**Goodwill Can Hurt: a Theoretical and Experimental Investigation of Return Policies in Auctions**

C. Bram Cadsby, Ninghua Du, Ruqu Wang and Jun Zhang*

*Will generous return policies in auctions benefit bidders? We investigate this issue using second-price common-value auctions. Theoretically, we find that the symmetric bidding equilibrium is unique unless returns are free, and when returns are free there exist multiple equilibria with different implications for sellers. Moreover, more generous return policies hurt bidders by eroding consumer surplus through higher bids. In the experiment, bids increase and bidders' earnings decrease with more generous return policies as predicted. With free returns, many bidders bid above the highest possible value, subsequently returning the item regardless of value. Though consistent with equilibrium behavior, this is not optimal for sellers.*

**Keywords:** Auctions, Return Policies, Common Value, Experiment.

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*Cadsby: Department of Economics and Finance, University of Guelph, 50 Stone Road East, Guelph, ON N1G 2W1, Canada (e-mail: bcadsby@uoguelph.ca), Corresponding Author.
Du: Key Laboratory of Mathematical Economics and School of Economics, Shanghai University of Finance and Economics, Shanghai 200433, P.R. China (e-mail: ninghua.du@mail.shufe.edu.cn)
Wang: Department of Economics, Queen's University, Kingston, ON K7L 3N6, Canada (e-mail: wangr@queensu.ca)
Zhang: Economics Discipline Group, School of Business, University of Technology Sydney, Sydney, NSW, Australia (e-mail: Jun.Zhang-1@uts.edu.au)

## 1. Introduction

The rapid growth of Internet commerce has resulted in the development of online auctions as a popular trading method over the past decades. Return policies are widely available in such online auctions. Return policies permit auction winners to change their minds by paying a pre-specified penalty fee when they receive relevant ex-post information after the auction concludes. A recent search for antique auctions on eBay.com yielded 35,758 such auctions with 23,014 (64%) of the sellers offering a 7-day or 14-day money-back guarantee. The percentage of art auctions offering refunds on eBay.com was even higher, with 131,944 out of 175,329 sellers offering a money-back guarantee, representing 75% of art auctions.

Return policies are sometimes observed in traditional auctions as well. For example, deposits required in auctions for valuable objects such as spectrum licenses, oil field leases, and mineral and gas rights can be treated as fixed-fee return policies. If an auction winner fails to pay his/her full bid upon winning, then the deposit is not refunded. For example, shortly after the conclusion of the 1996 "C-block" radio frequency spectrum auction in the U.S., the bidders re-evaluated the market values of the licenses they had just won and determined that the values were far less than the 10-billion-dollar winning bids that they were required to pay. As a result, several bidders declined to make their payments to the Federal Communications Commission, and thus forfeited their deposits.

How would a return policy affect bidders' behavior and what kind of return policy would most benefit them? What kind of return policy would most benefit sellers? How should a revenue-maximizing seller select the optimal return policy? These are some of the issues we will investigate in this paper. We focus on the common-value model in Wilson (1969), which fits reasonably well with auctions for oil field leases, gas and mineral rights, and spectrum licenses. Our model should also be informative for auctions of objects with a major common-value component, such as art and antiques.[1]

We analyze the behavior of bidders in second-price auctions and focus on linear return policies under which the seller can charge a percentage fee in addition to a fixed fee. Linear return policies are very popular because they are, like linear pricing, easy to implement in practice. We provide a closed-form solution for the unique symmetric equilibrium when returns are not completely free. When returns are free, there exist multiple equilibria, all of which yield zero payoffs for the bidders, but have different implications for the seller.

Results from the literature on return policies offered by retail stores, such as Che (1996), predict that consumers will be better off with a more generous return policy. However, perhaps surprisingly, it turns out that a more generous return policy actually hurts consumers in auctions. This counterintuitive result arises from the fact that a more generous return policy not only protects consumers from bad shocks, but also reduces bidders' fears of falling prey to the winner's curse. This induces them to bid more aggressively in the auction, resulting in higher bids and lower consumer surplus.[2]

We also examine how return policies affect the seller's revenue. On the one hand, with a more generous return policy, bidders bid more aggressively, which enhances the seller's revenue. On the other hand, a more generous return policy makes it more likely that the winner will return the object. By

[1]Resale can introduce a common-value component to a private-value good. See Cheng and Tan (2010) and Haile (2003) for examples.

[2]It can be shown that under independent private values with signals and valuations distributed independently across bidders, a more generous return policy causes bidders to bid more aggressively, but has no effect on consumer surplus. Thus the driving force behind our result is the common-value feature of the auction and the winner's curse effect. The proof is available in an online appendix. In contrast, with only one buyer in Che (1996), the winner's curse effect is absent as there are no other competitors. Che's paper allows buyers to be risk-averse. A full return policy insures such buyers against ex-post risk, thus making them better off.

selecting an appropriate return policy, the seller can achieve higher revenue by balancing the trade-off between higher bids and fewer returns.

We find that the optimal (linear) return policy should always be in the form of a fixed fee (or subsidy), implying that the seller should not charge a percentage fee. This resembles many return policies in reality: deposits in oil field leases, mineral and gas rights, and spectrum auctions are usually specified in fixed amounts, and many sellers on eBay provide money-back guarantees with fixed shipping subsidies or shipping and handling fees.

We conduct an experiment to test the predictions of our theory. In the experimental setting, items may have a high value of 100 or a low value of 0, with an *a priori* 50% probability of each outcome. We focus on return polices with fixed fees since our theory predicts that proportional fees are suboptimal for seller revenue maximization. There are four experimental treatments: No Return (NR), High Fee (HF), Low Fee (LF) and Free Return (FR). We observe that bids increase and bidders' earnings decrease when return policies are more generous as predicted by theory. Correspondingly, sellers' revenues increase with more generous return policies as long as some positive fee is charged for a return. However, when returns are free, many bidders bid above the highest possible value for the good, and subsequently return the item regardless of the revealed value. While this is consistent with theoretical equilibrium behavior, it is not an equilibrium that is optimal for the seller who receives zero revenue when such an outcome occurs.

This paper is related to the literature on the theory of public ex-post information. When ex-post information is public and can be contracted on, its effect has long been recognized in the auction literature pioneered by Hansen (1985). In general, it has been shown that ignoring such information is sub-optimal, and adopting a mechanism conditional on the realization of the information is revenue improving. Riley (1988) demonstrates that royalty bidding is better than cash bidding. Abhishek et al. (2011) show that by charging an initial amount plus requiring a profit-sharing contract, the seller can generate more revenue. DeMarzo et al. (2005) examine bidding with securities and show that it can enhance revenue. However, all these mechanisms require the seller to track down the realized value implied by the ex-post information, which could be quite costly. In addition, sometimes the ex-post information may be unobservable, and this is common for objects sold through online auctions. In such cases, mechanisms conditional on ex-post information may not be feasible. In contrast, return policies do not require the seller to observe any ex-post information; it is solely up to the winning bidder to decide whether or not to return the object.

This paper is also related to the dynamic mechanism design literature in which agents learn additional private information over time. As shown in Eső and Szentas (2007), Courty and Li (2007), and Zhang (2013), the seller can utilize a handicap system or a menu of refunds to discriminate dynamically among the agents and to extract more revenue with ex-ante participation constraints.[3] This literature usually assumes private values and independent signals. Instead of adopting a mechanism design approach, we consider a specific mechanism, namely a second price auction with a linear return policy, and focus on the effect of alternative return policies on consumers.

There is a huge literature on auctions. However, few papers consider return policies. Hafalir and

[3]Krähmer and Strausz (2015) show that if instead the participation constraint is an ex-post one, the value of eliciting the agent's information sequentially is eliminated, and it is optimal to design a simple contract conditioning only on the agent's final information.

Yektas (2011) consider second-price auctions under independent private values that are subject to shocks after the transaction and compare the revenues among spot auctions, forward auctions, and forward auctions with a full return policy. Our current paper considers common-value auctions with a full range of linear return policies. Huang et al. (2007) recently considered an algorithm for multi-unit auctions with a partial refund for bid withdrawals that occur for exogenous reasons. That paper provides an analysis from the perspective of artificial intelligence, and thus the strategic behavior of bidders is not its focus.

In the related experimental literature, bidding in common-value auctions is well documented in laboratory settings (see Kagel and Levin, 2002, for a survey). Assuming symmetric bidding behavior in common-value auctions, bidders only win when they have the highest signal. Unless this is accounted for when formulating bids, the winner of the auction will receive below normal or even negative profits. Such a judgmental failure is known as the "winner's curse." Previous experimental studies show that inexperienced bidders are vulnerable to the winner's curse (Kagel and Levin, 2002), while experienced bidders have learned to avoid the winner's curse by the time they appear for subsequent sessions (e.g., Casari et al., 2007; Garvin and Kagel, 1994; and Goertz, 2012). In our study, a return policy acts as insurance against overbids and thus mitigates the winner's curse. Nonetheless, we follow the earlier experiments by introducing the factor of experience to minimize any possible impact of the winner's curse on our results.

The rest of this paper is organized as follows. In Section 2, we set up the model. In Section 3, we characterize the bidders' equilibrium strategies in second-price auctions and perform some preliminary analysis. In Section 4, we illustrate the effect of return policies on consumer surplus, social welfare and seller's revenue. In Section 5, we describe the experimental design using a simplified version of the general model. In Section 6, we discuss the experimental results. In Section 7, we conclude. All proofs are relegated to appendices.

## 2. The Model

Suppose that there are $n$ bidders bidding for one object. The object value is the same for all bidders. Let $V$ denote this common value. Assume that $V = v_H$ with probability $\mu_H$, and $V = v_L$ with probability $\mu_L = 1 - \mu_H$, where $v_H > v_L$. The distribution for $V$ is common knowledge. Before bidding starts, bidder $i \in \{1, \cdots, n\}$ receives a private signal $x_i$, which is correlated with $V$. However, conditional on $V$, this signal is independently distributed across the bidders. If $V = v_H$, then $x_i$ follows the distribution with c.d.f. $F_H(\cdot)$ and p.d.f. $f_H(\cdot)$. If $V = v_L$, then $x_i$ follows the distribution with c.d.f. $F_L(\cdot)$ and p.d.f. $f_L(\cdot)$. Assume that $F_H(\cdot)$ and $F_L(\cdot)$ have a common support $[\underline{x}, \overline{x}]$.

The object in the auction can be returned by the winning bidder for a refund. We assume that there is a shipping cost for the winning bidder to return the object. This cost is denoted by $c_B$. It could include the time and effort taken by the winning bidder to ship the object back as well as the actual shipping charges. Let $p$ be the transaction price (i.e., the price the winning bidder paid) in the auction. A return policy is denoted by $(\alpha, \gamma)$; if the winning bidder returns the object, s/he gets back the price s/he paid (i.e., $p$), minus the return fees $\alpha + \gamma p$.[4] Here, $\gamma$ is a prespecified proportion of the price $p$, which may correspond to a proportional restocking fee in the real world. Meanwhile, $\alpha$ is simply a fixed fee or subsidy as explained below.

[4]We restrict our analysis to linear return fees. This simplifies the calculations significantly. Moreover, we are not aware of any other type of return policy in reality.

We place some restrictions on the return policy to simplify the analysis. We assume that $0 \leq \gamma \leq 1$ and that $\alpha \geq -c_B$. The former ensures that a bidder cannot make money by simply using the win-and-return strategy. The latter ensures that the winning bidder's shipping cost is not overcompensated. If $\alpha$ is positive, then it is a fixed fee, corresponding to a handling charge or a service charge in reality; if $\alpha$ is negative, it is a subsidy, corresponding to a refund or partial refund of the winning bidder's shipping cost. The difference between the shipping cost $c_B$ and the fixed fee $\alpha$ is that the former is paid to a third party (to cover the actual cost of shipping) while the latter is a pure transfer from the winning bidder to the seller.

The game proceeds in three stages:

1. Nature selects $V = v_H$ or $V = v_L$. Conditional on $V$, each bidder receives an independent signal ($x$).
2. A second-price auction with return policy $(\alpha, \gamma)$ is held. The winner pays accordingly and receives the object.
3. The winner learns the true $V$ and decides whether or not to return the object to the seller for a refund.

We assume that the winning bidder learns costlessly the true value of $V$ after s/he wins and obtains the object. In auctions for oil field leases and gas and mineral rights, for example, the winning bidders usually learn more information by doing more geological testing and analysis after winning the auction. Another example is online auctions where, once the winning bidder receives the object, s/he usually learns more about its value.

In our analysis, the likelihood ratio for bidders' signals plays an important role. Let

$$\rho_k(x) \equiv \frac{kf_H(x)F_H(x)^{k-1}}{kf_L(x)F_L(x)^{k-1}}$$

denote the likelihood ratio of $V = v_H$ versus $V = v_L$ for the highest signal among $k$ bidders. Then $\rho_1(x) = \frac{f_H(x)}{f_L(x)}$. Assume that $\rho_1(x)$ is increasing in $x$, i.e., $F_H$ dominates $F_L$ in likelihood ratio. This ensures that a higher signal implies a higher probability of $V = v_H$.

## 3. Equilibrium Analysis

In this section, we characterize the bidders' equilibrium bidding function. We focus on the symmetric perfect Bayesian equilibrium with a strictly increasing bidding function $B(\cdot)$ in the auction. We restrict our attention to bidding functions taking values in $[v_L, v_H]$. We do so because a bidder should not bid more than $v_H$ or less than $v_L$. Bidding more than $v_H$ sometimes gives the bidder a negative surplus and is dominated by bidding $v_H$. Moreover, if the bidder with the lowest possible signal bids less than $v_L$ in a proposed equilibrium, then it is a profitable deviation for that bidder to bid $v_L$ instead given that all other bidders follow the proposed equilibrium strategy. Doing so means s/he wins with positive probability and thus receives a positive expected surplus, while in the proposed equilibrium, the expected surplus was zero. Therefore bidding less than $v_L$ cannot be part of an equilibrium.

We choose bidder 1 as the representative bidder in our analysis. Let $y$ denote the second highest signal among all bidders, and $z$ denote the highest signal among bidders *2, ..., n*. If $V = v_H$, then $y$ and $z$ follow distributions with c.d.f. $G_H(y) = nF_H(y)^{n-1} - (n-1)F_H(y)^n$ and $J_H(z) = F_H(\cdot)^{n-1}$, respectively. Let $g_H(y) = n(n-1)f_H(y)F_H(y)^{n-2}[1 - F_H(y)]$ and $j_H(z) = (n-1)f_H(y)F_H(y)^{n-2}$ denote their respective p.d.f.s. Furthermore, $G_L(y)$, $J_L(z)$, $g_L(y)$ and $j_L(z)$ represent similar c.d.f.'s and p.d.f.'s when $V = v_L$.

We begin with the return stage. Suppose that bidder 1 receives signal $x$, bids $B(\tilde{x})$, and wins the object. Since it is a second-price auction, s/he pays $B(z)$. After winning, if s/he learns that $V = v_H$, s/he will not return the object since his/her payment is less than $v_H$. If s/he learns that $V = v_L$, s/he returns the object for a refund if and only if $v_L - B(z) < -[\alpha + \gamma B(z)] - c_B$.[5] The left-hand side of the inequality is the payoff s/he receives if s/he keeps the object, while the right-hand side is the payoff s/he receives if s/he returns the object for a refund.

Given the winning bidder's return decision in the return stage, we can examine the symmetric equilibrium bidding function in the auction stage. We focus on two hypothetical auctions because they will be helpful in describing the equilibria in our model. The first is a second-price auction in which no return is allowed, while the other is a second-price auction in which the winner is required to return the object when $V = v_L$. Let $B^1(x)$ and $B^2(x)$ denote the equilibrium bidding functions in the two hypothetical auctions. The first hypothetical auction is a standard second-price auction and a special case of Milgrom and Weber (1982). A bidder with signal $x$ bids $E(V|x_1 = x, z = x)$, the expected object value conditional on his/her own signal being $x$ and the highest signal among other bidders being $z = x$. Define this value as $\Gamma(x)$. Thus,

$$B^1(x) = \Gamma(x) = E(V|x_1 = x, z = x) = \frac{\mu_H v_H \rho_1(x)\rho_{n-1}(x) + \mu_L v_L}{\mu_H \rho_1(x)\rho_{n-1}(x) + \mu_L}.$$

For the second hypothetical auction, if $V = v_H$, s/he receives $v_H$; if $V = v_L$, s/he receives nothing but pays the proportion $\gamma$ of the price plus $\alpha + c_B$. Given that all other bidders bid according to the

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[5] We assume that if a winner is indifferent between keeping and returning the object, s/he keeps the object.

equilibrium bidding funciton $B^2(.)$, buyer 1's surplus when s/he pretends to have signal $\tilde{x}$ is given by

$$\Pi^2(x,\tilde{x})$$

$$= Pr(V = v_H|x_1 = x)E\{[V - B^2(z)]I\{y < \tilde{x}\}|x_1 = x, V = v_H\}$$

$$+Pr(V = v_L|x_1 = x)[-E\{\gamma B^2(z)I\{y < \tilde{x}\}|x_1 = x, V = v_L\} - a - c_B]$$

$$= \mu_H(x)\int_{\underline{x}}^{\tilde{x}}[v_H - B^2(z)]dJ_H(z) - \mu_L(x)\int_{\underline{x}}^{\tilde{x}}[a + \gamma B^2(z) + c_B]dJ_L(z).$$

where

$$\mu_H(x) \equiv \Pr(V = v_H|x_1 = x)$$

$$= \frac{\Pr(x_1=x|V=v_H)\Pr(V=v_H)}{\Pr(x_1=x|V=v_H)\Pr(V=v_H)+\Pr(x_1=x|V=v_L)\Pr(V=v_L)}$$

$$= \frac{f_H(x)\mu_H}{f_H(x)\mu_H+f_L(x)\mu_L},$$

and where $\mu_L(x) = \Pr(V = v_L|x_1 = x) = 1 - \mu_H(x)$.

The FOC yields:

$$B^2(x) = \frac{\mu_H v_H \rho_1(x)\rho_{n-1}(x) - \mu_L(a+c_B)}{\mu_H\rho_1(x)\rho_{n-1}(x)+\gamma\mu_L}. \tag{1}$$

Note that $B^1(x)$ and $B^2(x)$ are both strictly increasing. It is useful to discuss their relationship to each other. If $\frac{\alpha+v_L+c_B}{1-\gamma} < \underline{x}$, $B^1(x)$ is always below $B^2(x)$; if $\frac{\alpha+v_L+c_B}{1-\gamma} > \overline{x}$, $B^1(x)$ is always above $B^2(x)$; otherwise, $B^1(x)$ single crosses $B^2(x)$ from above at $\Gamma^{-1}(\frac{\alpha+v_L+c_B}{1-\gamma})$. Denote $x^*$ as follows:

$$x^* = \begin{cases} \underline{x}, & if\ \frac{\alpha+v_L+c_B}{1-\gamma} < \underline{x}; \\ \Gamma^{-1}\left(\frac{\alpha+v_L+c_B}{1-\gamma}\right), & if\ \underline{x} \le \frac{\alpha+v_L+c_B}{1-\gamma} \le \overline{x}; \\ \overline{x}, & if\ \frac{\alpha+v_L+c_B}{1-\gamma} > \overline{x}. \end{cases} \tag{2}$$

Now, we are ready to characterize the equilibrium of our model. Let $B(\cdot)$ denote the bidding function in this case. Suppose that bidder 1's signal is $x$ and s/he pretends to have signal $\tilde{x}$ and bids $B(\tilde{x})$. Given that s/he acts optimally in the return stage, his/her expected surplus in the auction is given by:

$$\Pi(x,\tilde{x}) = Pr(V = v_H | x_1 = x) E\{[V - B(z)] I\{z < \tilde{x}\} | x_1 = x, V = v_H\}$$

$$+\mathrm{Pr}\,(V = v_L | x_1 = x) E\{[\max\{V - B(z), -\gamma B - \alpha - c_B\}]$$

$$I\{z < \tilde{x}\} | x_1 = x, V = v_L\}$$

$$= \mu_H(x) \int_{\underline{x}}^{\tilde{x}} [v_H - B(y)] dJ_H(z)$$

$$+\mu_L(x) \int_{\underline{x}}^{\tilde{x}} [\max\{v_L - B(z), -\gamma B(z) - \alpha - c_B\}] dJ_L(z),$$

When the common value is revealed to be high, bidder 1 always keeps the object; when the common value is revealed to be low, bidder 1 can choose to keep or return the object depending on the realization of the payment.

In equilibrium, it is optimal for bidder 1 to report truthfully and the first order condition yields:

$$\mu_H(x)[v_H - B(x)] j_H(x) + \mu_L(x)[\max\{v_L - B(x), -\gamma B(x) - \alpha - c_B\}] j_L(x) = 0.$$

The FOC can be simplied to

$$B(x) = max\{B^1(x), B^2(x)\}.$$

It can also be verified that the FOC is also sufficient for the equilibrium. The proof is standard but tedious and is available in an online appendix.

We thus have the following proposition.

**Proposition 1:** *In a second-price common-value auction with return policy $(\alpha, \gamma)$, there exists a symmetric monotone perfect Bayesian equilibrium characterized as follows. In the auction stage, bidders bid according to the strictly increasing function $B(x) = max\{B^1(x), B^2(x)\}$; and in the return stage, the winner returns the object if and only if $V = v_L$ and the second highest signal is higher than $x^*$. This equilibrium is the unique symmetric monotone perfect Bayesian equilibrium unless $\gamma = 0$ and $\alpha = -c_B$.*

Our theoretical discussion assumes a continuous distribution of signals. However, under a second-price auction, the derived bidding function also applies to the discrete distribution of signals employed in our experimental design. This is in contrast to first-price auctions where the equilibrium for continuous signals will be quite different from that for discrete signals (e.g., Goeree, Holt and Palfrey, 2002).

Note that, except for the free-return policy case, the equilibrium we characterize is unique among symmetric equilibria. If we go beyond the class of symmetric equilibria, there exist other asymmetric equilibria in second-price auctions regardless of whether the signals are continuous or discrete. As pointed out in Birkhchandani and Riley (1991), whenever asymmetric equilibria are feasible, one such equilibrium involves more aggressive bidding behavior by a single buyer relative to the symmetric equilibrium and more passive behavior by the other buyers. For example, consider our model with two bidders. One bidder bidding higher than $v_H$ regardless of his/her signal and the other bidding zero regardless of his/her signal is an asymmetric equilibrium under any return policy. However, it is common in the literature for researchers to focus primarily on the symmetric equilibrium since asymmetric equilibria often involve dominated or discontinuous strategies or inefficiency. (See Birkhchandani and Riley, 1991, Chapter 8.2 in Krishna, 2009 and Milgrom, 1981 for detailed discussions on asymmetric equilibria.)

For the full return policy, i.e, when $\gamma = 0$ and $\alpha = -c_B$, in the equilibrium characterized by Proposition 1, we have $B(x) = v_H, \ \forall x$. Furthermore, the winner returns the object if and only if $V = v_L$. However, this equilibrium is not unique even within the class of symmetric equilibria. In fact, besides the above equilibrium, there exists a continuum of equilibria under which at least two bidders bid strictly higher than $v_H$, and the winner always returns the object. Obviously, bidding more than $v_H$ is weakly dominated by bidding $v_H$. For simplicity and continuity, when $\gamma = 0$ and $\alpha = -c_B$, we focus in the theory on the equilibrium described in Proposition 1.[6]

When the seller puts in place a no-return policy, bidders anticipate the winner's curse and adjust their bids downward from their estimates of the object's value using their own signals. When a return policy is in place, they bid more aggressively as they are somewhat protected from overbidding. In this sense, return policies mitigate the winner's curse. In fact, return policies can overdo this mitigating effect. When the return policy is generous enough, bidders may bid more than their estimates of the object's value. For example, when $\alpha = -c_B$ and $\gamma = 0$, players will bid $v_H$, the highest possible value of the object. This leads to the possibility of enhancing the seller's revenue by providing a return policy. Of course, return policies can negatively impact the seller's revenue as well as the efficiency of trading as the seller usually has a lower reservation value than the bidders. By selecting an appropriate return policy, the seller can achieve more revenue by balancing the tradeoff between higher bids and efficiency losses. In the following section, we will investigate this tradeoff in detail.

## 4. The effects of return policies on consumer surplus, social welfare and seller's revenue

In this section, we first study how return policies affect bidders' expected surplus (i.e., consumer surplus) and the expected gains from trade (i.e., social welfare). We then examine the effects of return

[6]Note that our experimental result shows that if , $\gamma = 0$ and $\alpha = -c_B$, bidders actually do not follow this equilibrium prediction, but instead often play one of the weakly dominated equilibria. However, as long as there is even a very small amount of cost to return an item, the data are qualitatively consistent with our equilibrium prediction.

policies on the seller's revenue (i.e., producer surplus) and characterize the optimal return policy for the seller.

### 4.1 Consumer surplus and social welfare

Denote the consumer surplus as $CS(\alpha,\gamma)$, and the total surplus as $W(\alpha,\gamma)$, respectively. Let $v_0$ be the seller's value of the object.[7]

Consumer surplus is given by:

$$CS(\alpha,\gamma)$$
$$= \mu_H\{\int_{\underline{x}}^{x^*} [v_H - B^1(y)]g_H(y)dy + \int_{x^*}^{\overline{x}} [v_H - B^2(y)]g_H(y)dy\}$$
$$+\mu_L\{\int_{\underline{x}}^{x^*} [v_L - B^1(y)]g_L(y)dy + \int_{x^*}^{\overline{x}} [-a - \gamma B^2(y) - c_B]g_L(y)dy\}. \quad (3)$$

The object is returned only when the common value turns out to be low and the second highest signal is higher than $x^*$. Note that $x^*$ is a function of $\alpha$ and $\gamma$. The following proposition illustrates how return policies affect consumers' surplus.

**Proposition 2:** *With a more generous return policy (a lower $\alpha$ or $\gamma$), the consumer surplus is lower.*

This result is somewhat counter-intuitive. In the case of return policies in retail stores, a more generous return policy protects consumers better when bad shocks occur, making them better off. This effect is also present in an auction. However, in an auction bidders are also competing with each other. A more generous return policy thus induces bidders to bid more aggressively and this effect reduces consumer surplus. In our model, the second effect always dominates the first one. This is because bidders always have a higher estimate of the probability of returns in their equilibrium strategy calculation than

[7]The analysis will not change if the seller's value depends on the realization of the common value as long as s/he does not know it ex-ante. This is because when the common value turns out to be high, the winner will not return the object anyway. Thus, in such a case, we can use $v_0$ to denote the seller's value when the common value is low.

what actually occurs. In his/her equilibrium calculation, because it is a second-price auction, a bidder assumes (correctly) that the other bidder has the same signal as him/herself when calculating his/her break-even bid. However, this bid is paid to the seller only when the other bidder has a higher signal and wins. This higher signal reduces the probability that $V = v_L$ and thus correspondingly reduces the probability that the winner will actually return the object relative to the probability correctly used in the equilibrium strategy calculation.

If we examine the above result from the perspective of the linkage principle, it seems less surprising and relatively intuitive: since the return policy links bidders' payments to additional information (the true value of the object), it erases bidders' informational rents. However, the intuition is less transparent than it appears. The traditional linkage principal following Milgrom and Weber (1982) applies only when the final allocations of the object are the same across the scenarios being compared. However, different return policies will, in general, induce different final allocations of the object. Our result suggests that the linkage principal sometimes applies even when the final allocation differs.

We can also consider how return policies affect social welfare:

$$W(\alpha,\gamma) = \mu_H v_H + \mu_L\left[G_L(x^*)v_L + \left(1 - G_L(x^*)\right)(v_0 - c_B)\right]. \tag{4}$$

**Proposition 3:** *With a more generous return policy (a lower $\alpha$ or $\gamma$), social welfare is higher if and only if $v_L + c_B \leq v_0$.*

A more generous return policy induces more returns: this is more efficient if the seller values the returned object highly enough.

### 4.2 Seller's revenue

We now examine the effect of the return policy on the seller's revenue and characterize the optimal linear return policy for the seller. Denote the seller's revenue as $R(\alpha,\gamma)$. It is obvious that $R(\alpha,\gamma) = W(\alpha,\gamma) - CS(\alpha,\gamma)$. If $v_L + c_B \leq v_0$, a more generous return policy (a lower $\alpha$ or $\gamma$) increases social welfare and decreases consumer surplus, therefore unambiguously increasing the seller's revenue. Note that we restrict the return policy to $\alpha \geq -c_B$ and $0 \leq \gamma \leq 1$. Thus, the unique optimal return policy is $\alpha = -c_B$ and $\gamma = 0$. This is summarized in the following proposition.

**Proposition 4:** *If $v_L + c_B \leq v_0$, a more generous return policy (a lower $\alpha$ or $\gamma$), means that the seller's revenue is higher, implying that the optimal return policy is $\alpha = -c_B$ and $\gamma = 0$.*

The condition $v_L + c_B \leq v_0$ requires that the seller values the object more than bidders do when the common bidder value is low. This could be true if $v_L$ represents a situation where some fixable problem occurs, and it is easier for the seller than for the bidder to fix the problem. However, in general such a condition could be violated.

For the rest of the analysis in this section, we focus on the case where $v_L + c_B > v_0$. Since $R(\alpha,\gamma) = W(\alpha,\gamma) - CS(\alpha,\gamma)$, the seller's revenue may not change monotonically with the return policy. There is no clear conclusion about how $\alpha$ and $\gamma$ would affect the seller's revenue.[8] We proceed as follows using an indirect method. The seller can choose $\alpha$ and $\gamma$, which then uniquely determine the cutoff $x^*$. Alternatively, if we allow the seller to choose $\gamma$ and $x^*$ directly, it is equivalent to allowing the seller to choose $\gamma$ and $\alpha$, thus determining $x^*$. Therefore, we can rewrite the seller's revenue as a

[8] This can be shown by examining Equations (11), (12), (13), and (14) in Appendix A.

function of $\gamma$ and $x^*$:

$$R(\gamma, x^*) = \mu_H \left\{ \int_{\underline{x}}^{x^*} B^1(y) g_H(y) dy + \int_{x^*}^{\overline{x}} B^2(y) g_H(y) dy \right\}$$

$$+\mu_L \left\{ \int_{\underline{x}}^{x^*} B^1(y) g_L(y) dy + \int_{x^*}^{\overline{x}} [a + \gamma B^2(y)] g_L(y) dy \right\}$$

$$+\mu_L \int_{x^*}^{\overline{x}} v_0 g_L(y) dy. \tag{5}$$

The following proposition summarizes how return policies affect the seller's revenue in this case.

**Proposition 5:** *When* $v_L + c_B > v_0$*, given* $x^*$*, the seller's revenue is strictly decreasing in* $\gamma$*, implying that* $\gamma = 0$ *(i.e., no proportional fee) is optimal.*

The intuition behind this proposition is as follows. Given the cutoff $x^*$, the seller can choose a combination of a fixed fee and a proportional fee consistent with this cutoff. However, using a proportional fee diminishes the seller's revenue since it incentivizes bidders to reduce their bids relative to the fixed-fee case consistent with the same cutoff. This is because higher winning bids imply a higher cost of returning the object in the proportional-fee case. In contrast, a fixed fee is a lump-sum transfer and does not have this distortion. Therefore, to maximize the seller's revenue, a proportional fee is inferior.

Now we examine the optimal cutoff level of $x^*$.

$$\frac{\partial R(\gamma, x^*)}{\partial x^*}$$

$$= \mu_H \underbrace{[B^1(x^*) - B^2(x^*)]}_{=0} g_H(x^*) \frac{dx^*}{d\gamma} + \mu_H \int_{x^*}^{\overline{x}} \frac{\partial B^2(y)}{\partial a} \frac{\partial a}{\partial x^*} g_H(y) dy$$

$$+\mu_L \int_{x^*}^{\overline{x}} \left[1 + \gamma \frac{\partial B^2(y)}{\partial a}\right] \frac{\partial a}{\partial x^*} g_L(y) dy + \mu_L \underbrace{[B^1(x^*) - a - \gamma B^2(x^*)]}_{=v_L + c_B} g_L(x^*)$$

$$-\mu_L v_0 g_L(x^*)$$

$$= \mu_L (v_L + c_B - v_0) g_L(x^*)$$

$$- \int_{x^*}^{\overline{x}} \frac{\mu_H \mu_L}{[\mu_H \rho_1(y) \rho_{n-1}(y) + \gamma \mu_L]} \{g_H(y) - \rho_1(y) \rho_{n-1}(y) g_L(y)\} \frac{\partial a}{\partial x^*} dy$$

$$= \underbrace{\mu_L(v_L + c_B - v_0)g_L(x^*)}_{social\ welfare\ effect \geq\ 0}$$

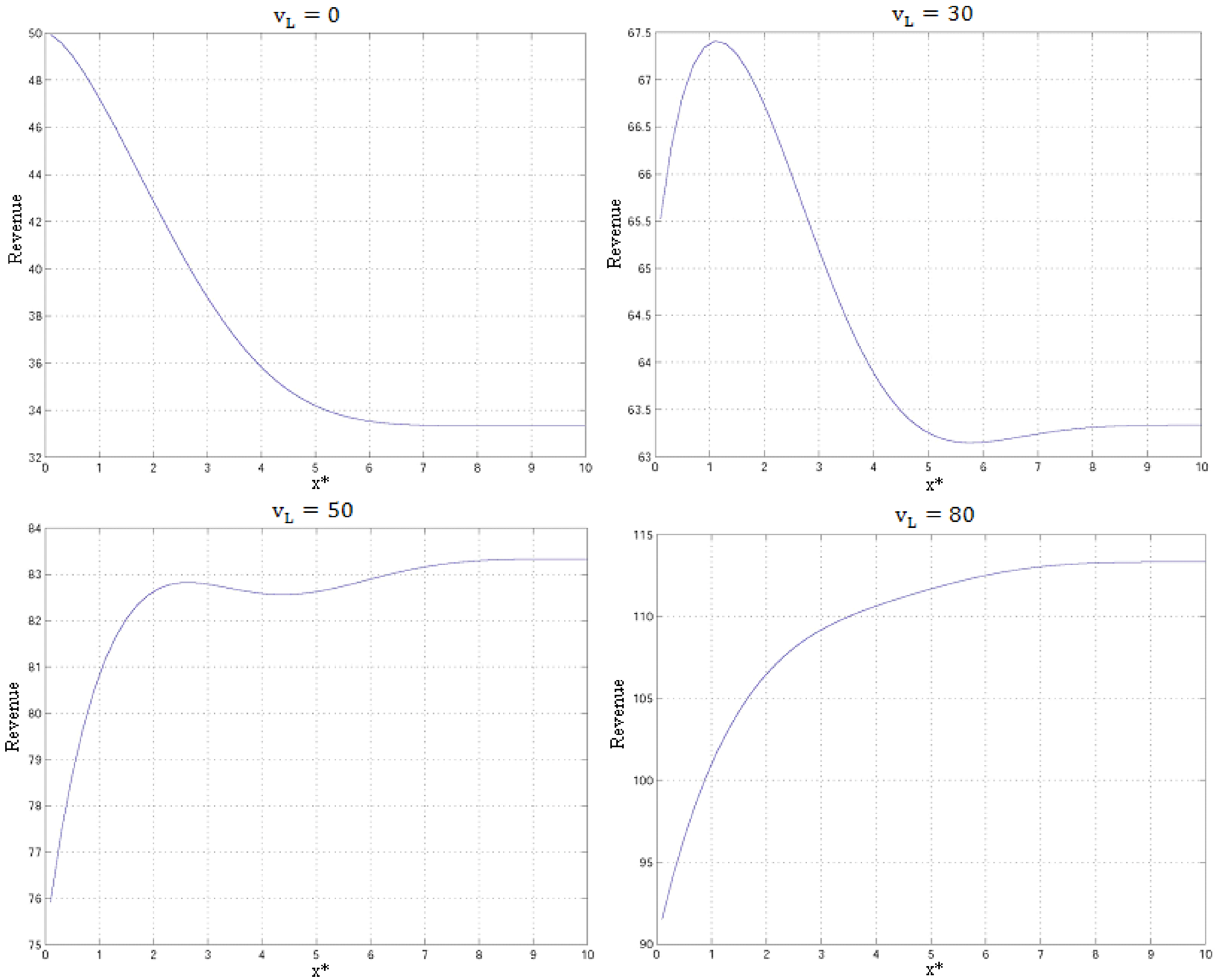
$$- \underbrace{\int_{x^*}^{\overline{x}} \frac{(v_H - v_L)\mu_H\mu_L}{[\mu_H\rho_1(x^*)\rho_{n-1}(x^*) + \gamma\mu_L]^2}\{g_H(y) - \rho_1(y)\rho_{n-1}(y)g_L(y)\}\frac{d[\rho_1(x^*)\rho_{n-1}(x^*)]}{dx^*}dy}_{consumer\ surplus\ effect \geq\ 0}$$

In the above expression, either the consumer surplus effect or the social welfare effect could dominate. One observation is that if $v_H - v_L$ is very small, then the overall sign is positive and it is optimal to induce no return in equilibrium. However, the following example shows that the seller's revenue is not necessarily monotonic in $x^*$ in general.

**Example 1**: Consider two players. Suppose that $v_0 = 0$, $v_H = 100 + v_L$, with $v_L$ to be specified later, and $\mu_H = \mu_L = 0.5$, $c_B = 0$. We set $\gamma = 0$ as this is always optimal for the seller, and examine how the seller's revenue is affected by the return policy by changing $x^*$, which then uniquely determines the value of $\alpha$. For $x \in (0,10]$, $F_H(x) = \frac{x^2}{100}$, $F_L(x) = \frac{x(20-x)}{100}$, $f_H(x) = \frac{x}{50}$, $f_L(x) = \frac{10-x}{50}$. Then $\rho(x) = \frac{f_H(x)}{f_L(x)} = \frac{x}{10-x}$. Note that $\frac{f_H(x)}{f_L(x)}$ is indeed strictly increasing as previously assumed. We will vary the value of $v_L$ and let it take the values of $0$, $30$, $50$ and $80$, respectively.

The results are shown in Figure 1. When $v_L = 0$, the seller's revenue is decreasing in $x^*$; the optimal return policy is $x^* = 0$, i.e., the full-refund with full-cost-reimbursement policy $\alpha = -c_B = 0$. When $v_L = 30$, the seller's revenue first increases, then decreases, and then increases in $x^*$; the optimal return policy is a partial-refund policy with $x^* = 1.2$. When $v_L = 50$, the seller's revenue first increases, then decreases, and then increases in x*; the optimal return policy is the no-refund policy. When $v_L = 80$, the seller's revenue is increasing in $x^*$; the no refund policy is optimal again. Note that as $v_L$ increases, the optimal return policy becomes less generous. This example also illustrates the difficulties in determining the condition for an interior optimal return policy as the revenue function is not well behaved.

**Figure 1: Plots of Revenue against *x****



## 5. Experimental Design

Our experiments adopt parameters from Example 1 in the previous section with $v_L = 0$. We implement second-price auctions with two bidders.[9] The auctioned item has either the common value $V = 100$ or the common value $V = 0$ in experimental dollars with equal probability. To make the experiments transparent, the signal generating procedure in practice is a discrete approximation to the continuous distributions in Example 1. In our experiments, the bidder receives a partially informative signal by drawing a numbered chip from an urn containing numbered chips. If $V = 100$, the urn contains one 1, two 2's, …, nine 9's. Alternatively, if $V = 0$, the urn contains one 9, two 8's, …, nine 1's. The number on the chip is the bidder's signal.

We consider a return policy with a fixed handling fee: if the winning bidder returns the item, s/he gets back the price paid minus the handling fee $\alpha$. Our experimental treatments differ by setting $\alpha$ at four different levels. (1) In the No-Return (NR) treatment, $\alpha = +\infty$, implying that the winning bidder cannot return the item. (2) In the High-Fee (HF) treatment, $\alpha = 20$. (3) In the Low-Fee (LF) treatment $\alpha = 5$. (4) In the Free-Return (FR) treatment $\alpha = 0$.

In this case, the unique symmetric monotone equilibrium bidding strategy reduces to

$$B(x) = \max\left\{\frac{100x^2}{(10-x)^2+x^2}, \frac{100x^2-\alpha(10-x)^2}{x^2}\right\}.$$

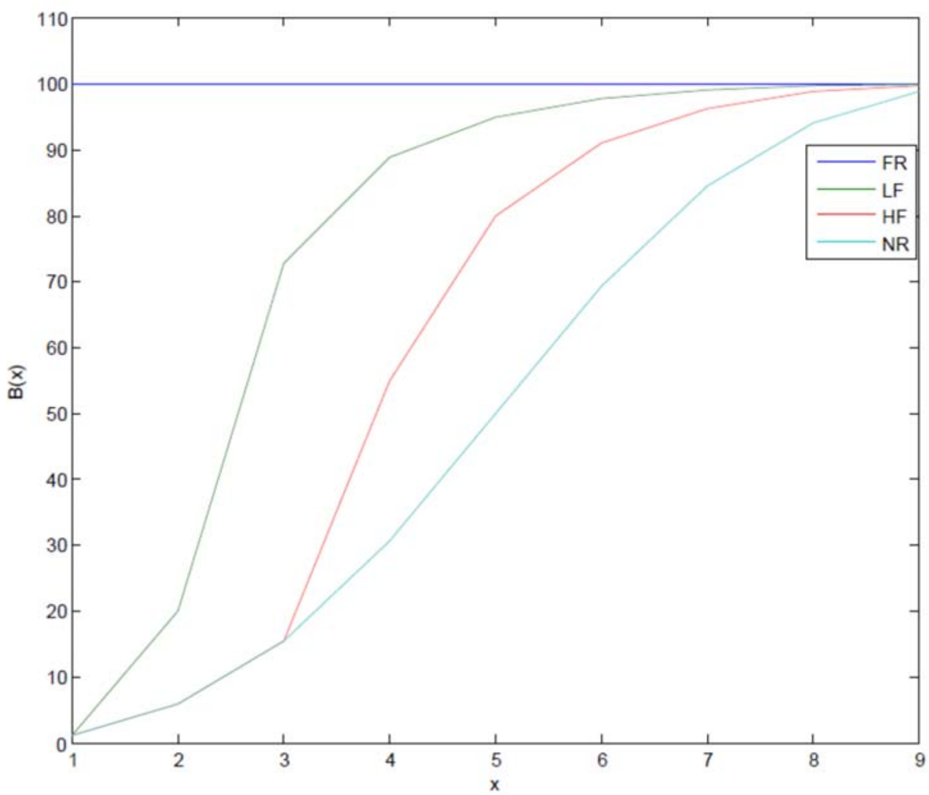
Table 1 indicates the predicted bids for each of the four treatments, while Figure 2 plots each of the bidding functions.

[9] We used two bidders in each auction since as the number of bidders increases, the bidding function becomes flatter, making it more difficult to test the impact of signals on bids.

**Table 1: The Predicted Bids**

| Signal | NR | HF | LF | FR |
|---|---|---|---|---|
| 1 | 1.2195 | 1.2195 | 1.2195 | 100 |
| 2 | 5.8824 | 5.8824 | 20 | 100 |
| 3 | 15.5172 | 15.5172 | 72.7778 | 100 |
| 4 | 30.7692 | 55 | 88.75 | 100 |
| 5 | 50 | 80 | 95 | 100 |
| 6 | 69.2308 | 91.1111 | 97.7778 | 100 |
| 7 | 84.4828 | 96.3265 | 99.0816 | 100 |
| 8 | 94.1176 | 98.75 | 99.6875 | 100 |
| 9 | 98.78049 | 99.7531 | 99.9383 | 100 |

**Figure 2**



Proposition 2 and Proposition 4 in section 4 predict that bidders' expected earnings fall while the seller's expected revenues rise as α decreases toward zero. However, when $\alpha = 0$, there are multiple equilibria. One equilibrium involves all bidders bidding 100 with the winner returning the item when $V = 0$. This equilibrium is efficient, creating the maximum possible surplus. If weakly dominated strategies are allowed, there are other inefficient equilibria that involve bids above 100 with the winner returning the item regardless of whether $V = 0$ or $V = 100$. These equilibria have very different implications for a seller selecting a free-return policy. In the case of the efficient equilibrium, the seller extracts the maximum possible revenue from the bidder. However, in the case of the inefficient equilibria, the seller receives no revenue at all. One goal of this study is to test empirically which equilibrium arises when $\alpha = 0$.

Treatments were implemented in two-day sequences consisting of two one-hour sessions, one on each of the two days. On day one of the two-day sequence, the recruited participants started the first one-hour session by participating in two rounds of practice auctions. The first round of practice auctions was hand-run and real urns with numbered chips were presented to participants. Starting from the second practice round and throughout the rest of the session, the auctions and the signal-generating procedure were computerized in a manner analogous to the hand-run method used during the first practice round. After the practice rounds, the participants began the 15 monetary-payoff rounds with 225 experimental dollars of capital endowment. In each round, participants were randomly and anonymously matched into markets of two bidders. Participants were informed that if their net balance dropped to zero or below, they would no longer be permitted to continue playing.[10] Day two of the two-day sequence took place one week later, and the same participants were invited back. On day two, procedures were the same as on day one except that there were no hand-run practice rounds. To give participants an incentive to return on day two, their earnings on day one were retained until the completion of the day-two session.

There were four two-day sequences for each of the NR, HF, LF and FR treatments. No participant was allowed to participate in more than one two-day sequence. There were 8-12 participants in each sequence. Table 2 presents details on the number of participants on days one and two of each sequence.

**Table 2: Number of Participants in Each Two-Day Sequence**

| NR | Day 1 | Day 2 | HF | Day 1 | Day 2 | LF | Day 1 | Day 2 | FR | Day 1 | Day 2 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 12 | 12 | 1 | 10 | 10 | 1 | 12 | 12 | 1 | 12 | 10 |
| 2 | 12 | 10 | 2 | 10 | 8 | 2 | 12 | 12 | 2 | 12 | 10 |
| 3 | 12 | 8 | 3 | 12 | 12 | 3 | 12 | 12 | 3 | 12 | 12 |
| 4 | 10 | 8 | 4 | 12 | 10 | 4 | 12 | 12 | 4 | 12 | 10 |

We conducted our experiments at the Experimental Economics Laboratory, Shanghai University of Finance and Economics (SUFE). The participants were recruited from a campus-wide list of undergraduate students who had previously responded to an announcement in a campus-wide required first-year undergraduate course. None of the participants had any experience with common-value auction experiments. All laboratory sessions were computerized using Visual Basic 6.0. Both the instructions and the information shown on the computer screen were in Chinese. The average payment was 44.07 RMB (15 experimental dollars were equivalent to 1 RMB and the exchange rate was US$1 = 6.23 RMB) for the two one-hour sessions making up a two-day sequence. Since the average hourly wage in Shanghai for a

[10]No participant went bankrupt in any of our experiments.

college graduate is about 15 to 20 RMB, 44.07 RMB is a considerable amount for undergraduate students.

## 6. Results

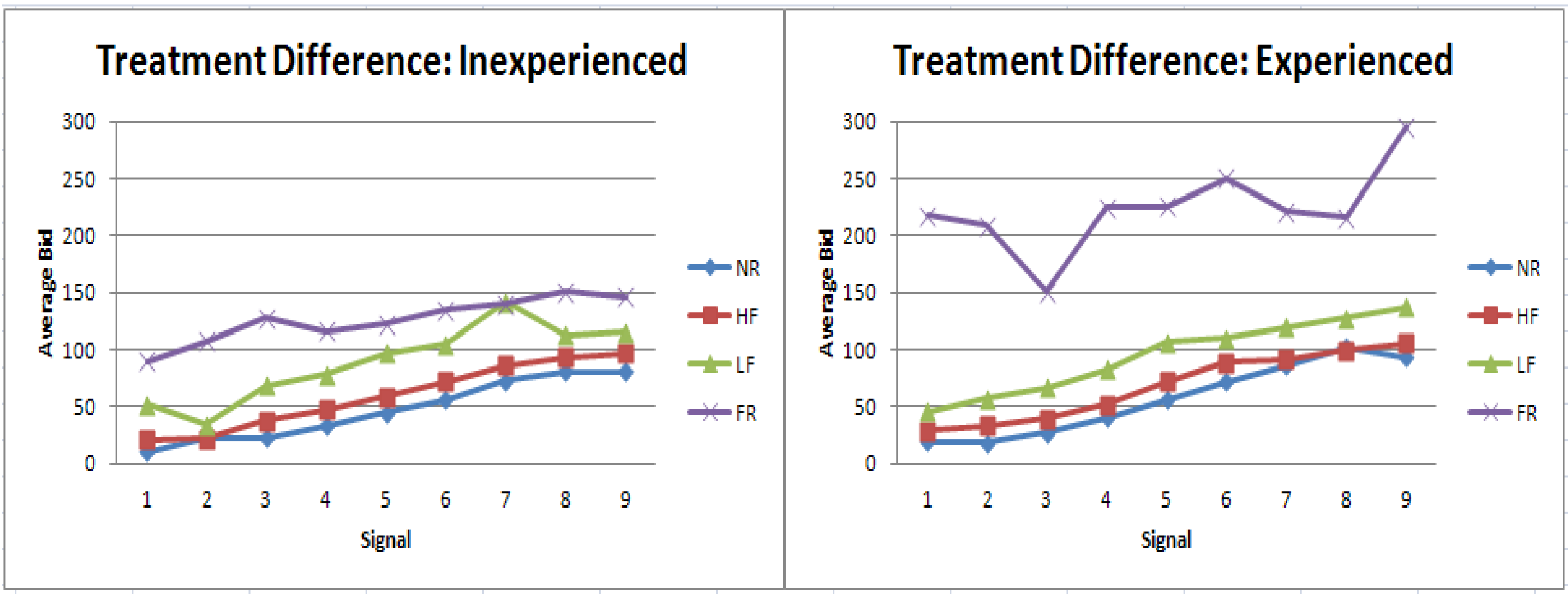
This section reports experimental results for the monetary-payoff rounds.[11]

### 6.1 Bids

Figure 3 shows the bidders' average bids for each treatment, conditional on the signal received.

Figure 3 suggests that a more generous return policy is associated with higher bids as predicted by theory.

**Figure 3: Treatment Difference in Bids**




Treating each session's average bid as one independent observation, Wilcoxon-Mann-Whitney rank-sum tests show that for inexperienced bidders (sessions on day 1), bids in the NR treatment were significantly lower than those in the HF treatment ($p = 0.043$), while bids in the HF treatment were significantly lower than those in the LF treatment ($p = 0.043$). However, the difference in bids was not significant between the LF and FR treatments ($p = 0.149$). For experienced bidders (sessions on day 2),

[11] The session averages and the standard deviations across sessions in each treatment are reported in Appendix C.

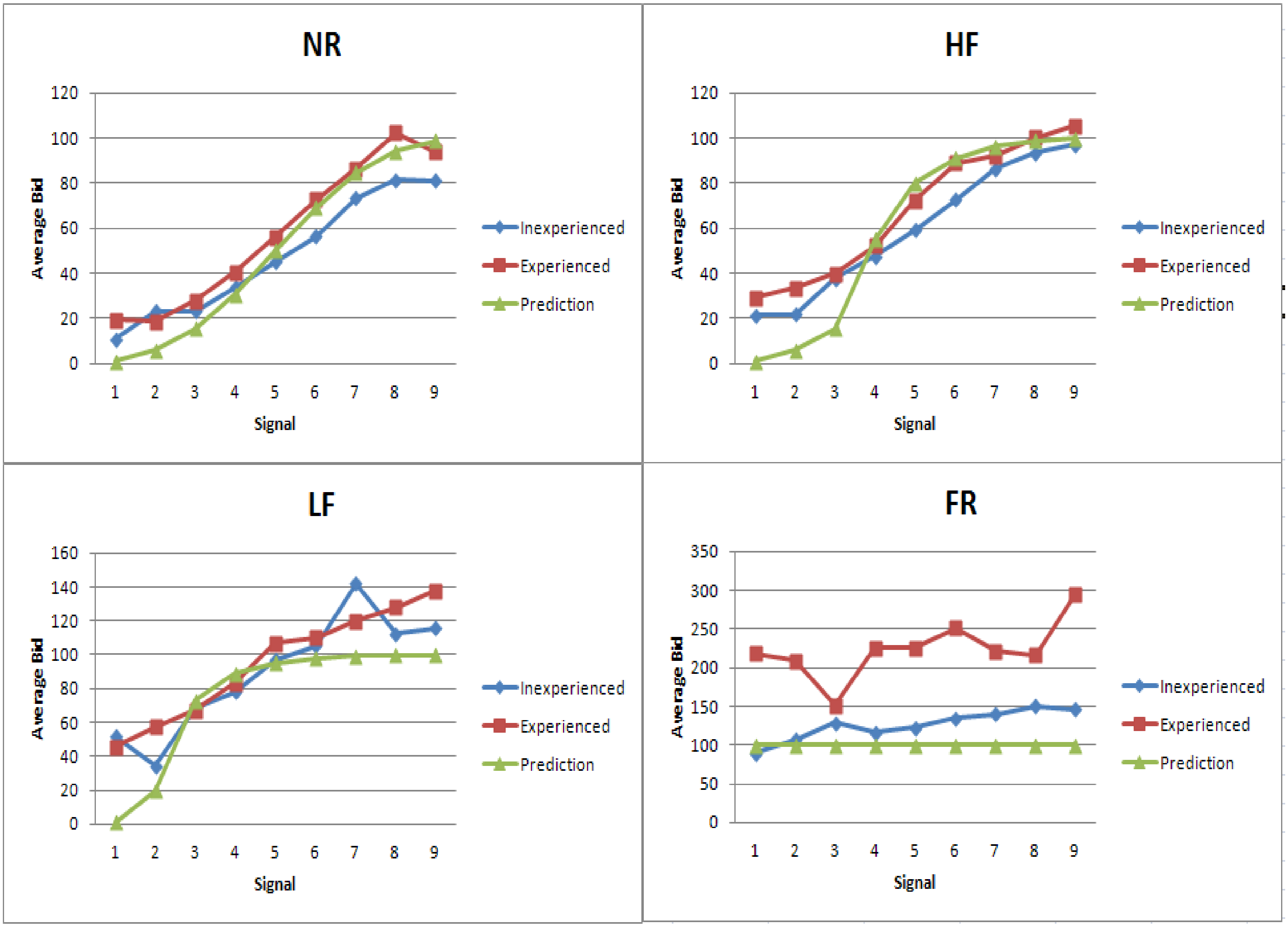
the pattern was similar, but not identical: while bids in the NR treatment were not significantly different from those in the HF treatment ($p = 0.248$), bids in the HF treatment were significantly lower than those in the LF treatment ($p = 0.021$), and bids in the LF treatment were lower than in the FR treatment with marginal significance ($p = 0.083$).

Next we examine whether experienced bidders bid closer than inexperienced bidders to the theoretically predicted bids. For the multiple-equilibrium FR treatment, we use the efficient equilibrium in which all bidders bid 100 regardless of the signal received as our theoretical benchmark. Figure 4, which plots the average bids by signal for each treatment and level of experience, suggests that experience does not help bring bids closer to the theoretical prediction in any of the four treatments. To study the impact of experience more rigorously, we use a measure of the mean squared deviation (MSD) from the theoretical equilibrium prediction. The MSD between the actual bids in the experimental market and the value predicted by the model is measured as follows:

$$\text{MSD}[b, b^*(x)] = \frac{1}{T}\sum_{i=1}^{T}(b - b^*(x))^2$$

where $b$ is the actual bid, $b^*(x)$ is the predicted bid conditional on the signal $x$ received by the bidder, and $T$ is the total number of bids in the monetary-payoff rounds within a session. Comparing the MSD in the inexperienced sessions with the MSD in the experienced sessions, the Wilcoxon signed-ranks test yields no significant difference in any of the four treatments ($p = 0.715$ in NR, $p = 1.000$ in HF, $p = 0.715$ in LF and $p = 0.144$ in FR). Moreover, in the FR treatment, many bidders bid higher than 100, behavior consistent with the equilibria involving weakly dominated strategies.

**Figure 4: Actual Bids vs. Predictions**




In Table 3 we report a random-effects regression (with random effects at the sequence level, at the session level and at the individual level, and robust standard errors clustered at the sequence level) for the determinants of bids over all monetary-payoff rounds. The clustered robust standard errors are robust to both heteroskedasticity and correlation within clusters (Arellano, 2003; 2010; Wooldridge, 2013). The regression shows that in the NR treatment bids increased significantly as the signal increased (the coefficient for Signal was positive with $p = 0.000$). In both the LF and HF treatments, the relationship between bids and signals was close to the NR relationship (neither the coefficient for Signal*LF nor that for Signal*HF was significantly different from zero with $p = 0.791$ and $p = 0.995$, respectively). However, in the FR treatment, the empirical bidding function was much flatter than in the NR treatment (the coefficient of Signal*FR is negative with $p = 0.088$), though the relationship between bids and signals was still positive (a Wald $\chi^2$ test shows that the sum of the coefficients of Signal and Signal*FR is positive with $p = 0.019$). The regression also indicates that bidders tended to bid higher during the later rounds of the FR treatment (a Wald $\chi^2$ test shows that the sum of the coefficients of Round and Round*FR is positive with $p = 0.006$), while round had no significant impact on bids in the other treatments (the coefficient for Round was positive with $p = 0.193$). Moreover, the regression demonstrates that the bids on day 2 were higher than the bids in day 1 (the coefficient of Experience is positive with $p = 0.000$). The increase in day-2 bids is significantly greater for the FR treatment (the coefficient of Experience*FR is positive with $p = 0.048$). The empirical bidding function for the FR treatment reflects the fact that many bidders place bids greater than 100 regardless of the signal received. Such behavior creates no surplus for either the bidder or the seller. In this treatment, bidders generally earned nothing since, as predicted by theory, the seller captured any surplus created by trade. We conjecture that as the experiment proceeded the fun of winning the auctioned item and then returning it began to dominate concern with monetary payoffs, which were always zero in any case. Moreover, since bidders generally earned nothing in the efficient equilibrium, they may have decided that the sellers shouldn't earn anything either. This could be achieved at no cost to themselves by bidding above 100 and then returning the item. Thus, bids rose as bidders competed to win (and then return) the item. As mentioned previously, bidding above 100 is consistent with the inefficient equilibria involving weakly dominated strategies.

**Table 3: Determinants of Bids**

| | Coef. | Robust Std. Err. |
|---|---|---|
| Constant | -9.829** | 4.69 |
| FR dummy | 53.910*** | 13.60 |
| LF dummy | 37.369** | 17.37 |
| HF dummy | 9.301 | 6.65 |
| Signal | 10.612*** | 0.77 |
| Signal*FR | -4.569* | 2.68 |
| Signal*LF | 0.934 | 3.52 |
| Signal*HF | -0.006 | 0.98 |
| Experience dummy | 10.281*** | 2.41 |
| Experience*FR | 87.997** | 44.49 |
| Experience*LF | -4.180 | 7.89 |
| Experience*HF | -2.032 | 4.03 |
| Round | 0.510 | 0.39 |
| Round*FR | 5.984** | 2.40 |
| Round*LF | -0.065 | 0.70 |
| Round*HF | 0.383 | 0.41 |
| Obs. | 5310 | |
| Wald Chi2 | N/A | |
| Log pseudolikelihood | -30499.979 | |

* indicates significance at $p = 0.10$ (two-tailed tests); ** indicates significance at $p = 0.05$ (two-tailed tests); *** indicates significance at $p = 0.01$ (two-tailed tests).

### 6.2 Earnings

Proposition 2 in section 4.1 predicts that consumer surplus is lower with a more generous return policy. Figure 5 suggests that this is true empirically. A bidder's total payoff (in experimental currency) in a session decreases as the handling fee for returning the auctioned item goes down. Compared with payoffs to inexperienced bidders on day 1, the average total payoffs for experienced bidders on day 2 were closer to the theoretical prediction (i.e., the *ex ante* expected total payoff in 15 monetary-payoff rounds plus 225).

**Figure 5: Average Total Payoff**


Treating each session's average total payoff as one independent observation, the Wilcoxon-Mann-Whitney rank-sum tests show that for inexperienced bidders (sessions on day 1), while total payoffs in the NR treatment were not significantly different from those in the HF treatment ($p = 0.248$), total payoffs in the HF treatment were higher than in the LF treatment with marginal significance ($p = 0.083$) and total payoffs in the LF treatment were also significantly higher than in the FR treatment ($p = 0.043$). For experienced bidders (sessions on day 2), the pattern is similar: while total payoffs in the NR treatment were not significantly different from those in the HF treatment ($p = 0.387$), total payoffs in the HF treatment were significantly higher than those in the LF treatment ($p = 0.043$) and total payoffs in the LF treatment were likewise significantly higher than in the FR treatment ($p = 0.021$).

A random-effects regression (with random effects at the sequence level, at the session level and at the individual level, and robust standard errors clustered at the sequence level) for treatment differences in bidders' payoffs in each auction in Table 4 confirms the observations in Figure 5. Bidders' payoffs are higher in the NR treatment, compared with the FR, LF and HF treatments (the signs of the coefficients of the FR and LF dummies are significantly negative while that of HF is negative and marginally significant) on day 1. Moreover, day-1 earnings are higher in the HF than in the LF treatment (a Wald $\chi^2$ test yields $p$ = 0.023) and higher in the LF than in the FR treatment (a Wald $\chi^2$ test yields $p = 0.011$). Compared with day 1, bidders earn less on day 2 when they have more experience while simultaneously bidding against more experienced opponents. This is demonstrated for the NR treatment by the significantly negative experience coefficient ($p$ = 0.013) and for the HF ($p$ = 0.000), LF ($p$ = 0.012), and FR ($p$ = 0.034) treatments by a series of Wald tests. Another series of Wald tests corroborates the results of the Wilcoxon-Mann-Whitney rank-sum tests for experienced bidders, indicating that while earnings in the HF treatment are not significantly higher than in the NR treatment ($p$ = 0.426), FR earnings are significantly higher than LF earnings ($p$ = 0.006), and LF earnings are in turn higher than HF earnings ($p$ = 0.013).

**Table 4: Comparing Bidders' Payoffs**

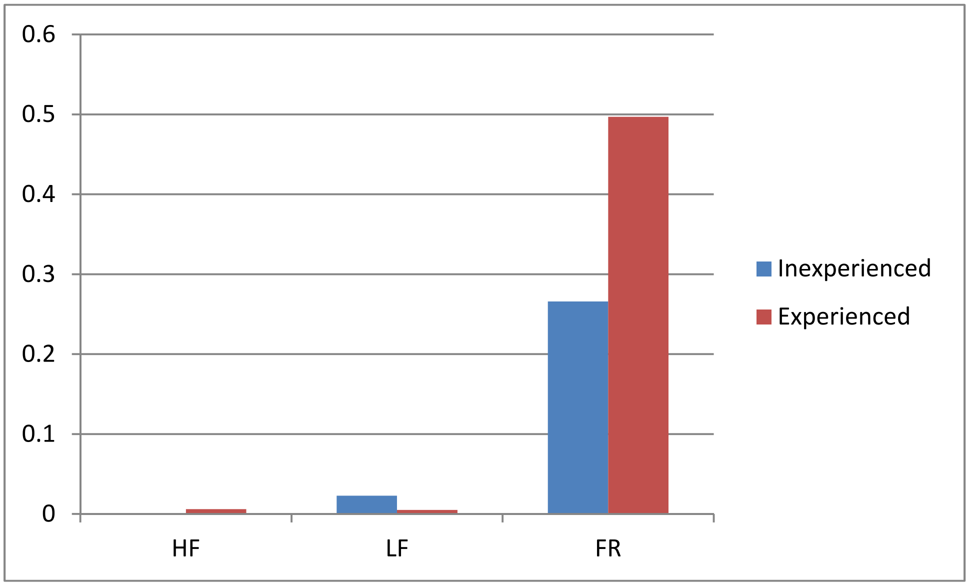
| | Coef. | Robust Std. Err. |
|---|---|---|

| | | |
|---|---|---|
| Constant | 13.377*** | 1.10 |
| FR dummy | -10.244*** | 1.42 |
| LF dummy | -6.095*** | 1.77 |
| HF dummy | -2.474* | 1.37 |
| Experience dummy | -4.345** | 1.75 |
| Experience*FR | 3.056* | 1.85 |
| Experience*LF | 0.844 | 2.23 |
| Experience*HF | 0.929 | 1.98 |
| Obs. | 5310 | |
| Wald Chi2 | 240.81 | |
| Log pseudolikelihood | -24801.37 | |

* indicates significance at $p = 0.10$ (two-tailed tests); ** indicates significance at $p = 0.05$ (two-tailed tests); *** indicates significance at $p = 0.01$ (two-tailed tests).

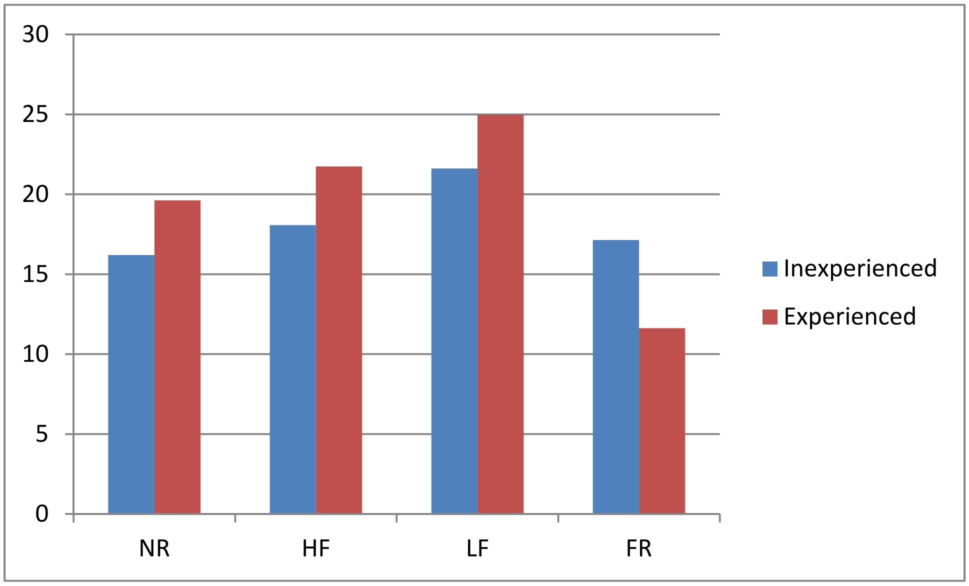
Figure 6 examines the efficiency loss associated with return policies. Setting the seller's value for the auctioned item at zero, there is a loss in aggregate surplus if the winner of the auction chooses to return the item when $V = 100$. In the HF and LF treatments, winners rarely return the item when $V = 100$. However, in the FR treatment, the frequency of returning the item when $V = 100$ is 0.266 for inexperienced bidders, and 0.497 for experienced bidders. We observe significant efficiency loss associated with the FR treatment. To compare the frequency of returning the high quality $\mathrm{V} = 100$ items across treatments, we run Wilcoxon-Mann-Whitney rank-sum tests with the following results: $\mathrm{HF} < LF$ ($p = 0.047$), $\mathrm{LF} < FR$ ($p = 0.021$) for inexperienced bidders; $\mathrm{HF} = \mathrm{LF}$ ($p = 0.850$), $\mathrm{LF} < FR$ ($p = 0.018$) for experienced bidders (treating the session average return frequency as one independent observation).

**Figure 6: Choice of Return when $\mathbf{V = 100}$ (in Percentage)**




Proposition 4 in section 4.2, predicted that given our experimental parameters (in particular $v_L = c_B = 0$) if the seller's value of the item is zero, seller revenue should increase with the generosity of the return policy and the free return policy should be optimal for the sellers. However, this proposition was derived under the assumption that the efficient equilibrium would prevail in the FR case. Figure 7 compares the bidders' payments to the sellers across treatments. In general, the bidders' average payment to the sellers increases as the handling fee for returning the auctioned item decreases as predicted. However, the payments are not highest in the FR treatment because many winning bids exceed 100 with the winners choosing to return the item when $V = 100$. Thus, the efficient equilibrium did not prevail in the FR case as was assumed in the theoretical derivation, and this was detrimental to seller revenues. The payments are actually highest in the LF rather than in the FR treatment.

**Figure 7: Bidders' Average Payment to the Sellers**




Treating the average payment in each session as one independent observation, Wilcoxon-Mann-Whitney rank-sum tests yield the following results: NR = HF ($p = 0.564$), HF $< LF$ ($p = 0.083$), LF $> FR$ ($p = 0.083$), LF $> NR$ ($p = 0.043$) for inexperienced bidders; NR = HF ($p = 0.248$), HF $< LF$ ($p = 0.043$), LF $> FR$ ($p = 0.021$), LF $> NR$ ($p = 0.021$) for experienced bidders.

A random-effects regression (with random effects at the sequence level, at the session level and at the individual level, and robust standard errors clustered at the sequence level) for treatment differences in bidders' payments to sellers in each auction in Table 5 confirms this observation. Notice that in the FR treatment, bidders transfer less money to the sellers in the day-2-sessions compared with the day-1 sessions (a Wald $\chi^2$ test shows that the sum of the coefficients of Experience and Experience*FR is negative with $p = 0.001$). This again reflects the behavior of many FR bidders who, after experiencing low payoffs during the day-1-sessions, bid above 100 and subsequently return the auctioned item for a full refund in the day-2-sessions.

**Table 5: Comparing Bidders' Payments to Sellers (with Robust Standard Errors)**

| | Coef. | Robust Std. Err. |
|---|---|---|
| Constant | 16.199*** | 1.24 |
| FR dummy | 0.946 | 1.69 |
| LF dummy | 5.408*** | 1.83 |
| HF dummy | 1.868 | 1.93 |
| Experience dummy | 3.423* | 1.88 |
| Experience*FR | -8.942*** | 2.48 |
| Experience*LF | -0.060 | 2.90 |
| Experience*HF | 0.252 | 2.03 |
| Obs. | 5310 | |
| Wald Chi2 | 96.06 | |
| Log pseudolikelihood | -26190.012 | |

* indicates significance at $p = 0.10$ (two-tailed tests); *** indicates significance at $p = 0.01$ (two-tailed tests).

In sum, our data suggest that a more generous return policy is associated with higher bids as predicted by theory. We also find that experienced bidders bid no closer than inexperienced bidders to the theoretically predicted bids. In our experiments, bids increase significantly as the signal increases, and bidders tend to bid higher during the later rounds of the Free-Return treatment. We empirically confirm the theoretical prediction that consumer surplus is lower with a more generous return policy. Finally, our experiments indicate that the seller's revenue increases as the handling fee decreases as long as the handling fee remains positive.

## 7. Conclusions

This paper investigates the role of linear return policies in second-price auctions. The symmetric equilibrium is unique unless returns are free. With a more generous return policy, bidders act more aggressively. Since the winning bidder pays more, the consumer surplus is lower in such auctions. For sellers, we demonstrate that a revenue-maximizing seller should never use a return fee that is proportional to the price paid for an item. Rather a fixed return fee should be used. Furthermore, since the winning bidder may return the object when s/he obtains more information regarding its value, a higher bid induced by a more generous return policy, while hurting bidders, may not always be beneficial to the seller. Only when the efficiency losses from returns are sufficiently small will a more generous return policy help the seller.

Our laboratory observations support the theoretical prediction that the seller's revenue increases as the handling fee for returning the auctioned item decreases, but remains positive. When returning the item is free, many bidders bid above the highest possible value and subsequently return the item regardless of the revealed value. This may be due to bidders deriving positive utility from the mere fact of winning the auction (e.g., Cox, Smith, and Walker,1992), even though they know that they will eventually return the object (at no cost). While this is consistent with equilibrium behavior, it is an inefficient equilibrium that is not optimal for the seller.

In theory, there exist optimal mechanisms for sellers to maximize revenue. For our case of common values, a seller can extract the full surplus from bidders.[12] However, those optimal mechanisms are not commonly observed in reality, partly because too much detail regarding the underlining environment is required for the seller to design an optimal mechanism. The discrepancy between theory and common practice prompts the claim that a set of simplicity and robustness criteria should be imposed on trading

[12]See Cremer and McLean (1988) and McAfee and Reny (1992).

mechanisms.[13] Our auctions with return policies are the sort of simple and familiar trading procedures that Hurwicz (1972), Lopomo (1998; 2001) and Wilson (1969) advocate. Furthermore, as we have shown in this paper, return policies, while being "simple" instruments, can be effective at increasing seller revenue under certain circumstances.

In real life auctions, the seller may choose to offer return policies for other reasons, such as to signal the quality of the object. This may occur when information about quality is asymmetric, and is known as the informed principal problem. It differs from the case considered here in which neither the bidders nor the seller can observe the quality of the object prior to the auction. In a related paper by two of the authors, Wang and Zhang (2015), we use a conditional independent private value model to explore whether return policies can be used to signal the quality of an object when the seller knows the quality of the object, while the bidders do not. We find that in a binary quality setting, signaling may lead to a full separation of qualities. However, a better refund policy may not correspond to a better quality.

[13]Hurwicz (1972) illustrates the need for mechanisms that are independent of the parameters of the model. Wilson(1969) points out that a desirable property of a trading rule is that it "does not rely on features of the agents". Lopomo (1998, 2001) requires mechanisms to exhibit "simplicity" and "robustness".

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