

an efficient equilibrium; however, in any equilibrium of simultaneous second-price auctions (either with or without resale), the final allocation is not guaranteed to be efficient. In spite of the theoretical attractiveness of the Vickrey format, in practice, simultaneous second-price auctions are used more often than Vickrey auctions. This is mainly due to the complexity of the Vickrey format (see e.g. Rothkopf, 2007). It is notable that the Vickrey auction does not work so well even in a relatively simple environment. Experimental evi-dence highlights the trade-off between simple pricing rules that may lead to exposure problems and complex combinatorial auctions (see Bichler et al., 2014; Brunner et al., 2010).

In our experiment, we took the efficiency rate of Vickrey as our benchmark, and analyzed the effect of resale on simul-taneous second-price auctions. According to our results, although the possibility of resale decreases the efficiency rate in the auction stage of simultaneous second-price auctions, the final efficiency is improved to the observed efficiency rate in a Vickrey auction. Furthermore, in simultaneous second-price auctions, preventing resale hurts efficiency without changing the auction revenue, and allowing resale benefits the locals without diminishing the global bidder's expected payoff. Based on these results, we can conclude that when simultaneous second-price auctions are inevitable or preferred due to simplic-ity of their implementation, resale markets should be allowed. Nevertheless, in practice, the resale of objects usually leads to transaction costs in bargaining and delays in the actual use of the auctioned objects. It may be important to investigate the effect of such costs on auction stage efficiency rates.

Finally, this paper contributes to the literature by combining theory and experiment. Our experiment highlights the importance of simplicity of the pricing rule that we cannot detect by simply focusing on the theoretical results. Along this line, perhaps rather than Vickrey auction, a simpler pricing rule, such as pay-as-bid package auctions, may be better for combinatorial auctions when resale is possible. We leave this fruitful exercise for future research.[18]

[18]Supplementary material related to this article can be found online at http://dx.doi.org/10.1016/j.geb.2014.10.008.

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Appendix A

Appendix to Chapter 1

A.1 Proofs to Propositions

Proposition 1

Proof. For simplicity, here I provide the proof for non-corner solutions and differentiable g. First, notice that in either choice problem (risk taking with *fair* risks and with *unfair* risks) DM and her counterpart face the exact same marginal risk. Therefore, $D = 0$ always and utility becomes $U = \mathbb{E}g(x, y)$. That is, this proposition is a result emerging purely emerging from ex post motives.

Consider now the problem of chosing the optimal risk taking with fair risks, α^{f*}. This problem can be expressed as:

$$\max_{\alpha \in [0,1]} g\left(\alpha \bar{Z}\,,\, \alpha \bar{Z}\right) + g\left((1-\alpha)\, \underline{Z}\,,\, (1-\alpha)\, \underline{Z}\right) \tag{A.1}$$

where I have used the fact that $p_A = 0.5$. The corresponding first order condition (FOC) is:

$$\frac{\underline{Z}}{\bar{Z}} = \frac{g_1\left(\alpha^f \bar{Z}\,,\, \alpha^f \bar{Z}\right) + g_2\left(\alpha^f \bar{Z}\,,\, \alpha^f \bar{Z}\right)}{g_1\left((1-\alpha^f)\, \underline{Z}\,,\, (1-\alpha^f)\, \underline{Z}\right) + g_2\left((1-\alpha^f)\, \underline{Z}\,,\, (1-\alpha^f)\, \underline{Z}\right)} \tag{A.2}$$

Similarly, for the problem of chosing the optimal risk taking with unfair risks, α^{uf*}, the corresponding problem can be expressed as:

$$\max_{\alpha \in [0,1]} g\left(\alpha \bar{Z}\,,\, (1-\alpha)\, \underline{Z}\right) + g\left((1-\alpha)\, \underline{Z}\,,\, \alpha \bar{Z}\right) \tag{A.3}$$

and its associated FOC is:

$$\frac{\underline{Z}}{\bar{Z}} = \frac{g_1\left(\alpha^{uf}\bar{Z}\,,\,\left(1-\alpha^{uf}\right)\underline{Z}\right) + g_2\left(\left(1-\alpha^{uf}\right)\underline{Z}\,,\,\alpha^{uf}\bar{Z}\right)}{g_1\left(\left(1-\alpha^{uf}\right)\underline{Z}\,,\,\alpha^{uf}\bar{Z}\right) + g_2\left(\alpha^{uf}\bar{Z}\,,\,\left(1-\alpha^{uf}\right)\underline{Z}\right)} \tag{A.4}$$

To look for a contradiction, suppose $\alpha^{uf} \geq \alpha^{f}$. In such case, we have:

$$\begin{aligned}
\frac{\underline{Z}}{\bar{Z}} &= \frac{g_1\left(\alpha^{uf}\bar{Z}\,,\,\left(1-\alpha^{uf}\right)\underline{Z}\right) + g_2\left(\left(1-\alpha^{uf}\right)\underline{Z}\,,\,\alpha^{uf}\bar{Z}\right)}{g_1\left(\left(1-\alpha^{uf}\right)\underline{Z}\,,\,\alpha^{uf}\bar{Z}\right) + g_2\left(\alpha^{uf}\bar{Z}\,,\,\left(1-\alpha^{uf}\right)\underline{Z}\right)} \\
&< \frac{g_1\left(\alpha^{uf}\bar{Z}\,,\,\alpha^{uf}\bar{Z}\right) + g_2\left(\alpha^{uf}\bar{Z}\,,\,\alpha^{uf}\bar{Z}\right)}{g_1\left(\left(1-\alpha^{uf}\right)\underline{Z}\,,\,\left(1-\alpha^{uf}\right)\underline{Z}\right) + g_2\left(\left(1-\alpha^{uf}\right)\underline{Z}\,,\,\left(1-\alpha^{uf}\right)\underline{Z}\right)} \\
&\leq \frac{g_1\left(\alpha^{f}\bar{Z}\,,\,\alpha^{f}\bar{Z}\right) + g_2\left(\alpha^{f}\bar{Z}\,,\,\alpha^{f}\bar{Z}\right)}{g_1\left(\left(1-\alpha^{f}\right)\underline{Z}\,,\,\left(1-\alpha^{f}\right)\underline{Z}\right) + g_2\left(\left(1-\alpha^{f}\right)\underline{Z}\,,\,\left(1-\alpha^{f}\right)\underline{Z}\right)}
\end{aligned} \tag{A.5}$$

where the first inequality holds because g satisfies strict supermodularity (see Definition 1), and the second inequality holds because g was assumed to be concave along the 45 degree line (to capture aversion to fair risks). Expression (A.5) contradicts the FOC for α^{f*}(Equation A.2) and therefore $\alpha^{f*} > \alpha^{uf*}$ □

Proposition 2

Proof. I prove 2.i by constructing outcomes A and B that satisfy the proposition for given preferences $\mathbb{E}g - \delta D$. Recall it is assumed g is increasing in x and y, $\mu(t) = t$ and $p > 1$. It can be seen that for some $k > 0$ we can always form outcomes $A = (x_l, y_h)$ and $B = (x_h, y_l)$ such that: (i) $g(A) = g(x_l, y_h) = g(x_h, y_l) = g(B)$, and (ii) $y_h - x_l = x_h - y_l = k$. Since $D = k$ when either outcome A or B occurs for sure, we also have that $B \sim A$. Therefore, to show that the optimal probability of A is non trivial – i.e. $p_A \in (0,1)$, we only need to work with the ex ante term D.

Define $L = \frac{1}{2}A \oplus \frac{1}{2}B$ and denote by F_x^L and F_y^L as the corresponding marginal risks associated with lottery L.

Claim: $D\left(F_x^L, F_y^L\right) < k$. To see this claim, notice that given the conditions imposed on A and B, we have either: $y_l \leq x_l \leq x_h \leq y_h$ or $x_l \leq y_l \leq y_h \leq x_h$. WLOG, let me assume the first one. Therefore, we have: $D\left(F_x^L, F_y^L\right) = \frac{1}{2}^p(x_l - y_l) + \frac{1}{2}^p(y_h - x_h) \leq 2^{1-p}k < k$. This implies $L \succ A \sim B$, as desired.[1]

[1] Importantly, notice I constructed outcomes A and B that will trigger ex ante fairness behavior

Next, I prove 2.ii. For simplicity, , I assume the exponent p inside equation (1.4) equals 2. Also, without loss of generality let me focus on the case where $\frac{y_A - y_B}{x_B - x_A} > 0$; that is, where each outcome is relatively advantagous to one of the agents (DM and her counterpart) and no outcome is dominated. Otherwise, optimal p_A will be zero or one.

First, recall again that, given the assumptions, the utility is given by $U = \mathbb{E}g(x, y) - \delta D(F_x, F_y)$. Because we are restricted to the two outcome (A and B) case, it can be shown that: (i) as in the standard EU theory, $\mathbb{E}g(x, y)$ is a linear form on p_A: $p_A g(x_A, y_A) + (1 - p_A) g(x_B, y_B)$, and (ii) D is a quadratic form over p_A: $D = c_0 - c_1 p_A + c_2 p_A^2$, with $c_j > 0$. Also, coefficients c_j will depend on x_A, y_A, x_B, y_B. If we assume non-corner solution and, therefore, the solution is given by the first order condition, $\frac{\partial U}{\partial p_A} = 0$, then the optimal p_A can be expressed as:

$$\begin{aligned} p_A &= \frac{g(x_A, y_A) - g(x_B, y_B) - \delta c_1}{\delta 2 c_2} \\ &= \frac{1}{\delta} \frac{g(x_A, y_A) - g(x_B, y_B)}{2c_2} - \frac{c_1}{2c_2} \end{aligned} \tag{A.6}$$

From this solution, we can see that for small enough δ, p_A will depend positively on x_A, y_A and negatively on x_B, y_B, regardless how these outcomes affect c_1 and c_2. The proof is complete. □

Proposition 3

Proof. For simplicity, I assume the case of a non-corner solution. In the GEIA model, $U(L) = \delta_s u(\mathbb{E}[x, y]) + (1 - \delta_s)\mathbb{E}[u(x, y)]$. Also, because the proposition is restricted to the case of fair lotteries, we can define $v(z) = u(z, z)$ which we have already assumed to be concave. Further, using the definition of fair lotteries $L^{fair}(\alpha)$ in the corresponding choice problem, we have that:

$$U(L^{fair}) = \delta_s v\left(\alpha \tfrac{\bar{Z} - \underline{Z}}{2} + \tfrac{\underline{Z}}{2}\right) + \left(\tfrac{1-\delta_s}{2}\right)\left(v\left(\alpha \bar{Z}\right) + v\left((1-\alpha)\underline{Z}\right)\right) \tag{A.7}$$

Using the first and second order conditions as well as the implicit function theorem, we have that:

$(p_A \in (0, 1))$ for any strictly positive δ, even if it is arbitrarily small.

$\frac{d\alpha^{fair*}}{d\delta_s} = -\left(\frac{\partial U_\alpha}{\partial \delta_s} / \frac{\partial U_\alpha}{\partial \alpha}\right)_{\alpha=\alpha^{fair*}}$, where $U_\alpha = \frac{\partial U(L^{fair}(\alpha))}{\partial \alpha}$, and $\alpha = \alpha^{fair*}$solves $U_\alpha = 0$. Furthermore,$\left(\frac{\partial U_\alpha}{\partial \alpha}\right)_{\alpha=\alpha^{fair*}}$ is negative as it is simply the second order condition (SOC) of a maximization problem. Next, I show $\left(\frac{\partial U_\alpha}{\partial \delta_s}\right)_{\alpha=\alpha^{fair*}} > 0$. To see this, notice that:

$$U_\alpha = \frac{\partial U(L^{fair}(\alpha))}{\partial \alpha} = \delta_s v'\left(\alpha\frac{\bar{Z}-\underline{Z}}{2} + \frac{\underline{Z}}{2}\right) + \left(\frac{1-\delta_s}{2}\right)\left(\bar{Z}v'\left(\alpha\bar{Z}\right) - \underline{Z}v'\left((1-\alpha)\underline{Z}\right)\right) \quad \text{(A.8)}$$

and therefore:

$$\frac{\partial U_\alpha}{\partial \delta_s} = v'\left(\alpha\frac{\bar{Z}-\underline{Z}}{2} + \frac{\underline{Z}}{2}\right) - \frac{1}{2}(\bar{Z}v'\left(\alpha\bar{Z}\right) - \underline{Z}v'\left((1-\alpha)\underline{Z}\right)) \quad \text{(A.9)}$$

If I show $\bar{Z}v'\left(\alpha\bar{Z}\right) - \underline{Z}v\left((1-\alpha)\underline{Z}\right) \leq 0$ at optimal α, then the proof is complete. By contradiction, if instead we have $\bar{Z}v'\left(\alpha\bar{Z}\right) - \underline{Z}v\left((1-\alpha)\underline{Z}\right) > 0$, then the corresponding α is not a solution as $U_\alpha > 0$ regardless α. Summing up, $\bar{Z}v'\left(\alpha\bar{Z}\right) - \underline{Z}v\left((1-\alpha)\underline{Z}\right) \leq 0$, therefore $\left(\frac{\partial U_\alpha}{\partial \delta_s}\right)_{\alpha=\alpha^{fair*}} > 0$, and consequently $\frac{d\alpha^{fair*}}{d\delta_s} > 0$. □

Proposition 4

Proof. This proof is immediate from the contunuity and differentiability of u, and from the fact that purely ex ante decision makers will choose to maximize the expected value regardless whether the lotteries are fair or unfair. That is, if $\delta_s = 1$, then $\alpha^{fair*} = \alpha^{unfair*} = 1$. □

Proposition 5

Proof. I assume that u is increasing in x everywhere, and u is increasing in y it $x > y$. I had already assumed that u is concave, I strenghten this by assuming u is also strictly concave at least somewhere (e.g. if u is the F&S utility, u is strictly concave along the 45 degree line). Under these rather general conditions, it is easy to see that there exist a and b such that this deterministic-dictator choice problem:

$$\max_{s\in[0,1]} u(s0 + (1-s)b\,,\, sa + (1-s)0) \quad \text{(A.10)}$$

has an non-corner solution $s^* \in (0,1)$.

Consider any arbitrary a and b such that the corresponding $s^*$is in fact in the interval $(0,1)$. We want to study the choice problem:

$$\max_{p\in[0,1]} \quad \delta_s u\left((1-p)\,b\,,\,p\,a\right)) + \\ (1-\delta_s)\left(pu(0,a)+(1-p)\,u(b,0)\right) \tag{A.11}$$

whose solution is denoted by p*. This is the probabilistic giving problem where $A=(0,a)$ and $B=(b,0)$. Let me assume, WLOG, that $B\succ A$ – i.e. $u(B)>u(A)$. The following four claims suffice for Proposition 5.

Claim 1: if $\delta_s=0$, then $p^*=0$.
This is an immediate result from the fact that in this case we are in the standard expected utility model.

Claim 2: if $\delta_s=1$, then $p^*=s^*$.
This is a result emerging from the fact that for purely ex ante driven decision makers the *probabilistic giving* problem (expression A.11) is equivalent to the standard *deterministic* giving problem (expression A.10). Therefore their solutions are equivalent as well.

Claim 3: if $\delta_s<1$, then $p^*<s^*$
Consider the following function:

$$h(p)=u\left((1-p)\,b\,,\,p\,a\right)) \tag{A.12}$$

which is concave in p necessarily. It is easy to see that the utility we are maximizing can be expressed as:

$$\delta h(p)+(1-\delta)\left(\,p\,h(1)+(1-p)\,h(0)\,\right) \tag{A.13}$$

and the corresponding FOC is:

$$U_p=\delta h'(p^*)+(1-\delta)\left(\,h(1)-h(0)\,\right)=0 \tag{A.14}$$

Suppose that $p^* \geq s^*$. Notice that $h(1) - h(0) < 0$ – as I assumed B is preferred over A – and $h'(s^*) = 0$. Then $h'(p^*) \leq 0$ and so $U_p < 0$ regardless p: a contradiction. Therefore $p^* < s^*$.

Claim 4: $\frac{dp^*}{d\delta_s} > 0$

Notice that (i) Claim 3 implies $h'(p^*) > 0$, (ii) $\frac{\partial U_p}{\partial \delta} > 0$ at $p = p^*$, and (iii) $\frac{\partial U_p}{\partial p} > 0$ at $p = p^*$. Then, by the implicit function theorem, $\frac{dp^*}{d\delta_s} > 0$. $\square$

A.2 Experimental Instructions

Experimental Instructions

This is an experiment in decision-making. Several research foundations have provided funds for this study. Your final earnings today will depend partly on your decisions, partly on the decisions of others and partly on chance. Precise rules will be explained below. Please pay careful attention to the instructions. At the end of the experiment, you will be paid in cash. All payments will be made in private. Also, you will receive $7 as a participation fee, simply for showing up on time.

During the experiment we will use *Experimental Tokens* instead of dollars. At the end of the experiment, your earnings in tokens will be translated into dollars. You will receive 1 dollar for every 5 tokens you have earned in the session.

It is important that you do not talk or in any way try to communicate with other people during the session. If you have a question, raise your hand and an experimenter will attend to your station to answer your question privately. The experiment should be finished in approximately one hour.

Pairs

At the beginning of the experiment, you will be randomly and anonymously matched with one other participant to form a *pair*. Within each pair there will be one person with the role of "*Decider*" and another person with the role of "*Partner*." These roles will be assigned randomly, and will remain for the entire session. No participant will learn in any way the identity of his/her counterpart at any moment of the session.

In each pair, only choices made by the *Decider* will determine final payoffs. Although the *Partner* will face the same kinds of tasks, his/her choices will not determine anyone's payoffs.

Tasks, Decision Rounds and Earnings

This experiment will consist of a series of *decision rounds* of five different types of tasks. Each kind of task will be detailed below. At the end of all decisions, the computer will randomly select one choice made by the *Decider* and generate payoffs for both *Decider* and *Partner* based on that selected choice. The selected choice as well as the final payoffs it generates will be disclosed to both participants.

Please, raise your hand if you have any questions. Do not ask any questions out loud. Remember not to discuss your role, choices or results with any other participant at any time during the experiment. When you are done, please wait quietly until the rest of participants finish their tasks. Thank you!

Task Type 1

Decider Task:

In this task, you are given two fixed, <u>mutually exclusive</u> outcomes. You are then asked to decide the probabilities of these two outcomes.

Figure 1: Task 1

[in text]

In the left-side graph, *your tokens* are represented on the horizontal axis and *Partner's tokens* on the vertical axis. Each of the two possible outcomes is represented by a cross or a bubble in this graph. You must decide what the probability of each outcome is, in percentage (%) terms. Figure 1 shows an example of this task where the two fixed outcomes are A = (You: 10, Partner: 90) and B = (You: 80, Partner: 10).

On the right side of the screen you have a slider tool where you can chose the *chance of Outcome A*, from 0% to 100%. Drag the *green triangle* onto your chosen percentage. If you choose 100, outcome *A* will occur for sure. If you choose 0, outcome *B* will occur for sure. In the graph, the size of each outcome bubble will increase with the chances it is given. You can try as many combinations as you want before you decide. The same information of the graph is displayed in the small table below the slider bar. Throughout this session, your tokens will be represented in blue and *Partner*'s tokens in orange. Once you make your choice, press the *submit decision* button and continue to the next round. Please think your decisions carefully.

Partner Task:

You will face the same kind of task as your counterpart, the *Decider*, except your choices will be hypothetical. They will not affect payoffs for any participant. Please think your decisions carefully.

Interface for Tasks 2 and 3

In each decision round, there will be two probable states: State A and State B. Think of these states as the weather: it could be either *sunny* or *cloudy*. However, when you make your decision, it is uncertain which state will occur.

Your decision will be represented by a point on a graph like the one in Figure E. In this graph, the horizontal axis indicates *Tokens paid if State A occurs*, and the vertical axis indicates *Tokens paid if State B occurs*. The chance that each state will occur is displayed in parentheses on the corresponding axis label. In Figure E, for instance, the probability of State A is 50%, and the probability of State B is 50%, as well. However, beware that these probabilities might be different in another decision rounds.

The position of a point on this graph represents a lottery. For example, in Figure E, the point on location (40, 27) indicates that if State A is realized, the lottery pays 40 tokens; and if State B is realized, the lottery pays 27 tokens. Decider's lottery will be depicted by a *blue square* and *Partner*'s lottery by an *orange circle.*

Figure E: Decision Interface Tasks 2, 3

[in text]

Task Type 2

Decider's Task:

For Task 2, both *Decider* and *Partner* share the same fortune: in each state, the amount of tokens both receive is the same. See for example, Figure 2. Here states A and B each occur with a 50% chance. Also, since both participants face the exact same fate, *Decider*'s blue square and *Partner*'s orange circle are always located on the same spot. In Figure 2, they both are on location (40, 27). This means, if State A happens, you and your *Partner* will both get 40 tokens and if State B occurs instead, you both get 27 tokens.

At the beginning of each decision screen, the square and the circle will appear by the (0, 0) combination. To make a choice drag the square or the circle to your chosen location. The other shape will follow. Only combinations on the purple line are feasible choices. The computer will not let you choose a combination outside the purple line. The same information displayed in the graph is shown in the table next to it. Each row represents one possible state and the tokens paid if such state occurs. You can try as many combinations as you want before you decide. Once you make your choice, press the *submit decision* button and continue to the next round.

Please beware that the probabilities of each State might vary across different decision rounds. Please think your decisions carefully.

Figure 2: Task 2

[in text]

Partner's Task:

You will face the same kind of task as your counterpart, the *Decider*, except your choices will be hypothetical. They will not affect payoffs for any participant. Please think your decisions carefully.

Task Type 3

Decider's Task:

For Task 3, *Decider* and *Partner* have *opposite fortunes*. What *Decider* would get in State A equals what *Partner* would receive in State B. Similarly, what *Decider* would get in State B is what *Partner* would get in State A.

See example in Figure 3 where states A and B both occur with 50% chance. Here, since both counterparts face reverse fate, *Decider*'s blue square and *Partner*'s orange circle are always in mirror positions on the graph. In Figure 4, for example, *Decider*'s square is at (A⟶20, B⟶54) and *Partner*'s circle at (A⟶54, B⟶20). This means, if State A happens, *Decider* receives 20 and *Partner* gets 54; and if State B happens *Decider* gets 54 and *Partner* gets 20. Also, beware that the probabilities of each State might vary across different decision rounds.

At the beginning of each decision screen, the square and the circle will appear by the (0, 0) combination. To make a choice drag either the square or the circle to your chosen location. The other shape will locate accordingly. For the *Decider*, feasible combinations are along the light blue line and for *Partner* along the light orange line. The computer will not let you choose a combination outside these lines. The same information displayed in the graph is shown in the table next to it. Each row represents one possible state and the tokens paid if such state occurs. You can try as many combinations as you want before you decide. Once you make your choice, press the *submit decision* button and continue to the next round. Please think your decisions carefully.

Figure 3: Task 3

[in text]

Partner's Task:

You will face the same kind of task as your counterpart, the *Decider*, except your choices will be hypothetical. They will not affect payoffs for any participant. Please think your decisions carefully.

Task Type 4

Decider Task:

In this task, you will be given a set of possible token combinations for you and your *Partner*. You are asked to choose one combination and submit your decision.

Figure 4: Task 4

[in text]

Figure 4 shows an example of this kind of task. You will see a graph on a white background representing token allocations. In all rounds of this task, *your tokens* will be indicated on the horizontal axis and your *Partner's tokens* on the vertical axis. The same information is also displayed in the table on the right of the screen. Throughout this session, your tokens will be represented in blue and *Partner*'s tokens in orange.

For example, the point (32, 38) depicted in Figure 4 by a red square indicates that you will receive 32 tokens and your counterpart will receive 38 tokens. This is also indicated in the label "You: 32, *Partner*: 38" and in the table (see projector screen).

At the beginning of each task, the red square will appear by the (0, 0) combination. To make a choice, click, hold and drag the red square with the mouse to any position within the *gray line*. Only combinations along this *gray line* are feasible, valid choices. The computer will not let you chose any point but those. You can try as many combinations as you want before you make your decision. Once you have the red square at the intended position, press the *submit decision* button and continue to the next round. Please think your decisions carefully.

Partner Task:

You will face the same kind of task as your counterpart, the *Decider*, except your choices will be hypothetical. They will not affect payoffs for any participant. Please think your decisions carefully.

Appendix B

Appendix to Chapter 2

B.1 Additional Results and Figures

Table B.1: Statistics by Pool

TAMU				
	FM	*OFU*	*SLTM*	*NM*
Number of pairs	25	29	19	21
Labor Income Type 1 ($)	10.3	10.3	10.3	10.3
Labor Income Type 2 ($)	10.3	10.3	10.3	10.3
Take ratio (percent)	38.8	62.7	62.2	58.3
Expected take ratio (percent)	58.6	50.9	47.8	50.5
WTP for msg. ($)		0.87	0.37	
Final Earnings Type 1 ($)	17.3	19.8	19.7	19.4
Final Earnings Type 2 ($)	9.3	6.7	6.8	7.3
UMD				
	FM	*OFU*	*SLTM*	*NM*
Number of pairs	32	42	25	43
Labor Income Type 1 ($)	10.4	10.3	10.4	10.4
Labor Income Type 2 ($)	10.4	10.4	10.4	10.4
Take ratio (percent)	57.1	65.0	67.6	77.4
Expected take ratio (percent)	48.5	61.7	63.5	59.4
WTP for msg. ($)		0.69	0.28	
Final Earnings Type 1 ($)	19.3	20.1	20.4	21.4
Final Earnings Type 2 ($)	7.5	6.5	6.3	5.4

Table B.2: Take Rate and Expected Take Rate Regressions

	Take Rate b/se	Expected Take Ratio b/se
OFU	17.087***	1.730
	(6.542)	(6.024)
SLTM	18.031**	0.977
	(7.057)	(6.885)
NM	20.677***	0.449
	(6.280)	(6.317)
Constant	46.675***	54.242***
	(4.636)	(4.510)
Observations	236	236
R2	0.05	0.00

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. FM is the comparison group.

Table B.3: Probit Regressions of Positive WTP in *OFU*

	Model 1 b/se	Model 2 b/se
Take Ratio	-0.068***	
	(0.022)	
Take Ratio (squared)	0.001***	
	(0.000)	
Surprise Take Rate		-0.003
		(0.004)
Surprise (squared)		0.000
		(0.000)
Constant	1.959***	0.501**
	(0.576)	(0.216)
Observations	71	71

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentesis.

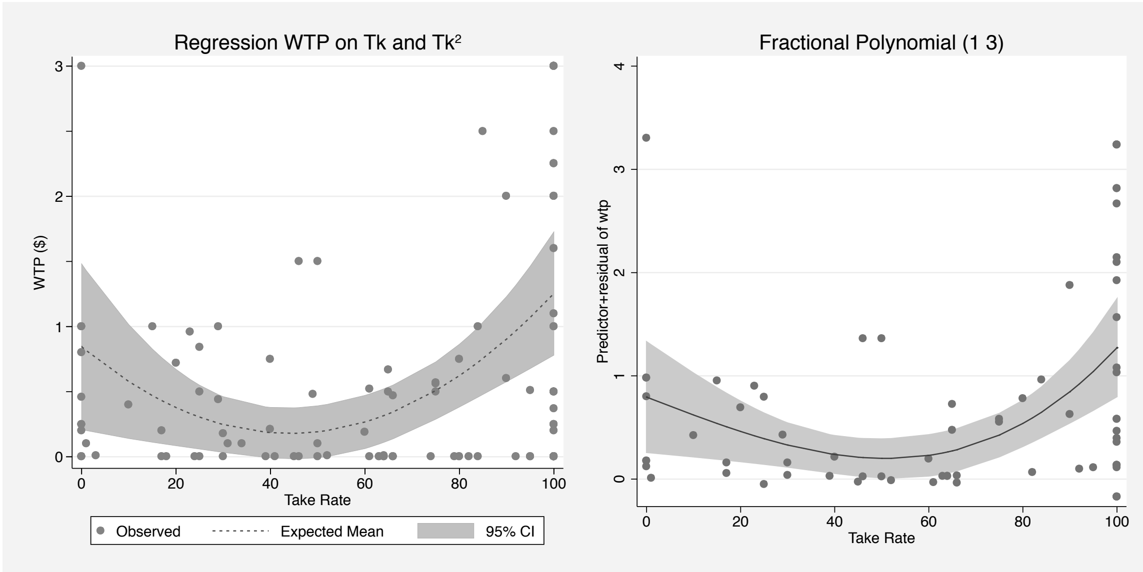


Figure B.1: Relationship between WTP and Take Rate

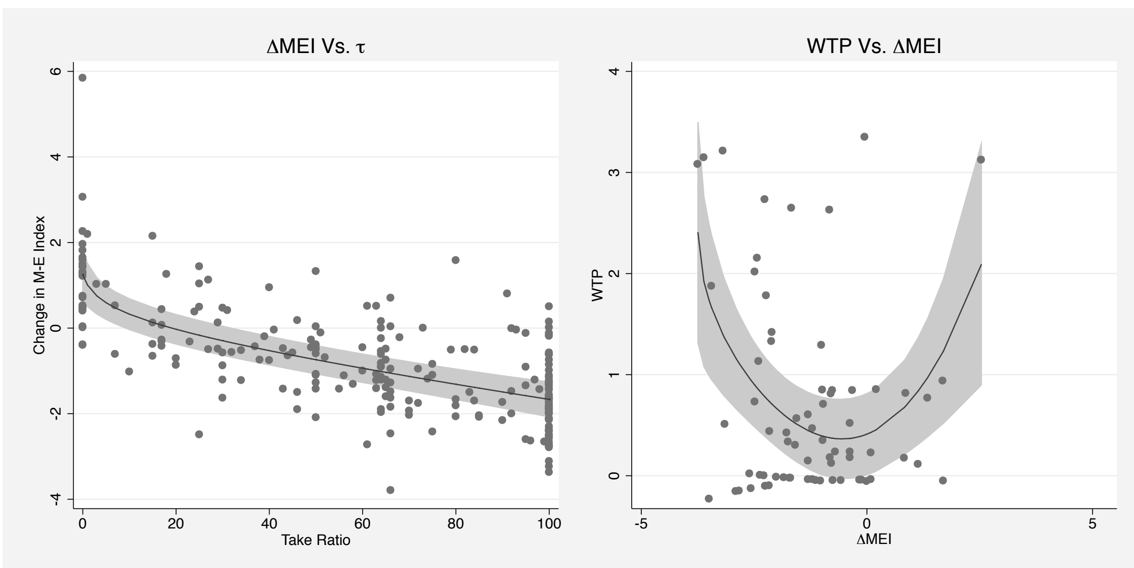


Figure B.2: Take Rate, MEI and WTP

Notes: One outlayer observation regarding the mood emotions reports was disregarded from this estimation.

B.2 Instructions

Welcome to the Economic Research Laboratory. This is an experiment in decision-making. The National Science Foundation has provided funds for this research. Just for showing up you have already earned 5 dollars. During the course of the experiment, you will be called upon to make a series of decisions. If you follow the instructions carefully and make good decisions, you can earn real money, which will be paid to you in cash at the end of the experiment. It is important that you remain silent and do not look at other people's work. If you have any questions, or need assistance of any kind, please raise your hand and an experimenter will come to you. If you talk, laugh, exclaim out loud, etc., you will be asked to leave and you will not be paid. We expect and appreciate your cooperation. We will first jointly go over the instructions. After we have read the instructions, you will have time to ask clarifying questions. Each of you will then need to answer a few brief questions to ensure everybody understands. Please do not touch the computer or its mouse until you are instructed to do so. Thank you.

Participants An even number people are participating in today's experiment. There are two possible roles for each participant, the role T and the role P. Each of you will be randomly assigned to have one of them. You will remain in the same role throughout the entire duration of the experiment. That is, you will either be T for the entire experiment or you will be P for the entire experiment. You will be informed about your role on your computer screen once the experiment starts. There will be an equal number of participants in role T and role P.

Today's experiment consists of four parts. Each of those is explained below.

Part 1 and Part 4: Questionnaires

For the first and the last part of the experiment you will not make any decisions. In these parts we ask you to answer a series of brief questions. Please, read each screen carefully and follow the instructions to answer those questions.

Part 2: Earning Money

The second part of the experiment is where you will generate earnings. In this part, each participant receives an endowment of $3.00 and then can earn additional income by completing a sequence of search tasks. In each of the search tasks you are asked to find the top of a mountain. The current location is given by a maroon square, which you have to drag with the mouse onto new locations until you get to the top. You will be assisted by an altitude instrument, called the Points Indicator, that will tell you the direction you should follow to the only peak of the mountain (up/down-right/left) (see Figure 1). At each location you will know how many points you will earn if you stopped searching. For each of the search tasks you can try as many locations as you want within a time limit of 35 seconds. The point indicator and a message saying “Well Done!” will tell you when you have reached the top of the mountain. You are given two untimed practice tasks before the real tasks start.

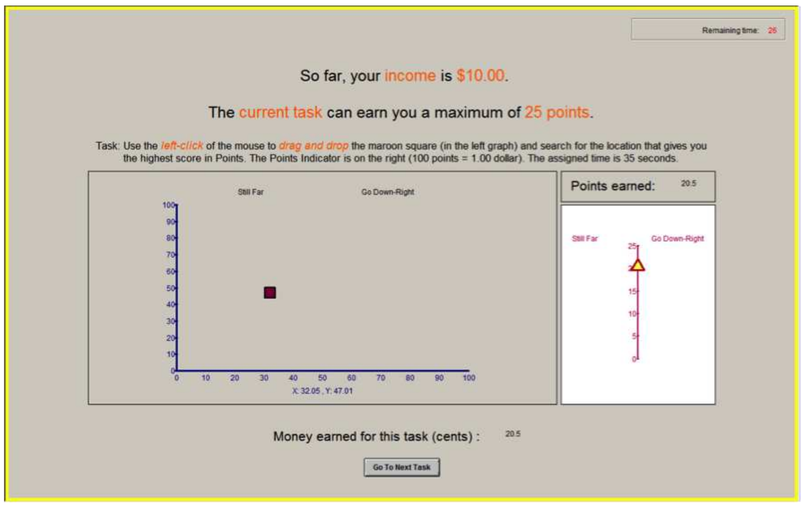


Figure B1: Search Task

All search tasks you will be given are exactly of the same type. Though, each of them has potentially different earnings possibilities. Do your best in each task, you will receive $1.00 for every 100 points you accumulate throughout this part of the experiment. Your endowment ($3.00) plus the income you make in these search tasks will be the balance in your account at the beginning of Part 3.

Part 3: Interacting

For this part of the experiment each of you will be randomly paired with another participant through the computer. Each pair will consist of one participant of role T and one participant of role P. Roles will be assigned randomly. You will never be informed about the identity of the person you are paired with, neither during nor after the experiment. Similarly, the participant you are matched with will never be informed about your identity. At the beginning of this part you will be informed about your role (either T or P) and about the previous earnings of your counterpart. Decisions made in this part of the experiment will determine the final amount of money you will take home.

T's Task T is given the authority to transfer money from P's account to T's own account. The maximum amount of money T can collect is what P has earned as income in the search tasks of Part 2. The endowment of $3.00 cannot be transferred. In the corresponding screen, T will be asked what percentage of P's task income T wants to transfer into his/her own account. T will use a percentage slider, as shown in Figure 2, to make his/her decision. The screen will show the percentage selected as well as the corresponding dollar amount. Additionally, T's final earnings given the selection will be displayed. After T has made this choice, no other decision made by him/her or P will affect T's final earnings.

P's Task After being informed about T's decision, each P will be given the opportunity to write a message for T to read it. The content of the message depends entirely on what P wants to express. Sending a message, however, is costly. Each P, before knowing the actual price of sending a message, will be asked about the highest amount (in $) he/she is willing to pay for doing so. After P submits this amount, the actual price will be randomly determined by the computer and revealed on a new screen.

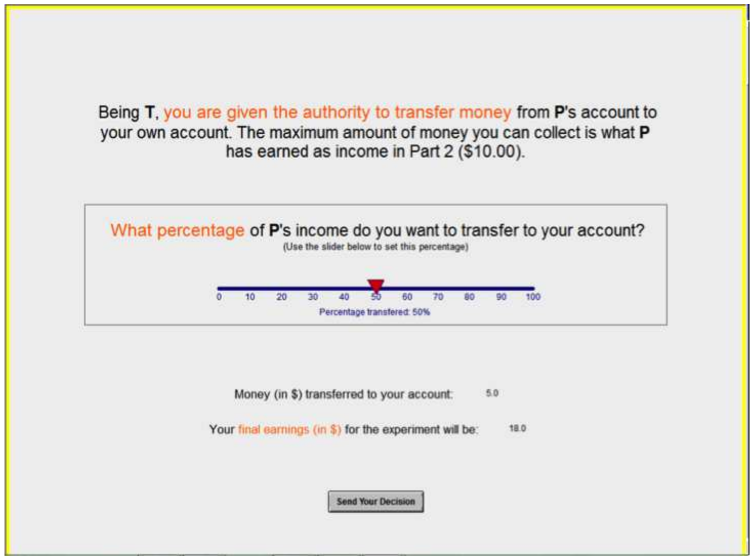


Figure B2: T's Decision Screen

If P's willingness to pay is greater than or equal to the actual price, then P will be able to send a message and will pay the actual price generated by the computer. If P's willingness to pay is lower than the actual price, then P will not be able to send any message and will not be charged. Before being asked to state a willingness to pay, each P will be informed about his/her available earnings (see Figure 3). Available earnings are defined as the balance P obtained in Part 2 MINUS what T transferred to T's own account ($3.00+ Task Income - Transfer to T). These earnings represent all of the money that P can spend at that point, i.e. the stated willingness to pay cannot exceed that amount. The computer draws the actual price randomly from a uniform distribution ranging from $0 (zero dollars) to $3 (three dollars). This means that all prices in that range are equally likely to be drawn as the actual price. A new price is drawn for each P, with each draw being independent from the price drawn for any other P. Notice that even though the price is randomly generated, it will never exceed the amount of the endowment ($3.00), which is the minimum possible amount that P can have available after T takes a proportion of P's task income.

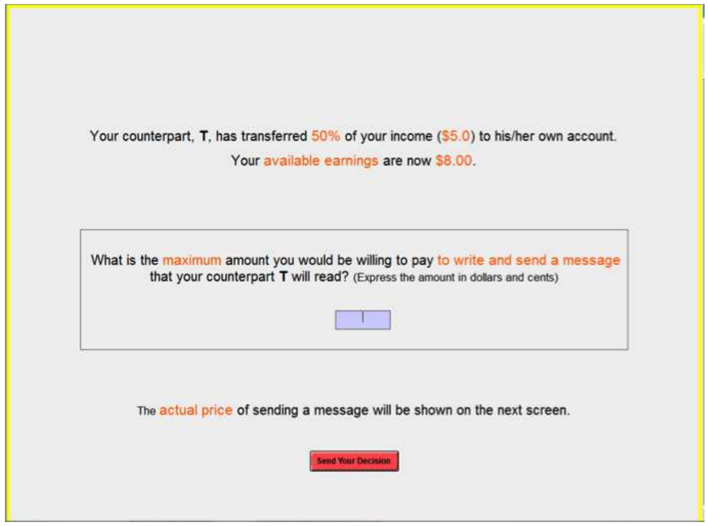


Figure B3: P's Information Screen and Willingness to Pay

Figure B4: P's Message Box

A screen with a message box like the one shown in Figure 4 will appear for P participants who are able to send a message. Those who get this screen must remember to press the ENTER key to record the written message. You will be able to verify if the message is in fact recorded by pressing the verify button. Once you have verified the message was recorded, you can press the SEND button. The message will not be recorded unless P presses the ENTER key and sees the message on the upper part of the message box. P will be informed once T has read the message.

Determination of Earnings

Earnings of T depend only on the decisions he/she makes. While earnings of P depend on both, T's as well as P's own decisions. The following three rules summarize the earnings.

1. T's final earnings are calculated as follows: *Endowment + Task Income + Money Transferred from P's Account*

P's earnings depend on whether or not P actually sent a message. A different rule applies for each of these cases:

2. Earnings of those participants P who were able to send a message are calculated as follows: *Endowment + Task Income - Money Transferred to T's Account - Actual Price of Messaging*

3. Earnings of those participants P who were NOT able to send a message are calculated as follows: *Endowment + Task Income - Money Transferred to T's Account*
At the end of the experiment, your total earnings in dollars (plus the $5 show up fee) will be privately paid to you in cash.

B.3 Mood - Emotions Variables Questionnaire

- Right now how would you describe yourself? 9-valued scale: Extremely Unhappy to Extremely Happy.

- Please, give the number that best describes the emotions you are experiencing at this moment: 7-valued scale: form "Emotion is not present at all" to "Emotion feels very intense"

  - Irritation, Anger, Contempt, Surprise, Envy, Jealousy, Sadness, Happiness, Fear, Joy, Shame.

- Below you are given pairs of opposite feelings. Use the following scale to indicate your current mood relative to these feelings (1: you are experiencing the feeling on the left side very strongly. 5: neutral. 9: you are experiencing the feeling on the right side very strongly.)

  - Bad mood/Good mood; Sad/Happy; Depressed/Elated; Gloomy/Cheerful; Displeased/Pleased; Sorrowful/Joyful

– Nervous/Calm; Tense/Relaxed; Uncomfortable/Comfortable; Apathetic/Carinf; Lethargic/Energetic; Unconfident/Confident; Unresponsive/Emotional; Passive/Active.

Appendix C

Appendix to Chapter 3

C.1 Proofs to Propositions

Proofs to Propositions

Proof of Proposition 1.

For contradiction, assume that there exists an equilibrium with bid profile $\{b_i(s_i), b_{g_i}(s_g)\}_{i\leq N}$ such that the auction stage allocates the objects efficiently. Consider a realization of signals such that $s_i = 0$ for all $i \geq 2$ and $s_g = \varepsilon > 0$. Notice that by strict superadditivity, $v^n(\varepsilon) - v^{n-1}(\varepsilon) > v^1(\varepsilon) = \varepsilon$ for $n > 1$.

Pick $s_1^* \in \left(\epsilon, \min_{n\geq 2}\{v^n(\epsilon) - v^{n-1}(\epsilon)\}\right)$. Since $v^N(\epsilon) - v^{N-1}(\epsilon) > s_1^*$, efficiency implies that the global should receive all objects under this signals realization. Since we assumed efficiency of this equilibrium, we should have $b_{g_1}(s_g = \epsilon) > b_1(s_1 = s_1^*)$. Note that we have not imposed any constraint on $\varepsilon > 0$, yet.

Now consider another set of realizations where local 1 and the global have the same signals as before ($i.e.\, s_1 = s_1^*, s_g = \varepsilon$) but all the other locals receive signal $\bar{s}$ which is the highest possible signal ($i.e.\, s_i = \bar{s}$ for all $i \geq 2$).

By the continuity of v^n and the strict superadditivity, there exists $\tilde{s} > 0$ such that for any $n \geq 2, v^n(\tilde{s}) < (n-1)\bar{s}$. So pick $\varepsilon \in (0, \tilde{s})$. It is easy to see that for all k such that $0 \leq k \leq N-2$, it is true that $v^{N-k}(\varepsilon) < (N-k-1)\bar{s} < (N-k-1)\bar{s} + s_1^*$. Then,

$k\bar{s} + v^{N-k}(\varepsilon) < (N-1)\bar{s} + s_1^*$.

This inequality means that for this realization it is efficient to allocate the objects to the locals. Since the equilibrium is assumed to be efficient at the auction stage, the global should lose the auction in market 1 for this realization of signals, *i.e.* $b_{g_1}(s_g = \varepsilon) < b_1(s_1 = s_1^*)$. This is a contradiction. □

Proof of Proposition 2.

For contradiction, let us assume there exists an equilibrium $\{b_i(s_i), b_{g_i}(s_g)\}_{i \le N}$ where the allocation after resale stage is efficient for any realization of signals. It can be easily shown that all $b_.(.)$ is weakly increasing since in the efficient equilibrium, the auction stage utility of a losing bidder cannot increase after resale. Assume that all $b_.(.)$ is right continuous.

By Proposition 1, the allocation at the auction stage is sometimes inefficient. Therefore, there exists a realization $(s_1, s_2, \ \dots\ , s_g)$ where at least in one market either the global or local loses inefficiently.

Without loss of generality, let us assume that the global loses market 1 inefficiently, *i.e.* $b_{g_1}(s_g) < b_1(s_1)$, or $b_{g_1}(s_g) = b_1(s_1)$ and the global loses as a result of tie-breaking rule. We know that in a neighborhood of s_g, $b_{g_1}(.)$ is strictly increasing. Otherwise, the global's signal would not be perfectly revealed and efficiency of the resale stage could not be guaranteed.[1] Hence, when $b_{g_1}(s_g) = b_1(s_1)$ and the global loses as a result of tie-breaking rule, consider s_g^- close enough to s_g from the left hand side such that the global loses market 1 inefficiently and $b_{g_1}(s_g^-) < b_1(s_1)$.

We require the following Lemma before we can proceed with the proof of Proposition 2.

[1] If Local 1 is winning inefficiently against a global who is playing on the flat part of her bid, then Local 1 must offer a price low enough so that in a neighborhood of s_g, all global types should accept. Instead, it is better to offer a slightly higher price for Local 1.

Lemma 1: There exist $(\underline{b}, \bar{b}) \subset b_{g_1}(s_g - \epsilon, s_g + \epsilon)$ *such that* $b_1(.)$ *is strictly increasing on* $b_1^{-1}(\underline{b}, \bar{b})$.

Proof: Assume not. Then there are two cases: (i) local 1 never bids on $b_{g_1}(s_g - \epsilon, s_g + \epsilon)$ or (ii) Local 1's bid on $b_{g_1}(s_g - \epsilon, s_g + \epsilon)$ is a step function.

In case (i), for any $s \in (s_g - \epsilon, s_g + \epsilon)$ bidding $b_{g_1}(s_g - \epsilon)$ is strictly preferred to $b_{g_1}(s)$. To see this, notice that $b_{g_1}(s_g - \epsilon)$ and $b_{g_1}(s)$ lead to the same winning/losing position in the auction. However, by bidding $b_{g_1}(s_g - \epsilon)$ the global will buy the object in resale at a lower price when she loses inefficiently. Such a resale trade is a positive probability event in a neighborhood of $(s_1, \ldots, s_N, s_g)$. This contradicts with $b_{g_1}(.)$ being part of an equilibrium.

For case (ii), consider $t \equiv max\{b_1(.): b_1(.) \in b_{g_1}(s_g - \epsilon, s_g + \epsilon)\} < b_1(s_1)$. So for any global with s such that $b_{g_1}^{-1}(t) \leq s \leq s_g + \epsilon$, bidding t rather than $b_{g_1}(s)$ does not affect her winning/losing position but in the event that she loses inefficiently, she gains in the resale market by making local 1 think that the global has lower signal than s. Such a resale trade is a positive probability event in a neighborhood of $(s_1, \ldots, s_N, s_g)$. This contradicts with $b_{g_1}(.)$ being part of an equilibrium.

Finally, take δ small enough that b_g is strictly increasing on $(s_g - \delta, s_g + \delta)$ and b_1 is strictly increasing on $b_1^{-1}(b_{g_1}(s_g - \delta), b_{g_1}(s_g + \delta))$. That is, define $\underline{b} \equiv b_{g_1}(s_g - \delta)$ and $\bar{b} \equiv b_{g_1}(s_g + \delta)$. □

Now, we can continue with the proof of Proposition 2. Next, we show that there exists a profitable deviation for global with signal s_g. To explain the idea of the proof without complicating the notation too much, we will show it for $N=2$, but the same result can be shown with any N.

To simplify the notation, we denote the four possible auction outcomes as $A_{LL},\ A_{LG},\ A_{GL}$ and A_{GG} when the equilibrium strategies are followed. A_{xy} represents the set of signals where by following the equilibrium strategies bidder *x* wins market 1 auction and bidder *y* wins market 2 auction. Analogously, the whole signal space can be partitioned in four regions based on the nature of efficient allocation: $E_{LL},\ E_{LG},\ E_{GL}$ and E_{GG}.

Consider the global's problem when she has signal $s \in \left(s_g-\delta, s_g+\delta\right)$ and she considers bidding $b_g(z)$ where $\in \left(s_g-\delta, s_g+\delta\right)$. This problem can be written as:

$$Max_{z\in(s_g-\delta,s_g+\delta)} \underbrace{\iint_{A_{LL}(z)} l(s_1,s_2,s,z)dF(\mathbf{s}_l)}_{L(s,z)} + \underbrace{\iint_{A_{LG}(z)} h^{LG}(s_1,s_2,s,z)dF(\mathbf{s}_l)}_{H^{LG}(s,z)}$$

$$+ \underbrace{\iint_{A_{GL}(z)} h^{GL}(s_1,s_2,s,z)dF(\mathbf{s}_l)}_{H^{GL}(s,z)} + \underbrace{\iint_{A_{GG}(z)} w(s_1,s_2,s)dF(\mathbf{s}_l)}_{W(s)}$$

Where, $A_{LL}(z) \equiv \{(s_1,s_2):(s_1,s_2,z) \in A_{LL}\};\ A_{LG}(z) \equiv \{(s_1,s_2):(s_1,s_2,z) \in A_{LG}\};$ and so on. Also, $l(.), h^{LG}(.), h^{GL}(.)$ and $w(.)$ represents the global's contingent payoffs in equilibrium conditional on auction outcomes $A_{LL},\ A_{LG},\ A_{GL}$ and A_{GG}, respectively. Note that $w(.)$ does not depend on *z* because, conditional on global winning both objects, locals' beliefs about the global's signal will not play any role in the resale stage. $dF(\mathbf{s}_l)$ denotes $f(s_1)f(s_2)ds_1ds_2$.

Now, we define $L^-(s,z) \coloneqq L(s,z)$ when $z<s$ and $L^+(s,z) \coloneqq L(s,z)$ when $z>s$ Then,

$$L^{-}(s,z) = \iint\limits_{A_{LL}(z)\cap E_{LL}(z)} 0dF(\mathbf{s}_l) + \iint\limits_{A_{LL}(z)\cap(E_{LG}(z)\cup E_{GL}(z))} (s-z)dF(\mathbf{s}_l)$$

$$+ \iint\limits_{A_{LL}(z)\cap E_{GG}(z)} (v^2(s) - v^2(z))dF(\mathbf{s}_l)$$

In the equation above, the first term is zero because in that region where the locals win the auctions and it is efficient, there is no trade. The second term has $(s-z)$ inside of the integral because in that region, where locals win the auctions but the global should receive exactly one object in efficient allocation, there is trade in one market and theglobal can keep the difference between the actual surplus and what the local seller believes it is. The third term has $v^2(s) - v^2(z)$ inside of the integral because in this region the global buys both objects in the resale stage and lying gives him the difference between the total surplus and what both local sellers believe as the global's value for the package.

To analyze $\frac{dL^{-}}{dz}$ we use a two-dimensional version of the Leibniz rule (see Flanders, 1973):

$$\frac{dL^-}{dz} = \iint_{A_{LL}(z)\cap\left(E_{LG}(z)\cup E_{GL}(z)\right)} (-1)dF(\mathbf{s}_l) + \iint_{A_{LL}(z)\cap E_{GG}(z)} (-v^{2'}(z))dF(\mathbf{s}_l)$$

$$+\frac{d}{dt}\left[\iint_{A_{LL}(t)\cap\left(E_{LG}(t)\cup E_{GL}(t)\right)} (s-z)dF(\mathbf{s}_l)\right]_{\mathrm{t=z}}$$

$$+\frac{d}{dt}\left[\iint_{A_{LL}(t)\cap E_{GG}(t)} (v^2(s)-v^2(z))dF(\mathbf{s}_l)\right]_{\mathrm{t=z}}$$

All square brackets converge to zero as z goes to s by the almost everywhere smoothness of the boundaries and the continuity of $v(.)$. Therefore:

$$\lim_{z\to s^-}\frac{dL^-}{dz} = \iint_{A_{LL}\cap(E_{LG}\cup E_{GL})} (-1)dF(\mathbf{s}_l) + \iint_{A_{LL}\cap E_{GG}} (-v^{2'}(s))dF(\mathbf{s}_l) < 0$$

On the other hand, it is easy to see that $L^+(s,z) = 0$ because making the locals think that the global's signal is higher than it actually is leads to rejection of locals' offers in the resale stage. This is because the locals will make unacceptable offers to the global when they believe that the global has higher signal than it actually has. Therefore, the global keeps the interim payoff from the auction stage, which is zero in this case. Therefore, if the relevant intersections are non-empty: $\lim_{z\to s^+}\frac{dL^+}{dz} = 0 > \lim_{z\to s^-}\frac{dL^-}{dz}$.

We now study $H^{LG}(.)$.

$$H^{LG-}(s,z) = \iint_{A_{LG}(z)\cap(E_{LL}(z)\cup E_{LG}(z))} \max\{s,s_2\} - b_2(s_2)dF(\mathbf{s}_l)$$

$$+ \iint_{A_{LG}(z)\cap E_{GL}(z)} s - z + \max\{z,s_2\} - b_2(s_2)dF(\mathbf{s}_l)$$

$$+ \iint_{A_{LG}(z)\cap E_{GG}(z)} v^2(s) - v^2(z) + max\{z,s_2\} - b_2(s_2)dF(\mathbf{s}_l)$$

Let χ be the indicator function, which is 1 when the statement is true and zero otherwise.

Then,

$$\frac{dH^{LG-}}{dz} = \iint_{A_{LG}(z)\cap E_{GL}(z)} (-1 + \chi\{z > s_2\})dF(\mathbf{s}_l)$$

$$+ \iint_{A_{LG}(z)\cap E_{GG}(z)} (-v^{2\prime}(z) + \chi\{z > s_2\})dF(\mathbf{s}_l)$$

$$+ \frac{d}{dt}\left[\iint_{A_{LG}(t)\cap(E_{LL}(t)\cup E_{LG}(t))} \max\{s,s_2\} - b_2(s_2)dF(\mathbf{s}_l)\right]_{\mathrm{t=z}}$$

$$+ \frac{d}{dt}\left[\iint_{A_{LG}(t)\cap E_{GL}(t)} s - z + \max\{z,s_2\} - b_2(s_2)dF(\mathbf{s}_l)\right]_{\mathrm{t=z}}$$

$$+ \frac{d}{dt}\left[\iint_{A_{LG}(t)\cap E_{GG}(t)} v^2(s) - v^2(z) + \max\{z,s_2\} - b_2(s_2)dF(\mathbf{s}_l)\right]_{t=z}$$

Therefore,

$$\lim_{z \to s^-} \frac{dH^{LG-}}{dz} = \iint\limits_{A_{LG}(s) \cap E_{GL}(s)} (-1 + \chi\{s > s_2\}) dF(\mathbf{s}_l)$$

$$+ \iint\limits_{A_{LG}(s) \cap E_{GG}(s)} (-v^{2'}(s) + \chi\{s > s_2\}) dF(\mathbf{s}_l)$$

$$+ \frac{d}{dt} \left[\iint\limits_{A_{LG}(t)} \max\{s, s_2\} - b_2(s_2) dF(\mathbf{s}_l) \right]_{\mathrm{t=s}}$$

Aside,

$$\lim_{z \to s^+} \frac{dH^{LG^+}}{dz} = \frac{d}{dt} \left[\iint\limits_{A_{LG}(t)} \max\{s, s_2\} - b_2(s_2) dF(\mathbf{s}_l) \right]_{\mathrm{t=s}} > \lim_{z \nearrow s} \frac{dH^{LG-}}{dz}.$$

The last inequality above holds because the derivative of value function is strictly increasing in , i.e. $v^{2'}(s) > v^{1'}(s) = 1 \geq \chi\{s > s_2\}$.

Similarly, if the relevant intersections are non-empty: $\lim_{z \to s^+} \frac{dH^{GL^+}}{dz} > \lim_{z \to s^-} \frac{dH^{GL-}}{dz}$.

Putting all together, for regions where global might lose inefficiently, $\lim_{z \to s^+} \frac{dL^+}{dz} + \lim_{z \to s^+} \frac{dH^{LG^+}}{dz} + \lim_{z \to s^+} \frac{dH^{GL^+}}{dz} > \lim_{z \to s^-} \frac{dL^-}{dz} + \lim_{z \to s^-} \frac{dH^{LG-}}{dz} + \lim_{z \to s^-} \frac{dH^{GL-}}{dz}$ necessarily. Therefore, bidding $b_{g.}(s)$ cannot be a locally optimal behavior since we assumed that in a neighborhood of $(s_1, \dots, s_N, s_g)$ the global loses inefficiently.

Similarly, in this equilibrium, if local 1 loses inefficiently when signals are $(s_1, \dots, s_N, s_g)$, one can show that there exists $(\underline{a}, \bar{a}) \subset b_1(s_1 - \epsilon, s_1 + \epsilon)$ such that $b_{g_1}(.)$ is strictly increasing on $b_1^{-1}(\underline{a}, \bar{a})$ (a similar statement to Lemma 1). In a neighborhood of s_1, we can show that the derivative of the expected payoff of local 1 when we approach to s_1 from right is greater than that from left.

We found that strictly increasing bidding in a neighborhood of signals where inefficient losing is possible is non-optimal, but the efficiency of the resale stage cannot be guaranteed. □

Proof of Proposition 3.

Consider the following strategies: In the auction, locals bid their signals in their markets. The global bids $v^n(s)$ for each package with n objects. After the auction, the winning locals may offer some price only if there exists signal s_g such that $b_{g_I}(s_g) = v^n(s_g)$ for any $I \subseteq \{1, \dots, N\}$ and $|I| = n$.

In the resale market, when the set of winning locals is $A \subseteq \{1, \dots, N\}$, the resale strategy of winning local j, when she makes the first offer, is $p = v^{N-|A|+1}(s_g) - v^{N-|A|}(s_g)$ only if $p \geq s_j$. If she is not the first local who makes an offer then she asks for $v^N(\bar{s})$.

In the resale market, when the set of winning locals is $A \subseteq \{1, \dots, N\}$ and a set of offers $\{q_j\}_{j \in K}$, where $K \subseteq A$, are made to the global, the global will offer $\{p_i\}_{i \in B}$ for $B \subseteq \{1, \dots, N\} \backslash A$ when global believes $s_i = p_i$ for $i \in B$ and only if

$$\sum_{i \in B} p_i \geq \max_{C \subseteq K} v^{N-|K \cup B|+|C|}(s_g) - v^{N-|A \backslash C|}(s_g)$$

If such B does not exist, global will not sell in the resale market. The condition above checks whether there exists any set of losing locals, B, such that the global is better off when she sells to those locals and buys from a subset, C, of winning locals rather than not selling to those locals in set B.

Define $(s_1, \dots, s_N, s_g) \coloneqq argmax_{A\subseteq\{1,\dots,N\}} v^{N-|A|}(s_g) + \sum_{i\in A} s_i$. Hence, $E(s_1, \dots, s_N, s_g)$ is the set of locals who receive objects in the efficient allocation.

Suppose locals play using the strategy above. We show next that it is the best response for the global with signal s_g to bid $v^n(s_g)$ for packages with n objects. The global's payoff from this strategy is $v^{N-|E|}(s_g) - \sum_{i\notin E} s_i$.

Assume that the global deviates and bids in a way that is not in line with any signal according to the locals' equilibrium belief (i.e. $\nexists s$ such that $b_{g_I} = v^n(s)$ for any $I \subseteq \{1, \dots, N\}$ and $|I|=n$.) In this case, the winning locals will not sell to the global but the global may sell some objects at a price that is equal to the sum of the values of the buying locals. Let A be the set of locals who holds some objects after resale stage. Then,

$$v^{N-|A|}(s_g) - \sum_{i\notin A} s_i = v^{N-|A|}(s_g) - \sum_{i\notin A} s_i + \sum_{i\in A} s_i - \sum_{i\in A} s_i$$

$$\leq v^{N-|E|}(s_g) - \sum_{i\notin A} s_i + \sum_{i\in E} s_i - \sum_{i\in A} s_i \leq v^{N-|E|}(s_g) - \sum_{i\notin E} s_i$$

The left hand side above is the global's payoff when she deviates; the right hand side is the global's payoff when she bids her value for the packages truthfully.

Now assume that the global deviates and bids as if her signal is $z \neq s_g$. Note that if $E(s_1, \ldots, s_N, z) = E(s_1, \ldots, s_N, s_g)$, then no trade occurs and, similar to the above argument, the global cannot be better off in the auction stage either. If, instead, $\tilde{E} \equiv E(s_1, \ldots, s_N, z) \neq E(s_1, \ldots, s_N, s_g) =: E$, then no winning local makes an offer to the global since from a winning local i's perspective, the outcome is efficient and therefore the highest price the global can pay is $v^{|\{N \backslash \tilde{E}\}|+1}(z) - v^{|\{N \backslash \tilde{E}\}|}(z) \leq s_i$. To see this, note that

$v^{N-|\tilde{E}|}(z) + \sum_{i \in \tilde{E}} s_i \geq v^{N-|K|}(z) + \sum_{i \in K} s_i$ for all $K \subseteq \{1, \ldots, N\}$.

In particular, for $K = \tilde{E} \backslash \{i\}$, $v^{N-|\tilde{E}|}(z) + \sum_{i \in \tilde{E}} s_i \geq v^{N-|\tilde{E}|+1}(z) + \sum_{i \in \tilde{E} \backslash \{i\}} s_i$

Therefore, $v^{N-|\tilde{E}|+1}(z) - v^{N-|\tilde{E}|}(z) \leq s_i$. Hence, local i will not sell. This implies that the only benefit for the global can come from selling some objects.

Consider any $A \subset N \backslash \tilde{E}$ (a subset of losing locals in the after deviation outcome of the auction.) The global can sell to locals in A at most at $\sum_{i \in A} s_i$. If some resale trade takes place

$$\textit{Global's payoff after resale} \leq \sum_{i \in A} s_i + v^{N-|A \cup \tilde{E}|}(s_g) - \sum_{i \in N \backslash \tilde{E}} s_i$$

$$= \sum_{i \in A} s_i + v^{N-|A \cup \tilde{E}|}(s_g) - \sum_{i \in N \backslash \tilde{E}} s_i + \left(\sum_{i \in \tilde{E}} s_i - \sum_{i \in \tilde{E}} s_i \right)$$

$$= v^{N-|A \cup \tilde{E}|}(s_g) + \left(\sum_{i \in A \cup \tilde{E}} s_i - \sum_{i \in N} s_i \right)$$

$$\leq v^{N-|E|}(s_g) + \left(\sum_{i \in E} s_i - \sum_{i \in N} s_i \right)$$

$$\leq v^{N-|E|}(s_g) - \sum_{i \in N \backslash E} s_i$$

$$= \textit{Global's payoff from the equilibrium strategy}$$

Therefore, there does not exist a profitable deviation for the global.

Next, consider a local, say local 1. Assume that all the bidders except local 1 follow the equilibrium strategies. Let us define $E^{-1} \coloneqq \arg\max_{A \subseteq N \setminus \{1\}} v^{N-|A|}\left(s_g\right) + \sum_{i \in A} s_i$.

Case 1: If $1 \in E$ (i.e. if local 1should receive an object in the efficient allocation.)

If local 1 bids s_1, then she wins and her payoff is:

$$s_1 - \left[\left(v^{N-|E^{-1}|}\left(s_g\right) + \sum_{i \in E^{-1}} s_i\right) - \left(v^{N-|E|}\left(s_g\right) + \sum_{i \in E \setminus \{1\}} s_i\right)\right]$$

If, instead, local 1 bids $b_1 > s_1$ she wins and does not trade later since $1 \in E$. Her payoff is: $s_1 - \left[\left(v^{N-|E^{-1}|}\left(s_g\right) + \sum_{i \in E^{-1}} s_i\right) - \left(v^{N-|\tilde{E}|}\left(s_g\right) + \sum_{i \in \tilde{E} \setminus \{1\}} s_i\right)\right]$

Where $\tilde{E}$ denotes the current allocation when local 1 bids b_1. However, efficiency implies that bidding truthfully will give a weakly better payoff to local 1 than bidding b_1.

Now consider a deviation of local 1 where she bids below her signal, i.e. $b_1 < s_1$. Let $\tilde{E} \coloneqq E\left(b_1, s_2, \dots, s_N, s_g\right)$

Case 1.1: If $1 \in \tilde{E}$ then 1 will not trade later, and her auction payment when she bids b_1 is not less than what it would be if she bid s_1. Therefore, it cannot be a profitable deviation.

Case 1.2: If $1 \notin \tilde{E}$, we need to check whether local 1 can buy from the global and be better off. As analyzed in the global's strategy above, the winning locals will not make any offer since they believe that the equilibrium is played and the allocation is efficient. Local 1 may buy from the global in resale since the current allocation is not efficient. For any subset of losing locals that contain local 1, i.e. $\forall B \subseteq \{1, \dots, N\} \setminus \tilde{E}$ such that $1 \in B$, the global thinks that the locals in *B* is are able to pay $\sum_{i \in B \setminus \{1\}} s_i + b_1$ in total. Note that

$v^{N-|\tilde{E}|}(s_g) + \sum_{i\in\tilde{E}} s_i \geq v^{N-|B\cup\tilde{E}|}(s_g) + b_1 + \sum_{i\in B\cup\tilde{E}\setminus\{1\}} s_i$ by the definition of $\tilde{E}$. Then

$$v^{N-|\tilde{E}|}(s_g) - v^{N-|B\cup\tilde{E}|}(s_g) \geq b_1 + \sum_{i\in B\setminus\{1\}} s_i$$

Hence, the global will not sell to any subset of losing locals that include local 1 at the resale stage. Therefore, the local 1's payoff from the deviation is zero, which is not profitable.

Case 2: If $1 \notin E$. Then local 1 loses market 1 when she bids s_1 and her payoff is zero.

If she bids $b_1 < s_1$, she loses and the global thinks that local will pay at most b_1. Note that by definition of E

$v^{N-|E|}(s_g) + \sum_{i\in E} s_i \geq v^{N-|E|-1}(s_g) + \sum_{i\in E} s_i + s_1$.

Then $v^{N-|E|}(s_g) - v^{N-|E|-1}(s_g) \geq s_1 > b_1$ and the global will not sell at any price that she thinks that local 1 is willing to pay.

If local 1 bids $b_1 > s_1$ and she loses, the global will offer at least b_1, which will not be accepted by local 1 and then local 1's payoff will be zero.

If she bids $b_1 > s_1$ and she wins then she can sell it at $v^{N-|\tilde{E}|+1}(s_g) - v^{N-|\tilde{E}|}(s_g)$. In this event, her payoff is

$$v^{N-|\tilde{E}|+1}(s_g) - v^{N-|\tilde{E}|}(s_g) - \left[\left(v^{N-|E^{-1}|}(s_g) + \sum_{i\in E^{-1}} s_i\right) - \left(v^{N-|\tilde{E}|}(s_g) + \sum_{i\in\tilde{E}\setminus\{1\}} s_i\right)\right]$$

$$= v^{N-|\tilde{E}|+1}(s_g) + \sum_{i\in\tilde{E}\setminus\{1\}} s_i - \left(v^{N-|E^{-1}|}(s_g) + \sum_{i\in E^{-1}} s_i\right)$$

≤ 0 (by definition of E^{-1})

and zero was her payoff if she bid s_1. Recall that zero was local 1's payoff when she bid s_1, truthfully. The last inequality above holds because E^{-1} achieves the highest total bid among all the allocations where the global receives the object in market 1.

Cases 1 and 2 together show that for local 1 there is no profitable deviation from truthful signal bidding, while other bidders follow the equilibrium strategies. □

Proof of Proposition 4.

Each local is participating in a second-price auction for a single privately valued object. Therefore, truthful signal bidding is their weakly dominant strategy.

Define $\Pi\left(b_{g_1}, b_{g_2}; s\right)$ as the global's expected payoff of bidding b_{g_1} and b_{g_2} in markets 1 and 2, respectively when her signal is s. Then

$$\Pi\left(b_{g_1}, b_{g_2}; s\right) = \frac{b_{g_1}}{100}\frac{b_{g_2}}{100}\left(3s - E\left[p \middle| b_{g_1}\right] - E\left[p \middle| b_{g_2}\right]\right)$$

$$+\frac{b_{g_1}}{100}\left(1-\frac{b_{g_2}}{100}\right)\left(s - E\left[p \middle| b_{g_1}\right]\right) + \frac{b_{g_2}}{100}\left(1-\frac{b_{g_1}}{100}\right)\left(s - E\left[p \middle| b_{g_2}\right]\right)$$

$$= \frac{b_{g_1}}{100}\frac{b_{g_2}}{100}s + \frac{b_{g_1}}{100}\Delta^1 + \frac{b_{g_2}}{100}\Delta^2$$

where $E\left[p \middle| b_{g_i}\right]$ is the expected auction price when the global wins in market *i* by bidding b_{g_i}, and $\Delta^i = s - E\left[p \middle| b_{g_i}\right]$.

First, we show that the global's optimal bidding function is object-symmetric (i.e. $b_{g_1} = b_{g_2}$). For contradiction, suppose not, and assume without loss of generality that $b_{g_1} > b_{g_2}$ at the optimum and $\Pi\left(b_{g_1}, b_{g_2}; s\right) > \Pi\left(b_{g_2}, b_{g_2}; s\right)$. Then the following hold:

$$\frac{b_{g_1}}{100}\frac{b_{g_2}}{100}s + \frac{b_{g_1}}{100}\Delta^1 + \frac{b_{g_2}}{100}\Delta^2 > \left(\frac{b_{g_2}}{100}\right)^2 s + 2\frac{b_{g_2}}{100}\Delta^2$$

$$\Leftrightarrow \left(\frac{b_{g_1}}{100}\frac{b_{g_2}}{100} - \left(\frac{b_{g_2}}{100}\right)^2\right)s + \frac{b_{g_1}}{100}\Delta^1 > \frac{b_{g_2}}{100}\Delta^2$$

$$\Leftrightarrow \left(\left(\frac{b_{g_1}}{100}\right)^2 - \frac{b_{g_1}}{100}\frac{b_{g_2}}{100}\right)s + \frac{b_{g_1}}{100}\Delta^1 > \frac{b_{g_2}}{100}\Delta^2 \text{ (since } b_{g_1} > b_{g_2})$$

$$\Rightarrow \left(\frac{b_{g_1}}{100}\right)^2 s + 2\frac{b_{g_1}}{100}\Delta^1 > \frac{b_{g_1}}{100}\frac{b_{g_2}}{100}s + \frac{b_{g_1}}{100}\Delta^1 + \frac{b_{g_2}}{100}\Delta^2$$

$$\Leftrightarrow \Pi\left(b_{g_1}, b_{g_1}; s\right) > \Pi\left(b_{g_1}, b_{g_2}; s\right)$$

This contradicts with $\left(b_{g_1}, b_{g_2}\right)$ being optimal. Therefore, in equilibrium $b_{g_1} = b_{g_2}$.

The global's optimization problem can be expressed as: $Max_b\, \Pi(b;s) = \left(\frac{b}{100}\right)^2 s + 2\frac{bs}{100} - 2\int_0^b p\frac{dp}{100}$.

It is easy to see that, when complementarities exist, the global's optimization problem has an interior solution for low signals and a corner solution at $b = 100$ for high signals. The interior solution is a solution to the first order condition $\frac{\partial \Pi(b;s)}{\partial b} = 0$, or equivalently it solves $\frac{bs}{100} + s - b = 0$. Hence, $b = \frac{100s}{100-s}$ for s<50. When $s \geq 50$, the global is indifferent between 100 or anything more than 100. When the bidding space is restricted to the signal space, for example, the best response of the global with signal s is

C.2 Experimental Instructions

Experimental Instructions

INSTRUCTIONS FOR VICKREY AUCTION

This is an experiment in the economics of decision-making. Various research foundations have provided funds for this research. The instructions are simple, and if you follow them carefully and make good decisions, you may earn a considerable amount of money, which will be paid to you in cash at the end of the experiment.

All amounts in the experiment are expressed in Experimental Currency Units (ECU). The money you make in ECUs will be converted to US Dollars at a rate of 50 ECU= $1, and paid to you in addition to your $10 participation fee.

- This experiment will have 30 periods.
- You will be randomly assigned one of the two following roles: Local bidder and Global bidder.
- Your role will be the same in all 30 periods.
- In every period two Locals and a Global will be randomly matched into a group of 3 people.
- Matching will change every period: you are not playing against the same people every time.
- Each period consists of an **Auction** where you will bid.
- The exact rule of earning calculation will be explained shortly.

AUCTION

- In each group of 3, bidders will bid for items of two markets (Market A and B).
- In each of these markets, there is one item for sale and two bidders (one Local and the Global).
- In each market, there is one Local bidder who is able to bid only for the item in that market.
- The Global bidder is interested in both markets, so the Global is able to bid for the items in both markets.

<u>Values:</u>

- In each period, prior to bidding, Global and Local bidders are assigned values for the items.
- There are three values: one for Global bidder (Global value) and one for each Local bidder (Local values).
- Values are privately known. That is, Global bidder does not know the values of the Local bidders. Similarly, a Local bidder does not know the value of the Global bidder or the other Local bidder.
- For each Local bidder, her Local value represents the amount she will receive if she wins an item in the auction.
- The Global value represents instead the amount that the Global will receive if she wins <u>only one item</u> (either in market A or in market B).

- If the Global wins both items, she receives **3 TIMES the Global value**. (for example: when the Global value is 40, the global receives 40 if she ends up with a single item and receives 3x40=120 if she ends up with both items).
- All values are random integer numbers between 0 and 100. Each number is equally likely.
- All values are drawn independently (meaning they are most likely different).

Bidding:

- The item in Market A and the item in Market B are auctioned simultaneously.
- Each Local bidder will submit a bid only for the item in her market.
- The Global bidder will submit bids for each item and a bid for the package containing both items. Therefore, Global submits three bids (a bid for item A, a bid for item B and a bid for the package)
- Bids can be any integer number from {0, 1, 2, 3,…,300}. So the smallest possible bid is zero and the largest one is 300 in an auction.

Example:

In this example, you see the values of everybody to understand the environment. However, in the real experiment, values are private information and you only observe your own value.

Note first that each Local has a single column that indicates variables that are specific to her or decisions she makes. Global instead has three columns representing her value from getting only the item in market A, the package including both items, and only the item in market B. After observing the values, bidders enter their bids.

	Market A			Market B	
	Local	Global	Global Package	Global	Local
Value	45	32	96	32	64
Bid	42	25	76	30	39

Auction Outcome:

- The computer allocates the items to the bidders who submitted the highest combined bids for the two items.
- In particular, the computer has four cases to look at:
    1) Locals win in both markets,
    2) Local wins in Market A, Global wins in Market B,

3) Global wins in Market A, Local wins in Market B,
4) Global wins both markets.

- The computer will compute the total bids in each case. Then it will allocate the items as in the case with the highest total bids.

Example:

Allocation of the Items

	Case 1	Case 2	Case 3	Case 4
Market A	**Local A**	Local A	Global	Global
Market B	**Local B**	Global	Local B	Global
Total bids for two items	**42+39=81**	42+30=72	25+39=64	76 (package bid)

In this example, Case 1 has the highest total bids for the two items; therefore, Local bidders will get the items.

Prices:

- If you did not get an item, you do not pay anyting.
- Only the winning bidders pay some amount for the item(s) they get in the auction.
- A winning bidder, however, will not pay her bid. Instead, she will pay the difference between how much the highest total bid would be if she was not present and how much the other winning bidder bid in the current highest total bid.

  That means, if you win, the price you pay is

(the highest total bid if you were NOT present) – (the other winner's bid in the current highest total bid)

- Notice that when the Global bidder wins both items, there is no other bidder in the wining allocation. Therefore, in that case the Global just pays the sum of the Local bids.

Example:

In the example above Locals won the items and this allocation has a total bid of 81.

- *Price paid by Local A:* Note that if Local A did not participate, the allocation would be as in Case 4, and Global would get both items. This is because when we sorted the total submitted bids in cases where Local A is not present (cases 3 and 4), the highest total bid would be 76 (see the table below). In the highest total bids in the presence of Local A, the other bidder's bid is 39. Hence, Local A will pay 76 - 39 = 37.

	Case 1	Case 2	Case 3	Case 4
Market A	Local A	Local A	Global	Global
Market B	Local B	Global	Local B	Global
Total bids for two items	42+39=81	42+30=72	25+39=64	76 (package bid)

- *Price paid by Local B:* Note that if Local B did not participate, the allocation would be as in Case 4, and the Global would get both items. This is because when we sort the total submitted bids in cases where Local B is not present (Cases 2 and 4), the highest total bid would be 76 (see the table below). In the highest total bids in the presence of Local B, the other bidder's bid is 42. Hence, Local B will pay 76 – 42 = 34.

	Case 1	Case 2	Case 3	Case 4
Market A	Local A	Local A	Global	Global
Market B	Local B	Global	Local B	Global
Total bids for two items	42+39=81	42+30=72	25+39=64	76 (package bid)

Earnings:

- Your earnings in a period will depend on two things: (1) the values of the items you get in the auction (if any), and (2) the price that you paid.

- If a bidder does not win any item in the auction then her payoff will be zero.

  - If a Local bidder wins an item, her payoff is: Local Value – Price
  - If Global wins a single item, her payoff is: Global Value – Price
  - If Global wins both items, her payoff is: (3 x Global Value) – Price

The computer will randomly pick 20 periods out of 30 periods. The selection of each period is equally likely. Your final earnings will be the sum of your earnings in those 20 periods and $10 participation fee.

Example:

Consider the values, bids, the winning allocation and the prices in the previous example, the earnings of bidders become:

Local A: 45 - 37 = 8

Global: 0

Local B: 64 - 34 = 30

Questionnaire

Answer the following questions:

	Market A			Market B	
	Local	*Global*	*Global* Package	*Global*	Local
Values	54	46	138	46	60
Bids	54	34	110	10	90
Got Item					
Auction Price					

	Case 1	Case 2	Case 3	Case 4
Market A	Local A	Local A	Global	Global
Market B	Local B	Global	Local B	Global
Total bids for two items				

1) Compute the Total Bid for each of the four possible allocations of the two items in the second table above.
2) Complete the table identifying the auction winners and how much each bidder pays in the first table above.
3) Find the earning of each bidder?

Local A: Local B: Global:

INSTRUCTIONS FOR SIMULTANEOUS SECOND PRICE AUCTIONS WITH RESALE

This is an experiment in the economics of decision-making. Various research foundations have provided funds for this research. The instructions are simple, and if you follow them carefully and make good decisions, you may earn a considerable amount of money, which will be paid to you in cash at the end of the experiment.

All amounts in the experiment are expressed in Experimental Currency Units (ECU). The money you make in ECUs will be converted to US Dollars at a rate of 50 ECU= $1, and paid to you in addition to your $10 participation fee.

- This experiment will be 30 periods.
- You will be randomly assigned one of the two following roles: Local bidder and Global bidder.
- Your role will be the same in all 30 periods.
- In every period two Locals and a Global will be randomly matched into a group of 3 people.
- Matching will change every period: you are not playing against the same people every time.
- Each period consists of two stages: an **Auction Stage** where you will bid, followed by a **Resale Stage** where you may trade the items allocated in the Auction stage.
- The exact rule of earning calculation will be explained shortly.

1. AUCTION STAGE

Bidding:

- In each group of 3, bidders will bid for items in auctions in two markets (Market A and B).
- In each of these markets, there is one item for sale and two bidders (one Local and the Global).
- In each market, there is one Local bidder who participates in the auction only in that market.
- The Global bidder is interested in both markets, so the Global is present in both markets.
- Therefore, the Global and Local A bid in Market A auction and the Global and Local B bid in Market B auction.
- How much a person values an item will be explained later.
- Each Local bidder will submit a bid for the item in her market.
- The Global bidder will submit bids for the items in both markets.
- Bids can be any integer number from {0, 1, 2, 3,…,300}. So the smallest possible bid is zero and the largest one is 300 in an auction.
- In each market the bidder with the higher bid wins the item:

- If the Global's bid is greater than the Local's bid in a given market, the item of that market goes to the Global bidder.
- If instead the Local's bid is greater than the Global's bid, the item goes to the Local bidder in that market.

Auction Prices:

- If a Local bidder gets the item in a market, she pays the Global's bid in that market.
- Similarly, if the Global bidder gets the item in a market, she pays the Local's bid in that market.

2. RESALE STAGE

- Once the Auction Stage is over, a Resale Market for each item will open: Resale Market A, and Resale Market B.
- The same three people who participated in the auction stage continue in the resale stage.
- In each resale market, the bidder who got the item of that market in the auction stage may sell it to the other bidder.
- For each item, the current owner of the item will offer a price to sell the item.
- After seeing the offer, the other bidder either accepts the offer and buys the item at the offered price, or rejects the offer and have no item.
- This is a take-it-or-leave-it offer, and there is no room for further negotiation.
- The exact timing of the resale offers will depend on the outcome of the auction and are explained below.

Timing of the Resale Market Offers

Since we have two markets, we have four different cases for the outcome of the Auctions. The timing of the resale market is explained below for each of these cases.

Case 1: Global bidder wins the auctions in both markets.

- In this case, the Global bidder makes simultaneous offers to each Local bidder. The Global may offer different prices to each Local.
- Upon observing the offers, each Local bidder decides whether or not to accept the offer.
- If an offer is accepted, the buyer receives the item and pays the offered price to the seller.

Case 2: In Market A, Local bidder wins the auction; in Market B, Global bidder wins the auction.

- First, Local bidder in market A makes an offer to sell the item to the Global bidder.
- After seeing that offer, the Global bidder makes an offer to sell the item of market B to the Local bidder in market B.
- Local bidder B sees Global's offer and decides whether or not to accept it.

- After learning the decision of Local bidder in market B, Global bidder decides whether or not to accept the offer in Market A.
- If an offer is accepted, the buyer receives the item and pays the offered price to the seller.

Case 3: In Market B, Local bidder wins the auction; in Market A, Global bidder wins the auction.

- This is analogous to Case 2 switching A and B.
- First, Local bidder in market B makes an offer to sell the item to the Global bidder.
- After seeing that offer, the Global bidder makes an offer to sell the item of market A to the Local bidder in market A.
- Local bidder A sees Global's offer and decides whether or not to accept it.
- After learning the decision of Local bidder in market A, Global bidder decides whether or not to accept the offer in Market B.
- If an offer is accepted, the buyer receives the item and pays the offered price to the seller.

Case 4. Local bidders win the auctions in both markets.

- In this case, at the beginning of the resale market the computer randomly determines which local bidder offers a price first. Both local bidders have 50% chance to make the first offer. The rest of the timing goes as follows.
- The local that goes first, makes the offer to sell the item to the Global bidder.
- The local that goes second sees the first offer in the other market and makes her own offer to the Global bidder.
- The Global bidder sees both offers and decides which items she wants to buy if any.
- If an offer is accepted, the buyer receives the item and pays the offered price to the seller.

Earning of the Period

- Earnings of the period will depend on three things: (1) the values of the items to their final owners, (2) the prices paid in the Auction stage, and (3) the prices paid or received in the Resale stage.
- Prices in the Auction and in the Resale markets have been explained previously. It only remains to explain how values of the items to their final owners are determined.

Values:

- In each period, prior to bidding, Global and Local bidders are assigned values for the items. There are three values: one for Global bidder (Global value) and the values for each Local bidder (Local values).
- Values are privately known. That is, Global bidder does not know the values of the Local bidders. Similarly, a Local bidder does not know the value of the Global bidder or the other Local bidder.

- Each Local value represents the amount that the Local bidder with that value will receive if she becomes the final owner of an item after the Resale Market.
- The Global value represents instead the amount that the Global will receive if she becomes the final owner of only one item (either in market A or in market B).
- If the Global gets both items at the end of the period, she receives **3 TIMES the Global value**. (for example: if the Global value is 40, the global receives 40 if she ends up with a single item and receives 3x40=120 if she ends up with both items).
- Values are random integer numbers between 0 and 100. Each number is equally likely.
- All values are drawn independently (meaning they are most likely different).

Earnings:

Values are not equal to earning of the period. Prices paid or received during the Auction and the Resale stages must be taken into account as well. When a period is over, you will receive the value of the item(s) you own after the resale stage, if any, and the amount of money you got in the resale stage (if you sold some item). From this amount, all the payments you made in the auction and resale stages will be subtracted.

The computer will randomly pick 20 periods out of 30 periods. The selection of each period is equally likely. Your final earning will be the sum of your earnings in those 20 periods and $10 participation fee.

Example 1

In this example, you see the values of everybody to understand the environment. However, in the real experiment, values are private information and you only observe your own value.

	Market A			Market B	
	Local	*Global*	*Global* Package	*Global*	Local
Values	54	46	138	46	60
Bids	30	55		40	65
Got Item in Auction	No	Yes		No	Yes
Auction Price		30			40
Resale Offer		45			70
Decision	Accepted			Rejected	
Owns Item after Resale	Yes	No		No	Yes

In this table you can see the whole sequence of events within one period. Note first that each Local has a single column that indicates variables that are specific to her or decisions she makes. Global instead has three columns representing her value from getting only the item in market A, the package including both items, and only the item in market B.

Each bidder sees her value privately (i.e. no one else can see it in the whole period.). In this example, Local A has a value of 54 and Local B has 60. Global has values of 46 for single items, and 138 for the package of two items.

Immediately below, bidders are allowed to bid simultaneously in their corresponding fields (no one sees your bid at the time of bidding). Locals bid 30 and 65 in markets A and B, respectively;

and Global bid 55 and 40 in markets A and B, respectively. In each market the highest bidder wins and pays the other bid of that market. As 30 < 55, the Global wins item A and pays 30; and as 65 > 40 local bidder wins the item in market B, and pays 40.

The second part of the table represents the resale stage. The resale starts when each winner of the auction puts for sale the item she got in the auction. An auction winner does that by posting a *Resale Offer* that indicates at which price she wants to sell her item. In our example, first the Local B asks 70 for item B. After observing this, Global asks 45 for item. Then Local A decides to accept or reject and in this example Local A accepted the Global's offer. Then Global decides whether to accept or reject Local B's offer. Here the Global rejects to buy item B at price 70.

In the end, in our example, Local bidders own the corresponding items and Global does not own any item.

Earnings are as follows.

- Local A, did not win the auction so paid nothing in the auction. However, she bought the good in the resale market at price of 45. Since she is the final owner of item A, she receives her value of 54 and her earning is 54 – 45 = 9.
- Local B won the auction and paid 40. Later, she put item B for sale at price of 70, but the Global rejected the offer so there was no resale trade in Market B. In the end Local B kept the item and since her value is 60, her earning is 60-40=20.
- Global won item A in the auction and paid 30. Later Global put that item for sale at 45 and Local bidder A bought it in market A. In market B, Global did not win the auction and rejected Local's offer in the Resale. Since Global owns nothing in the end, she does not receive any value. In sum, Global receives the resale price of 45 for item A and pays the auction price of item A, 30. The Global's earning is 45-30=15.

Example 2

In this example, you see the values of everybody to understand the environment. However, in the real experiment, values are private information and you only observe your own value.

	Market A			Market B	
	Local	*Global*	*Global* Package	*Global*	Local
Values	63	20	60	20	39
Bids	42	30		25	34
Got Item in Auction	Yes	No		No	Yes
Auction Price	30				25
Resale Offer	70				35
Decision		Rejected		Rejected	
Owns Item after Resale	Yes	No		No	Yes

As before, each Local has a single column that indicates variables that are specific to her or those decisions she makes. Global instead has three columns in the middle representing, respectively, her value from getting only the item in market A, the package including both items, and only the item in market B.

Each bidder sees only her value privately (i.e. no one else can see it in the whole period.). In this example, Local A has a value of 63 and Local B has 39. Global has values of 20 for single items, and 60 for the package of two items. Immediately below, bidders are allowed to bid simultaneously in their corresponding fields (no one sees other's bid while bidding). Locals bid 42 and 34 in markets A and B, respectively; and Global bid 30 and 25 in markets A and B, respectively. In each market the highest bidder wins and pays the other' bid of that market. As 42 < 30, the Local wins item A and pays 30; and as 34 > 25 Local bidder wins the item in market B, and pays 25. So in this example Global wins nothing.

The second part of the table represents the resale stage. The resale starts when each winner of the auction puts for sale the item she got in the auction. An auction winner does that by posting a *Resale Offer* that indicates at which price she wants to sell her item. If both locals win the auction (as here), the computer randomly picks one local to post the first resale price. In our example, first the Local A asks 70 for item A and Local B asks 35 to resale item B. After observing these offers, Global rejects both. So none of the resale deals takes place and Locals keep the items (meaning they are the final owners) and Global does not own any item in the end.

Earnings are as follows:

- Local A won the auction in market A and paid 30 to the auctioneer. Since she is the final owner of item A, she receives her value of 63 and her earning is 63 – 30 = 33.
- Local B won the auction and paid 25. Later, she put item B for sale at price of 35, but the Global rejected the offer so Local B could not sell the item and she is the final owner of item B. Her value is 39 and so her earning for the period is 39-25=14.
- Global did not win any item in the auction so she paid nothing to the auctioneer. In the resale market, Global is offered 70 and 35 ECUs for each item but she rejected them. Since Global owns nothing in the end, she does not receive any value. In sum, Global paid nothing and received nothing so her earning for the period is zero.

Questionnaire

Answer the following questions:

1) In the example below, who wins each auction and how much do they pay?

	Market A			Market B	
	Local	*Global*	*Global* Package	*Global*	Local
Values	54	46	138	46	60
Bids	54	34		10	90
Got Item in Auction					
Auction Price					

2) In the example below, who is the final owner of each item and what is each bidder's earning?

	Market A			Market B	
	Local	*Global*	*Global* Package	*Global*	Local
Values	54	46	138	46	60
Bids	54	34		10	90
Got Item in Auction	Yes	No		No	Yes
Auction Price	34				10
Offer Resale	45				70
Decision		Accepted		Rejected	
Owns Item after Resale					

Earning: Local A _____ Earning: Global _____ Earning: Local B ____

INSTRUCTIONS FOR SIMULTANEOUS SECOND PRICE AUCTIONS WITHOUT RESALE

This is an experiment in the economics of decision-making. Various research foundations have provided funds for this research. The instructions are simple, and if you follow them carefully and make good decisions, you may earn a considerable amount of money, which will be paid to you in cash at the end of the experiment.

All amounts in the experiment are expressed in Experimental Currency Units (ECU). The money you make in ECUs will be converted to US Dollars at a rate of 50 ECU= $1, and paid to you in addition to your $10 participation fee.

- In this experiment, you will participate in 30 auction periods.
- You will be randomly assigned one of the two following roles: Local bidder and Global bidder.
- Your role will be the same in all 30 periods.
- In every period two Locals and a Global will be randomly matched into a group of 3 people.
- Matching will change every period: you are not playing against the same people every time.
- The exact rule of earning calculation will be explained shortly.

Bidding:

- In each group of 3, bidders will bid for items in auctions in two markets (Market A and B).
- In each of these markets, there is one item for sale and two bidders (one Local and the Global).
- In each market, there is one Local bidder who participates in the auction only in that market.
- The Global bidder is interested in both markets, so the Global is present in both markets.
- Therefore, the Global and Local A bid in Market A auction and the Global and Local B bid in Market B auction.
- How much a person values an item will be explained later.
- Each Local bidder will submit a bid for the item in her market.
- The Global bidder will submit two bids: one for each item in each market.
- Bids can be any integer number from {0, 1, 2, 3,…, 300}. So the smallest possible bid is zero and the largest one is 300 in an auction.
- In each market the bidder with the higher bid wins the item:
    - If the Global's bid is greater than the Local's bid in a given market, the item of that market goes to the Global bidder.
    - If instead the Local's bid is greater than the Global's bid, the item goes to the Local bidder in that market.

Auction Prices:

- If a Local bidder gets the item in a market, she pays the Global's bid in that market.
- Similarly, if the Global bidder gets the item in a market, she pays the Local's bid in that market.

Values:

- In each period, prior to bidding, Global and Local bidders are assigned values for the items. There are three values: one for Global bidder (Global value) and the values for each Local bidder (Local values).
- Values are privately known. That is, Global bidder does not know the values of the Local bidders. Similarly, a Local bidder does not know the value of the Global bidder or the other Local bidder.
- Each Local value represents the amount that the Local bidder with that value will receive if she wins an item in the auction.
- The Global value represents instead the amount that the Global will receive if she wins <u>only one</u> item (either in market A or in market B).
- If the Global wins <u>both auctions</u>, she receives <u>**3 TIMES the Global value**</u>. (for example: if the Global value is 40, the global receives 40 if she ends up with a single item and receives 3x40=120 if she ends up with both items).
- Values are random integer numbers between 0 and 100. Each number is equally likely.
- All values are drawn independently (meaning they are most likely different).

Earnings:

In each period, you will receive the value of the item(s) you won in the auction. From this amount, the price you paid in the auction will be subtracted.

Auction Payoff = Value of the Item(s) – Auction Price (If you win any auction)

Auction Payoff = 0 (If you do not win)

The computer will randomly pick 20 periods out of 30 periods. The selection of each period is equally likely. Your final payoff will be the sum of your earnings in those 20 periods and $10 participation fee.

Questionnaire

1) In the example below, answer the following questions: Who wins each auction? How much do they pay? What are the earnings of each bidder?

	Market A			Market B	
	Local	*Global*	*Global* Package	*Global*	Local
Values	54	46	138	46	60
Bids	54	34		10	90
Got Item in Auction					
Auction Price					

Earning of Local A = _____

Earning Local B = _____

Earning Global = _____

2) In the example below, answer the following questions: Who wins each auction? How much do they pay? What are the earnings of each bidder?

	Market A			Market B	
	Local	*Global*	*Global* Package	*Global*	Local
Values	93	50	150	50	12
Bids	90	67		48	11
Got Item in Auction					
Auction Price					

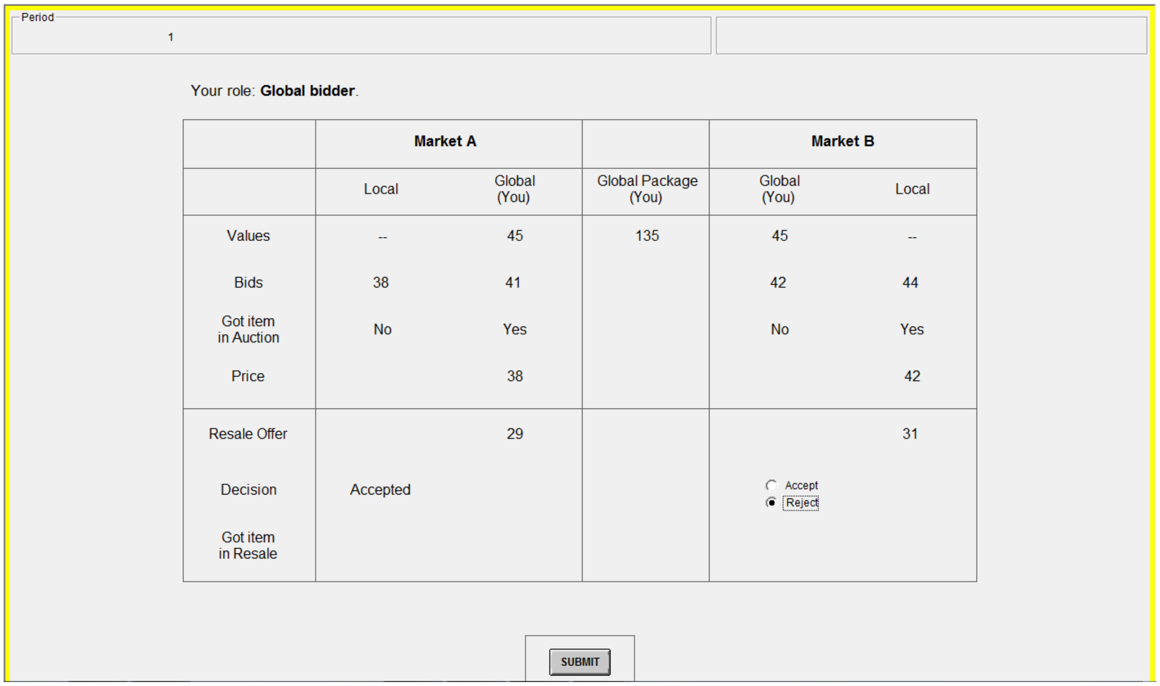
Earning of Local A = _____

Earning Local B = _____

Earning Global = _____

Appendix - EXPERIMENT SCREENSHOT

SIMULTANEOUS SECOND PRICE WITH RESALE



Period
1

Your role: **Global bidder**.

	Market A			Market B	
	Local	Global (You)	Global Package (You)	Global (You)	Local
Values	--	45	135	45	--
Bids	38	41		42	44
Got item in Auction	No	Yes		No	Yes
Price		38			42
Resale Offer		29			31
Decision	Accepted			Accept / Reject	
Got item in Resale					

SUBMIT

C.3 Report of Periods 16-30

Empirical Results for all Treatments in Periods 16-30

Table B1: Efficiency Leaks in VNR Format - Periods 16-30

Observed Outcomes	Efficient Outcomes						
	Count			%			
	Local-Local	LG/GL	Global-Global	Local-Local	LG/GL	Global-Global	Total
Local-Local	120	10	49	**90.9**	41.7	16.7	39.8
LG/GL	9	13	40	6.8	**54.2**	13.6	13.8
Global-Global	3	1	205	2.3	4.2	**69.7**	46.4
Total	132	24	294	100.0	100.0	100.0	100.0

Table B2: Efficiency Leaks in VR Format - Periods 16-30

Observed Outcomes	Efficient Outcomes						
	Count			%			
	Local-Local	LG/GL	Global-Global	Local-Local	LG/GL	Global-Global	Total
Local-Local							
Auction Stage	111	10	53	**84.1**	41.7	18.0	38.7
Resale Stage	106	11	32	**80.3**	45.8	10.9	33.1
LG/GL							
Auction Stage	15	10	47	11.4	**41.7**	16.0	16.0
Resale Stage	15	8	53	11.4	**33.3**	18.0	16.9
Global-Global							
Auction Stage	6	4	194	4.6	16.7	**66.0**	45.3
Resale Stage	11	5	209	8.3	20.8	**71.1**	50.0
Total	132	24	294	100.0	100.0	100.0	100.0

Table B3: Efficiency Leaks in SPNR Format - Periods 16-30

Observed Outcomes	Efficient Outcomes						
	Count			%			
	Local-Local	LG/GL	Global-Global	Local-Local	LG/GL	Global-Global	Total
Local-Local	112	8	21	**84.9**	33.3	7.1	31.3
LG/GL	15	15	80	11.4	**62.5**	27.2	24.4
Global-Global	5	1	193	3.8	4.2	**65.7**	44.2
Total	132	24	294	100.0	100.0	100.0	100.0

Table B4: Efficiency Leaks in SPR Format - Periods 16-30

Observed Outcomes	Efficient Outcomes						
	Count			%			
	Local-Local	LG/GL	Global-Global	Local-Local	LG/GL	Global-Global	Total
Local-Local							
Auction Stage	107	9	63	**81.1**	37.5	21.4	39.8
Resale Stage	110	10	26	**83.3**	41.7	8.8	32.4
LG/GL							
Auction Stage	21	15	105	15.9	**62.5**	35.7	31.3
Resale Stage	19	14	44	14.4	**58.3**	15.0	17.1
Global-Global							
Auction Stage	4	0	126	3.0	0.0	**42.9**	28.9
Resale Stage	3	0	224	2.3	0.0	**76.2**	50.4
Total	132	24	294	100.0	100.0	100.0	100.0

Table B5: Locals' Median Bids and Item-Level Winning Rates by Signal Ranges

Periods 16-30

Signal Range	Median Bids				Frequency of winning at the auction stage			
	VNR	VR	SPNR	SPR	VNR	VR	SPNR	SPR
0-10	10	10	9	10	0.17	0.2	0.17	0.24
11-20	20	20	19	21	0.28	0.26	0.16	0.21
21-30	30	30	29	31	0.25	0.42	0.24	0.38
31-40	43	50	40	46	0.33	0.39	0.29	0.46
41-50	52	60	50	52	0.47	0.39	0.38	0.54
51-60	69	70	60	65	0.6	0.59	0.55	0.71
61-70	80	75	70	70	0.59	0.55	0.61	0.62
71-80	90	80	80	80	0.68	0.59	0.65	0.75
81-90	99	100	91	100	0.54	0.59	0.55	0.8
91-100	111	100	99	100	0.77	0.67	0.77	0.84

Table B6: Globals' Median Bids and Item-Level Winning Rates by Signal Ranges
Periods 16-30

Signal Range	Median Bids						Frequency of winning at the auction stage			
	VNR		VR		SPNR	SPR				
	Single Item	Package	Single Item	Package	Single Item	Single Item	VNR	VR	SPNR	SPR
0-10	4	15	4	15	7	10	0.05	0.07	0.03	0.12
11-20	14	45	14	49	16	20	0.13	0.15	0.11	0.13
21-30	23	70	22	70	30	30	0.22	0.2	0.27	0.22
31-40	30	110	30	100	43	42	0.35	0.47	0.4	0.28
41-50	40	132	40	125	62	51	0.55	0.56	0.61	0.51
51-60	48	160	45	151	80	62	0.69	0.53	0.74	0.45
61-70	50	198	56	180	90	75	0.82	0.79	0.81	0.61
71-80	56	220	60	210	111	95	0.87	0.89	0.9	0.74
81-90	78	250	75	240	124	110	0.81	0.92	0.94	0.74
91-100	75	275	80	266	150	111	0.91	0.91	0.94	0.77

Figure B1: Bidding Behavior in VNR - Periods 16-30

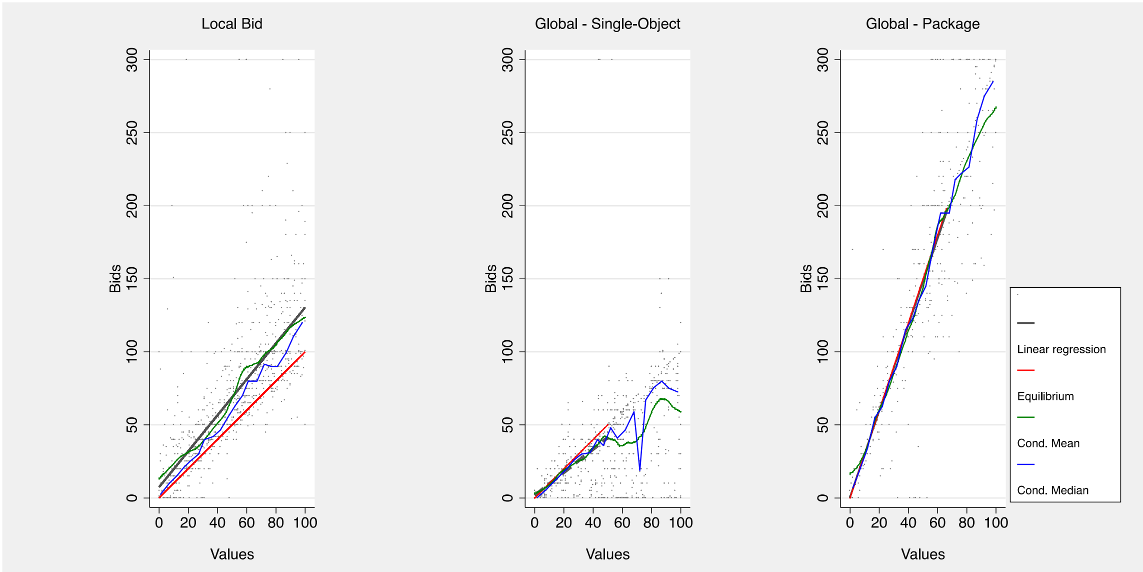


Table B7: Bid Regressions for VNR - Periods 16-30

	Locals' Bids	Globals' Single-Object Bids For Signal < 50	Globals' Package Bids For Signal <67
Signal	1.233***	0.818***	2.990***
	(0.036)	(0.071)	(0.105)
Constant	0.608	2.313	-0.497
	(6.146)	(2.929)	(6.017)
N	900	446	323

The standard errors are in parentheses. These are regressions with random effect at individual level and fixed effect at session level. * <0.10, ** < 0.05, and *** <0.01.

Figure B2: Bidding Behavior in VR - Periods 16-30

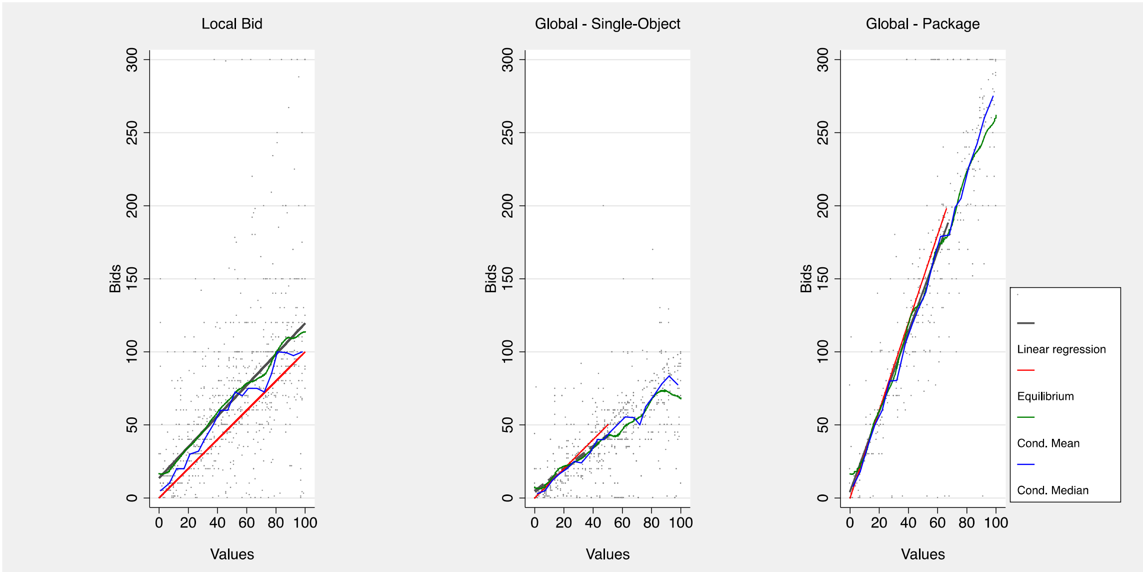


Table B8: Bid Regressions for VR - Periods 16-30

	Locals' Bids	Globals' Single-Object Bids For Signal < 50	Globals' Package Bids For Signal <67
Signal	1.079***	0.737***	2.632***
	(0.039)	(0.056)	(0.110)
Constant	8.925	9.642***	5.567
	(8.755)	(2.329)	(6.277)
N	900	446	323

The standard errors are in parentheses. These are regressions with random effect at individual level and fixed effect at session level. * <0.10, ** < 0.05, and *** <0.01.

Figure B3: Bidding Behavior in SPNR - Periods 16-30

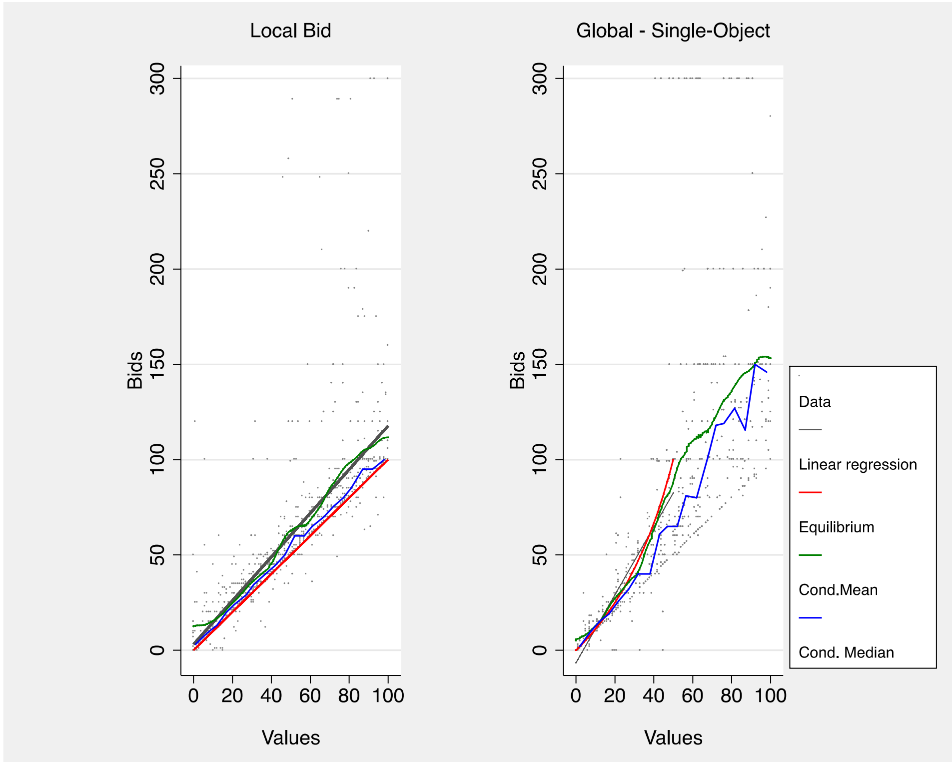


Table B9: Bid Regressions for SPNR - Periods 16-30

	Locals' Bid	Globals' $log(b_g)$ if $S_g \leq 50$
Signal	1.153***	
	(0.026)	
$ln(\frac{100}{s_g} - 1)$		-0.843***
		(0.020)
Constant	7.305	4.274***
	(5.823)	(0.057)
N	900	436

The standard errors are in parentheses. These are regressions with random effect at individual level and fixed effect at session level. * <0.10, ** < 0.05, and *** <0.01.

Figure B4: Bidding Behavior in SPR - Periods 16-30

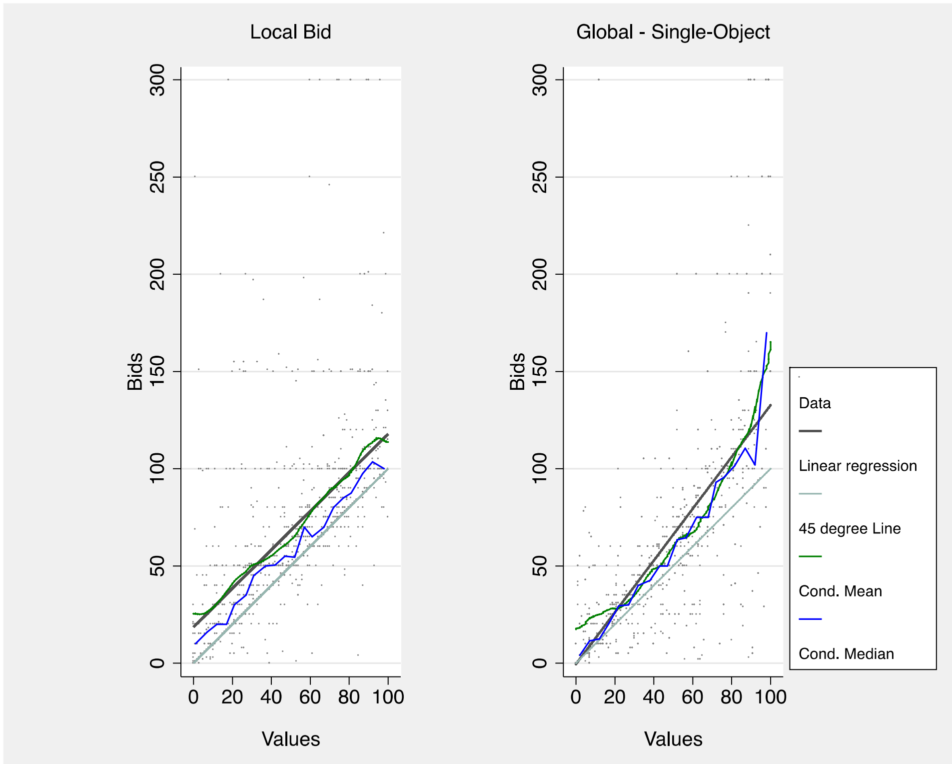


Figure B5: Locals' Bids in VNR and VR (CDF) - Periods 16-30

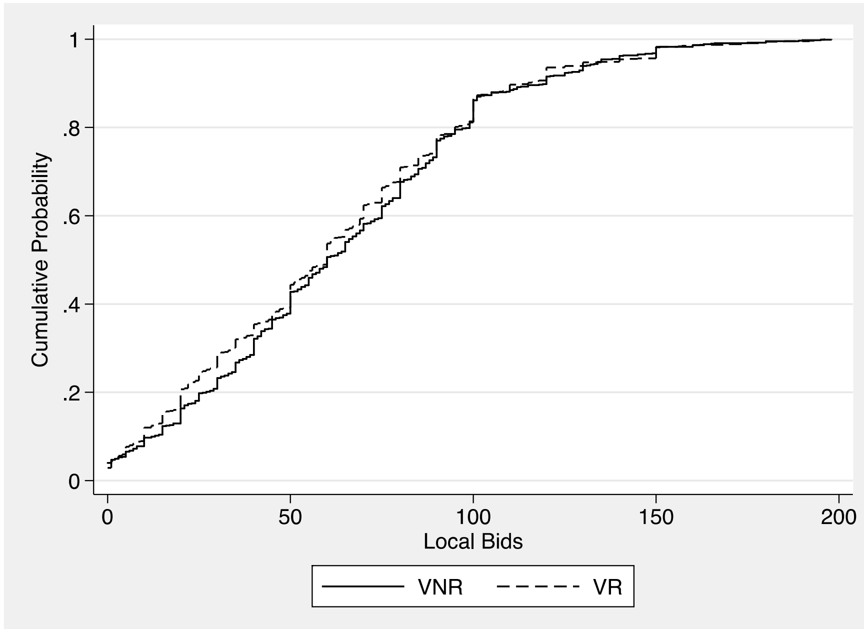


Figure B6: Globals' Single-Item Bids in VNR and VR (CDF) - Periods 16-30

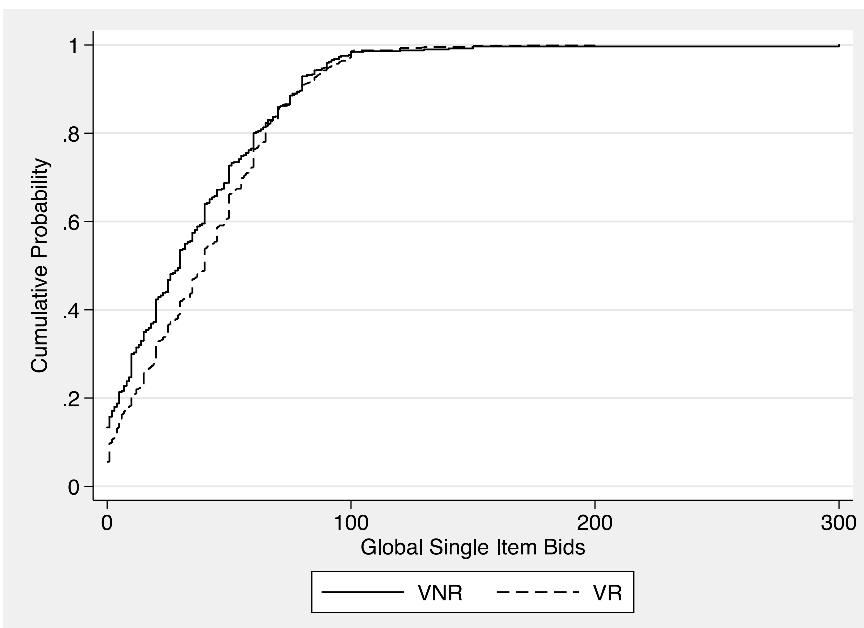


Figure B7: Globals' Package Bids in VNR and VR (CDF) - Periods 16-30

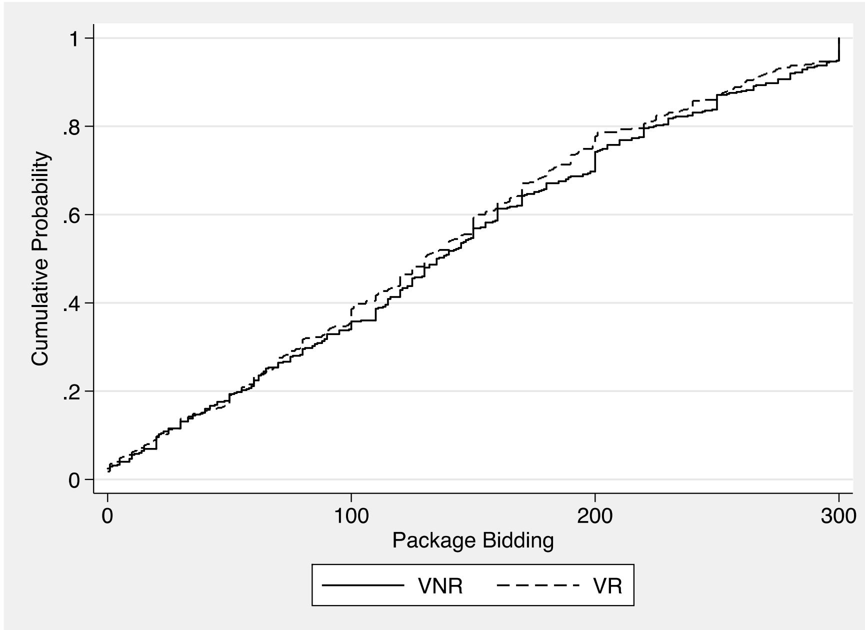


Figure B8: Locals' Bids in SPNR and SPR (CDF) - Periods 16-30

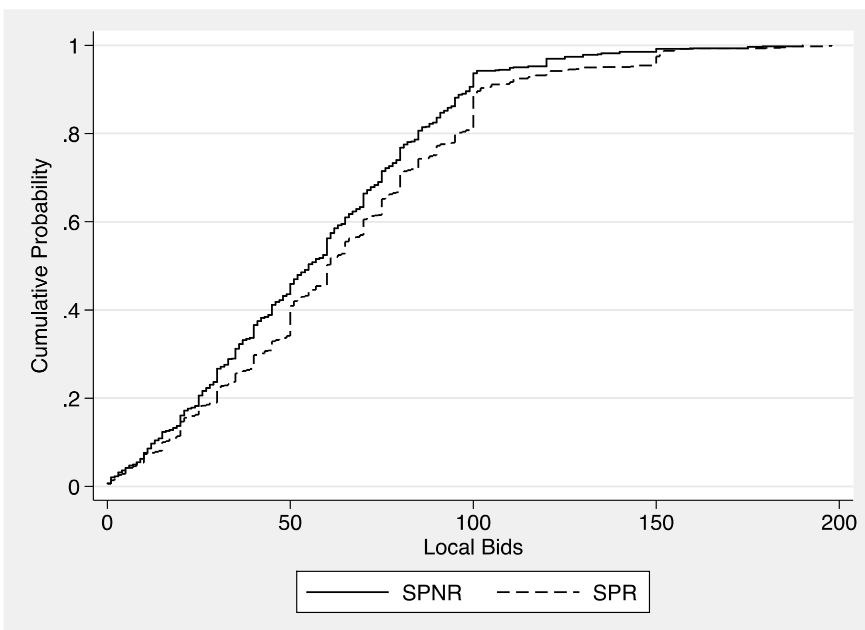


Figure B9: Globals' Single-Item Bids in SPNR and SPR (CDF) - Periods 16-30

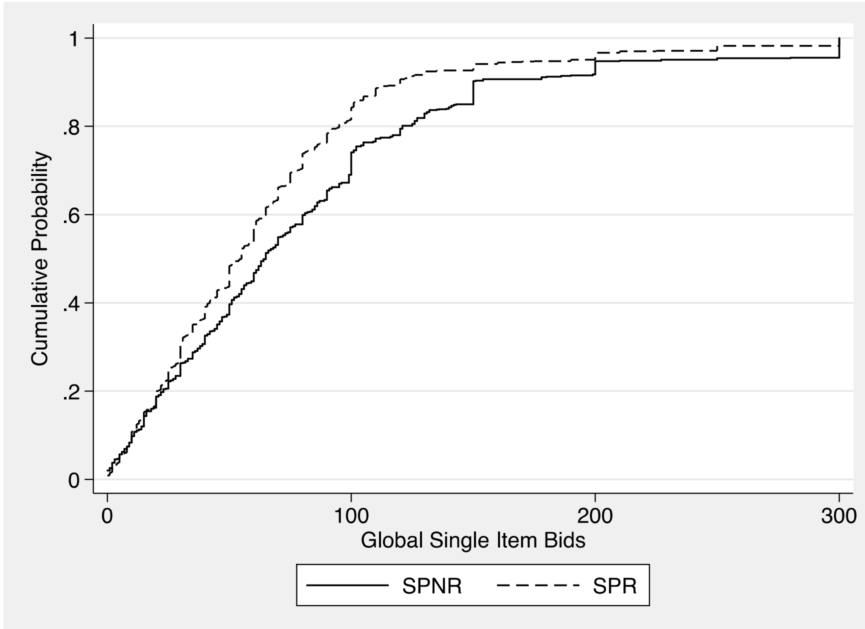


Figure B10: Locals' Bids Box-Plots for VNR and VR - Periods 16-30

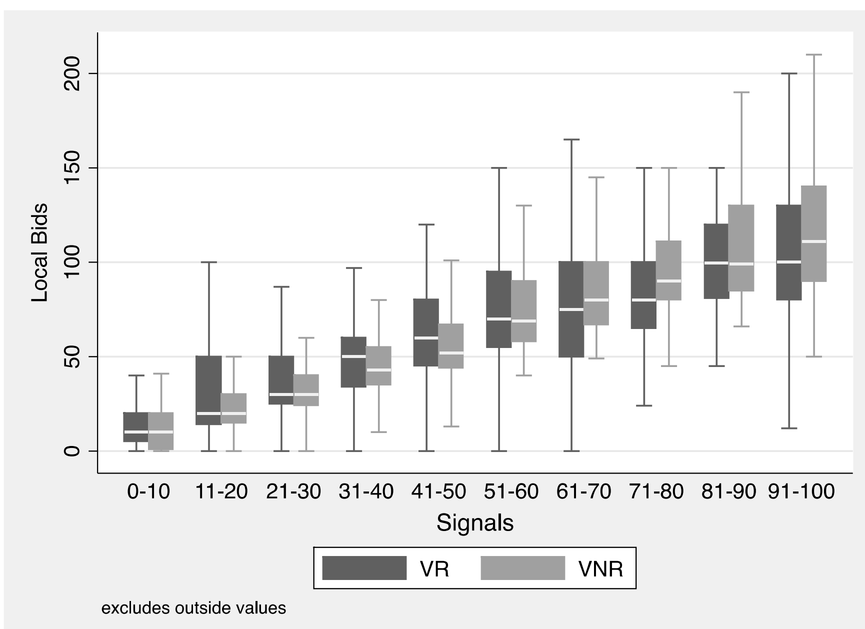


Figure B11: Globals' Single Bids Box-Plots for VNR and VR - Periods 16-30

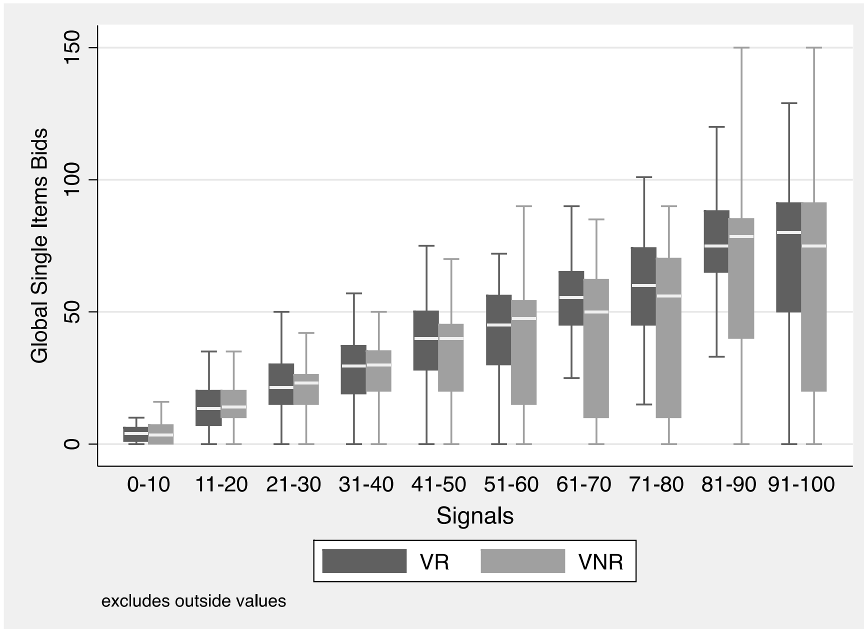


Figure B12: Globals' Package Bids Box-Plots for VNR and VR - Periods 16-30

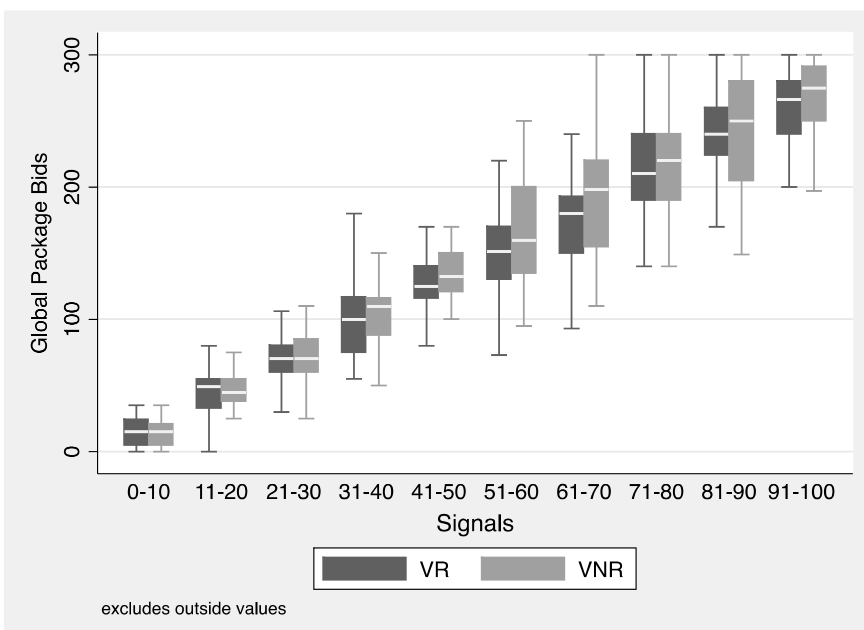


Figure B13: Local Bids Box-Plots for SPNR and SPR - Periods 16-30

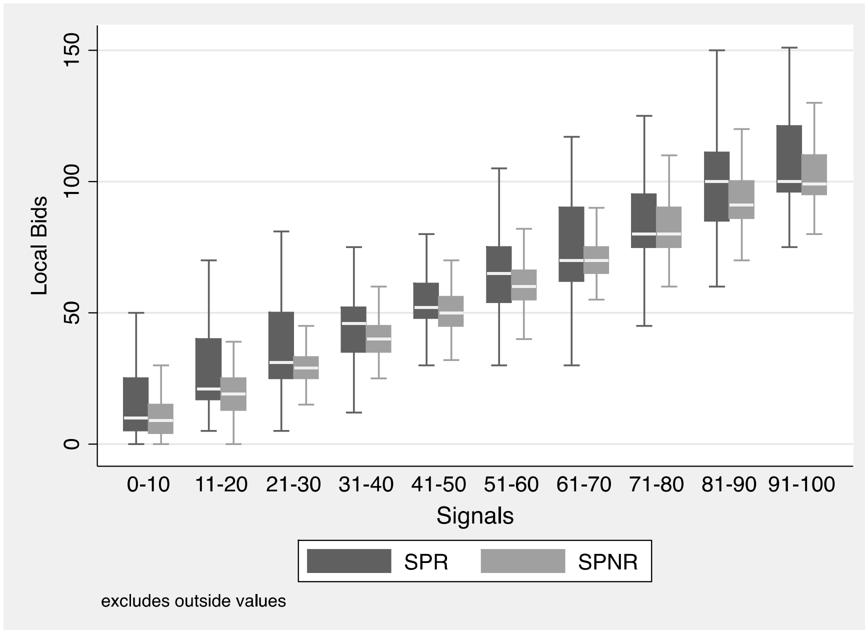


Figure B14: Globals' Bids Box-Plots for SPNR and SPR - Periods 16-30

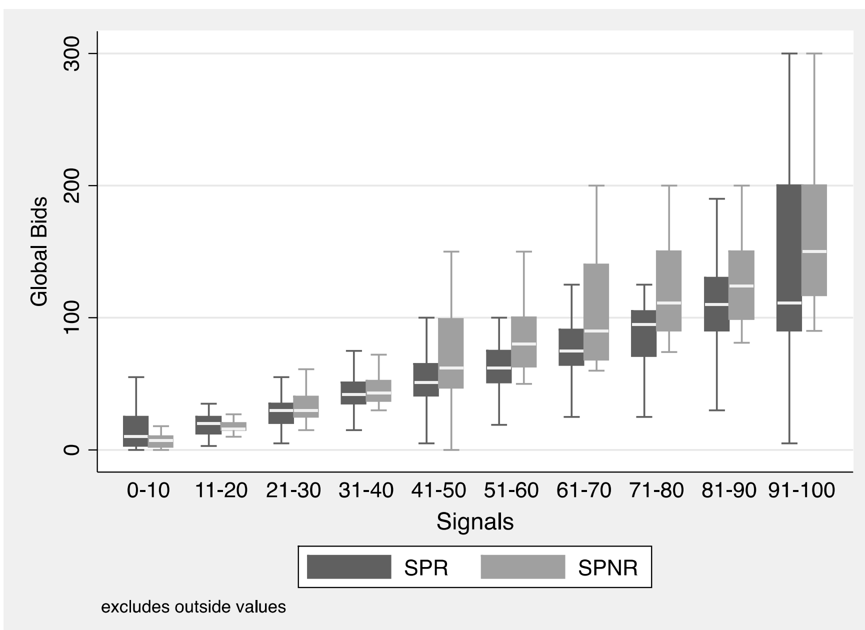


Table B10: Average Resale Prices in VR - Periods 16-30

Auction Outcome	**Resale Prices Paid by**	
	Global	Locals
LL	63.1 (5.78) n=80	-
LG / GL	89.8 (3.71) n=27	34.0 (4.86) n=24
GG	-	48.6 (10.13) n=37

Standard errors are in parentheses.

Table B11: Average Resale Prices in SPR - Periods 16-30

Auction Outcome	**Resale Prices Paid by**	
	Global	Locals
LL	75.0 (2.72) n=78	-
LG / GL	84.8 (4.18) n=69	34.6 (3.99) n=8
GG	-	47.6 (7.04) n=9

Session-clustered standard errors are in parentheses.

Table B12: Regressions for Locals' Resale Offers in VR - Periods 16-30

	First Offer / Locals win both objects	**Second Offer / Locals win both objects**	**Locals win only one object**
Signal	0.769***	0.569***	0.683***
	(0.144)	(0.160)	(0.241)
Global Bid (same object)	-0.685	1.747	-0.799**
	(1.187)	(1.394)	(0.357)
Global Bid (other object)	0.618	-1.960	0.209
	(1.191)	(1.392)	(0.258)
Global Package Bid	-0.026	0.044	0.429**
	(0.108)	(0.119)	(0.176)
Other Local Bid	0.069	0.012	-0.061
	(0.079)	(0.075)	(0.310)
First (local) Offer		0.011	
		(0.074)	
Constant	23.816	47.476***	28.696
	(16.320)	(17.856)	(20.332)
N	174	174	72

The standard errors are in parentheses. These are regressions with random effect at individual level and fixed effect at session level. * <0.10, ** < 0.05, and *** <0.01.

Table B13: Regressions for Globals' Resale Offers in VR - Periods 16-30

	Global wins one object	**Global wins both objects Both offers**
Signal	0.727***	0.222***
	(0.150)	(0.082)
Local Bid (same object)	0.112	0.243***
	(0.126)	(0.062)
Local Bid (other object)	-0.008	0.050
	(0.064)	(0.056)
Other Offer	-0.018	
	(0.048)	
Constant	12.653	39.841***
	(7.773)	(5.845)
N	62	190

Restricted to offers below 100 ECUs. The standard errors are in parentheses. These are regressions with random effect at individual level and fixed effect at session level.* <0.10, ** < 0.05, and *** <0.01.

Table B14: Regressions for Locals' Resale Offers in SPR - Periods 16-30

	First Offer / Locals win both objects	**Second Offer / Locals win both objects**	**Locals win only one object**
Signal	0.912***	0.875***	0.484***
	(0.083)	(0.076)	(0.120)
Global Bid (same object)	0.095	0.008	0.436***
	(0.164)	(0.166)	(0.163)
Global Bid (other object)	-0.149	-0.016	0.183
	(0.174)	(0.159)	(0.176)
Other Local Bid	-0.005	0.059	-0.105
	(0.051)	(0.048)	(0.137)
First (local) Offer		-0.041	
		(0.058)	
Constant	35.895***	18.979**	44.457***
	(9.284)	(8.275)	(10.935)
N	179	179	141

The standard errors are in parentheses. These are regressions with random effect at individual level and fixed effect at session level. * <0.10, ** < 0.05, and *** <0.01.

Table B15: Regression for Globals' Resale Offers in SPR - Periods 16-30

	Global wins one object	**Global wins both objects Both offers**
Signal	0.718***	0.655***
	(0.113)	(0.096)
Local Bid (same object)	0.244**	-0.076
	(0.119)	(0.074)
Local Bid (other object)	-0.004	0.024
	(0.063)	(0.056)
Other Offer	-0.140**	
	(0.054)	
Constant	36.116***	39.762***
	(7.977)	(6.211)
N	93	94

Restricted to offers below 100 ECUs. The standard errors are in parentheses. These are regressions with random effect at individual level and fixed effect at session level.* <0.10, ** < 0.05, and *** <0.01.

Table B16: Average Revenues - Periods 16-30

Treatment	**Theoretical Revenue**	**Observed Revenue**
VNR	76.1	83.75
	(2.41)	(4.09)
VR	76.1	80.9
	(2.41)	(2.59)
SPNR	77.5	81.2
	(2.76)	(2.98)
SPR	NA	81.65
	NA	(5.41)

Session-clustered S.E. reported in parentheses.

Table B17: Bidders' Average Profits - Periods 16-30

Treatment	**Locals**		**Globals**	
	Theoretical	Observed	Theoretical	Observed
VNR	11.7	12.7	66.8	47.0
	(1.09)	(1.89)	(2.49)	(3.47)
VR	11.7	13.3	66.8	46.5
	(1.09)	(1.47)	(2.49)	(3.20)
SPNR	11.05	12.0	65.7	51.9
	(1.21)	(1.34)	(2.84)	(3.08)
SPR	NA	15.5	NA	46.5
	NA	(2.62)	NA	(3.59)

Session-clustered S.E. reported in parentheses.

Figure B15: Globals' Mean and Median Profits - Periods 16-30

Mean Median

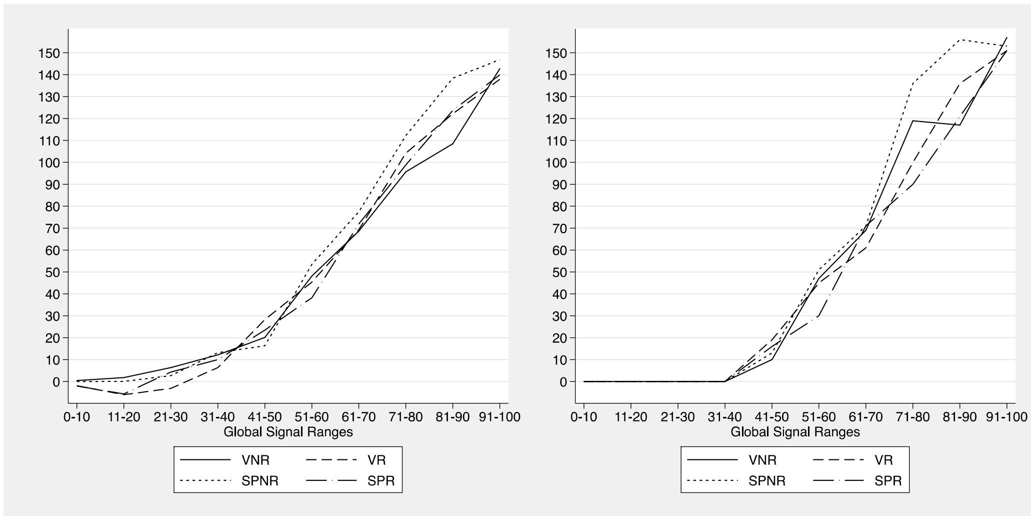


Figure B16: Locals' Mean and Median Profits - Periods 16-30

Mean Median