Non-clairvoyant Dynamic Mechanism Design: Experimental Evidence

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Abstract

Dynamic mechanisms provide a powerful means for optimizing the revenue and efficiency of repeated auctions. However, implementing them is complicated due to a number of conditions that are difficult to satisfy in practice. These include the fact that the auction designer must be clairvoyant, in the sense that they must have reliable forecasts of participants' valuation distributions in all future periods. Recently, Mirrokni et al. (2020) introduced a non-clairvoyant dynamic mechanism and showed that it is optimal within the class of dynamic mechanisms that do not rely on strong assumptions regarding knowledge about the future. We showed, however, that an optimal static mechanism (a Myerson auction) can under certain conditions outperform their dynamic mechanism. Here, we report data from an experiment designed to test the performance of the Mirrokni et al. (2020) mechanism in relation to the Myerson auction. Our results support the theory: the optimal non-clairvoyant dynamic mechanism either outperforms or underperforms the repeat static Myerson according to theory predictions. Our results highlight the practical importance of non-clairvoyant mechanisms as implementable approaches to dynamic auction design.

Keywords: Non-clairvoyant, Dynamic, Mechanism, Experiment

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1. Introduction

Dynamic auction environments are ubiquitous. They include the many types of repeated procurement activities of a firm within long-term principal-agent relationships. Another important example is online advertising markets where advertisers (the buyers) submit bids for the impressions (items) arriving one-by-one from the platform (the seller). While advertisers possess private information regarding the item valuations, the public information about the valuation distribution can change suddenly due to naturally occurring events. Consequently, both seller and buyer face Knightian uncertainty[3].

The theory literature on the dynamic mechanism design is rich and sophisticated; however, to obtain results, the literature has traditionally assumed "clairvoyance," in the sense that the distributions of buyers' valuations across all periods past, present and future are common knowledge. Under this assumption, the dynamic mechanism design can be shown to achieve more revenue for the seller (Courty and Li, 2000; Pavan et al., 2014) and to generate more efficient outcomes (Bergemann and Välimäki, 2010; Athey and Segal, 2013). Indeed, Papadimitriou et al. (2016) demonstrate that the revenue from clairvoyant dynamic mechanisms can be arbitrarily large compared to the Myerson (1981) repeated static optimal mechanism (henceforth RS).

We see few examples of natural environments implementing optimal dynamic mechanisms, despite decades of theory advances on dynamic mechanisms, and the practical interest in optimal auction design. A key reason is that such mechanisms require both sellers and buyers to hold identical and correct beliefs about the future. This condition is obviously difficult to satisfy. Moreover, optimal dynamic mechanisms are environment-dependent, complex, and lacking in general form (Mirrokni et al., 2020). The complexity of optimal clairvoyant dynamic auction mechanisms may also explain why they have not been studied

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[3]As opposed to Bayesian uncertainty, Knightian uncertainty is a lack of any distributional knowledge.

in the experimental literature, which has otherwise devoted substantial attention to various single- and multi-good static or repeated-static auction environments[4].

Mirrokni et al. (2020) developed a non-clairvoyant dynamic mechanism (henceforth NC) that is optimal among non-clairvoyant mechanisms where designers are restricted from using future distributional information. It does not require information about future valuations, but is also robust to differences in beliefs across participants; simple in form; and scenario-independent. Here, our study focuses on the two-period single-buyer environment, where the optimal non-clairvoyant mechanism can theoretically guarantee revenues equal to at least 50% of those produced by the optimal clairvoyant mechanism.

At a high level, the two-period single-buyer non-clairvoyant mechanism proceeds as follows: In the first period, sellers provide half of the items at no cost. The other half of the items are sold according to Myerson's auction. In the second period, sellers ask for an up-front buyer-specific fee to enter the auction. They then conduct auctions with buyer-specific reserve prices. When the auction concludes, half the buyers are refunded their up-front entry fee. As detailed below, a key result in Mirrokni et al. (2020) is that it guarantees the inter-period revenue that comes from using past bid information: the second period entry fees and reserve prices can be set so that buyers have an incentive to enter, while the inter-period revenues of sellers (which comes from linking past information and current information together) are bounded below by one-half of the expected inter-period revenue from an optimal clairvoyant mechanism. Depending on realizations of second-period buyer values and corresponding inter-period revenues, total sellers' revenues in NC can be much greater than expected revenues using the repeat Myerson mechanism. The reason is that repeat static generates optimal intra-period revenues that comes from using only current information, but zero inter-period revenues.

[4]For the single good dynamic mechanism, see Courty and Li (2000), Eső and Szentes (2007), Board (2007) Filiz-Ozbay and Ozbay (2007); for single good repeated selling, see Baron and Besanko (1984), Papadimitriou et al. (2016), Balseiro et al. (2018), Devanur et al. (2019), Chawla et al. (2022), etc; for multiple good static mechanism design, see McAfee and McMillan (1988), Armstrong (1996), Manelli et al. (2006). See more discussion in section 2, Literature Review.

The non-clairvoyant approach incorporates several mechanisms that are widely used in natural environments: auctions with reserve prices are common on eBay and online advertising markets; upfront fees have the same form as membership fees used in Amazon Fresh and Costco; and individualized reserve prices are closely related to customized coupons, like those used by CVS. As a practical matter, however, one would only choose to implement Mirrokni et al. (2020) when it is likely to outperform the repeated static Myerson's auction under the non-clairvoyant environment. Intuitively, in the two-period case, the non-clairvoyant dynamic mechanism outperforms the repeated static mechanism whenever expected revenues from the entry fee and associated reserve price in the second period more than offset the reduced revenue due to giving away items in the first period. This occurs whenever inter-period revenue is sufficiently higher than intra-period revenue. More specifically, this occurs whenever buyers' expected second-period valuation is sufficiently great in relation to the expected revenue from the Myerson auction[5]. When the intra-period revenue is sufficiently greater than inter-period revenues, then the repeated static is preferable to NC (e.g., if the buyer consistently values the item at zero in the second period, RS generates more revenue than NC). The reasoning is similar: the expected buyers' valuation is an upper bound for a sellers' expected revenue in every period. When expected revenue in the second period is not sufficient to offset the loss in the first period, the non-clairvoyant mechanism will underperform in relation to a Myerson auction.

Note that buyers' willingness to pay an upfront participation fee in the second period is crucial to the theoretical performance of the non-clairvoyant mechanism. Theory requires only that buyer behavior satisfy ex-post individual rationality, rather than single-period individual rationality. That is, the buyer need only have non-negative total utility given the up-front fee. However, whether buyers actually behave as theory predicts remains an open and empirical question. Davis et al. (2014) observed that buyers do not enter 100% of auctions they should enter. One example in natural environments is Amazon, where

[5] For example, if there are possible "target buyers" with high valuations but low probability, Myerson's auction sets low reserve price and generates low revenue, while NC can extract more revenue by setting upfront fee and higher reserve price in the second period.

customers can shift to monthly Prime fees by canceling their membership at the beginning of the month. Considering this, the non-clairvoyant mechanism might not achieve its theoretically promised revenues, as agents can opt out at any time during the dynamic game. Perhaps especially when buyers are risk-averse, prepaid upfront fees can perceived as a risky investment and may deter participation.

We conducted laboratory experiments to study behavior under the Mirrokni et al. (2020) non-clairvoyant mechanism and compare its performance to Myerson's auctions. To our knowledge, we are the first to investigate behavior under dynamic auction mechanisms in general, and optimal non-clairvoyant mechanisms in particular. We consider two scenarios, one where the repeated static Myerson's auction theoretically outperforms the optimal non-clairvoyant dynamic mechanism, and the other where theory predicts the reverse outcome.

We observe that revenue differences between auction formats are qualitatively consistent with theory predictions, despite the presence of systematic behavioral deviations from theory. In particular, we observe that: (1) in the non-clairvoyant dynamic mechanism, buyers enter less than predicted in the second period; and (2) in the repeated static mechanism, buyers substantially overbid. We provide evidence that both of these behavioral anomalies seem to be associated with risk aversion.

2. Literature Review

2.1. Optimal dynamic mechanism design

Our paper contributes to the optimal dynamic mechanism design literature[6], which studies how to determine price-discovery and allocation rules as agents (buyers) receive information over time. Since the seminal work of Baron and Besanko (1984), which analyzed monopoly regulations, it has been widely assumed that agents are "clairvoyant," in the sense that they know that everyone perfectly knows the stochastic process governing all future economic outcomes (information and states).

[6]For efficient dynamic mechanism design, see dynamic pivot mechanism (Bergemann and Välimäki, 2010), extended VCG in the interdependent-value case (Liu, 2018), and team mechanism (Athey and Segal, 2013).

The optimal clairvoyant dynamic mechanism lacks general form and but rather must be tailored to specific environments. For example, when agents face asymmetric uncertainty, the optimal mechanism involves subsidizing agents with lower future uncertainty in order to reduce rent-seeking by consumers facing higher uncertainty (Courty and Li, 2000). Alternatively, in the case where agents obtain a private value signal from the seller, the optimal mechanism includes a premium paid for extra information, combined with a second price auction where the winner pays the second-highest bid plus the premium (Eső and Szentes, 2007).[7] The optimal mechanism should be randomized when private information over periods is a Markov process (Pavan et al., 2014). Jackson and Sonnenschein (2007), Balseiro et al. (2018), and others have also found environment-specific results. In general, the optimal clairvoyant mechanism is environment-dependent. The reason is that because different environments constrain dynamic incentive compatibility and individual rationality, both of which are crucial for optimality, and different environments constrain them in different ways.

While clairvoyant mechanisms require participants' valuation distributions to be known across all future periods, yet this is difficult to achieve as a practical matter. Empirical results show that agents tend to have biased beliefs about the future (DellaVigna and Malmendier, 2006). Of course, one can design optimal clairvoyant mechanisms that try to take this into account. For example, if one assumes agents will be overconfident regarding the precision of their demand forecasts, it can be shown that the optimal mechanism is a three-part tariff similar to what is used for the kind used for cell-phone contracts (Grubb (2009); see also Eliaz and Spiegler (2008)).

Our paper studies a non-clairvoyant environment where future distributional knowledge is not available. As a result, reliable future forecasts regarding future distributions and outcomes are not needed. Mechanisms restricted from using future distributional knowledge can be shown to have a general form applicable to any non-clairvoyant environment (Mirrokni et al., 2020).

[7] Extension of infinite time horizon see Board (2007).

2.2. Non-clairvoyant dynamic mechanism design

There are two feasible mechanisms under the non-clairvoyant environment where sellers are restricted from using future information in designing current rules. The first option is to implement Myerson's auction (Myerson, 1981) in each period. We denote this as the repeated static mechanism (RS). In RS, rules in each period are independent of each other, in order to maximize the intra-period revenue that arises from using only current-period information. Given that there is no inter-period revenue (derived from linking past information to current information), the revenue from the RS as compared with optimal clairvoyant revenue can be arbitrarily small (Papadimitriou et al., 2016).

The second option we study is the optimal non-clairvoyant dynamic mechanism (NC) introduced by Mirrokni et al. (2020). NC uses past bid information to design future roles to maximize the revenue guarantee. We focus on the two-period single buyer case, where NC can guarantee revenues equal to at least 50% of those produced by the optimal clairvoyant mechanism under all scenarios, regardless of the size of the inter-period revenues.

In broad terms, to guarantee 50% of the optimal intra-period revenue, NC always allocates one-half of items in each period using Myerson's auction. In the two-period case we study here, to guarantee 50% of the optimal inter-period revenue, it allocates the other half of the items at a price of zero in the first period. Then, in the second period, it charges half the buyers a buyer-specific upfront entry fee to participate in the auction and sets buyer-specific reserve prices. Both the upfront entry fee and the reserve prices are set according to each buyer's first-period bid decisions.

NC cannot always outperform RS. The revenue comparison between the two mechanisms is determined by the relative size of intra- and inter-period revenues and is scenario dependent. To compare the performance of the two mechanisms, we design two different scenarios, one which theoretically favors the non-clairvoyant mechanism and one which favors the repeat-static approach.

Mechanism design under non-clairvoyance contributes to the recent interest in "simple" mechanisms that do not require players to make contingent plans across the entire future of a dynamic game (Li, 2017; Pycia and Troyan, 2022). Within this context, the optimal non-clairvoyant dynamic mechanism is the best response of sellers who perceive only their own current information set as simple. Both the optimal non-clairvoyant dynamic mechanism and the optimal repeated static mechanism with simple forms are implementable in the lab. We take advantage of laboratory experiments to provide comprehensive comparisons of the two mechanisms under different designated scenarios.

2.3. Experiments informing dynamic mechanism design

Experiments informing dynamic mechanism design have focused primarily on revenue or efficiency comparison among multi-unit sequential auctions. This literature assumes clairvoyance, and reports experiments where a Myersonian approach can be used. Manelli et al. (2006) compared efficiencies and found similar efficiency between the Vickrey auction and the ascending-price auction; Ledyard et al. (1997) observed that the simultaneous discrete auction outperforms the sequential auction in efficiency. Lucking-Reiley (1999) compared revenues and showed that revenue equivalence survives in all-pay and winner-pay auctions in the multi-unit setting; Brunner et al. (2010) observed revenues that vary among several non-deterministic combinatorial mechanisms; and Back and Zender (2015) showed lower experimental revenue than theoretically predicted in sealed bid auctions. Our paper differs from this line of experiments, as we study the feasibility of dynamic mechanisms in a non-clairvoyant environment, where agents' valuations evolve over time and future distributional knowledge is not available. This approach necessarily differs from environments with fixed agent's valuation but dynamic arrival or departure.

Whether buyers actually behave as theory predicts remains an important open and empirical question. Bidders' behavior has also been studied in the experimental literature to explain how experimental observations might differ from theoretical prediction: both overbidding (Neri, 2015) and underbidding (Chen and Takeuchi, 2010) have been observed; Kagel and Levin (2009) demonstrated the bounded rationality of bidders; and Bernard (2005) found affiliation of bids in repeated identical trials. Particularly in an environment where bidders incur a cost to learn their valuations, Davis et al. (2014) found fewer bidders entering an English auction where entry decisions were made simultaneously among bidders than the sequential entering and bidding mechanism. Results show that the sequential mechanism outperforms the English auction with regard to revenue, which overturns the theoretical prediction on revenue comparison.

Davis et al. (2014) also questioned whether auctions in experiments can meet the requirement of individual rationality. This is an important question for our study. The reason is that the possible upfront fee in the second period of the optional non-clairvoyant dynamic mechanism also serves as the entry cost for bidders. Risk-averse buyers in particular may perceive prepaid upfront fees as risky; as a result, such fees may deter their participation. In light of this, NC might fail to achieve its theoretically promised revenues. Therefore, in our experiments, we investigate whether buyers enter in the second period, as well as the extent to which partial entry of buyers impacts the revenue of NC.

3. Theoretical Framework

3.1. Non-clairvoyant dynamic environment

We study a two-period repeated selling environment with a single buyer. Each period introduces a new item the buyer can purchase. We use a single buyer over two periods to create a simple environment in which to apply the non-clairvoyant dynamic mechanism. We keep the setup simple to help participants understand the incentives of the environment. In both periods, it is common knowledge that there is no cost associated with producing an item; however, valuations are private information. The first-period valuation is independent of the second period's.[8]

The non-clairvoyant dynamic environment differs from the clairvoyant environment in that the latter assumes that prior distributions of the buyer's valuation in the two periods, (F_1 and F_2) are common knowledge for both the buyer and the seller at the beginning of the first period. By contrast, in the non-clairvoyant setting, the future distribution F_2 is

[8]Devanur et al. (2019) studied the repeated selling of fresh copies to consumers who have fixed valuation through multi-period. They focus on the effect of commitment power of seller on revenue, while we assume fully commitment power.

not available until the second period. Consequently, allocation rules and prices in the first period cannot take into account the second period distributional information.

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

a) The seller and the buyer learn the distribution of buyer's valuation for this period, F_t.

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

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

d) The seller implements their allocation rule $x_t(b_t)$ and price policy $p_t(b_t)$.

e) The buyer accrues period utility $u_t = u_t(b_t, v_t) = v_t * x_t(b_t) - p_t(b_t)$.

Here, we follow the common setting in the literature (Bergemann and Välimäki, 2019) and assume quasilinear preferences for the buyer. The total payoff of the buyer is the sum of utility in both periods without discounting: $U = u_1 + u_2$.

We focus on direct mechanisms satisfying the buyer's participation constraint. That is, 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.

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

Dynamic Incentive Compatibility implies that the buyer's best response to the seller's decisions is to report the buyer's true value in every period. DIC in the non-clairvoyant environment can be illustrated by backward induction: in the second period, the buyer maximizes their payoff by bidding the valuation; in the first period, the buyer also has an incentive to report the true value given that the buyer bids their value in the next period. Ex-Post Individual Rationality requires the total utility the agent obtains to exceed total payments after the realization of the value for all periods so that the buyer is incentivized to participate.

In a nutshell, under a non-clairvoyant environment, the mechanism uses no future distributional knowledge, but is required to satisfy DIC and EPIR. The optimal repeated static mechanism (Myerson, 1981) and the optimal non-clairvoyant dynamic mechanism (Mirrokni et al., 2020) are feasible under the non-clairvoyant environment described above. We introduce and compare the two mechanisms in Section 3.4.

3.2. Repeated Static Mechanism

While the non-clairvoyant environment restricts the seller from using future distributional knowledge, the seller can implement the optimal mechanism (Myerson, 1981) in each period independently. This is denoted as a repeated static mechanism. The reason is that the seller maximizes revenue in each of the two periods separately.

In the single-buyer case, the optimal revenue is obtained by conducting the auction with monopoly reserve price $r_t = arg\max r(1-F_t(r))$. Denoting the optimal reserve price in each period as r_1^*, r_2^*, respectively, optimal revenue in the two periods is $Rev_1^* = r_1^*(1 - F_1(r_1^*))$, $Rev_2^* = r_2^*(1 - F_2(r_2^*))$. Thus, the revenue in repeated optimal static mechanism is the sum of optimal revenues in the two periods, $Rev^S = Rev_1^* + Rev_2^*$.

The repeated static optimal mechanism satisfies DIC and EPIR, as it is incentive compatible in each period and satisfies single period individual rationality. In each period, it is a weakly dominant strategy for a buyer to bid their true value. The buyer obtains the item if their valuation exceeds the reserve price. Given that the seller is conducting Myerson's auctions in each period, we use the superscript M to denote the repeated static mechanism and summarize the allocation and price rules as follows:

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

Thus, in the repeated static mechanism, there is maximized intra-period revenue in each period, but zero inter-period revenue. The reason is that the mechanism does not use first-period knowledge in determining rules of allocation and price in the second-period. We denote the optimal clairvoyant dynamic revenue with both maximized intra-period revenue and inter-period revenue as Rev^*; the ratio $\frac{Rev^S}{Rev^*}$ can be arbitrarily small (Papadimitriou et al., 2016).

3.3. Optimal Non-clairvoyant Dynamic Mechanism

The objective of the non-clairvoyant dynamic mechanism (Mirrokni et al., 2020) is to guarantee maximum revenue, i.e., to maximize the non-clairvoyant revenue to clairvoyant revenue ratio, $\frac{Rev^{NC}}{Rev^*}$, for all second-period distributions which are unknown at the beginning of the first period. Therefore, in contrast to the repeated static mechanism, where rules in the two periods are independent, the optimal non-clairvoyant dynamic mechanism must consider past information when designing rules in the second period to ensure the inter-period revenue is also guaranteed.

In the two-period case, the optimal non-clairvoyant dynamic mechanism with at least one-half optimal clairvoyant revenue guarantee has a simple and general form: it guarantees one-half maximized intra-period revenue by allocating one-half item in each period via the Myerson's auction (M). It further guarantees at least one-half of the maximized inter-period revenue by allocating the other-half item in the first period via the Give For Free auction (F) to accumulate the most consumer surplus and allocating the other half-item in the second period via the Posted Price auction (P) to recoup all of the accumulated consumer surplus.

The Give for Free auction (F) allocates the item to any buyer for free, regardless of bid: $x_t^F = 1$ and $p_t^F = 0$. The Posted Price auction (P) exploits all trading surplus by setting an upfront fee in advance for all buyers and then conducting an auction with a reserve price. The upfront fee in the second period is customized for each buyer based on the buyer's bids in the first period, $s_2 = \min\{b_1, \mathbb{E}_{v_2}\}$. It is bounded by the second period expected valuation to ensure participation of the buyer *ex ante*. The associated reserve price r_2^P is set to ensure that the buyer's payoff in this period is zero, to maximize the intra-period revenue. That is, $\mathbb{E}_{v_2 \sim F_2}[v_2 - r_2^P]^+ - s_2 = 0$.

The optimal non-clairvoyant dynamic mechanism is dynamic incentive compatible: in each period, it is a uniform combination of mechanisms incentivizing a buyer to report true values. In ensuring the upfront fee is bounded by the first-period valuation, it also satisfies the EPIR. Below, we summarize the rules of allocation and price rule of the non-clairvoyant dynamic mechanism design.

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

The optimal non-clairvoyant dynamic mechanism design can thus be applied to environments, as its design does not use future distributional knowledge.

3.4. Theoretical revenue comparison

In contrast to the repeated static mechanism maximizing intra-period revenue independently with zero inter-period revenue, the optimal non-clairvoyant dynamic mechanism guarantees one-half optimal inter-period revenue in all scenarios with the loss of one-half optimal intra-period revenue. As a result, the revenue comparison of the optimal non-clairvoyant dynamic mechanism and repeated static mechanism is determined by the relative size of intra- and inter-period revenues and is specific-scenario dependent.

In the scenario where there is a thin market in the second period, *i.e.*,the distribution of the buyer's valuation is long-tailed, the optimal static revenue produced by Myerson's auction is relatively small compared to the high expected value in that period. This means that the optimal non-clairvoyant dynamic mechanism outperforms the repeated static mechanism: it loses one-half less intra-period revenue, but guarantees one-half greater inter-period revenue through the upfront fee in the Posted Price auction in the second period. We describe a specific scenario using distributions of buyers' valuations in each period (F_1, F_2). We first define Scenario A as below.

Scenario A (S_A): under which the non-clairvoyant mechanism has more revenue than the repeated mechanism.

$$
\begin{cases}
F_1 = F_A = & \{(v, p(v))\} = \{(2, \frac{1}{2}), (4, \frac{1}{2})\} \\
F_2 = F_B = & \{(v, p(v))\} = \{(2, \frac{1}{2}), (4, \frac{1}{4}), (8, \frac{1}{8}), (16, \frac{1}{16}), (32, \frac{1}{16})\},
\end{cases}
$$

where F_1 and F_2 are discrete distributions shown in pairs of values and associated probabilities $(v, p(v))$ in each period.

In Scenario A, the repeated static mechanism can achieve revenue of 4, as the reserve price of Myerson's auction (M) is the same in both periods, $r^M = 2$. The revenue in M is 2 in each period, which is relatively low compared to the high expected value of the long-tailed distribution F_2 in the second period, $\mathbb{E}_{v_2} = 6$. Thus, the non-clairvoyant dynamic mechanism can outperform the repeated static mechanism through high inter-period revenue produced by Posted Price auction in second-period. The upfront fee in the Posted Price auction (P) is $s_2 = \min\{b_1, 6\}$; the associated reserve price is $r_2^P = 0$ if $b_1 \geq 6$; $r_2^P = 2$ if $b_1 = 4$; $r_2^P = 8$ if $b_1 = 2$; and $r_2^P = 32$ if $b_1 = 0$. This leads to a revenue of 5 in Posted Price auction. By assuming the buyer bids their true value in Period 1 and fully participates in both periods, we derive the theoretical revenue comparisons of the two mechanisms in Table 1.

S1-Revenue	Non-clairvoyant Dynamic		Repeated Static	
Period 1	Give for Free (F)	0	Myerson's Auction (M)	2
	Myerson's Auction (M)	2		
Period 2	Post Price Auction (P)	**5**	Myerson's Auction (M)	2
	Myerson's Auction (M)	2		
Total		4.5		4
Intra-period revenue		2		4
Intra-period revenue		2.5		0

Table 1: Theoretical Revenues under Scenario A.

While switching the distribution of the two periods does not alter the revenue in the repeated static mechanism, it affects the performance of the non-clairvoyant dynamic mechanism design. If we switch the scenario described above, in the non-clairvoyant dynamic mechanism, the revenue loss in the first period in Give for Free auction (F) cannot be covered by the upfront fee bounded by the low expected value in the second period. This leads to an overturn of previous revenue comparison. We define Scenario B as below.

Scenario B (S_B): under which non-clairvoyant mechanism has less revenue than the repeated static mechanism.

$$F_1 = F_B, F_2 = F_A.$$

In scenario B, the expected value in the second is not sufficiently great, $\mathbb{E}_{v_2} = 3$. The upfront fee in Posted Price auction (P) is $s_2 = \min\{b_1, 3\}$, and the associated reserve price is $r_2^P = 0$ if $b_1 \geq 3$; $r_2^P = 1$ if $b_1 = 2$; and $r_2^P = 4$ if $b_1 = 0$. Although the Posted Price auction in the second period produces revenue of 3, extracting all the trading surplus, it still cannot make up the loss of a half-optimal intra-period revenue. Thus, the repeated static mechanism produces more revenue than the non-clairvoyant dynamic mechanism in S_B, as shown in Table 2.

S2-Revenue	Non-clairvoyant Dynamic		Repeated Static	
Period 1	Give for Free (F)	0	Myerson's Auction (M)	2
	Myerson's Auction (M)	2		
Period 2	Post Price Auction (P)	**3**	Myerson's Auction (M)	2
	Myerson's Auction (M)	2		
Total		3.5		4
Intra-period revenue		2		4
Intra-period revenue		1.5		0

Table 2: Theoretical Revenues under Scenario B.

4. Experimental Design and Hypotheses

We design our experiment to compare the performance of the non-clairvoyant dynamic mechanism and repeated static mechanism, as discussed in Section 3.4. To further investigate the extent to which incentive compatibility and individual rationality impact these mechanisms, we also examine truthful valuation revelation and participation behaviors.

In our experiments, participants act as buyers by trading with a robot seller individually for two items (one item per period). Participants know that there is zero cost associated with producing the items. Participants also know that the buyer may value the same item differently in different periods, and the robot seller will never know the buyer's value for the item.

At the beginning of each period, participants learn the possible valuations in that period via a pie chart. They know that the robot seller will set the reserve price in that period based on the distribution of possible buyer values. If there is an upfront fee for the period, participants learn their value of the item only after they pay the upfront fee. To win the item, a buyer must bid greater than or equal to the seller's reserve price. When this occurs, the buyer pays a price equal to the reserve price.

We create the non-clairvoyant environment by waiting until the second period to reveal possible values of the second item, so that neither the robot seller nor the participants have any knowledge in the first period regarding the future value distribution. Treatments vary both in the mechanism used to allocate the items, and in the buyer value distributions.

4.1. Experimental design

Our experiments have a two-mechanism-by-two-scenario design. Participants are randomly assigned to one of four treatments. Each treatment consists a two-period treading game (one round).[9] The two scenarios are S_A and S_B, as discussed in Section 3.4. In the two scenarios, we switch the distributions in the two periods, which derives reversed theoretical revenue comparison prediction.

For the two treatments conducting the repeated static mechanism, participants are told that there is no upfront fee[10] in each period and the robot seller sets reserve prices for each period based on that period's value distribution. Buyers purchase the item if they bid greater than or equal to the reserve price. They only need to pay the reserve price, even if they actually bid higher. The reserve price in each period is set as r_M, as described in Section 3.4.

For the two treatments conducting the non-clairvoyant mechanism treatment, the buyer knows there is no upfront fee in the first period. They also know that they have a 50%

[9]We used a one-shot game to establish a non-clairvoyant environment where both buyers and sellers are not aware of future distributional knowledge. Also, buyers' expectations about the future cannot play a role in a one-shot game.

[10]For subjects' ease of understanding, we used "membership fee" instead of "upfront fee," and "secret price" instead of reserve price in the experiment.

chance of purchasing the item for nothing; otherwise, they need to bid greater than or equal to the reserve price to earn the right to buy the item at the reserve price. In the second period, after learning the distributional knowledge F_2, they observe the upfront fee and decide whether to enter the auction. If they decide to pay the upfront fee, they can they learn their valuation for the item and make a bid accordingly. They are told that there is a 50% chance for the upfront fee to be refunded. They purchase the item if their bid is greater than or equal to reserve price, in which case the purchase price is equal to the reserve price. The reserve price in the first period is set as r_M. In the second period, half of the buyers are assigned to Myerson's auction, with reserve price r_M, and the remaining buyers are assigned to the Posted Price auction, with reserve price r_P.

The timeline for the NC treatments is as follows:

In Period 1,

a) The seller sets a reserve price r_1 based on the distributional knowledge F_1.
b) The buyer learns their value (v_1) and makes a bid, b_1.
c) The buyer has a 50% chance to get the item for free, $p_1 = 0$;
   Otherwise, the buyer can buy the item only when $b_1 \geq r_1$ and pays $p_1 = r_1$.
d) The buyer receives information about the reserve price and the buyer's payoff.

In Period 2,

a) The seller sets an upfront fee $s_2 = min(b_1, \mathbb{E}_{v_2})$.
b) The buyer decides to pay the upfront fee ($enter = 1$) or to leave ($enter = 0$). If the buyer leaves, the game is be over.
c) If the buyer pays, ($enter = 1$):
   i) The buyer learns their value, v_2, and makes a bid, b_2;
   ii) The buyer has a 50% chance to be refunded the upfront fee;
   iii) The seller sets two reserve prices r_2 based on the F_2, s_2 and whether the buyer receives the refund on the entry fee. The buyer can buy the item only when $b_2 \geq r_2$ and pays $p_2 = r_2$.

To mitigate potential losses, we restrict the bid to any positive integral less than twice the buyer's valuation. Each buyer starts with 50 points and can lose points during the experiment. After the two-period trading experiment we elicit risk attitudes using Holt and Laury (2002).

4.2. Hypotheses

We implement the environments detailed in Section 3.4 above, and our first hypotheses are based on the theoretical revenue comparison results derived in that section. We predict that the non-clairvoyant dynamic mechanism outperforms the repeated static mechanism in scenario S_A. When we flip the two distributions in the two periods in scenario S_B, the second period does not provide enough intra-period revenue to compensate for the loss from giving half of the items for free in the first period. We predict that the repeated static mechanism outperforms the optimal non-clairvoyant dynamic mechanism design. Our Hypothesis 1 is as follows.

Hypothesis 1. *In S_A, the non-clairvoyant mechanism generates greater revenue than the repeated static mechanism;*

In S_B, the non-clairvoyant mechanism generates less revenue than the repeated static mechanism.

We also investigate the bidding and participation behaviors of buyers. We first state a simple proposition:

Proposition 1. *Any non-clairvoyant mechanism achieving more revenue than repeated optimal Static mechanism violates single period Individual Rationality (IR).*

The proof is direct. Myerson's auction is the solution that satisfies single-period incentive compatibility and single-period individual rationality (IR). Likewise, the non-clairvoyant mechanism satisfies IC for each period. Thus, if the non-clairvoyant mechanism has more revenue under some market environment (e.g., Scenario A), it must violate IR in the second period.

It is worth noting that to ensure high revenue, the robot seller sets the upfront fee before the buyer decides whether to enter the market. Risk-averse buyers should take into consideration the risk[11] that the upfront fee will not be refunded. Thus, rational buyers facing high upfront fees have an incentive not to enter the second period. When upfront fees are not paid, the revenue of the non-clairvoyant mechanism declines. We have our Hypothesis 2:

Hypothesis 2. *Some buyers choose not to pay the upfront fee, such that the experimental revenue of the non-clairvoyant mechanism is less than its theoretical prediction.*

Additionally, whether participants in experiments bid their true value impacts the performance of dynamic mechanism design. Particularly in the non-clairvoyant dynamic mechanism, the upfront fee in the second period is based on the bid in the first period. Given that buyers, in general, overbid in experiments, we might observe less overbidding in the non-clairvoyant dynamic mechanism. There are two reasons for this: first, buyers will be less aggressive as they have one-half chance to get a free item in the first period; second, buyers are deterred by a possible nonrefundable upfront fee, so they bid less in case they lose more. This suggests our Hypothesis 3:

Hypothesis 3. *Participants' bids are closer to true value under NC than RS.*

4.3. Procedures

The study was pre-registered on OSF Registries (`https://osf.io/a2ber/`). We recruited our participants from George Mason University. We advertised our study on the recruiting system (experiments.gmu.edu). We pre-selected only subjects over 18-years-old. The advertisement specified that the experiment would last for 45 minutes. Subjects were informed that they could receive a participation bonus of $10, as well as additional payments, depending on their decisions in the experiment.

The experiment was programmed in oTree (Chen et al., 2016) and conducted from September to October in 2021. We used a between-subject design where 256 Subjects

[11]We view it as risk rather than loss as the non-clairvoyant dynamic mechanism is designed to satisfy the EPIR, which means the buyer is guaranteed of non-negative expected total payoff after the realization of valuations in two periods. In addition, the buyer is not informed whether the upfront fee is refunded or not before making a bid in Period 2.

were randomly assigned to one of the four treatments. For each treatment, we collected 64 independent observations.[12]

Subjects received instructions and then took a quiz. After answering all quiz questions correctly, they proceeded to a two-period practice session and a two-period bidding task, followed by a risk-aversion elicitation (Holt and Laury, 2002). They were paid in cash privately after completing a demographic questionnaire.

5. Results

Demographic summary statistics are reported in Table 3. We have balanced gender for each treatment. Among 256 subjects, 47% are male, with an average age of 22. The average risk attitude index[13] from is 4.63 (risk aversion),[14] and the average payoff is $17.1 (including $10 show-up bonus).

Treatment	**Scenario A**		**Scenario B**	
	NC	**RS**	**NC**	**RS**
Age	21.6	22.3	21.9	22.7
Gender (Male=1)	0.48	0.43	0.50	0.47
Risk aversion	4.45	4.91	4.51	4.63
Observation	64	64	64	64

Table 3: Summary Statistic

[12]We ran G^* power analysis:for $\alpha = 0.05$, balanced sample size of 64 in each treatment, one-tail t-test has power $= 1 - \beta = 0.85$ for mechanism comparison in Scenario A, power $= 1 - \beta = 0.99$ in scenario B. We assume 10% of buyers quit the second period in NC, and 20% buyers deviate from bidding true value in both NC and RS in determining the pairs (mean, standard deviation): (3.78, 0.80) for RS, (4.20, 0.96) , (3.10, 0.83) for NC in Scenario A, and in Scenario B, respectively.

[13]The risk attitude index is the point where the subject switches from choosing a risky lottery to a safe lottery. We observe 14.8% of subjects to switch at least twice in the experiment, and there is no significant difference between treatments in switching more than once.

[14]We do not observe significant differences on gender, age, or risk attitude among treatment.

5.1. Experimental observations match with theoretical prediction

We first test Hypothesis 1 by comparing revenues between the two mechanisms under two scenarios. Theory predicts that the non-clairvoyant dynamic mechanism should outperform the repeated static mechanism in Scenario A, but not in Scenario B. Our experimental results verify the theoretical prediction.

The revenue of the first period is shown in Figure 1[15]. In S_A, the first-period revenue in the non-clairvoyant dynamic mechanism (0.97) is only half of the revenue in the repeated static mechanism (1.93). The reason is that the non-clairvoyant dynamic mechanism gives half of the buyers a free item in the first period. The experimental revenue is consistent with the theoretical prediction. Given that the optimal reserve price is the same in both scenarios, the revenue comparison under Scenario B has exactly the same result as Scenario A.

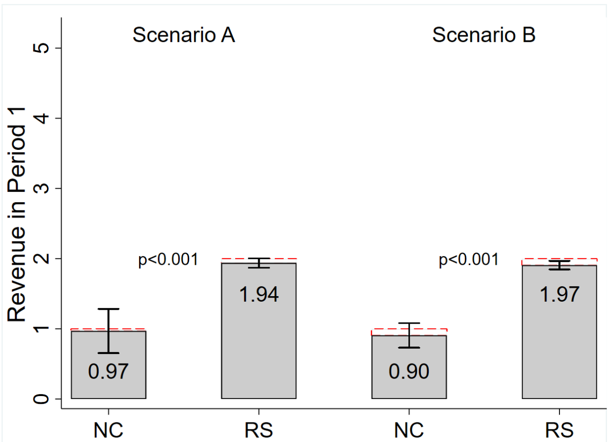

Figure 1: Revenue of Period 1 in each Treatment

In the second period, the non-clairvoyant dynamic mechanism sets up the upfront fee after both seller and buyer learn the distributional knowledge. Observing the customized upfront fee, buyers decide whether to enter the second period trade and bid on the item or to quit. When buyers are assigned to the Myerson's auction, the reserve price is the optimal reserve price (2), and the upfront fee is refunded; otherwise, they cannot redeem

[15] Standard errors are shown in those error bars

the upfront fee, and usually pay a lower reserve price. The upfront fee, which is bounded by the expected valuation of buyers, plays a critical role in the success of the non-clairvoyant dynamic mechanism. As a result, if the economy is in Scenario A, where the expected valuation of buyers is increasing in the second period, the seller can set a higher upfront fee. This leads to the outperformance of the non-clairvoyant dynamic mechanism compared to the repeated static mechanism. On the other hand, if the economy is in Scenario B, where the second-period valuation is lower on average, the non-clairvoyant dynamic mechanism is out-performed by the repeated static mechanism.

Total revenue is shown in Figure 2: bars with red dash outlines represent the theoretical revenue prediction; light gray bars represent the first-period revenue; dark grey bars represent the second-period revenue; and the whisker bars represent one standard error. The experimental revenue of the non-clairvoyant dynamic mechanism is significantly greater than the repeated static mechanism in Scenario A ($p = 0.057$, one-sided t-test[16]), but is significantly less in Scenario B ($p < 0.001$, one-sided t-test)[17].

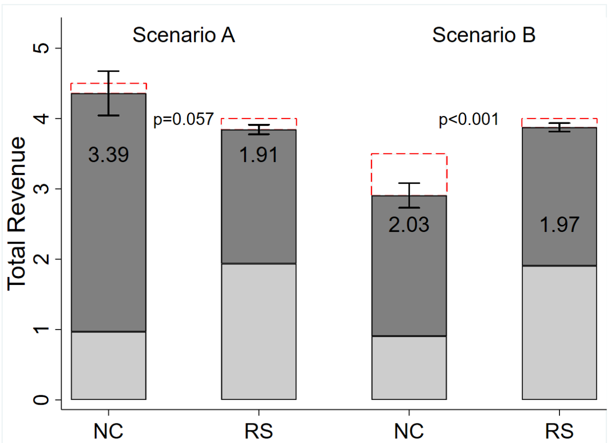

Figure 2: Total Revenues in each Treatment

[16]We do not use Wilcoxon–Mann-Whitney rank sum test as the variance of non-clairvoyant revenue is greater than the variance of repeated-static revenue. For one-sided Wilcoxon–Mann-Whitney rank sum test, $p = 0.495$ in Scenario A, $p < 0.001$ in Scenarios B.

[17]To be more specific, we use t-test with unequal variance here. And we apply one-side test as a response to the theoretical prediction

The revenue decomposition of the two mechanisms in S_A is reported in Table 4. In the first period, the non-clairvoyant dynamic mechanism is the uniform combination of the Give For Free mechanism and Myerson's auction. In the second period, the non-clairvoyant dynamic mechanism combines Posted Price Auction with Myerson's auction in the same way. The theoretical revenue prediction and the experimental data on revenue are shown in the third and the fourth columns, respectively. The repeated static mechanism conducts Myerson's auction in each period. Theoretically, Myerson's auction achieves the same revenue in both periods. By comparing the theoretical revenue with the experimental revenue, we further verify that the experimental result supports the theory.

Revenue in S_A	**Non-clairvoyant Dynamic**			**Repeated Static**		
	Theory		**Experiment**	**Theory**		**Experiment**
Period 1	Give it for free	0	0	Myerson's	2	1.94 (0.04)
	Myerson's auction	2	1.94 (0.06)			
Period 2	Post Price Auction	**5**	4.84 (0.47)	Myerson's	2	1.91 (0.05)
	Myerson's auction	2	1.94 (0.06)			
Total		5	4.35 (0.32)		4	3.84 (0.07)

Notes: Standard errors in parentheses.

Table 4: Revenue Decomposition in Scenario A

It is worth noting that the Posted Price auction in the second period gives the non-clairvoyant dynamic mechanism the most revenue in Scenario A: the theoretical revenue of the Posted Price auction is 5 and the experimental revenue is 4.84. However, the Posted Price auction cannot always provide good revenue, as the upfront fee sellers can charge has an upper bound equal to the second-period expected valuation of the buyer. This is why in Scenario B, the Posted Price auction can only achieve a revenue of 3, as the second-period expected valuation of buyers is decreasing from 6 to 3. Accordingly, even though the Posted Price can compensate for part of the revenue loss from the Give For Free mechanism in the first period, the non-clairvoyant dynamic mechanism fails to outperform the repeated static mechanism, both theoretically and experimentally. The revenue decomposition of the two mechanisms in Scenario B is reported in Table 5.

Revenue in S_B	Non-clairvoyant Dynamic			Repeated Static		
	Theory		Experiment	Theory		Experiment
Period 1	Give it for free	0	0	Myerson's	2	1.91 (0.05)
	Myerson's auction	2	1.81 (0.10)			
Period 2	Post Price Auction	**3**	2.31 (0.92)	Myerson's	2	1.97 (0.03)
	Myerson's auction	2	1.75 (0.12)			
Total		3.5	2.93 (0.18)		4	3.88 (0.06)

Notes: Standard errors in parentheses.

Table 5: Revenue Decomposition in Scenario B

We conclude our first result as below.

Result 1. *Hypothesis 1 is supported. Experimental observations match theoretical predictions.*

In S_A, the non-clairvoyant dynamic mechanism gains more revenue than the repeated static mechanism.

In S_B, the non-clairvoyant dynamic mechanism gains less revenue than the repeated static mechanism.

5.2. Risk aversion and participation decisions

At the beginning of the second period in the non-clairvoyant dynamic mechanism, buyers can refuse to pay upfront fees and choose to quit. In Scenario A, four buyers quit the second period; this number doubles in Scenario B. Buyers choosing not to pay upfront fees negatively impacts the revenue of the non-clairvoyant dynamic mechanism.

As shown in Figure 3, if the four buyers paid the upfront fee, entered in the second period, and bid their true value, the revenue of the non-clairvoyant mechanism in S_A would increase by 78% of the gap between the theoretical prediction and the experimental observation[18]. The remaining 22% of the gap is attributable to underbidding during both periods. Underbidding in the first period results in fewer paid upfront fees, and therefore less revenue in Period 2. Underbidding in the second period means buyers do not get to buy the item, as their bid is less than reserve price.

[18]The revenue of NC (4.47) if all buyers enter in Scenario A is less than its theoretical revenue (4), but the difference is not significant (p=0.46, one-sided t-test)

If the eight buyers paid the upfront fee, entered in the second period, and bid their true value, the revenue of the non-clairvoyant mechanism in S_B would increase by 45% of the gap between theoretical prediction and experimental observation[19]. The remaining 55% comes from their underbidding.

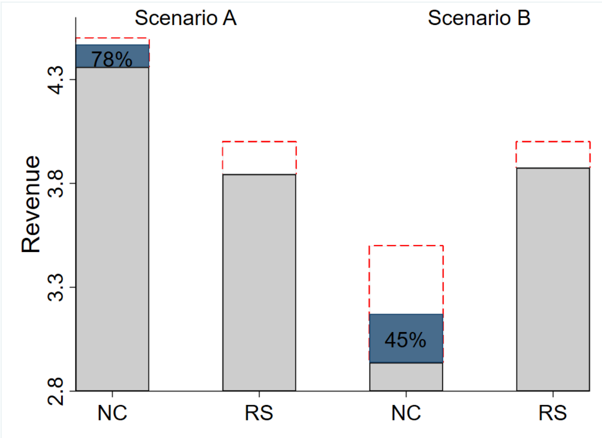

Figure 3: Revenues Increase if all Buyers Enter in Second Period.

We use OLS regressions[20] to further explore how buyers make participation decisions in Period 2. Based on comments of buyers who choose not to enter in Period 2 (see Appendix A), we include scenario (Scenario A =1), risk attitude index (i.e., number of safe choices, the higher the risk attitude index, the more risk averse is the buyer), whether the buyer receives the item for free in Period 1 ($not\ free_1 = 1$), the amount of upfront fee in Period 2 ($upfront_2$), the payoff in Period 1 ($payoff_1$), and the bid-value ratio in Period 1 ($bid_1/value_1$) as independent variables. We find buyers participate less in Scenario B even after controlling for the payoff in Period 1. This suggests that buyers view participation in Period 2 with low expected value in Scenario B not worthy of a risky upfront fee. The risk attitude index does not directly affect the participation decision in Period 2. However, we find that, in Scenario A, buyers participate less in Period 2 when they do not receive the item for free in Period 1. A possible reason is that buyers who do not receive the item for

[19]The revenue of NC (3.17) if all buyers enter in Scenario B is less than its theoretical revenue (3.5), the difference is still significant (p=0.01, one-sided t-test).

[20]We find similar results with Probit regressions.

free might think they were more likely to not receive the refund on the upfront fee, so that they view the participation in Period 2 an even more risky choice.

	DV: Enter in Period 2 (=1)	
	(1)	(2)
Scenario A (=1)	0.17^{**}	0.25^{*}
	(0.08)	(0.13)
$notfree_1 (= 1)$	0.07	0.08
	(0.07)	(0.11)
Scenario A * $notfree_1$	-0.18^{*}	-0.14
	(0.10)	(0.17)
$payoff_1$	0.00	0.00
	(0.01)	(0.01)
risk aversion	-0.01	-0.03
	(0.01)	(0.02)
$upfront_2$	-0.01	-0.03
	(0.03)	(0.05)
$bid/value_1$	-0.02	-0.09
	(0.07)	(0.11)
Constant	0.91^{***}	1.28^{***}
	(0.11)	(0.43)
Controls	No	Yes
R^2	0.05	0.14
Adj. R^2	-0.01	0.00
Num. obs.	128	128

Note: For Regressions (2), gender (male =1), age and graduate student (=1) are introduced as controls. We do not find significant controls.

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table 6: Regression of Participation Decision

We have our second result:

Result 2. *Hypothesis 2 is supported. Some buyers choose not to pay the upfront fee, leaving the revenue of the non-clairvoyant mechanism less than its theoretical prediction.*

5.3. Buyers overbid less under Non-clairvoyant Mechanism

In the experiment, the highest amount the buyer can bid is twice their valuation. We switch the distributions of buyers' valuation in two periods for our two scenarios. Scenario A has low-variance distribution (F_A) in the first period and high-variance distribution (F_B) in the second period. Scenario B has high-variance distribution (F_B) in the first period and low-variance distribution (F_A) in the second period. In general, buyers overbid in both distributions in both mechanisms. We report the bid-value ratio in Table 7. We find that buyers overbid in both mechanisms, as the ratio is greater than one for both distribution F_A and F_B. Under the repeated static mechanism, buyers overbid more ($p = 0.008$*, two-sided t-test) in F_A (low variance distribution). The difference between the two distributions disappears under the non-clairvoyant dynamic mechanism. For the low-variance distribution, we find that buyers under the non-clairvoyant mechanism overbid less ($p = 0.06$*, two-sided t-test) compared to buyers under the repeated static mechanism.

Bid/value	**Non-clairvoyant Dynamic**	**Repeated Static**	p-value
F_A (low variance)	1.264 (0.04)	1.379 (0.04)	0.060
F_B (High variance)	1.194 (0.05)	1.251 (0.04)	0.392
p-value	0.116	0.008	

Note: Standard errors in parentheses.

Table 7: Bid-Value Ratio Comparison

We use OLS regression to further investigate the different bidding behaviors under the two mechanisms. We consider bid-value ratio in each period separately. In Regressions (1) and (2), we regress bid-value ratio in Period 1 on mechanism (NC=1), scenario (Scenario A=1), valuations, and risk attitude index. We regress bid-value ratio in Period 2 also on valuation in Period 2 ($value_2$), the upfront fee ($upfront_2$), and whether the buyer gets the free item in Period 1 ($free_1$) in Regressions (3) and (4). From Regression (1), we find that buyers in the non-clairvoyant dynamic mechanism overbid less compared to those in the repeated static mechanism in Period 1 for both Scenario A and Scenario B. Perhaps buyers overbid less under NC in Period 2 due to the fact that a 50% chance of receiving a free item encourages less overbidding. This finding supports Hypothesis 3. When controls are included in Regression (2), risk aversion plays a role in mitigating the overbidding behavior. The overbidding lasts across periods, as shown in Regressions (3) and (4). The higher the bid-value ratio in Period 1, the higher the bid-value ratio in Period 2. Regression (4) further supports our Hypothesis 3 that buyers overbid less in NC, as the upfront fee in Period 2 mitigates the overbidding behavior, and the higher the upfront entry fee, the lower the bid-value ratio in Period 2. We report an analysis of whether a bid is greater than the valuation in Appendix A, and find similar results.

	DV: Bid-Value Ratio			
	Period 1		Period 2	
	(1)	(2)	(3)	(4)
NC (=1)	-0.10	-0.09	0.03	0.35
	(0.06)	(0.08)	(0.14)	(0.20)
Scenario A (=1)	0.03	0.1	-0.10*	-0.1
	(0.06)	(0.08)	(0.06)	(0.09)
$value_1$	-0.02	-0.02		
	-0.01	-0.01		
Risk aversion	-0.03	-0.06	0.04	0.03
	(0.02)	(0.02)	(0.02)	(0.03)
$bid_1/value_1$			0.39	0.35
			(0.06)	(0.10)
$value_2$			-0.01	-0.01
			(0.01)	(0.01)
$upfront_2$			-0.02	-0.10
			(0.04)	(0.06)
$free_1$			0.04	0.01
			(0.08)	(0.12)
Constant	1.51	1.17	0.78	0.57
	(0.11)	(0.32)	(0.13)	(0.36)
Controls	No	Yes	No	Yes
Observations	256	256	244	244
R-squared	0.08	0.14	0.19	0.19

Note: For Regression (3) and (6), gender (male =1), age, and graduate student (=1) are introduced as controls. We do not find significant controls.

Standard errors in parentheses.

Table 8: Regression of bid-value ratio on mechanisms

We then have our third result:

Result 3. *Hypothesis 3 is supported. Buyers overbid less under non-clairvoyant mechanism.*

6. Conclusion

We use laboratory experiments to test the mechanisms feasible under a non-clairvoyant dynamic environment (Mirrokni et al., 2020), where designers are restricted from using future distributional information. To our knowledge, our paper is the first to do so. In contrast to the traditional clairvoyant assumption that everyone perfectly knows the stochastic process governing all future economic outcomes, the non-clairvoyant environment is more practical. The reason is that mechanism design under this environment does not require a reliable future forecast regarding future distributions and outcomes; as a result, it follows a general, simple, implementable form. This environment is particularly related to online advertising markets, where advertisers repeatedly purchase impressions on webpages from advertising platforms like Google Ads, Microsoft Advertisement, Meta for Business, etc. In this market, both advertisers and advertising platforms are non-clairvoyant about possible values of future impressions, as internet traffic patterns can change suddenly due to naturally-occurring events. Other potential scenarios for deploying mechanism design under non-clairvoyant dynamic environments include designing airplane tickets, setting up rules for repeated selling, and constructing long-term contracts.

This paper tests two dynamic mechanisms feasible under a non-clairvoyant environment. Using past bids to design rules for later periods, the optimal non-clairvoyant dynamic mechanism (Mirrokni et al., 2020) links auctions in multiple periods to ensure inter-period revenue. By contrast, the repeated static mechanism (Myerson, 1981) optimizes each period individually and generates the most intra-period revenue. While the optimal non-clairvoyant dynamic mechanism provides the best revenue guarantee (at least 50% of that produced by the optimal clairvoyant mechanism in the two-period single-buyer case) its ability to outperform the repeated static mechanism depends on the relative size of intra- and inter- period revenues. We design two experimental scenarios with different inter-period revenues. Our findings support theoretical predictions: when the inter-period revenue is important, NC achieves more revenue than RS, as it guarantees 50% of the inter-period revenue; otherwise, NC has less revenue, as the loss of intra-period revenue from allocating half of the item for free cannot be recovered.

Our experiments illustrate that risk attitude matters in non-clairvoyant dynamic mechanism design. The customized upfront fee in the second period and the associated reserve price are critical in the inter-period revenue of the optimal non-clairvoyant dynamic mechanism. The upfront fee in the second period is well-designed to ensure non-negative expected total payoff of buyers. However, in our experiments, we observe many buyers choosing not to enter in the second period. The revenue loss from the buyer choosing not to participate comprises at least 45% of the revenue gap that we find between our experiments and theory. We find risk attitudes and first-period experience can help to explain second-period participation decisions. More generally, our data raises the question of how to promote entry in natural environments with risk-averse buyers.

Bidding behaviors also vary between mechanisms and valuation distributions. We find that buyers overbid in general, and more so when the valuation distribution has high variance in the repeated static mechanism. However, this gap disappears under the non-clairvoyant dynamic mechanism. We find that the non-clairvoyant dynamic mechanism mitigates overbidding behavior.

A limitation of our study is that it considers only a two-period single-buyer environment. Both non-clairvoyant dynamic mechanisms and repeat static mechanism can, of course. be applied to multi-period multi-buyer environments, and studying these might be interesting, particularly to those designing auctions for natural environments. Future studies can also investigate sellers' decisions regarding how to choose mechanisms, complementing our focus on buyers' behaviors.

Our main finding is that non-clairvoyant dynamic mechanisms appear to work as intended, and may represent an alternative to repeated static mechanisms in dynamic environments. They are generally applicable, simple in form, and come with a revenue guarantee. But NC mechanisms cannot provide value if they are not used. Knowing when and whether sellers in non-clairvoyant environments choose to implement NC mechanisms, especially as compared to the potentially sub-optimal RS alternative, is an important open question. Additionally, understanding how to promote buyer participation decisions under NC mechanisms promises to be a profitable avenue for future research.

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Appendix A. Subjects' Comments

After the two-period trading experiment and before the exit survey, subjects are invited to answer questions on how they made decision in each period. The two questions are not required. Subjects did not gain payment from answering them. We report some comments of buyers who choose not to pay the upfront fee in the second period.

- "Since I got a profit the first time I didn't want to go again with my luck"
- "Risk vs Reward...... I got lucky and did not have to pay."
- "Based on the membership fee. "
- "didn't want to take any big risks so I just lowballed my offers and refused to take the membership"
- "i read the instructions carefully. i think the second period isn't worth losing the points - i had to pay membership fee and could only get the item by bidding higher than the price set by the seller...... honestly, i haven't been feeling lucky so i'd rather not take my chances. so i tried not to lose money in the first period and just left it as is."

Appendix B. Additional Analysis

In this section we use a greater-than-valuation bid as the measure of overbidding. We report the percentage of overbid in each mechanism and in each period in Table B.9 We find that significant less buyers overbid in NC than in RS (43.75% vs. 55.46%, $p = 0.061$, two-sided t-test) in Period 1. We don't find significant difference of overbidding behaviors in Period 2 (55.46% vs. 55.48%, $p = 0.900$, two-sided t-test)[21].

Bid/value	**Non-clairvoyant Dynamic**	**Repeated Static**	p-value
F_A (low variance)	43.75 (4.38)	55.46 (4.39)	0.061
F_B (High variance)	55.46 (4.39)	54.68 (4.40)	0.900

Note: Standard errors in parentheses.

Table B.9: Percentage of Overbid Comparison

We use OLS regressions[22] to further investigate the different bidding behaviors under the two mechanisms. We consider whether a bid is greater than the valuation (=1) in each period separately. In Regressions (1) and (2), we regress overbid in Period 1 on mechanism (NC=1), scenario (Scenario A =1), valuation in Period 1 ($value_1$), and risk attitude index. We regress bid-value ratio in Period 2 also on valuation in Period 2 ($value_2$), the amount of upfront fee ($upfront_2$), and whether the buyer gets the free item in Period 1 ($free_1$) in Regressions (3) and (4). From Regression (1), we find that buyers in the non-clairvoyant dynamic mechanism are less likely to overbid compared to those in the repeated static mechanism in Period 1 for both Scenario A and Scenario B. Perhaps buyers overbid less under NC in Period 1 due to the fact that a 50% chance of receiving a free item encourages less overbidding. This finding supports Hypothesis 3. When controls are included in Regression (2), risk aversion plays a role in mitigating the overbidding behavior. The overbidding lasts across periods, as shown in Regressions (3) and (4): if buyers overbid in Period 1, they are more likely to overbid in Period 2.

[21]For two-sided Proportion tests, p=0.061 for Period 1, p=0.095 for Period 2.

[22]We find similar results with Probit regressions.

	DV: Overbid =1)			
	Period 1		**Period 2**	
	(1)	(2)	(3)	(4)
NC (=1)	-0.12	-0.12	-0.09	0.21
	(0.06)	(0.08)	(0.15)	(0.20)
Scenario A (=1)	0.00	0.05	-0.09	-0.05
	(0.06)	(0.09)	(0.07)	(0.10)
$value_1$	-0.01	-0.01		
	(0.01)	(0.01)		
Risk attitude	-0.04	-0.06	0.02	0.01
	(0.02)	(0.02)	(0.02)	(0.02)
$Overbid_1$			0.33	0.26
			(0.06)	(0.10)
$value_2$			-0.01	-0.01
			(0.01)	(0.01)
$upfront_2$			0.03	-0.05
			(0.04)	(0.06)
$free_1$			0.03	-0.04
			(0.09)	(0.13)
Constant	0.76	0.51	0.39	0.36
	(0.08)	(0.34)	(0.09)	(0.36)
Controls	No	Yes	No	Yes
Observations	256	256	244	244

Notes: Coefficients of Probit regressions are reported.
For Regression (2) and (4), gender (male =1), age, and graduate student (=1) are introduced as controls. We do not find significant controls.

Standard errors in parentheses.

Table B.10: Regression of Overbid on mechanisms

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:

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

You will start with 50 points.

Your decision in the one practice session will not influence your earning. You will be paid according to your decision in the one experimental session. The experiment will be conducted only once.

Your experimental task

In this experiment, you will trade with a robot seller. 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.

There are two periods. You can buy one item in each period from the robot seller by making a bid. The cost of producing the item for the robot seller is zero.

The value of the item for you in each period might be different. **The value of the item is only known to you**. The robot 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.

RS only Instructions

In each Period:

The robot seller will set a secret price based on the possible values for each period. The secret price in period 1 might be different from the secret price in period 2.

In each period you only get the item if your bid is greater than (or equal to) the secret price. However, you only have to pay the secret price, even if you bid more.

NC only Instructions

In the First Period:

There is no membership fee in this period.

Chance of getting the item for free:

You have an equal chance to get the item for free or not.

If you cannot get the free item, you win the item only if your bid is greater than (or equal to) the secret price that the seller chooses.

However, you only have to pay the secret price, even if you bid more.

In the Second Period:

The robot seller will set a membership fee and another secret price based on your bid in the first period.

If you don't pay the membership fee, the game ends.

If you pay the membership fee, you get to learn your value in the second period.

Chance of getting the item for free:

You have an equal chance to waive the membership fee or not.

If you have to pay the membership fee, the higher the membership fee you pay, the lower the secret price in this case.

Whether you can waive the membership fee or not, you only get the item if your bid is greater than (or equal to) the secret price. However, you only have to pay the secret price, even if you bid more.