How sellers choose mechanisms: Information matters

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Abstract

Dynamic mechanisms are quite complex, and few experiments have studied how sellers choose them. Here, we propose an experimental design to investigate how human sellers choose between two easily-conducted dynamic mechanisms: the optimal non-clairvoyant dynamic mechanism (NC) (Mirrokni et al., 2020) and the optimal repeated static mechanism (RS) (Myerson, 1981). Our results indicate that human sellers can harness their experience in an environment to choose the optimal mechanism later in the experiment. In addition, sellers tend to adjust their choice of mechanism based on past revenue. We further find that: (i) sellers generally overprice; and (ii) buyers participate less in NC mechanism environments due to the greater-than-suggested upfront fee, leading to the theoretical-experimental revenue gap. Our results shed light on how sellers choose dynamic mechanisms and can potentially help improve mechanism design.

Keywords: Dynamic, Auction, Experiment, Non-clairvoyant, Learning

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1. Introduction

Understanding how sellers select dynamic mechanisms in the real world can aid in designing more accessible mechanisms. Since the seminal work of Baron and Besanko (1984), theorists have provided fruitful findings on the optimal price-discovery and allocation rules sellers should choose (see Bergemann and Välimäki (2019) for a recent survey). However, dynamic mechanisms are not widely used, due to their complexity and a lack of general form (Mirrokni et al., 2020). Thus, it is difficult to determine the mechanism human sellers would actually choose.

Designing an optimal dynamic mechanism[3] is complicated, in that its "clairvoyance" should allow sellers to use all information, including future demand. Therefore, the optimal dynamic mechanism must be tailored to a specific trading environment (Jackson and Sonnenschein, 2007; Pavan et al., 2014; Balseiro et al., 2018). For example, in Courty and Li (2000), where agents faced asymmetric uncertainty, the optimal mechanism involved subsidizing agents with less future uncertainty to reduce rent-seeking by consumers facing greater uncertainty. Similarly, in Eső and Szentes (2007), where agents obtained a private value signal from the seller, the optimal mechanism included a premium paid for extra information, combined with a second price auction where the winner paid the second-highest bid plus the premium.[4] The complexity of the clairvoyant dynamic mechanism means few experimental studies have focused on sellers' behaviors in a dynamic mechanism.

Recently, Mirrokni et al. (2020) introduced a new family of dynamic mechanisms: the "non-clairvoyant" dynamic mechanism, which restricts sellers from using future demand information. Non-clairvoyant dynamic mechanisms are scenario-independent, simple in form, and robust to differences in beliefs across participants. They can also be conducted in a lab. As a result, they offer a helpful resource for experimental studies on how human sellers choose dynamic mechanisms.

[3]Dynamic mechanism design studies how to determine the optimal price-discovery and allocation rules as buyers receive information over time.

[4]See Board (2007) for extension to infinite time horizon.

Here, we design experiments to study how sellers choose between two easily-conducted non-clairvoyant dynamic mechanisms: the optimal non-clairvoyant dynamic mechanism (henceforth NC, Mirrokni et al. (2020)) and the optimal repeated static mechanism (henceforth RS, Myerson (1981)). We focus on a two-period single-buyer environment. In this setting, RS conducts two Myerson's auctions to maximize each period's revenue independently, while NC works to guarantee revenues equal to at least 50% of those produced by the optimal clairvoyant mechanism. In Period 1, NC allocates half by give-for-free auction (buyer gets item for free) and the other half by Myerson's auction; in Period 2, NC first asks for a buyer-specific upfront entry fee, and then conducts auctions with buyer-specific reserve prices, after which half of the buyers can receive a refund on their upfront entry fee. (Myerson's auction is used if the upfront fee is refunded; otherwise, a posted-price auction is used.) Importantly, buyers who participate in the first period are not required to pay the upfront fee and participate in period 2. While it is theoretically optimal to participate, they may nevertheless choose not to participate in period 2 after participating in period 1.

Deciding on a dynamic mechanism involves a mapping from received information to the chosen mechanism and the price. Using NC and RS as the starting points, we attempt to determine the information human sellers use in choosing a dynamic mechanism, as well as whether that information changes over time. Specifically, we focus on three aspects of information: (i) the relative simplicity of a mechanism; (ii) the scenario-specific demand; and (iii) the feedback on revenue.

To investigate whether the relative simplicity of a mechanism affects sellers' choice of dynamic mechanism, we design two treatments with varying relative simplicity of NC. In treatment "Set 4", if NC is chosen, sellers must set four prices: two Myerson's reserve prices; the upfront fee; and the reserve price when the upfront fee is not refunded. In treatment "Set 2", sellers must only set two reserve prices for the Myerson's auction. The other two prices are set by the computer optimally. NC is relatively more challenging than RS to set up in treatment Set 4. Based on cognitive burden theory (Sweller, 1988), we expect sellers to choose NC more in treatment Set 2 due to the relative ease of NC in that treatment.

Learning the optimal mechanism for each scenario is challenging, as all prices in NC and

RS depend on specific demand in each period, and the revenue comparison between NC and RS lacks a general form. Special examples in Papadimitriou et al. (2022) and Gui and Houser (2023) provide intuitions for the revenue comparison between NC and RS. In their examples, Myerson's revenue is the same in both periods, and the revenue comparison between NC and RS depends only on the expected demand in Period 2, which is the upper bound for the revenue of the posted-price auction (revenue from the upfront fee and the associated reserve price) to ensure the buyer's participation in Period 2. Intuitively, if the expected demand in Period 2 is low, the revenue lost by NC in Period 1 (giving the buyer the item for free) cannot be made up, so NC generates less revenue than RS. For a similar reason, NC can potentially outperform RS only when the expected demand is high in Period 2. This happens when Period 2 involves "target buyers" who value the item highly but exist in low probability. In this case, the posted-price auction captures more revenue than Myerson's auction, and NC thus generates more revenue than RS.

To study whether sellers choose a mechanism based on scenario-specific demand, we extend examples in Papadimitriou et al. (2022) and Gui and Houser (2023) and design 12 distinct scenarios (one for each round) with different theoretical comparisons between NC and RS. Those scenarios further simplify the decision-making problem and help sellers learn the intuition. As Harstad (2000) determined, subjects with experience in English auctions appear to transfer much of what they learned in that institution to later second-price auctions. In our experiment, we expect sellers to learn[5] the intuition of revenue comparison between NC and RS, particularly in the later stages after gaining experience in the trading environment. Feedback is also provided in each round to further study how sellers learn mechanisms according to past revenue.

Results show that sellers are indifferent to the relative simplicity in choosing a mechanism, as shown by no treatment difference in choosing NC. Strikingly, human sellers in our

[5]Learning of participants in multi-round experiments is intensively studied in the literature (see Bigoni and Suetens (2012) for the public goods game; see Matthey and Regner (2013) for the dictator game, the ultimatum game, and the trust game; see Benndorf et al. (2017) for a summary. The learning effect varies in context (Pritchett and Sandefur, 2015).

experiment can learn the intuition of revenue comparison between NC and RS in different scenarios and choose the correct mechanism with greater revenue for that scenario in the later stages of the experiment, after they have gained experience in the trading environment. We further find that sellers adjust mechanisms over time based on previously achieved revenue. Our findings shed light on how sellers choose mechanisms, which could provide helpful insight for designing more accessible dynamic mechanisms in the future.

In the experiment, sellers who make good decisions receive more revenue than sellers who choose the wrong mechanism. Consistent with Gui and Houser (2023), the theoretical revenue gap derives mostly from some buyers not participating in Period 2 in NC. Our results further indicate that buyers quit more in Period 2 in treatment Set 4, as sellers set greater-than-suggested upfront fees. We note the concern about the role of upfront fees in a dynamic mechanism design, as well as that sellers' behavioral considerations might play an important for future dynamic mechanism design.

The remainder of the paper is organized as follows. Section 2 illustrates the theoretical framework. Section 3 presents our experimental design based on the theoretical revenue comparison of NC and RS. Section 4 states corresponding hypotheses. Section 5 provides experimental results. Section 6 concludes.

2. Theoretical Framework

2.1. Two-period Dynamic Trading

We study a two-period repeated selling environment. In each period, a newly-arrived item must be sold to a single buyer. It is common knowledge that producing an item in both periods exerts zero cost, and valuations are the private information of the single buyer.

A specific scenario is defined as the pair of distributions of the buyer's valuation (F_1, F_2), i.e., the demand for the item in each period. The two distributions are common knowledge from the beginning of Period 1. The first period valuation is independent of the second period valuation.[6]

[6] For similar settings, see Devanur et al. (2019). In Devanur et al. (2019), the buyer's valuation follows

The sequence of events and actions in the selling game in each period $t \in \{1, 2\}$ are summarized as follows:

a) The seller describes their allocation rule $x_t \in [0, 1]$ and price policy $p_t \in \mathbb{R}^+$.

b) The buyer who enters the trade learns their valuation of the item $v_t \sim F_t$, and makes a bid b_t.

c) The seller implements their allocation rule x_t and price policy p_t.

d) The buyer gains periodical utility $u_t = u_t(b_t, v_t) = v_t \cdot x_t - p_t$.

We focus on direct mechanisms satisfying the buyer's participation constraint. That is, the dynamic mechanisms with allocation rules (x_1, x_2) and price policy (p_1, p_2) are subject to Dynamic Incentive Compatibility (DIC) and Ex Post Individual Rationality (EPIR) as detailed below.

$$\begin{aligned} DIC: &\quad \begin{cases} u_2(v_2, v_2) \geq u_2(b_2, v_2), & \forall v_2 \in F_2 \\ u_1(v_1, v_1) + \mathbb{E}_{v_2} u_2(v_2, v_2) \geq u_1(b_1, v_1) + \mathbb{E}_{v_2} u_2(v_2, v_2), & \forall v_1 \in F_1 \end{cases} \\ EPIR: &\quad u_1 + u_2 \geq 0, \qquad\qquad\qquad\qquad \forall v_1 \in F_1, v_2 \in F_2 \end{aligned}$$

Here, DIC is illustrated using backward induction: in Period 2, the buyer can achieve the greatest payoff by bidding their valuation; then, in Period 1, the buyer also has an incentive to report truthfully, given that true value is the optimal bid in Period 2. EPIR requires a non-negative total utility of the buyer $(u_1 + u_2)$ after the realization of the value for both periods.

Denote $\mathcal{M}$ as the set of mechanisms satisfying DIC and EPIR. For any dynamic mechanism $DM \in \mathcal{M}$, we define its revenue Rev^{DM} as a function of (F_1, F_2), the cumulative distribution functions of the demand in each period, in the natural way:

$$Rev^{DM} = Rev_1^{DM} + Rev_2^{DM} = \mathbb{E}_{v_1} p_1(v_1; F_1, F_2) + \mathbb{E}_{v_2} p_2(v_2; F_1, F_2).$$

Rev^{DM}, the revenue of a dynamic mechanism, can be further decomposed into intra-period revenue and inter-period revenue (Mirrokni et al., 2020). The intra-period revenue derives

the same distribution in both periods. By contrast, in our setting, the distribution in each period is not necessarily the same.

from rules that use only information within a period. The remainder of Rev^{DM} is the inter-period revenue derived from linking information across periods.

2.2. Two Simple Dynamic Mechanisms

Fixing the pair of distributions on demand in the two period (F_1, F_2), the optimal dynamic mechanism (denoted as $*$) generates revenue:

$$Rev^* = \max\ [\mathbb{E}_{v_1} p_1(v_1; F_1, F_2) + \mathbb{E}_{v_2} p_2(v_2; F_1, F_2)].$$

The optimal dynamic mechanism with the greatest revenue Rev^* requires the rules in Period 1 to use the distributional knowledge in Period 2. That is, $p_1^*(v_1; F_1, F_2)$, the optimal price rule in Period 1, is a function of the demand in Period 2. The optimal dynamic mechanism thus lacks general form and is complicated to calculate (Mirrokni et al., 2020; Papadimitriou et al., 2022).

In this section, we introduce two fixed-form mechanisms: the optimal repeated static mechanism (RS) and the optimal non-clairvoyant dynamic mechanism (NC). Both mechanisms belong to the family of "non-clairvoyant" dynamic mechanisms in that they do not use future distributional knowledge (F_2) in determining rules in Period 1. That is, their price rule in Period 1 $p_1(v_1; F_1)$ is not a function of the demand in Period 2. While RS and NC have different objectives, they both satisfy DIC and EPIR.

2.2.1. Optimal Repeated Static Mechanism

A dynamic mechanism can be viewed as a repeated static mechanism if x_t, the allocation rule, and p_t, the price policy at time t, depend only on information in period t (i.e., the distributional knowledge F_t and the bid b_1 in that period). A repeated static mechanism separates the dynamic two-period as two static periods. Likewise, the optimal repeated static mechanism (RS) implements Myerson's auction (Myerson (1981), denoted as M) in each period independently.

In the single-buyer case, Myerson's auction charges a reserve price and allocates the item to the buyer with the bid that is greater than or equal to the reserve price. The reserve price in Myerson's auction is the monopoly price in each period (denoted as r_t^*). The price rule in Myerson's auction is $x_t^M = r_t^* = arg\max r(1 - F_t(r))$, and the allocation rule in M is $p_1^M = r_1^* \cdot \mathbb{1}\{v_1 \geq r_1^*\}$ for $t = 1, 2$. Accordingly, x_t^{RS} , the allocation rule, and p_t^{RS} , the price policy in RS, are summarized as follows:

$$\begin{cases} x_1^{RS} = x_1^M = \mathbb{1}\{v_1 \geq r_1^*\}, \\ p_1^{RS} = p_1^M = r_1^* \cdot \mathbb{1}\{v_1 \geq r_1^*\}, \\ p_1^{RS} = x_2^M = \mathbb{1}\{v_2 \geq r_2^*\}, \\ p_2^{RS} = p_2^M = r_2^* \cdot \mathbb{1}\{v_2 \geq r_2^*\}. \end{cases}$$

Thus, the revenue in the optimal repeated static mechanism is the sum of revenues in Myerson's auction in the two periods, $Rev^{RS} = Rev_1^M + Rev_2^M$, where Myerson's revenue in the two periods is $Rev_1^M = r_1^*(1 - F_1(r_1^*))$ and $Rev_2^M = r_2^*(1 - F_2(r_2^*))$ respectively.

In RS, there is maximized intra-period revenue in each period, but zero inter-period revenue. The reason is that the mechanism does not use any information in Period 1 to determine rules in Period 2. Given that the optimal dynamic revenue Rev^* contains the maximized intra-period revenue and inter-period revenue, the ratio $\frac{Rev^{RS}}{Rev^*}$ can be arbitrarily small (Papadimitriou et al., 2022).

2.2.2. Optimal Non-clairvoyant Dynamic Mechanism

The objective of the non-clairvoyant dynamic mechanism (Mirrokni et al., 2020) is to have the greatest revenue guarantee, i.e., to maximize the non-clairvoyant revenue to clairvoyant revenue ratio, $\frac{Rev^{NC}}{Rev^*}$ for any demand in Period 2. The optimal non-clairvoyant dynamic mechanism (NC) can guarantee 50% of the optimal dynamic revenue in the two-period case. In Period 1, NC allocates half of the items by Myerson's auction and the other half by a give-for-free auction (denoted as F). In Period 2, NC allocates half of the items by Myerson's auction and the other half by a posted-price auction (denoted as P).

Specifically, in Period 1, the give-for-free auction allocates the item to the buyer regardless of bid and with no charge: the allocation rule is $x_1^F = 1$, and the price rule is $p_1^F = 0$, so that the revenue in F is $Rev_1^F = 0$. In Period 2, the posted-price auction sets an upfront fee in advance for the buyer and then conducts an auction with reserve price. The upfront fee is customized for each buyer based on the buyer's bid in Period 1, $s_2 = \min\{b_1, \mathbb{E}_2\}$, where

$\mathbb{E}_2$ is the expected valuation in Period 2. To ensure the buyer's participation *ex ante*, it is bounded by the second period expected valuation. To satisfy the EXIP, it is bounded by the first period bid. The associated reserve price r_2^P is set to ensure the buyer's payoff in Period 2 is zero, so that all dealing surplus is exploited. That is, $\mathbb{E}_{v_2}[v_2 - r_2^P]^+ - s_2 = 0$. The allocation rule in the posted-price auction is $x_2^P = \mathbb{1}\{v_2 \geq r_2^P\}$; the price rule in P is $p_2^P = s_2 + r_2^P \cdot \mathbb{1}\{v_2 \geq r_2^P\}$; and the revenue in P is $Rev_2^P = \mathbb{E}p_2^P$. Accordingly, we summarize the allocation rule (x_t^{NC}) and the price rule (p_t^{NC}) of NC below.

$$\begin{cases} x_1^{NC} = \frac{1}{2}[x_1^M + x_1^F] = & \frac{1}{2}(1 + \mathbb{1}\{v_1 \geq r_1^*\}), \\ p_1^{NC} = \frac{1}{2}[p_1^M + p_1^F] = & \frac{1}{2}r_1^* \cdot \mathbb{1}\{v_1 \geq r_1^*\}, \\ x_2^{NC} = \frac{1}{2}[x_2^M + x_2^P] = & \frac{1}{2}[\mathbb{1}\{v_2 \geq r_2^*\} + \mathbb{1}\{v_2 \geq r_2^P\}], \\ p_2^{NC} = \frac{1}{2}[p_2^M + p_2^P] = & \frac{1}{2}[r_2^* \cdot \mathbb{1}\{v_2 \geq r_2^*\} + s_2 + r_2^P \cdot \mathbb{1}\{v_2 \geq r_2^P\}]. \end{cases}$$

The revenue of NC is half of Myerson's revenues in the two periods and half of the revenue from the posted-price auction in Period 2, $Rev^{NC} = \frac{1}{2}(Rev_1^M + Rev_2^M + Rev_2^P)$. As shown in Mirrokni et al. (2020), the optimal inter-period revenue is bounded by $\mathbb{E}(s_2)$, which is exactly the expected upfront fee in the posted-price auction in Period 2. Hence, NC captures exactly half of the optimal intra-period revenue ($\frac{1}{2}Rev_1^M + \frac{1}{2}Rev_2^M$), and at least half of the optimal inter-period revenue $\frac{1}{2}Rev_2^P$.

2.3. Theoretical Revenue Comparison

The theoretical revenue difference between NC and RS is denoted below:

$$Rev^{NC} - Rev^{RS} = \frac{1}{2}[Rev_2^P - (Rev^{M_1} + Rev^{M_2})].$$

The relative size of inter-period revenue from a posted-price auction (Rev_2^P) with respect to the optimal intra-period revenue ($Rev^{M_1} + Rev^{M_2}$) determines the theoretical revenue comparison between RS and NC. Given that revenues from both the Myerson's auction and the posted-price auction depend on demand in the two periods (F_1, F_2), the theoretical revenue comparison is specific-scenario dependent. In a natural way, we characterize scenarios into three categories according to the theoretical revenue comparison between RS and NC:

scenarios with $Rev^{NC} > Rev^{RS}$ are "NC Better"; scenarios with $Rev^{NC} < Rev^{RS}$ are "RS Better"; and scenarios with $Rev^{NC} = Rev^{RS}$ are "Same".

The sufficient and necessary condition for those categories is challenging to quantify. The reason is that Rev_2^P, the revenue of the posted-price auction in Period 2, derives not only from the upfront fee (i.e., the optimal inter-period revenue), but also the associated reserve price. However, we know that to ensure the buyer's participation *ex ante.*, Rev_2^P is bounded by $\mathbb{E}_2$, the expected buyer's valuation in Period 2. As a result, $\mathbb{E}_2 < Rev^{RS}$ implies an RS Better scenario. This rule is helpful, particularly when the Myerson's auction generates the same revenue in both periods. In this case, when the expected value in Period 2 is less than twice the Myerson's revenue in Period 2 ($\mathbb{E}_2 < 2Rev_2^M$), RS generates more revenue than NC.

For a similar reason, an NC Better scenario requires the posted-price auction to generate sufficiently more revenue than Myerson's auction in Period 2. This happens when there are "target buyers" (high valuation but low probability) in Period 2, i.e., the demand in Period 2 is long-tailed. In this case, Myerson's auction sets a low reserve price and generates low revenue, while NC might extract more revenue by setting an upfront fee and greater reserve price in the second period.

We use the example below to further illustrate the intuition.

Example 1. *Consider scenarios with discrete distributions in both Periods. Let $n_1 > 1$ and $n_2 > 1$ be the number of possible valuations for the buyer in Period 1 and in Period 2. The valuation for the buyer in Period 1 takes 2^i with probability 2^{-i} for $i = 1, ..., n_1 - 1$ and value 2^{n_1} with probability $2^{-(n_1-1)}$. The valuation for the buyer in Period 2 takes 2^i with probability 2^{-i} for $i = 1, ..., n_2 - 1$ and value 2^{n_2} with probability $2^{-(n_2-1)}$. Note that $\mathbb{E}_1$ the expected valuation in Period 1 is $n_1 + 1$, and $\mathbb{E}_2$ the expected valuation in Period 2 is $n_2 + 1$. The distribution in each period can be specified by its expected value. We thus denote the scenario as $S^E(\mathbb{E}_1, \mathbb{E}_2)$.*

This example is a variation of Papadimitriou et al. (2022). In this example, revenue from Myerson's revenue in both periods is the same: consider setting any possible value in each period as the reserve price in Myerson's auction. That is, $Rev_1^M = Rev_2^M = 2$, so that Rev^{RS}

the revenue in RS, is 4. Note that Rev^{RS} is fixed in both periods. This is very convenient, as it allows us to focus more on the revenue from posted-price auctions in NC. Given that $\mathbb{E}_2$, the expected valuation in Period 2, is the upper bound for Rev_2^P, it is straightforward that if $\mathbb{E}_2 < 4$, then $S^E(\mathbb{E}_1, \mathbb{E}_2)$ belongs to RS Better. An NC Better scenario thus requires $\mathbb{E}_2$, the expected valuation in Period 2, to exceed 4. This implies that the buyer's valuation in Period 2 should take more possible values (larger n_2) and have greater maximum value (larger 2^{n_2}). Hence, the thinner the market in Period 2, the more likely NC will generate more revenue than RS.

Rev_2^P can be quantified in our example. Consider a scenario $S^E(\mathbb{E}_1, 4)$ where $\mathbb{E}_2$, the expected buyer's valuation in Period 2, is 4. For any F_1, the distribution of the buyer's valuation in Period 1, the buyer's valuation takes value 2 with probability 50% and value greater than 2 with probability 50%. Recall that the upfront fee in the posted-price auction (P) is $s_2 = \min[v_1, \mathbb{E}_2]$, so the revenue of P from the upfront fee is 3. To extract the whole dealing surplus, the associated reserve price in P is 2 for the buyer with value of 2 in Period 1, and 0 for the buyer with value greater than 2. The reserve price contributes 1 of the revenue in P. As a result, Rev_2^P is 4, which is equal to the sum of Myerson's revenue in both periods; thus, NC generates the same revenue as RS. Further, if $\mathbb{E}_2$, the expected buyer's valuation in Period 2, is greater than 4, then either the expected upfront fee is greater than 3 or the expected associated reserve price is greater than 4. In both cases, we have $Rev^{NC} > Rev^{RS}$.

We summarize the theoretical comparison between NC and RS in the scenario $S^E(\mathbb{E}_1, \mathbb{E}_2)$ in Proposition 1.

Proposition 1. *For scenario $S^E(\mathbb{E}_1, \mathbb{E}_2)$ defined in Example 1, the revenue comparison between NC and RS depends only on $\mathbb{E}_2$:*

a). $Rev^{NC} > Rev^{RS}$ *if* $\mathbb{E}_2 > 4$ *;*
b). $Rev^{NC} = Rev^{RS}$ *if* $\mathbb{E}_2 = 4$ *;*
c). $Rev^{NC} < Rev^{RS}$ *otherwise.*

Those theoretical findings provide a foundation for our experimental design in Section 3.

3. Experimental Design

Our experiment is designed to answer two research questions: (i) what information do human sellers use in deciding on a dynamic mechanism?; and (ii) how does the information they use change over time? Thus, our experiment uses both within-subject design and between-subject design. Participants are randomly assigned to one of two treatments: treatment *Set 4*, and treatment *Set 2*. All participants attend all 12 rounds with distinct trading scenarios in each round. Section 3.1 illustrates the treatment differences in experimental tasks. Section 3.2 explains how we construct those 12 trading scenarios. Section 3.3 introduces the experimental procedure.

Participants in the experiment play the role of *seller* or *buyer*, with equal chance. The role is fixed for the entire experiment. In each round, sellers and buyers are randomly matched. There are two practice rounds, followed by 10 experimental rounds. Participants are paid for only one of the 10 experimental rounds.

Each round is a two-period trading game, in which the buyer can buy one item from the seller in each period. It is common knowledge that production cost is 0 for sellers. At the beginning of each round, both the buyer and the seller have access to pie charts showing the possible values of the item in both periods. This setting allows us to investigate whether scenario-specific demand affects a human seller's choice of dynamic mechanism. The seller must then choose between two mechanisms for this round: NC and RS. Afterward, the seller sets prices, and the buyer bids according to seller's chosen mechanism. At the end of each round, participants receive feedback on their earnings.

3.1. Experimental Task

In each round, if RS is chosen, the seller must set two prices. Treatments vary on the number of prices the seller must set in each round if NC is chosen. In treatment Set 4, a seller choosing NC must set four prices: one in Period 1, and three in Period 2. However, in treatment Set 2, a seller choosing NC must only set two prices (one in each period), with the other two prices in Period 2 set by the computer. Compared with treatment Set 4, Set 2 makes NC a relatively easier mechanism for the seller.

The experimental task in Period 1 is the same in both treatments. After the seller chooses between NC and RS, the buyer is informed of the structure of the chosen mechanism. Then the seller sets a private reserve price r_1^M, and the buyer learns the private value of the item and makes a bid. If RS is chosen, the buyer purchases the item if their bid is greater than or equal to the reserve price. The buyer then pays the seller's reserve price. If NC is chosen, the buyer has a 50% chance of purchasing the item by paying nothing; otherwise, the buyer purchases the item from the seller by paying the reserve price if their bid is greater than or equal to the reserve price. We summarize the timeline for Period 1 below, followed by a flowchart in Figure 1.

Period 1

1. The seller chooses a dynamic mechanism, DM (=NC or RS), and the buyer is informed.
2. The seller sets a reserve price r_1^M for Period 1; buyer learns the value of the item v_1 and makes a bid b_1.
   - in RS: the buyer pays r_1^M if $b_1 \geq r_1^M$
   - in NC: the buyer has 50% chance to get free item;
     otherwise, the buyer pays r_1^M if $b_1 \geq r_1^M$.

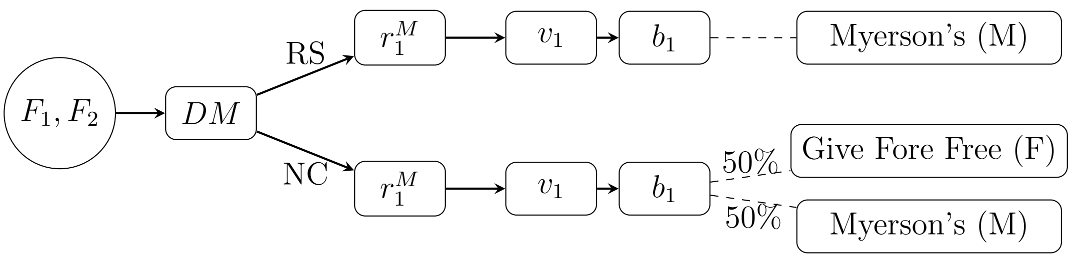


Figure 1: Experimental Task in Period 1

The experimental task in Period 2 is the same in both treatments if RS is chosen in this round, with the same structure as the task in Period 1. The seller sets another private reserve price r_2^M. The buyer privately learns the new private value of the item in Period 2 and makes a bid. The buyer purchases the item if their bid is greater than or equal to the reserve price. The buyer then pays the reserve price to the seller.

The experimental tasks in Period 2 vary between treatments if NC is chosen by the seller for this round. In treatment Set 4, the seller must set three prices in Period 2: (i) the upfront fee s_2, which the buyer can pay to learn their private valuation on the item in Period 2 and make a bid; and (ii) two reserve prices: one for the case when the buyer receives the refund on the upfront fee (r_2^M, for Myerson's auction), and one for the case where the buyer has to pay the upfront fee (r_2^P, for the posted-price auction). The buyer has a 50% chance of receiving the refund on the upfront fee and a 50% chance of not receiving the refund. The same rules for the buyer receiving the item apply in either case: if the buyer's bid is greater than or equal to the secret price, they receive the item and pay the seller the secret price. The seller is informed of the suggested upfront fee, i.e., the theoretical optimal upfront fee that captures the whole trading surplus in the posted-price auction.

In treatment Set 2, s_2, the upfront fee, and r_2^P, the reserve price for the buyer (as shown inside dashed rectangles in Figure 2 below), are set by the computer optimally and automatically. The buyer cannot obtain a refund on the upfront fee. This setting makes NC an easier mechanism for the seller, allowing us to investigate whether the relative simplicity between mechanisms affects the seller's choice of mechanism. Meanwhile, we can test whether the buyer is more likely to accept and pay the upfront fee set by the computer than a fee set by a human seller. The timeline for Period 2 is summarized below. Figure 2 further illustrates the experimental task in Period 2.

Period 2

1. The seller sets reserve prices for Period 2.
    - In RS: the seller sets the reserve price r_2^M;
    - In NC in treatment Set 4: the seller sets r_2^M, s_2, and r_2^P;
    - In NC in treatment Set 2: the seller sets r_2^M; the computer sets s_2 and r_2^P.
2. (NC only) The buyer chooses whether to pay the upfront fee s_2.
3. The buyer learns the value of the item v_2 and makes a bid b_2 in RS or in NC when entering the market.

4. Allocation and pricing implementation:

   - in RS: the buyer pays r_2^M if $b_2 \geq r_2^M$;
   - in NC: the buyer has a 50% chance of obtaining a refund on the upfront fee, and pays r_2^P if $b_2 \geq r_2^M$;
     otherwise, the buyer pays r_2^M if $b_2 \geq r_2^M$.

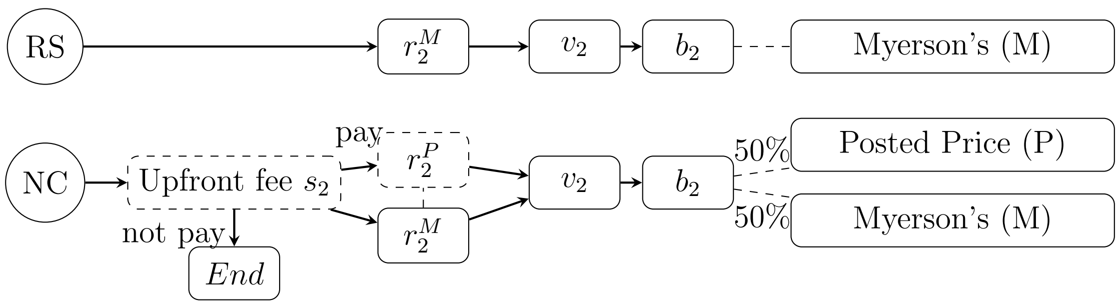


Figure 2: Experimental Task in Period 2

To reduce overbidding, we restrict the bid to any non-negative integer no greater than twice the buyer's valuation. We also restrict all reserve prices set by the seller such that they are bound by the highest value of the item in that period. For the upfront fee in treatment Set 4, the seller can set any non-negative integer no greater than twice the suggested optimal upfront fee. Participants begin with 60 points, as buyers may lose some points during the experiment. In the experiment, to improve participants' understanding, we use "entry fee" instead of "upfront fee," and "secret price" instead of reserve price.

3.2. Three Categories of Scenarios

We construct 12 distinct scenarios based on Example 1 in Section 2.3. For a symmetric design, each category (NC Better, RS Better, and Same) contains four scenarios. That is, theoretically, four NC Better scenarios generate more revenue in NC than in RS; four RS Better scenarios generate more revenue in RS than in NC; and four Same scenarios generate the same revenue in NC and in RS.

In our experiment, the distribution of the value of items in a period follows one of four distributions: F_a, F_b, F_c, and F_d. Each distribution is discrete, as shown in pairs of values and associated probabilities $(v, p(v))$ below:

$$\begin{cases} F_a &= \{(v,p(v))\} = \{(2,\frac{1}{2}),(4,\frac{1}{4}),(8,\frac{1}{8}),(16,\frac{1}{16}),(32,\frac{1}{16})\}, & \mathbb{E}(F_a)=6 \\ F_b &= \{(v,p(v))\} = \{(2,\frac{1}{2}),(4,\frac{1}{2})\}, & \mathbb{E}(F_b)=3 \\ F_c &= \{(v,p(v))\} = \{(2,\frac{1}{2}),(4,\frac{1}{4}),(8,\frac{1}{4})\}, & \mathbb{E}(F_c)=4 \\ F_d &= \{(v,p(v))\} = \{(2,\frac{1}{2}),(4,\frac{1}{4}),(8,\frac{1}{8}),(16,\frac{1}{8})\}, & \mathbb{E}(F_d)=5 \end{cases}$$

For example, the distribution F_a, takes value 2 with probability $\frac{1}{2}$, value 4 with probability $\frac{1}{4}$..., and value 32 with probability $\frac{1}{16}$. The expected values for distributions F_a, F_b, F_c, and F_d are 6, 3, 4, and 5, respectively.

We capture a scenario as (F_1, F_2), the pair of distributions of buyer's value in Period 1 and Period 2. Myerson's revenue is 2 for both periods if the buyer's valuation draws from one of those four distributions. Thus, Rev^{RS}, the revenue of RS, equals 4 for all scenarios. From Proposition 1, the revenue comparison between NC and RS depends only on $\mathbb{E}(F_2)$: given that $\mathbb{E}(F_a) = 6 > 4$, if F_a is the distribution of buyer's valuation in Period 2, the scenario (F_1, F_a) belongs to NC Better regardless of F_1; the scenario (F_1, F_b) belong to RS Better, as the revenue in the posted-price auction in Period 2 is at most $\mathbb{E}(F_b) = 3$; and the scenario (F_1, F_c) belongs to Same, as the posted-price auction generates the same revenue as the sum of Myerson's revenue in Period 1 and in Period 2. We thus construct 12 scenarios, summarized below.

Twelve Scenarios in Three Categories:

NC Better: (F_a, F_a), (F_b, F_a), (F_c, F_a), and (F_d, F_a).

RS Better: (F_a, F_b), (F_b, F_b), (F_c, F_b), and (F_d, F_b).

Same: (F_a, F_c), (F_b, F_c), (F_c, F_c), and (F_d, F_c).

In these four NC Better scenarios, we have $REV^{RS} = 4$ and $REV^{NC} = 4.5$. The revenue of NC is 12.5% greater than that of RS. In all four RS Better scenarios, we have $REV^{RS} = 4$ and $REV^{NC} = 3.5$. The revenue of NC is 12.5% less than that of RS. And in all four Same scenarios, we have $REV^{RS} = REV^{NC} = 4$. The revenue of NC is the same as that of RS.

Figure 3 provides a summary of the theoretical total revenue: dark bars represent the revenue in Period 1, while light bars represent the revenue in Period 2. Theoretically, the

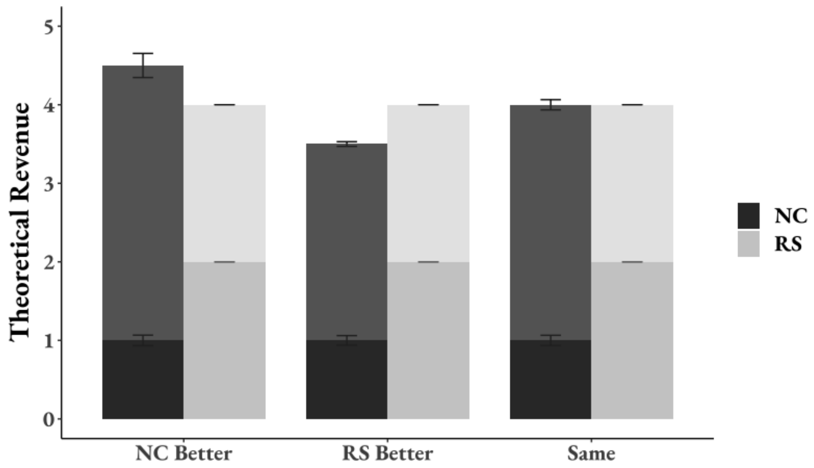


Figure 3: Theoretical Revenue (Total)

revenue in Period 1 in NC is always half that of RS, as half of the buyers receive the item for free. Thus, the total revenue comparison depends on whether NC can make up the first-period revenue loss in the second period: NC will generate more (less) revenue than RS in NC (RS) Better scenarios, while in Same scenarios, the total revenue will be the same.

Given that buyers and sellers are re-matched for each round, we randomize the order of scenarios for each session rather than for each pair of buyers and sellers. Thus, for one session, participants (from 16 to 26) have the same order of scenarios. It is behaviorally interesting to examine how human sellers choose dynamic mechanisms when NC and RS generate the same revenue in Same scenarios; however, to minimize confusion for human sellers, we randomly select two out of four scenarios in Same scenarios (Practice) as the two practice rounds and assign the remaining two scenarios in Same scenarios as the final two experimental rounds (Tail). Appendix B.1 analyzes behaviors of participants in Same scenarios. For the remaining eight experimental rounds, we randomly select two NC Better scenarios and two RS Better scenarios for the early stages (first four experimental rounds), and the remaining four scenarios for the later stages (experimental rounds 5-8). This setting not only controls for sequential effect, but also maintains a symmetrical design between the early stages and the later stages.

3.3. Experiment Procedure

We recruited participants from George Mason University. We advertised our study on the recruiting system (`experiments.gmu.edu`), specifying that the experiment would last for 70 minutes. Subjects over 18-years-old were pre-selected. Subjects were informed that they could receive a participation bonus of $10 and additional payments depending on their decisions in the experiment.

The experiment was programmed in oTree (Chen et al., 2016). We conducted the experiment in October and November 2022. We had 256 participants (64 sellers and 64 buyers per treatment).[7]

Participants took a quiz after receiving instructions (see Appendix C). They then advanced to two practice rounds and 10 experimental rounds, followed by a risk-aversion elicitation (Holt and Laury, 2002) and an ambiguity-aversion elicitation in a random order. After completing a demographic questionnaire, participants learned their payments and were paid in cash privately.

Participants took a quiz after receiving instructions. Then they proceeded to 2 practice rounds and 10 experimental rounds, followed by a risk-aversion elicitation (Holt and Laury, 2002) and a ambiguity-aversion elicitation in a random order. After completing a demographic questionnaire, participants learned their payments and were paid in cash privately.

4. Hypotheses

The first hypothesis concerns treatment differences on choosing a mechanism. Recall that in treatment Set 4, sellers need to set four prices in a round if NC is chosen, while

[7]We ran G$*$ power analysis: for $\alpha = 0.5$, sample size of 44 has the power of 0.8 if we run Wilcoxon Signed-Rank Test on whether sellers can set optimal mechanisms more in the later stages than in the early stages. We assume that sellers start with randomizing between mechanisms but can choose the optimal mechanism more easily over rounds (the correct rate increases by 2% per round in the early stages and 3% per round in the later stages). Simulation results show that the average likelihood of choosing the correct mechanism for the early stages is 53% (std: 0.12). The likelihood increases by 12% with (std: 0.33). The effective size of 0.37 is moderate.

in treatment Set 2, NC sellers need to set two prices per round. Setting proper prices is a challenging task, requiring intuition, calculation, and strategic adjustment based on feedback. Cognitive burden Sweller (1988) may make sellers less likely to choose NC due to the fact that they would need to set four prices for a round (rather than two prices in RS). As a result, it is reasonable to expect more sellers to choose NC if some of the prices in NC are set optimally and automatically by computer. We state our first Hypothesis as below:

Hypothesis 1 (Relative Simplicity). *Sellers choose NC more in treatment Set 2 than in treatment Set 4.*

Our second hypothesis concerns whether sellers choose a dynamic mechanism based on scenario-specific demand information. In the experiment, sellers are informed of the specific scenarios by learning the distribution of the buyer's valuation in Period 1 and Period 2 at the beginning of each round. Sellers are not informed which mechanism is optimal in each scenario. However, our 12 designated simple scenarios provide intuition that helps sellers choose between NC and RS (whether NC is worthy of choosing depends only on the expected value of buyer's valuation in Period 2). In the early stages of the experiment, sellers might choose between NC and RS randomly to explore the trading environment. In the later stages, sellers might gain some experience with the environment. We thus expect that sellers will choose NC (RS) more than RS (NC) in NC (RS) Better scenarios, particularly in the later stages (experimental rounds 5-8). We state our second Hypothesis as below:

Hypothesis 2 (Scenario-specific Demand). *In each treatment, sellers choose NC more (less) than 50% in NC (RS) Better scenarios in the later stages.*

The byproduct of Hypothesis 2 is that sellers will choose the correct mechanism more in the later stages. This should translate to revenue improvement from choosing the correct mechanism. We investigate this in the Results section.

The third hypothesis concerns how sellers choose a mechanism according to feedback. We expect sellers to adjust their choice of mechanism according to the feedback on realized revenue. Given that the variance in revenue from NC is greater than that from RS, sellers might react more to the revenue from NC in the preceding round. We expect sellers to choose

NC more (less) when they received greater-(less-) than average revenue in the preceding round. We have our Hypothesis 3:

Hypothesis 3 (Feedback on Revenue). *In each treatment, sellers choose NC more (less) when past revenue from NC is high (low).*

In the final hypothesis, we turn to buyers' behaviors. Based on Gui and Houser (2023)'s finding that some buyers refuse to pay the upfront fee in NC, we further hypothesize a treatment effect on buyers' participating decisions. Specifically, we expect buyers to be more likely to pay the upfront fee in NC when the upfront entry fee is determined by the computer in treatment Set 4, as compared to when the upfront fee is set by the human seller in treatment Set 2. Our expectation is an extension of previous literature finding that subjects are more likely to accept unfair offers proposed by computers versus humans (Blount, 1995).

Hypothesis 4 (Bidders' Behaviors). *Buyers are more likely to pay the upfront fee in NC in treatment Set 2 than in treatment Set 4.*

5. Results

Demographic summary statistics are reported in Table 1. We have balanced gender for each treatment. Among 256 subjects, 56% are male, with an average age of 22.[8] The average payoff is $17.66.

In the Results section, we focus on behaviors in the eight experimental rounds on NC Better scenarios and RS Better scenarios. We divide those experimental rounds into the early stages (experimental rounds 1-4) and the later stages (experimental rounds 5-8). We provide analyses on behaviorally interesting Same scenarios in Appendix B.1.

5.1. Relative Simplicity of NC in Choosing Mechanism

We first test Hypothesis 1 on relative simplicity by comparing the percentage of sellers choosing NC between the two treatments. We predict that sellers would choose NC more in

[8]We do not observe significant differences on gender, age, risk attitude, or ambiguity attitude among treatments.

Treatment	**Set 2**		**Set 4**	
Role	**Sellers**	**Buyers**	**Sellers**	**Buyers**
Age	22.6	22.2	21.2	22.5
Gender (Male=1)	0.59	0.62	0.52	0.50
Risk aversion	3.14	3.95	3.90	3.70
Ambiguity	3.30	3.02	3.67	3.32
Observation	64	64	64	64

Table 1: Summary Statistics

treatment Set 2 as compared with treatment Set 4, as treatment Set 2 reduces the cognitive burden by automating half of the prices in NC. However, our experimental results appear to indicate that the relative simplicity of NC does not influence sellers' choice of mechanism.

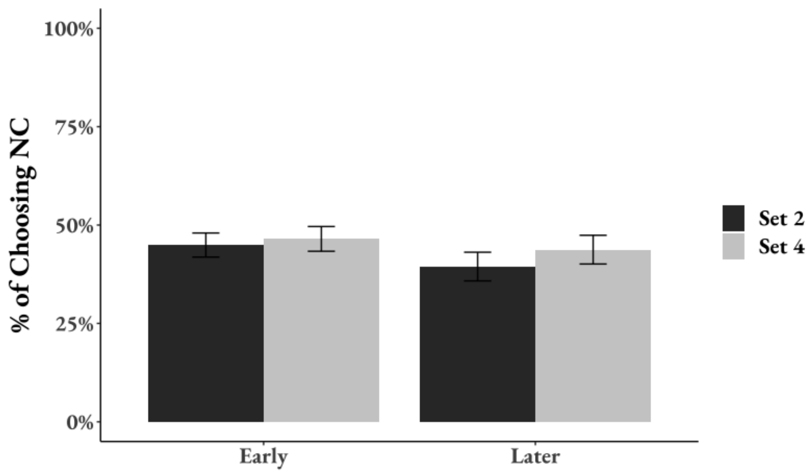


Figure 4: % of Choosing NC

The percentage of sellers choosing NC in each treatment for each stage is shown in Figure 4. There is no treatment difference in choosing NC either in the early stages (Set 2 vs. Set 4: 44.92% vs. 46.48%, $p = 0.64$, one-sided t-test) or the later stages (Set 2 vs. Set 4: 39.45% vs. 43.75%, $p = 0.80$, one-sided t-test). In the early stages, the percentage of choosing NC in both treatments does not significantly differ from 50% ($p = 0.10$ in Set 2, $p = 0.27$ in Set 4, two-sided t-test). This indicates that the behaviors of sellers in the early stages mimic randomizing. However, when sellers become familiar with the trading environment, their behavior differs significantly from randomly choosing ($p < 0.01$ in Set 2, $p = 0.09$ in Set 4, two-sided t-test). The Results section further discusses how sellers gain experience in the later stages.

We now have our first result:

Result 1. *Hypothesis 1 is not supported. The simplicity of NC in treatment Set 2 does not make sellers choose NC more, as compared with treatment Set 4.*

5.2. Discover the Optimal Mechanism

Recall that theoretically, NC will generate more (less) revenue than RS in NC (RS) Better scenarios in our experiment. We further expect that after gaining experience in the later stages, sellers in both treatments will choose NC (RS) more than RS (NC) in NC (RS) Better scenarios. That is, we expect that in the later stages, the percentage of choosing NC will be greater (lower) than 50% in NC (RS) Better scenarios in each treatment. Our results support this hypothesis: we find that sellers gain experience in the later stages, particularly in RS Better scenarios.

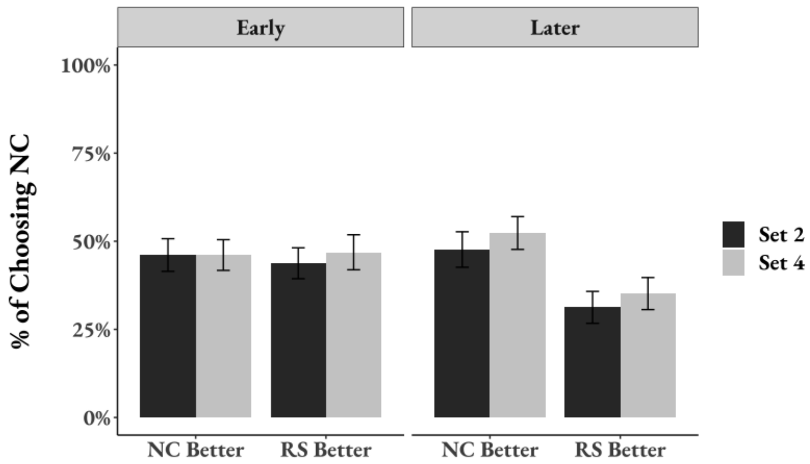


Figure 5: % of Choosing NC by Group of Scenario

Figure 5 shows the percentage of choosing NC in each treatment, in each stage, and in different scenarios. We first investigate sellers' decisions in RS Better scenarios. In the early stages, the percentage of choosing NC does not differ significantly from 50% (43.75% in Set 2, $p = 0.16$, and 46.88% in Set 4, p = 0.53, two-sided t-test). However, in the later stages, the percentage is significantly less than 50% (31.52% in Set 2, $p < 0.01$, and 35.16% in Set 4, $p < 0.01$, two-sided t-test). This implies that sellers make better decisions in the later stages in RS Better scenarios.

However, sellers gain experience only in RS Better scenarios. In NC Better scenarios, sellers seem to randomize, even in the later stages. The percentage of choosing NC is not significantly different from 50% in the later stages (46.66% in Set 2, $p = 0.64$, and 52.34% in Set 4, $p = 0.62$, two-sided t-test) or the early stages (46.09% in Set 2, $p = 0.40$, and 46.09% in Set 4, $p = 0.37$, two-sided t-test).

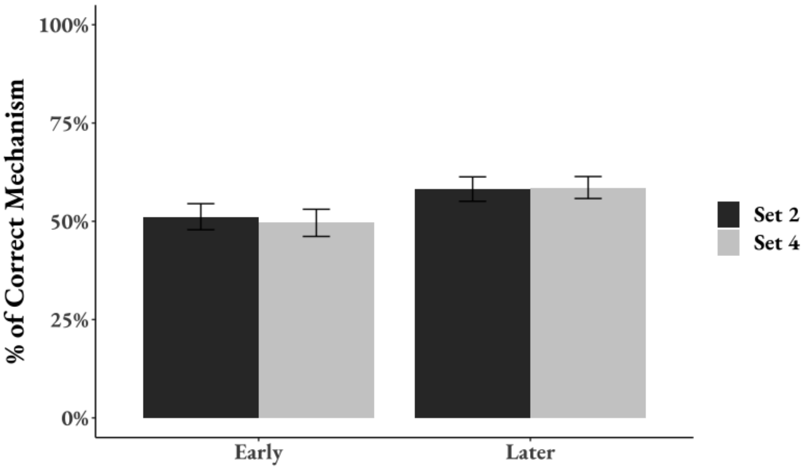


Figure 6: % of Choosing correct Mechanism

Further, we find that sellers choose the correct mechanism more in the later stages. The percentage of choosing the correct mechanism in each treatment and stage is shown in Figure 6. In the early stages, the percentage of choosing the correct mechanism in both treatments does not significantly differ from 50% (51.17% in Set 2, $p = 0.72$, and 49.61% in Set 4, $p = 0.91$, two-sided t-test), indicating that seller behavior in the early stages mimics randomizing. However, when sellers become familiar with the trading environment, they choose the correct mechanism significantly more than 50% of the time in the later stages (58.20% in Set 2, $p = 0.01$, and 58.59% in Set 4, $p < 0.01$, two-sided t-test). Meanwhile, there is no treatment difference in choosing the correct mechanism either in the early stages ($p = 0.38$, one-sided t-test) or the later stages ($p = 0.54$, one-sided t-test), supporting the Result 1.

We now have our second result:

Result 2. *Hypothesis 2 is supported. Compared with the early stages, sellers choose NC less in RS Better scenarios in the later stages, and sellers choose the optimal mechanism more in the later stages.*

5.3. Reaction to Negative Feedback

The other byproduct of Hypothesis 2 is that sellers should earn more revenue when choosing the correct mechanism. Experimental results support this prediction. We find that sellers earn more revenue in the later stages in treatment Set 4.

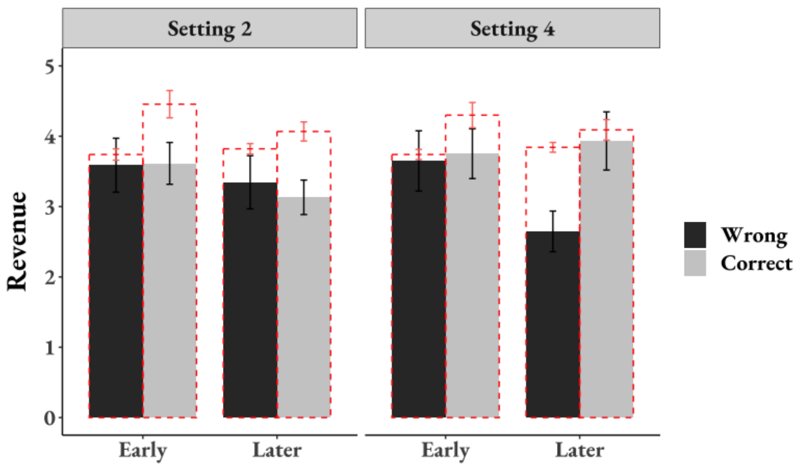


Figure 7: Experimental Revenue

Figure 7 reports experimental revenue in each treatment for each stage, noting whether the correct mechanism was chosen. We find that choosing the correct mechanism benefits sellers in treatment Set 4[9]: in the early stages, while the revenue from the correct mechanism (3.75) does not different significantly from that of the wrong mechanism (3.65, $p = 0.85$, one-sided t-test), in the later stages, the revenue from the correct mechanism (3.93) is significantly greater (2.65, $p = 0.01$, one-sided t-test).

Figure 7 also shows a gap between the theoretical revenue (in red dashed line) and the achieved experimental revenue. This gap mainly results from the revenue loss of NC due to buyers not entering Period 2.[10] This means that NC generates less than theoretically predicted, particularly in NC Better scenarios where NC should be the optimal mechanism. Meanwhile, NC has randomization in each period, and the variance of the revenue from NC is greater than that from RS, making NC generate lower revenue than RS, as a rule.

At the end of each round, the results of the trading (i.e., whether the buyer received the item, the price, and the revenue) are provided to sellers. In the next round, sellers might adjust their decisions based on the feedback, particularly revenue. We find that sellers adjust their mechanism decision based on negative feedback. Specifically, sellers are less likely to choose NC in the next round as a reaction to lower-than-average revenue of NC in the current round.

[9]In treatment Set 2, choosing the correct mechanism generates similar revenue as choosing the wrong mechanism in both stages (in the early stages, correct vs, wrong: 3.61 vs 3.59, $p = 0.96$; in the later stages, correct vs, wrong: 3.35 vs 3.13, $p = 0.64$, one-sided t-test).

[10]On average, the percentage of buyers choosing not to enter Period 2 in NC is 23.94%. If those buyers paid the upfront fee, entered in the second period, and bid their true value, the revenue of sellers would increase by 79.94% of the gap between the theoretical prediction and the experimental observation.

	DV: Choosing NC	
	(1)	(2)
β_1: Last (Revenue of NC < Average)	-0.21	-0.21
	(0.07)	(0.07)
β_2: Later * Set 4	0.01	-0.00
	(0.04)	(0.04)
β_3: Later * RS Better	-0.18	-0.18
	(0.06)	(0.06)
β_4: Later * Last (NC)	0.16	0.17
	(0.09)	(0.09)
β_5: Later * Last (NC is Correct)	0.02	0.01
	(0.10)	(0.10)
Constant	0.46	0.31
	(0.04)	(0.13)
Controls	No	Yes
R^2	0.05	0.05
Adj. R^2	0.03	0.03
Num. obs.	1024	1024

Note: The unit of observation is round i answered by participant j. OLS regressions are reported, and we find similar results using Probit Models. The regression consists of four rounds in the early stages and four rounds in the later stages. Cluster-robust standard errors at individual level were used in the regressions. Controls include index of risk attitude, index of ambiguity attitude, age, gender, and whether the participant is a graduate student.

Table 2: Regression of Choosing NC

Table 2 reports regressions to investigate the determinants of choosing NC in the current round. We consider whether revenue of NC from the preceding round was less than average (β_1). The remaining four independent variables are: interaction between whether in the later stages and whether in RS Better scenarios (β_2); interaction between whether in the later stages and whether choosing NC in the preceding round (β_3); interaction between whether in the later stages and whether NC is the optimal mechanism in the preceding round (β_4); and interaction between whether in the later stages and whether in treatment Set 4 (β_5).

The significant negative β_1 implies that when revenue in the preceding round was low (less than average) and from NC, sellers are less likely to choose NC again in the next round. This supports Hypothesis 3, i.e., sellers react to negative feedback. We find no treatment difference in choosing NC in the later stages (the insignificant β_2). This confirms our Result 1. We further confirm our Result 2, i.e., that sellers are able to determine that NC is not the optimal mechanism in RS Better scenarios in the later stages (the significant negative β_3). Meanwhile, sellers' mechanism choice tends to be persistent in the later stages[11] (the significant negative β_4), while the optimal mechanism (theoretically) in the previous round does not affect decisions about mechanism in the current round (the insignificant β_5). Those findings further support the idea that sellers adjust mechanism decisions based on both current condition and past revenue.

We now have our third result:

Result 3. *Hypothesis 3 is supported. Sellers are less likely to choose NC if past revenue from NC is low (less than average).*

5.4. Entry Fee and Participation

The revenue achieved in our experiment depends on both mechanism choice and price setting. In this section, we focus on the entry fee in Period 2. The reason is that this fee directly affects the participation behavior of buyers. We leave the discussion of reserve prices and bids for Appendix B.2.

[11] In the later stages, six (13) sellers chose NC (RS) in all four rounds in treatment Set 2, and four (10) sellers chose NC (RS) in all four rounds in treatment Set 4. In the early stages, three (five) sellers chose NC (RS) in all four rounds in treatment Set 2, and two (five) sellers chose NC (RS) in all four rounds in treatment Set 4.

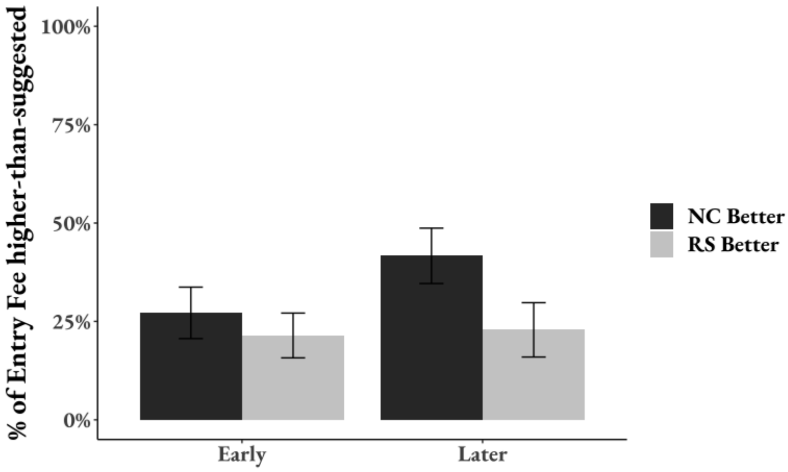


Figure 8: % of Setting Entry Fee Higher than Suggested

Recall that in treatment Set 2, the entry fee in NC is set by the computer automatically and optimally. In treatment Set 4, sellers are informed of the optimal entry fee (based on the bid in Period 1 and the valuation distribution in Period 2) and are free to set any entry fee lower than the suggested fee. The percentage of higher-than suggested entry fee by scenarios and by stage in treatment Set 4 is shown in Figure 9. In the early stages, 27.17% (21.43%) of the entry fees set by sellers in NC (RS) Better were higher than the suggested optimal fee, and the fraction is significantly more than 0% ($p < 0.01$ in NC better; $p < 0.01$ in RS better; one-sided t-test). In the later stages, 41.67% (22.86%) of the entry fees were higher than suggested by sellers, and the fraction is significantly more than 0% ($p < 0.01$ in NC better; $p < 0.01$ in RS better; one-sided t-test). Between scenarios, in the early stages, there is no significant difference in the percentage of setting the entry fee higher than suggested ($p = 0.51$, two-sided t-test). However, in the later stages, the entry fee is significantly more frequently set higher than suggested in NC Better than in RS better ($p = 0.06$, two-sided t-test).

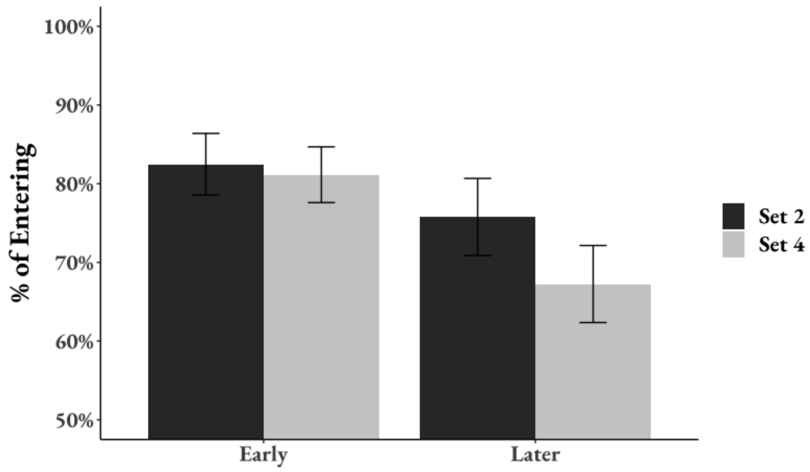


Figure 9: % of Entering Period 2

Accordingly, buyers participated less in the second period in NC. The percentage of entering Period 2 in NC is shown in Figure 9. In the early stages, the percentage of entering Period 2 in both treatments is significantly less than the theory prediction of 100% (82.47% in treatment Set 2, $p < 0.01$, 81.14% in treatment Set 4, $p < 0.01$, one-sided t-test). In treatment Set 2, the participation rate in the later stages (75.78%) is not significantly different from that in the early stages ($p = 0.14$, two-sided t-test). However, in treatment Set 4, the participation rate in the later stages in treatment Set 4 is 67.25%. The decline in participation is significant compared with the early stages ($p = 0.01$, two-sided t-test).[12]

[12]The direct treatment difference in participation rate is not significant in either the early stages ($p = 0.81$, one-sided t-test) or later stages ($p = 0.11$, one-sided t-test).

	DV: Enter in Period 2	
	(1)	(2)
β_1 : Set 4	-0.03	-0.06
	(0.05)	(0.06)
β_2 : Later * Set 4	-0.03	-0.05
	(0.08)	(0.08)
β_3 : Entry Fee	-0.07	-0.06
	(0.01)	(0.01)
β_4 : RS Better	-0.15	-0.13
	(0.06)	(0.04)
β_5 : Later	-0.10	-0.10
	(0.06)	(0.06)
β_6 : Risk Seeking		0.02
		(0.01)
Constant	1.10	1.15
	(0.07)	(0.17)
Controls	No	Yes
Num. obs.	447	447

Note: The unit of observation is round i answered by participant j. OLS regressions are reported. We find similar results using Probit models. The regression consists of four rounds in the early stages and four rounds in the later stages. Cluster-robust standard errors at individual levels were used in the regressions. Controls include a dummy for value in Period 1, whether the buyer received the item in Period 1, index of risk attitude, index of ambiguity attitude, age, gender, and whether the participant is a graduate student.

Table 3: Regression of Enter in Period 2

To disentangle whether the treatment difference of participating in Period 2 in NC is due to pure treatment effect (i.e., buyers feel the price set by sellers is more unfair than the price set by computer), or due to price effect, or both, we regress whether the buyer is entering Period 2 on treatment; stage; interaction between treatment and stage; scenario; entry fee amount; and risk attitude. Results are reported in Table 3. The significant β_3 supports the price effect, implying that the higher the entry fee, the less likely buyers are to choose to participate in Period 2. After controlling for the entry fee amount, the insignificant β_1 and β_2 reject the pure treatment effect. In other words, whether the entry fee is set by computer or a human does not affect buyers' participation behaviors. The significant negative β_4 shows that buyers participate less in RS Better scenarios. The reason may be that buyers think RS Better scenarios with low expected value in Period 2 are not worthy of their participation. This is consistent with the finding of Gui and Houser (2023). The significant negative β_5 shows that in the experiment, buyers tend to participate less in the later stages as the experiment goes on. It is worth noting that β_6 shows that risk attitude might play a role in participation decisions: the more risk averse the buyer, the less likely they will participate in Period 2.

We now present our fourth result:

Result 4. *Hypothesis 4 is supported. Buyers participate significantly less in the later stages only in treatment Set 4. This is explained by the higher entry fee set by sellers in treatment Set 4.*

6. Conclusion

To our knowledge, our paper is the first to investigate how human sellers choose dynamic mechanisms and adjust their choices over time. Our study could provide guidance for, e.g., designing airplane tickets, implementing rules for repeated selling, designing online advertising markets, and constructing long-term contracts.

We use laboratory experiments to investigate how human sellers choose between the optimal non-clairvoyant dynamic mechanism (NC) (Mirrokni et al., 2020) and the optimal repeated static mechanism (RS) (Myerson, 1981) for scenarios with different revenue comparisons. Experimental results indicate that sellers choose a dynamic mechanism based on distributional knowledge. While sellers tend to randomize between NC and RS in the early stages of the experiment, they learn from their experiment gained in the trading environment and implement that knowledge in the later stages. They are less likely to choose NC for scenarios where the revenue gain from an upfront fee in Period 2 would not sufficiently compensate for the loss suffered in Period 1 due to providing some of the items for free. Meanwhile, sellers react to negative feedback by choosing NC less when the revenue from NC in the preceding round was extremely low.

Combining Myerson's auction with two other mechanisms, NC is a more complex mechanism than RS. In the experiment, we have one treatment (Set 4) where sellers must set all four prices in a round if they choose NC. We then have another treatment (Set 2) where sellers set the same two reserve prices in NC as in RS, with the automated optimal upfront fee and associated reserve prices. We find no treatment differences in mechanism choice. This implies that relative simplicity does not affect sellers' choice of mechanism. Nevertheless, buyers participate less in treatment Set 4, likely due to the higher upfront fee set by sellers.

We note that NC is more sensitive to prices, particularly the upfront fee, which directly affects future participation behaviors of buyers. Similarly, in the natural environment, a high subscription fee might lead buyers to cancel a subscription immediately after a free trial expires (e.g., one-month Amazon Prime, three-month Spotify, etc.). Future dynamic mechanism design with upfront fees should consider the possibly of less-than-full participation of buyers due to upfront fees.

A limitation of our study is that it considers only a two-period single-buyer environment. Both non-clairvoyant dynamic mechanisms and repeat static mechanisms can, of course, be applied to multi-period multi-buyer environments. Indeed, studying these environments would be interesting, particularly to those designing auctions for natural environments. Future research will benefit from focusing on how sellers choose mechanisms in a non-clairvoyant environment.

Appendix A. Selected comments

In Period 1

- "Go big or go home".
- Aimed high, looking for a heavy bid
- You'd be surprised when I say - I based it off the charts.
- Random.

In Period 2

- Again, attempted high roll, but failed greedily.
- Higher price didn't work so I went lower.
- buyer bid for 1?? which makes no sense so I wanted to get some out of him and set the price to 6 as possible values could have been pretty high. Then set price to 4 as I would get it 50% of the time
- Set a low price, however, buyer decided not to purchase.

Appendix B. Additional Analysis

Appendix B.1. "Same" Scenarios

The percentage of choosing NC in each treatment in "Same" scenarios is shown in Figure B.10. There is no treatment difference in choosing NC either in the Practice stages (Set 2 vs. Set 4: 50.00% vs. 45.31%, $p = 0.53$, one-sided t-test) or in the Tail stages (Set 2 vs. Set 4: 42.19% vs. 39.84%, $p = 0.80$, one-sided t-test). In the Practice stages, the percentage of choosing NC in both treatments does not significantly differ from 50% ($p = 1$ in Set 2, $p = 0.26$ in Set 4, two-sided t-test). This finding further indicates that the behavior of sellers at the beginning of the experiment mimics randomizing. However, at the end of the experiment, sellers tend to choose NC significantly less than 50% ($p = 0.13$ in Set 2, $p = 0.02$ in Set 4, two-sided t-test).

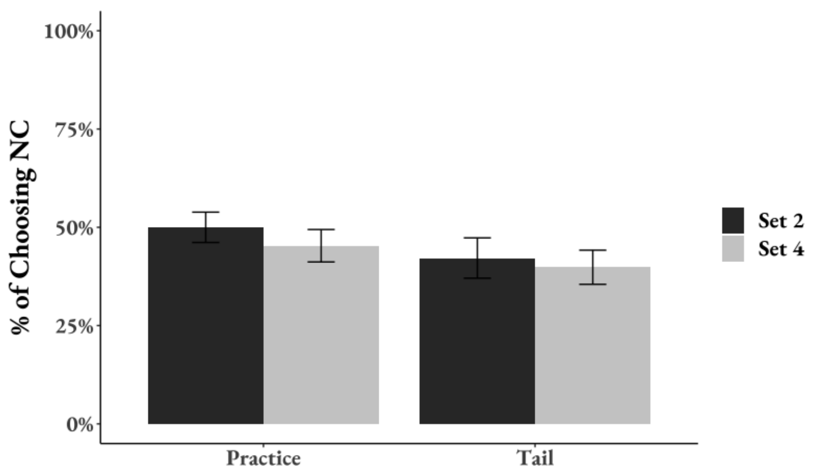


Figure B.10: % of Choosing NC in Same Scenarios

Appendix B.2. Reserve Prices and Bids

Figure B.11 shows the associated reserve price (r_2^P) set by sellers in the case that the upfront fee is not refunded. We find that, in the early stages, r_2^P in treatment Set 4 is significantly greater than that in treatment Set 2 (Set 2 vs. Set 4: 2.61 vs. 6.46, $p < 0.01$, two-sided t-test). While, there is no treatment difference in the later stages (Set 2 vs. Set 4: 5.87 vs 7.67, $p = 0.28$, two-sided t-test).

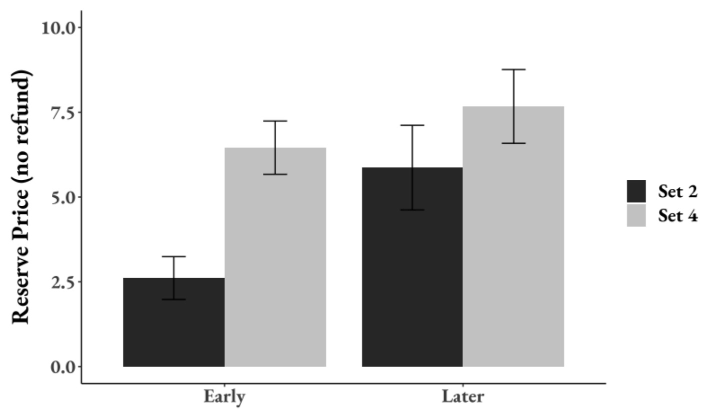
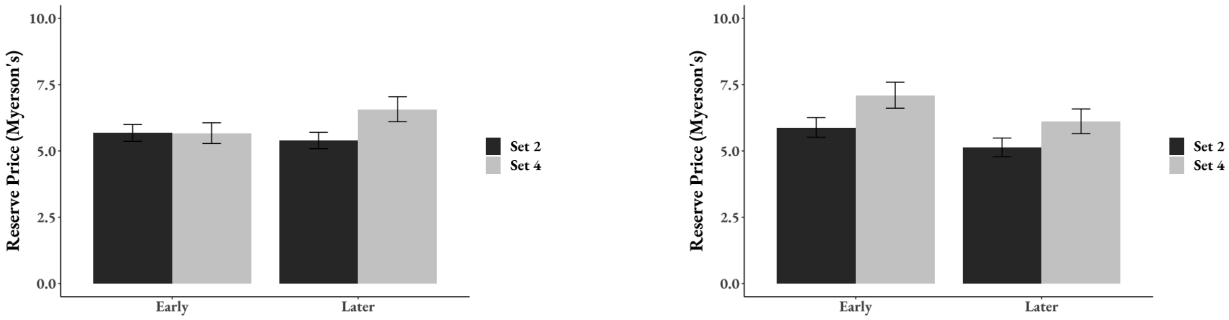


Figure B.11: Reserve Price in Period 2 (No Refund on Upfront Fee)

Figure B.12 shows that sellers in treatment Set 4 set higher Myerson's reserve prices than those in treatment Set 2. (Set 2 vs. Set 4: 5.39 vs. 6.57 in in the later stages of Period 1, $p = 0.04$; 5.88 vs. 7.10 in the early stages of Period 2, $p = 0.05$. Two-sided t-test.)

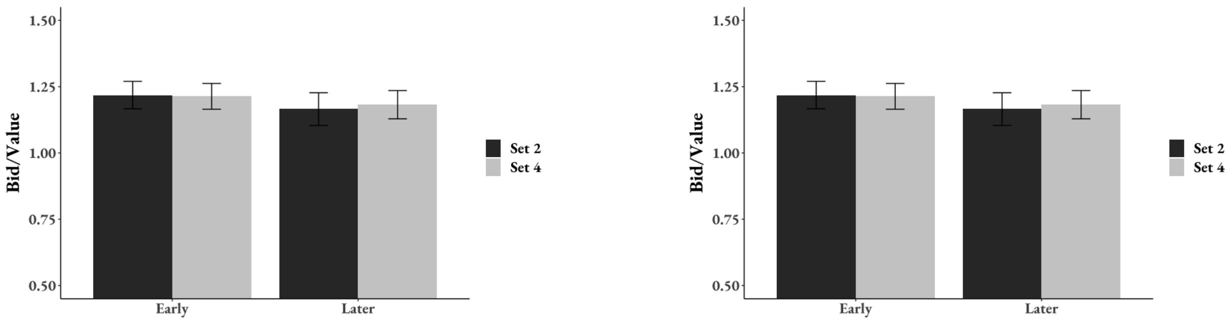


(a) In Period 1

(b) In Period 2

Figure B.12: Myerson's Reserve Price

We find that buyers overbid in general. The overall bid-value ratio is significantly greater than 1 in the two periods (1.19 in Period 1, p¡0.01 in Period 1; 1.20 in Period 2, $p < 0.01$). Figure 1 shows the bid-value ratio in each treatment and in each stage. We do not observe any treatment difference in overbidding (1.22 vs. 1.21 in the early stages in Period 1, $p = 0.92$; 1.17 vs. 1.18 in the later stages in Period 1, $p = 0.77$; 1.20 vs. 1.21 in the early stages in Period 2, $p = 0.91$; 1.19 vs. 1.20 in the early stages in Period 2, $p = 0.89$. Two-sided t-test).



(a) In Period 1

(b) In Period 2

Figure B.13: Bid/Value Ratio

Appendix C. Instructions

Welcome

This is an experiment in the economics of decision making. Your earnings will depend on your decisions. If you follow the instruction carefully and make thoughtful decisions, you may earn a considerable amount of money.

Your payoff will be determined by the experimental points that you earn during the experiment. The points will be converted into dollars at the end of the experiment at the following rate:

$$10 \text{ Points} = 1 \text{ Dollar.}$$

Roles in the two-period experiment

There are two roles in this experiment, the Seller and the Buyer. Half of you will be selected at random to have the role the Seller, the other half of you will have the role of Buyer. Your role will NOT change during the whole experiment.

You will learn whether you are the Seller or the Buyer prior to making any decision.

There are 2 practice rounds and 10 experimental rounds. In each round, one Buyer and one Seller will be randomly paired. The Buyer will be paired with a different Seller in different rounds. Each round has 2 periods.

Your experimental task in each round

The Buyer can buy one item in each period from the Seller by making a bid. The cost of producing the item for the Seller is zero.

The value of the item for the Buyer in each period might be different. The value of the item is **only known to the Buyer**. The Seller is not told the true value of the item but they are told what the possible values are, and how likely that value is to be selected.

If you are the Buyer:

You can gain points when you buy the item from the Seller. The amount of points you receive is equal to your given value of the item minus the amount you pay the Seller.

In another round you may have to pay an entry fee. If you pay this, you lose some points but have a chance to buy the item. If you don't pay, you have no chance to buy the item.

If you are the Seller:

You can gain points when you sell the item to the Buyer. The amount of points you receive is equal to the amount the Buyer pays you.

You will start with **60 points** in each round.

Trading Procedure

To start:

The Seller first decides on the trading structure for the two periods. The Seller will choose between structure A and structure B, which will be explained in detail on the following page.

After the structure is chosen, in each period:

The Buyer and Seller are shown the possible values of the item. The Seller chooses a secret price for the item and this price is kept hidden from the Buyer.

The Buyer is told the value of the item, and the possible values that the Seller is given. The Buyer then has the opportunity to make a bid on the item.

After the Seller has set the price and the Buyer has made a bid (if they chose to make a bid), results from this are shown and the Buyer's bid amount is revealed to the Seller. Whether the Buyer wins the item and how much they must pay is partially determined by the trading structure that the Seller chose.

The next few pages go over the two trading structures that the Seller will choose from.

Trading Structure A

In Period 1

The Buyer has a 50% chance of getting the item **for free**. If the Buyer does get the item for free, the Buyer receives the item without paying the Seller any point.

If the Buyer does not get the item for free, the Buyer can buy the item if their bid is greater or equal to the secret price set by the Seller. Even if the Buyer's bid is higher than the Seller's price, the Buyer only has to pay the Seller's price to receive the item.

In Period 2

Entry fee is required for the Buyer.

In treatment Set 2 it reads:

The Buyer must pay an entry fee to be able to bid on the item. At this point, they know the potential values of the item but not their true value.

Instead of the Seller choosing the amount of the entry fee, The Computer will set an entry fee that is beneficial to the Seller, based on the Buyer's bid in Period 1 and the possible values for the item in this period.

In treatment Set 4 it reads:

The Buyer must pay an entry fee set by the Seller to be able to bid on the item. At this point, they know the potential values of the item but not their true value.

If the Buyer doesn't pay the entry fee, the game ends.

If the Buyer pays the entry fee, the Buyer gets to learn their true value of the item for Period 2. Once they pay this fee, the Buyer has a chance to earn a refund on the entry fee, meaning they receive all the points they paid for the entry fee back.

The Buyer has a 50% chance to receive the refund on the entry fee and a 50% chance of not receiving the refund.

In treatment Set 2 it reads:

If the Buyer does not receive the refund, the secret price for the item will be chosen by the computer. Instead of the Seller choosing the price, the Computer will set a price that is optimal for the Seller.

If the Buyer does receive the refund, the secret price for the item will be chosen by the Seller.

In treatment Set 4 it reads:

The Seller might set different secret price for the two cases.

The same rules for the Buyer receiving the item apply in either case, if their bid is higher than the secret price, then they receive the item and pay the Seller the secret price.

Summary of Structure A:

In Period 1, the Buyer has a 50% chance of receiving the item for free.

In Period 2, the Buyer has a 50% chance of receiving a refund on the entry fee if they choose to pay it.

Trading Structure B

In period 1

There is no opportunity for a free item.

Both the Buyer and the Seller receive the possible values for the item.

The Seller sets a secret price for the item that is hidden from the Buyer.

The Buyer receives their true value of the item and makes a bid on the item. The Buyer can buy the item if their bid is greater or equal to the secret price set by the Seller. Even if the Buyer's bid is higher than the Seller's price, the Buyer only has to pay the Seller's price to receive the item.

In Period 2

There are no entry fees required.

Repeats the process of Period 1. The Seller makes a new secret price and the Buyer receives a new value for the item and makes a bid.

Summary of Structure B:

In Period 1, there is no opportunity for a free item.

In Period 2, there is no entry fee required.

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