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Developing an Online Market Mechanism for Trading Perishable Agricultural Commodities

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One-sided auctions are used for trading perishable agricultural commodities because their production cost is already "sunk." Moreover, the promptness and simplicity of one-sided auctions are beneficial for trading in perishable commodities. However, sellers cannot participate in the price-making process in these auctions. A standard double auction market collects bids from both sides of traders and matches them to find the most efficient allocation, assuming that the value of unsold items remains unchanged. Nevertheless, in the market for perishable commodities, sellers suffer a loss when they fail to sell their commodities, because their salvage values are lost when the commodities perish without being sold. To solve this problem, we investigate the design of an online double auction for perishable commodities, where bids arrive dynamically with their time limits. Our market mechanism aims at improving the profitability of traders by reducing trade failures in the face of uncertainty of incoming/departing bids.

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1 Introduction

Agricultural products such as vegetables are traded mainly in the spot market because their yield and quality are unsteady and unpredictable. In the spot markets, the production costs of the goods are typically *sunk costs* because these costs are not only *fixed* but also *irretrievable* when the goods remain unsold and perish. Therefore, sellers of *perishable* agricultural commodities may suffer large losses if the trade fails in the markets (Bastian et al., 2000).

In traditional markets for perishable goods, one-sided auctions such as a *Dutch auction* are widely practiced because their simplicity and promptness are vital for smoothly consummating large volume transactions of perishable goods with many participating buyers. In the one-sided auction, a seller can influence price-making only subsidiarily by limiting the quantity of goods to be traded. Nevertheless, sellers cannot always maximize their profit by selling the optimum amount of goods because finding the optimal quantity is difficult for sellers in real auctions where precise demands are unknown. Moreover, the markets make a loss in *social surplus* (called *deadweight loss*) when sellers manipulate quantities of goods to be traded.

To solve the problems by realizing fair price-making among traders while reducing allocation failures, we develop a prototypical market for the perishable goods, which adopts online *double auction* (DA) as a market mechanism (Miyashita, 2013). In the online DA, multiple buyers and sellers arrive dynamically over time with their time limits. Both buyers and sellers tender their bids for trading commodities. The bid expresses a trader's offer for valuation and quantity of the commodity to be traded. The arrival time, time limit, and bid for a trade are all private information to a trader. Therefore, the online DA is uncertain about future trade. It collects bids over a specified interval of time, and clears the market on expiration of the bidding interval by application of pre-determined rules.

The online DA market for perishable commodities should decide the bids with different prices and time limits that should be matched to increase the utility of traders and reduce trade failures in the face of uncertainty about future trade. The online market also presents the tradeoff for clearing all possible matches as they arise versus waiting for additional buy/sell bids [1] before matching. Although waiting could engender better matching, it can also hurt matching opportunities because the time limit of existing bids might expire.

1.1 Related works

Double auction mechanism in the spot market has been investigated in the fields of agricultural economics (Krogmeier et al., 1997) and experimental economics (Mestelman, 2008). They observed the behavior of human subjects in the experimental periodic market and found that their decisions are influenced by the inability to carry unsold goods over trading periods. The double auction mechanism is adopted to reduce communication costs for trading agricultural products via Internet in Uganda (Ssekibuule et al., 2013).

Until recently, few works of research in computational economics have addressed online double auction mechanisms (Blum et al., 2006; Bredin et al., 2007; Zhao et al., 2011). They examine several important aspects of the problem: design of matching algorithms with good worst-case performance within the framework of competitive analysis (Blum et al., 2006), construction of a general framework that facilitates truthful dynamic double auction by extending static double auction rules (Bredin et al., 2007), and development of computationally efficient matching algorithms using weighted bipartite matching in graph theory (Zhao et al., 2011). Although their research results are theoretically significant, we cannot readily apply their mechanisms to our online DA problem because their models incorporate the assumption that trade failures never cause a loss to traders, which is not true in markets for perishable goods.

In this paper, we advocate a heuristic online DA mechanism for the spot markets of perishable goods, which improves revenue of the traders by reducing allocation failures. The remainder of the paper is organized as follows. Section 2 introduces our market model and presents desiderata and objectives of

[1] When we must distinguish between claims made by buyers and claims made by sellers, we refer to the *bid* from a buyer and the *ask* from a seller.

the market. Section 3 proposes the allocation policy to prevent trading failures in the online DA market. Section 4 explains the settings of multi-agent simulations used to evaluate the developed market mechanism. Section 5 empirically studies the effectiveness of our allocation policy in two types of market. Section 6 analyzes the performance of various types of agents in the markets and investigates the market equilibria. Section 7 concludes the paper and discusses future research directions.

2 Preliminaries

In our market model, we consider discrete time rounds, $T = \{1, 2, \cdots\}$, indexed by t. For simplicity, we assume the market is for a single commodity. Agents are either sellers (S) or buyers (B), who arrive dynamically over time and depart according to their time limit. In each round, the agents trade multiple units of goods. The market is cleared at the end of every round to find new allocations.

Each agent i has a private information called *type*, $\theta_i = (v_i, q_i, a_i, d_i)$, where v_i, q_i, a_i, d_i are non-negative real numbers, v_i is agent i's valuation of a single unit of the good, q_i is the quantity of the goods that agent i wants to trade, a_i is the arrival time, and d_i denotes the departure time. The duration between the arrival time and the departure time defines the agent's trading period $[a_i, d_i]$ indexed by p, and agents can repeatedly participate in the auction over several trading periods.

We model our market as a wholesale market for B2B transactions. In the market, seller i brings her goods by the arrival time a_i. Therefore, seller i incurs production cost before the trade starts and considers the production cost together with its associated opportunity cost as the valuation v_i of the goods. Furthermore, at the departure time d_i of seller i, the salvage value of the goods evaporates because of its perishability unless it is traded successfully. Because of advance production and perishability, sellers face the distinct risk of failing to recoup the production cost in the trade. Buyers in our market procure the goods to resell them in retail markets. For buyer j, valuation v_j represents the maximum budget for procuring the goods. The arrival time a_j is the first time when buyer j values the item. Furthermore, buyer j is assumed to gain some profit by retailing the goods if she succeeds to procure them before the departure time d_j. In other words, d_j denotes the due time for the buyer to procure the goods for a coming retail opportunity.

Agents are self-interested and their types are private information. At the beginning of a trading period, agent i submits a bid by making a claim about its type $\hat{\theta}_i = (\hat{v}_i, \hat{q}_i, \hat{a}_i, \hat{d}_i) \neq \theta_i$ to the auctioneer. In succeeding rounds in the trading period, the agent can modify the value of its unmatched bid.

2.1 Misreports by agents

— Table 1 should be inserted here. —

An agent's self-interest is exhibited in its willingness to misrepresent its type when this will improve the outcome of the auction in its favor. As explained in Table 1, misrepresenting its type is not always beneficial or feasible for agents. As for quantity, it is impossible for a seller to report a larger quantity $\hat{q}_i > q_i$ because the sold goods must be delivered immediately after trade in a spot market. Moreover, it is unreasonable for a buyer to report a larger quantity $\hat{q}_j > q_j$ because excess orders may produce dead stocks. Reporting an earlier arrival time is infeasible for a seller and buyer because the arrival time is the earliest timing that they decide to participate in the market. Reporting a later arrival time or an earlier departure time can only reduce the chance of successful trade for the agents. For a seller, it is impossible to report a later departure time $\hat{d}_i > d_i$ since her goods perish by the time d_i. For a buyer, misreporting a later departure time $\hat{d}_j > d_j$ may delay retailing the procured goods.

Additionally, Table 1 shows that a seller can misreport a smaller quantity $\hat{q}_i < q_i$ with the intention of raising the market price, but in that case, she needs to throw out some of her goods before she arrives at the market. If a buyer misrepresents a smaller quantity $\hat{q}_j < q_j$ to lower the market price, she loses a chance of retailing more goods. Therefore, we assume that the agents do not like to misrepresent a quantity value in their type. On the other hand, we suppose that an agent has incentives to misreport its valuation for increasing its profit because it is the most instinctive way for the agent to influence market prices. In ordinary markets, a seller has an incentive to report a higher valuation and a buyer reports a lower valuation. However, in a market for perishable goods, a seller may report a lower valuation $\hat{v}_i < v_i$ when she desperately wants to sell the goods before they perish.

Hence, we consider that agent i can misreport only its valuation v_i for improving its utility among all the components of its type information θ_i.

2.2 Desiderata and objectives

Let $\hat{\theta}^t$ denote the set of all the agent's types reported in round t; $\hat{\theta} = (\hat{\theta}^1, \hat{\theta}^2, \ldots, \hat{\theta}^t, \ldots)$ denote a complete reported type profile; and $\hat{\theta}^{\leq t}$ denote the reported type profile restricted to the agents with reported arrival no later than round t. In each trading period p, agent i has a specific type $\theta_i^p = (v_i^p, q_i^p, a_i^p, d_i^p)$. Report $\hat{\theta}_i^t = (\hat{v}_i^t, q_i^t, a_i^p, d_i^p)$ is a bid made by agent i in round t within trading period p (i.e., $t \in [a_i^p, d_i^p]$). The report represents a commitment to trade at most q_i^t units [2] of goods at a limit price of $\hat{v}_i^t$ in round t within trading period p. As discussed previously, we assume agent i always reports truthful values about quantity q_i, arrival time a_i, and departure time d_i.

In the market, a seller's ask and a buyer's bid can be matched when they satisfy the following condition.

Definition 1 (Matching condition) *Seller i's ask $\hat{\theta}_i^t = (\hat{v}_i^t, q_i^t, a_i^p, d_i^p)$ and buyer j's bid $\hat{\theta}_j^t = (\hat{v}_j^t, q_j^t, a_j^p, d_j^p)$ are matchable when*

$$(\hat{v}_i^t \leq \hat{v}_j^t) \wedge ([a_i{}^p, d_i^p] \cap [a_j^p, d_j^p] \neq \emptyset) \wedge (q_i^t > 0) \wedge (q_j^t > 0). \tag{1}$$

An online DA mechanism, $M = (\pi, x)$, is composed of an allocation policy π and a pricing policy x. The allocation policy π is defined as $\{\pi^t\}^{t \in T}$, where $\pi_{i,j}^t(\hat{\theta}^{\leq t}) \in \mathbb{I}_{\geq 0}$ represents the quantity traded by agents i and j in round t, given reports $\hat{\theta}^{\leq t}$. The pricing policy x is defined as $\{x^t\}^{t \in T}, x^t = (s^t, b^t)$, where $s_{i,j}^t(\hat{\theta}^{\leq t}) \in \mathbb{R}_{\geq 0}$ represents the payment seller i receives from buyer j as a result of the trade in round t, given reports $\hat{\theta}^{\leq t}$. Furthermore, $b_{i,j}^t(\hat{\theta}^{\leq t}) \in \mathbb{R}_{>0}$

[2] Successful trade in previous rounds of period p reduce the current quantity to $q_i^t (\leq q_i^p)$.

represents a payment made by buyer j as a result of the trade with seller i in round t, given reports $\hat{\theta}^{\leq t}$. In this paper, an auctioneer is supposed to make neither profit nor loss in the trade, so that $b^t_{i,j}(\hat{\theta}^{\leq t}) = s^t_{i,j}(\hat{\theta}^{\leq t})$.

Most studies on DA mechanisms assume agents with simple quasi-linear utility, $\sum_j (s_{i,j} - \pi_{i,j} v_i)$ for seller i and $\sum_i (\pi_{i,j} v_j - b_{i,j})$ for buyer j. However, for representing idiosyncratic motivation of agents in a wholesale spot market for perishable goods, we define the utility for sellers and buyers as follows.

Definition 2 (Seller's utility) *Seller i's utility at time round t is*

$$U_i(\hat{\theta}^{\leq t}) = \sum_{\{p|a^p_i \leq t\}} \sum_{t' \in [a^p_i, d^p_i]} \sum_{j \in B} (s^{t'}_{i,j}(\hat{\theta}^{\leq t}) - \pi^{t'}_{i,j}(\hat{\theta}^{\leq t}) v^p_i) - \sum_{\{p|d^p_i \leq t\}} (q^p_i - \sum_{t' \in [a^p_i, d^p_i]} \sum_{j \in B} \pi^{t'}_{i,j}(\hat{\theta}^{\leq t})) v^p_i. \quad (2)$$

The second term in Equation 2 represents the loss of unsold and perished goods, which are calculated dynamically at the bid's departure time (i.e., when $d^P_i \leq t$). With the effect of the second term, sellers are motivated to lower their valuation in the bid when the departure time approaches.

Definition 3 (Buyer's utility) *Buyer j's utility at time round t is*

$$U_j(\hat{\theta}^{\leq t}) = \sum_{\{p|a^p_j \leq t\}} \sum_{t' \in [a^p_j, d^p_j]} \sum_{i \in S} ((\pi^{t'}_{i,j}(\hat{\theta}^{\leq t}) v^p_j - b^{t'}_{i,j}(\hat{\theta}^{\leq t})) + \pi^{t'}_{i,j}(\hat{\theta}^{\leq t}) r^p_j). \quad (3)$$

The second term in Equation 3 represents that buyer j makes profit $\pi^t_{i,j} r^p_j$ by retailing the procured goods at price $v^p_j + r^p_j$. Since v^p_j represents the maximum budget allowed to buyer j, she has no incentive to bid with valuation higher than v^p_j. Within the budget limitation, buyer j is motivated to procure as much goods as possible up to q^p_j for satisfying the demand of her retail customers.

Agents are modeled as risk-neutral and utility-maximizing. As Equation 2 shows, a seller gains profits by selling low-value goods at high prices but loses money if the goods perish without being sold. The seller's bidding strategy on valuation of the goods is intricate because she can enhance her utility in the trade by either raising the market price with high valuation bidding or increasing successful trades (i.e., preventing the goods from perishing) with low valuation bidding. Equation 3 reveals that a buyer makes profits by procuring high-value goods at low prices and retailing the procured high-value goods. Therefore, in this market, the buyer also has difficulty in finding the optimal bidding strategies since she can improve her utility by either lowering the market price with low valuation bidding or by increasing successful trades (i.e., enhancing retail opportunities) with high valuation bidding.

Based on the defined utility for sellers and buyers, our market's objective is not only maximizing social surplus produced by trade (i.e., $\pi^{t'}_{i,j}(v^{p'}_j - v^p_i)$) but also increasing retailing profits of buyers (i.e., $\pi^{t'}_{i,j} r^{p'}_j$) and reducing loss to sellers from unsold and perished goods (i.e., $(q^p_i - \sum \pi^{t'}_{i,j})v^p_i$).

We also require that the online DA satisfies the *budget-balance*, *feasibility*, and *individual rationality*. Budget-balance ensures that in every round the mechanism collects and distributes the same amount of money from and to the agents (i.e., an auctioneer makes neither profit nor loss). Feasibility demands that the auctioneer takes no short position on the commodity traded in any round. Individual rationality guarantees that no agent loses by participating in the market.

3 Market design

In spot markets for perishable goods, sellers raise their asking price and buyers lower their bidding price as a rational strategy to improve their surplus as long as they can avoid possible trade failures. In such markets, agents have to manipulate their valuation carefully for obtaining higher utilities. Our goal is to design a market that secures desirable outcomes for both individual agents and the whole market without the need for strategic bidding by the agents.

The well-known result of (Myerson and Satterthwaite, 1983) demonstrates that no Bayes-Nash incentive-compatible exchange mechanism can be simultaneously efficient, budget-balanced, and individually rational. Therefore, we aim to design an online DA mechanism that imposes budget-balance, feasibility, and individual rationality while promoting reasonable efficiency and moderate incentive-compatibility. We discuss our design for an allocation policy and a pricing policy in the following sections.

3.1 Allocation policy

Many studies on the DA mechanism investigate a static market and use social surplus from successful trade as the objective function, with the assumption that agents never suffer a loss from trade failures. The ratio of achieved social surplus against the maximal social surplus at the competitive equilibrium is called *allocative efficiency*. The allocation policy that maximizes allocative efficiency in a static DA market arranges the asks according to the ascending order of the seller's price and the bids according to the descending order of the buyer's price, and matches in the sequence. We designate this allocation rule as a *price-based* allocation policy.

The price-based allocation policy is efficient for the DA markets that assume trade in future markets or trade in durable goods, in which agents do not make any loss by trade failures. However, sellers of perishable goods in the spot market can lose the value of perished goods which they fail to sell during the trading period. Consequently, in addition to increasing social surplus, increasing the number of successful trades is also important in the spot market for perishable goods.

For static DA markets, several maximal matching mechanisms have been developed (Zhao et al., 2010; Niu and Parsons, 2013). The basic idea is not to simply match high-valuation bids and low-valuation asks, but to match low-valuation asks with low-valuation bids that are priced no lower than the asks, and match high-valuation bids with high-valuation asks that are priced no higher than the bids. However, their methods cannot address the problem of an online market where each bid is valid only in its limited trading period. In the allocation policy of online DA mechanisms, *criticality* of bids must be evaluated and taken into consideration properly to increase the bids that can be traded successfully within their fixed trading period.

In this paper, we define criticality of asks and bids as follows:

1. Let M^t represent a set of all the pairs of bids that are matchable at

time round t. At this time, buyers have as many as $\sum_{\{\hat{\theta}_j^t | (\hat{\theta}_i^t, \hat{\theta}_j^t) \in M^t\}} q_j^t$ quantity of bids that are matchable with seller i's ask $\hat{\theta}_i^t$. This value is used as the estimated matchability of the ask in calculating its criticality. At time round t, seller i in trading period p has as many as $q_i^p - \sum_{t' \leq t} \sum_{j \in B} \pi_{i,j}^{t'}(\hat{\theta}^{\leq t'})$ remaining goods to sell. Furthermore, at time round t, seller i has a slack time as long as $d_i^p - t$ till the unsold goods perish. We first define unsatisfiability of the ask as quantitative unbalance of supplies against demands as follows.

Definition 4 (Ask unsatisfiability) *Unsatisfiability of seller i's ask at time round t in trading period p is*

$$u_i^p(\hat{\theta}^{\leq t}) = \frac{q_i^p - \sum_{t' \leq t} \sum_{j \in B} \pi_{i,j}^{t'}(\hat{\theta}^{\leq t'})}{\sum_{\{\hat{\theta}_j^t | (\hat{\theta}_i^t, \hat{\theta}_j^t) \in M^t\}} q_j^t}. \tag{4}$$

Taking temporal limitation of the ask into consideration, we define criticality of the ask as follows.

Definition 5 (Ask criticality) *Criticality of seller i's ask at time round t in trading period p is*

$$c_i^p(\hat{\theta}^{\leq t}) = \frac{u_i^p(\hat{\theta}^{\leq t})}{d_i^p - t + 1}. \tag{5}$$

2. Buyer j has as many as $q_j^p - \sum_{t' \leq t} \sum_{i \in S} \pi_{i,j}^{t'}(\hat{\theta}^{\leq t'})$ remaining goods to procure at time round t in trading period p. At this timing, sellers have as many as $\sum_{\{\hat{\theta}_i^t | (\hat{\theta}_i^t, \hat{\theta}_j^t) \in M^t\}} q_i^t$ quantity of asks that are matchable with buyer j's bid $\hat{\theta}_j^t$. Additionally, at time round t, buyer j has a slack time as long as $d_j^p - t$ for trading period p.

Unsatisfiability and criticality of bids are defined as follows.

Definition 6 (Bid unsatisfiablity) *Unsatisfiability of buyer j's bid at time round t in trading period p is*

$$u_j^p(\hat{\theta}^{\leq t}) = \frac{q_j^p - \sum_{t' \leq t} \sum_{i \in S} \pi_{i,j}^{t'}(\hat{\theta}^{\leq t'})}{\sum_{\{\hat{\theta}_i^t | (\hat{\theta}_i^t, \hat{\theta}_j^t) \in M^t\}} q_i^t}. \tag{6}$$

Definition 7 (Bid criticality) *Criticality of buyer j's bid at time round t in trading period p is*

$$c_j^p(\hat{\theta}^{\leq t}) = \frac{u_j^p(\hat{\theta}^{\leq t})}{d_j^p - t + 1}. \tag{7}$$

In the price-based allocation policy, bids and asks are sorted according to the value of claimed valuation and matched in the sequence. In other words, in the price-based allocation policy, the priority of bid is $\hat{v}_j^t$ and that of ask is $1.0/\hat{v}_i^t$, and bids and asks with larger priorities are matched accordingly. And, in this paper, we propose a *criticality-based* allocation policy, which sets the priority of bid and ask equal to their criticality. The criticality-based allocation policy does not guarantee allocative efficiency. However, considering the possible loss by trade failures, the criticality-based allocation policy is expected to earn more profit for the agents by increasing successful trades in certain market situations.

In online DA markets, quality of the allocation can be improved if we accumulate the bids without matching them immediately at their arrival and decide the allocation from the aggregated bids. However, deferring allocation decisions might prevent the existing bids from being matched, and hence, increase trade failures. In order to investigate the effectiveness of deferred allocation decisions in the online DA market, we define *elapse rate* as follows.

Definition 8 (Elapse rate) *Elapse rate of agent i's bid at time round t in trading period p is*

$$e_i^p(t) = \frac{t - a_i^p}{d_i^p - a_i^p}. \tag{8}$$

Using the elapse rate, the third step of our priority based allocation policy described above is enhanced to wait for additional bids before matching the existing bids and avoid expiration of the bids in the market as follows.

Allocation policy enhanced with elapse rate

1. At the beginning of allocation, asks from sellers are sorted in descending order with regard to their priorities.

2. Starting with the ask of the largest priority, matchable bids with the ask are sorted in descending order with regard to their priorities.

3. The ask and the next bid in the sorted queue are matched *only when both their elapsed rates are not smaller than a predetermined threshold value* $\mathscr{E}$. This process continues in this sequence until the quantity requested by the ask is satisfied or there are no matchable bids in the queue.

4. The allocation process continues until no matchable ask is left.

We call the above threshold *elapse rate threshold* and for experiments in this paper we search for its appropriate value $\mathscr{E}$ empirically using multi-agent simulation in Section 5.

3.2 Misreports in criticality-based allocation policy

It should be noted that an auction using the criticality-based allocation policy depends on the assumption that agents misreport neither their arrival time nor departure time to increase priorities of their bids. We show that agents should report their truthful arrival time and departure time in order to improve the outcome of the auction using the criticality-based allocation policy.

— Figure 1 should be inserted here. —

As explained in Section 2.1, reporting an earlier arrival time or a later departure time is not feasible both for a seller and a buyer. However, since the auction with the criticality-based allocation policy tends to give a higher criticality to a bid with a shorter trading period and a bid with the bigger accumulated criticality has more chance of being matched in the auction, misreporting a later arrival time or an earlier departure time may be beneficial for agents. To investigate effectiveness of such misreports, we consider a case shown in Figure 1, supposing that an agent misrepresents its departure time d as earlier time d' (i.e., $d > d'$) and two bids have the same unsatisfiability. The difference of the accumulated criticality between the bid with departure time d' and the bid with departure time d is calculated as follows:

$$\int_a^{d'} \frac{1}{d' - t + 1} dt - \int_a^{d} \frac{1}{d - t + 1} dt = \log \frac{d' - a + 1}{d - a + 1} < 0 \qquad (9)$$

It shows that the bid with earlier departure time d' has less chance of being matched. Therefore the agent has no incentive of misreporting an earlier departure time in the auction using the criticality-based allocation policy.

The following equation shows that summation of the accumulated criticality of n-divided consecutive bids is larger than the accumulated criticality of an original bid:

$$n \int_0^{d/n} \frac{1}{d/n - t + 1} dt - \int_0^{d} \frac{1}{d - t + 1} dt = \log \frac{(d/n + 1)^n}{d + 1} > 0 \qquad (10)$$

It proves that agents have an incentive to divide their bid into multiple consecutive bids with shorter trading periods for increasing a chance of successful trades. Nevertheless this strategic behavior of agents can be easily prevented by charging an entry fee for bidding on the agents. Therefore, in this paper, we do not assume the agents adopt such bid-dividing strategies.

3.3 Pricing policy

The pricing policy is important to secure truthfulness and prevent strategic manipulation by agents, which should promote stability of agent bidding and increase efficiency of a market. However, obtaining truthfulness in DA markets while guaranteeing other desirable properties such as efficiency, individual rationality, and budget balance is impossible (Myerson and Satterthwaite, 1983).

We impose budget-balance and promote reasonable efficiency in our market, so we adopt k-double auction (Satterthwaite and Williams, 1989) as our pricing policy. And we set the value of k as 0.0 because of the following reasons.

1. When $k = 0.0$, seller i does not have an incentive to overstate her true valuation v_i^p, because it does not change the clearing price without losing

matching opportunities. She does not have a strong incentive to understate her valuation either, if our allocation policy can reduce the risk of loss caused by perished goods.

2. If the retail profit of buyer j, which is $\sum \pi_{i,j}^{t'} r_j^p$, is much larger than her surplus $\sum(\pi_{i,j}^{t'} v_j^p - b_{i,j}^{t'})$, which is usually the case in wholesale markets, she likes to offer her true valuation for increasing successful trades.

With the above defined allocation policy and pricing policy, we speculate that our mechanism can make the online DA market for perishable goods yield a high utility with moderate incentive-compatibility while maintaining properties of budget-balance and individual rationality. Since our market model and mechanism are much more complex than traditional continuous double auctions, even for which theoretical analysis is intractable, we perform empirical evaluation of the market mechanism using multi-agent simulation.

4 Market simulation

— Figures 2 and 3 should be inserted here. —

In the simulation, five sellers and five buyers participate in the market. For the simulations, we use two types of market depicted in Figures 2 and 3, which have a common supply curve and different demand curves. Figure 2 depicts the market with a high risk of trade failures, where buyers' valuation distributes equally with sellers' valuation. Figure 3 depicts the market with a low risk of trade failures, in which the average valuation by the buyers is higher than that by the sellers. In the simulations, buyer j's retailing profit rate in trading period p (i.e., r_j^p in Equation 3) is set equal to his true valuation v_j^p.

Each simulation runs for 12 days and the market is cleared every hour. Every day, the agents submit one bid or ask, each of which has 24 units of demands or supplies for the homogeneous perishable goods. Its arrival time is picked up randomly for every bid submission. The seller's ask departs the market 72 hours after its arrival, which implies that a seller's goods lose their value in the market three days after their production because of perishability. The departure time of a buyer's bid is 24 hours after its arrival, which simulates the situation of buyers procuring goods for retail sales of the next day. For each result shown in the following sections, 20 randomized trials are executed to simulate diversified patterns of agents' arrival and departure.

4.1 Bidding strategies of agents

Empirical analyses of complex markets necessarily focus on a restricted set of bidding strategies. In this paper, we prepare several types of bidding strategies for both sellers and buyers to simulate the behavior of different agents in their bidding, and investigate market outcomes in different situations.

The bidding strategies of agents used in the simulations are as follows.

1. Modest strategy (MOD)

   This strategy is only for seller agents. With this strategy, seller i always reports her valuation as

   $$\hat{v}_i^t = 0. \tag{11}$$

   This strategy is developed to simulate one-sided auction markets where only buyers submit their bids.

2. Truth-telling strategy (TT)

   With this strategy, agent i always reports its valuation truthfully as

   $$\hat{v}_i^t = v_i^p. \tag{12}$$

3. Monotonous strategy (MONO)

   With this strategy, an agent monotonously tunes its report on valuation along with the elapsed time after the arrival of the bid in the market.

   In trading period p, seller i and buyer j report their valuation as follows.

   (a) Seller i's reported valuation at time round t is

   $$\hat{v}_i^t = v_i^p(1.0 + \delta)\frac{d_i^p - t}{d_i^p - a_i^p}. \tag{13}$$

   (b) Buyer j's reported valuation at time round t is

   $$\hat{v}_j^t = v_j^p(1.0 - \delta\frac{d_j^p - t}{d_j^p - a_j^p}). \tag{14}$$

δ is a parameter to control aggressiveness of the agent's bidding behavior. In this paper, we set 0.2 as the value of δ.

As the bid's departure time gets closer, the seller's reported valuation monotonously decreases from $v_i^p(1.0+\delta)$ to 0, and the buyer's reported valuation monotonously increases from $v_j^p(1.0-\delta)$ to its true valuation v_j^p. Since this is a very intuitive behavior for traders, this strategy is widely used in the field of revenue management as a dynamic pricing rule.

4. Zero-intelligent aggressive strategy (ZIA)

   With this strategy, by reporting the valuation randomly within a certain range, an agent seeks a larger surplus when there is little risk of trade failure and gives up making a profit when its departure time approaches. In trading period p, seller i and buyer j report their valuation as follows.

   (a) Seller i's reported valuation at time round t is

   $$\hat{v}_i^t = rand(v_i^p(1.0+\delta)\frac{d_i^p - t}{d_i^p - a_i^p}, v_i^p(1.0+\delta)). \tag{15}$$

   (b) Buyer j's reported valuation at time round t is

   $$\hat{v}_j^t = rand(v_j^p(1.0-\delta), v_j^p(1.0-\delta\frac{d_j^p - t}{d_j^p - a_j^p})). \tag{16}$$

   In the above equations, $rand(x,y)$ is a function to produce a random value in between x and y.

   Seller i's bidding starts with value $v_i^p(1.0+\delta)$ when she arrives in the market, and ends within a range of $[0.0, v_i^p(1.0+\delta)]$ when she leaves the market. Buyer j's bidding starts with value $v_j^p(1.0-\delta)$ and ends within a range of $[v_j^p(1.0-\delta), v_j^p]$. Thus, ZIA strategy is a randomized variation of MONO strategy.

5 Empirical evaluation of allocation policy

We empirically evaluate the performance of an online DA market with different values assigned to elapse rate threshold $\mathscr{E}$ defined in Section 3.1. In the experiments, we ran a set of simulations assuming that all the agents in the market report truthfully (i.e., all the traders adopt TT strategy for bidding).

To evaluate the effects of the threshold value on the performance of the online DA mechanism, we tested ten values of the elapse rate threshold—0.0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, and 0.9. We examined the effects of changing threshold values in the two markets, one of which has a high risk of trade failures (shown in Figure 2) and the other has a low risk of trade failures (shown in Figure 3). The graphs in the succeeding subsections show the several aspects of market performance along with corresponding values of the elapse rate threshold. Each of the two lines in the graphs represents the result by the price-based allocation policy and the criticality-based allocation policy.

5.1 Experimental results in high-risk market

— Figures 4 and 5 should be inserted here. —

Figure 4 presents average matching rates of online DA in the market with a high risk of trade failures. From the graph, we find that the criticality-based allocation policies, which prioritizes more critical bids in the matching, improves matching rates as the elapse rate threshold value increases. This occurs because of the following reasons.

1. The large elapse rate inhibits instant matching of bids and builds a pool of bids from which the allocation policy can find better matching.
2. The pool of bids developed by the large elapse rate also increases accuracy of estimated matchability used in Equations 4 and 6 for calculating unsatisfiability of bids in the allocation policy.

The graph also reveals that the price-based allocation policies, which prioritizes matches with larger surplus in the allocation, initially improves but later deteriorates matching rates as the elapse rate threshold value becomes larger. The intuitive explanation of the results is as follows.

1. The allocation policy with the elapse rate gives early-arriving high-price asks a chance of being matched with late-arriving high-price bids while it restrains late-arriving low-price asks to be matched. As a result, the allocation policy with the small elapse rate reduce trade failures.

2. However, when the pool of bids developed by the big elapse rate becomes large, the price-based allocation policy tends to find matches with larger surplus instead of avoiding trade failures.

Figure 5 presents average clearing prices of online DA in the market with a high risk of trade failures. Our pricing policy defined in Section 3.3 decides the clearing price as the lowest buyer's valuation in the matching bids. Therefore, high average clearing price in the market indicates that the low-valuation bids by buyers cannot be matched with sellers' asks. The graph shows that the criticality-based allocation policy clears the market with lower prices when the value of elapse threshold increases. Additionally, the graph also reveals that the price-based allocation policy produces higher clearing prices when the value of elapse threshold increases.

Results in Figures 4 and 5 suggest that when the allocation policy is allowed to defer matching decisions in the high-risk market, the criticality-based allocation policy achieves higher matching rates by lowering the average clearing price. This implies that a large elapse rate threshold enables the criticality-based allocation policy to match low-valuation bids with low-valuation asks. In other words, the criticality-based allocation policy prevents the high-valuation bids from matching with low-valuation asks, and results in producing allocations with smaller surplus.

— Figures 6 and 7 should be inserted here. —

Figure 6 shows the total utilities of sellers in the high-risk market with different elapse rate threshold values. We find that sellers can obtain a larger utility using the criticality-based allocation policy in the high-risk market. The price-based allocation policy deteriorates utility of the sellers with an increase in elapse rate threshold, because lower matching rates in these conditions (as shown in Figure 4) cause great losses to the sellers through the perished goods.

Figure 7 shows the total utilities of buyers in the high-risk market. This graph reveals that buyers obtain much larger utilities than sellers. It is also shown that the criticality-based allocation policy improves buyers' utility with larger elapse rate threshold values. However, the price-based allocation policy degrades buyers' utility with larger elapse rate threshold values because low matching rates in these conditions cause loss of resale opportunities for buyers.

With these results shown in the above graphs, we set $\mathscr{E}$ to 0.9 for maximizing the utilities of sellers and buyers in the high-risk market.

5.2 Experimental results in low risk market

— Figures 8 and 9 should be inserted here. —

Figure 8 presents average matching rates of online DA in the market with a low risk of trade failures. On comparison with Figure 4, it is clear that matching rates in the low risk market are higher than those in the high-risk market. From the graph, we find that the criticality-based allocation policy achieves perfect matching rates when the elapse rate threshold value is larger than 0.3. The graph also reveals that the price-based allocation policy deteriorates matching rates as the elapse rate threshold value becomes larger.

Figure 9 presents average clearing prices of online DA in the market with a low risk of trade failures. The graph shows that for the criticality-based allocation policy, the market-clearing price is stable at the low price range without regard to the values of elapse threshold. This suggests that in the low risk market, the criticality-based allocation policy can easily match low-valuation bids with low-valuation asks without the need for keeping a pool of bids waiting to be matched.

— Figures 10 and 11 should be inserted here. —

Figure 10 shows the total utilities of sellers in the low-risk market with different elapse rate threshold values. Although the price-based allocation with large elapse rate threshold values deteriorates utility of the sellers, we find that utility of sellers are similar for the criticality-based allocation policy in the low-risk market. The possible reason for these results is that in the low-risk market sellers do not suffer from the loss of perished goods and clearing prices of the market are stable as shown in Figure 9.

Figure 11 shows the total utilities of buyers in the low-risk market. This graph reveals that buyers can obtain much larger utilities than sellers. It is also shown that the price-based allocation policy reduces buyers' utility with larger elapse rate threshold values. These damages to the buyer's utility are larger than those to the seller's utility because the buyers suffer from both the increase in clearing prices, as shown in Figure 9, and loss of resale opportunities caused by trade failures.

With these results shown above, we set $\mathscr{E}$ to 0.9 for maximizing the utilities of sellers and buyers in the low-risk market. These settings are same as those in the high-risk market, implying that in the spot market for perishable goods, the allocation policy should take the criticality of bids into consideration and save matching judgments until the departure time of the bids.

6 Empirical analysis of market equilibria

Understanding the interaction among agents with various bidding strategies is important in market design to ensure favorable market properties such as efficiency and stability. The Nash equilibrium is an appropriate solution concept for understanding and characterizing the strategic behavior of self-interested agents. However, computing the exact Nash equilibria is intractable for a dynamic market with non-deterministic aspects such as our online DA market. Therefore, we evaluate the market design by computing the Nash equilibria across the restricted strategy space through simulations (Walsh et al., 2002).

Sellers and buyers in the B2B market for perishable goods have different utilities and adopt different bidding strategies for maximizing their utility. In the experiments, we perform a limited strategic analysis by looking for Nash equilibria between restricted types of sellers and buyers based on the simplified market model in which all the agents on the seller side or the buyer side are homogeneous and follow the same pure strategy. The results obtained in the experiments is not completely accurate, but the degree of success achieved in predicting agent behavior and market outcomes can be used as a benchmark against which more sophisticated mechanisms of online DA can be judged.

— Tables 2 and 3 should be inserted here. —

Tables 2 and 3 show the payoff matrix between sellers and buyers in the high-risk market and the low-risk market, respectively. In the experiments, we use the criticality-based allocation policy and set the value of $\mathscr{E}$ to 0.9 as decided in Section 5. Seller agents adopt four biding strategies—MOD, MONO, TT, and ZIA, and buyer agents use three strategies—MONO, TT, and ZIA. Each cell in the tables represents the result of interaction between the sellers and buyers with the corresponding strategy. The cell is separated into two parts: the upper part of the cell shows the average matching rate and the average clearing price, and the bottom left corner in the lower part of the cell reveals the average and standard deviation (inside parentheses) of the utility of seller agents and the top right corner shows those of utility of buyer agents.

In Table 2, two cells in gray are considered to be Nash equilibria. Between them, the Nash equilibrium (TT, TT) achieves the higher total utility (i.e., $79,134$). Furthermore, although it is difficult for the sellers to make profits in the high-risk market, the Nash equilibrium (TT, TT) achieves larger sellers' utility (i.e., 42.0) than the other results in Table 2. Hence, the Nash equilibrium (TT, TT) is preferable to the other Nash equilibrium (MONO, ZIA) not only because it saves the agents the cost of reporting strategically for more profits in the market, but also because it achieves a higher total utility and fair utility distribution among sellers and buyers.

Table 3 shows that there is no Nash equilibrium in this market, and the table also shows that the matching rate is almost 100% and the total utility is around $11,000$, which is distributed among sellers and buyers reasonably, regardless of the agents' strategy [3] except when buyers adopt the ZIA strategy. When buyers use the ZIA strategy, sellers' utility is largely damaged no matter what strategy the sellers adopt. Table 3 reveals that buyers lose incentive to adopt the ZIA strategy only when sellers use the TT strategy due to the resultant low utility and large deviation. Therefore, the best strategy for the sellers in this market is the TT strategy, and the best response of the buyers

[3] It should be noted that even when sellers use the MOD strategy, they can make reasonable profits in the low-risk market.

to the sellers' TT strategy is adopting the MONO strategy. The corresponding strategy profile (TT, MONO) is represented as the light-gray cell in Table 3. It should be noted that considering the value of standard deviation, buyers' utility in the light-gray cell does not significantly differ from the buyers' utility in the adjacent cell corresponding to the strategy profile (TT, TT). Hence, the buyers might like to choose the TT strategy in the low-risk market.

From the above results, we find that our market mechanism for perishable goods succeeds in leading the sellers and buyers to behave truthfully for maximizing their utilities in both the high-risk market and the low-risk market.

7 Conclusion

We developed an online DA mechanism for the spot market of perishable goods to achieve efficient and fair allocations among traders by considering the loss from trade failures. We explained that sellers have a high risk of losing money by trade failures because their goods are perishable and must be produced in advance to compensate for their unsteady yield and unpredictable quality. To reduce trade failures in the spot markets for perishable goods, our DA mechanism prioritizes the bids that have a smaller chance of being matched in their time period. Empirical results using multi-agent simulation showed that our DA mechanism was effective in promoting truthful behavior on the part of traders for realizing efficient and fair allocations between sellers and buyers in both the high-risk market and the low-risk market.

The results reported in this paper are very limited for any comprehensive conclusion on the design of online DA for perishable goods. For this purpose, we need to investigate other types of bidder strategies in a wide variety of experimental settings. Additionally, behavior of human subjects in the market must be examined carefully to evaluate the effectiveness of the designed mechanism. Furthermore, the current mechanism can be improved by incorporating some knowledge about future bids statistically predicted from past bidding records.

Tables and Figures

Table 1: Possibility of agents misreporting their type information

		Seller	Buyer
Valuation	Lower	◯	◯
	Higher	◯	× (Deficit)
Quantity	Smaller	× (Less trades)	× (Less trades)
	Larger	× (Delivery failure)	× (Dead stock)
Arrival Time	Earlier	× (Infeasible)	× (Infeasible)
	Later	× (Less trading chances)	× (Less trading chances)
Departure Time	Earlier	× (Less trading chances)	× (Less trading chances)
	Later	× (Perished goods)	× (Delay of resale)

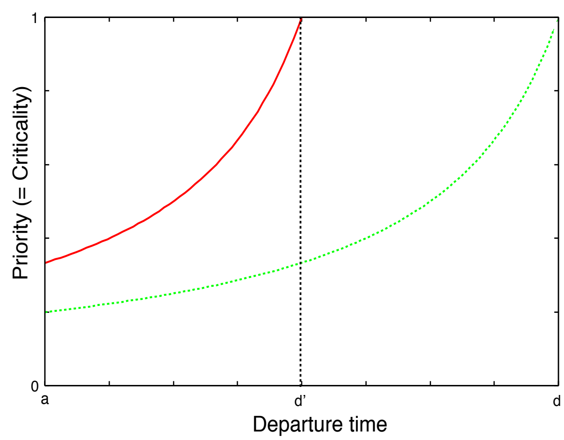

Figure 1: Priorities of two bids with different departure times

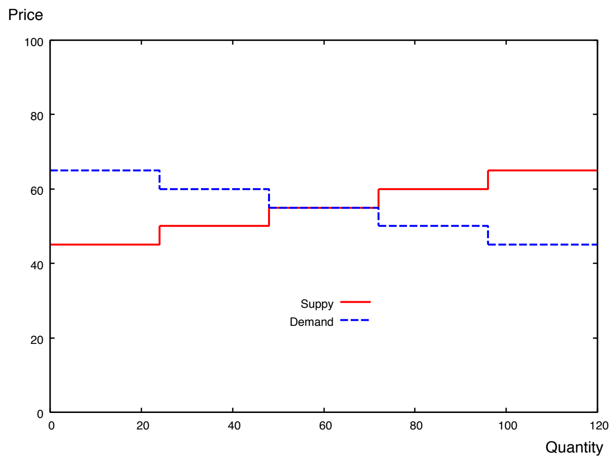

Figure 2: Market with high risk of trade failures

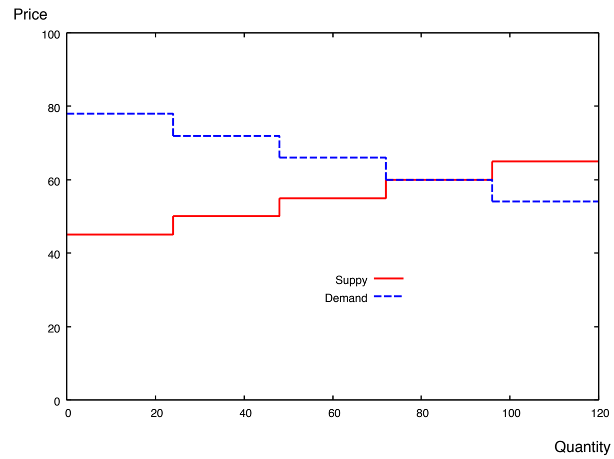

Figure 3: Market with low risk of trade failures

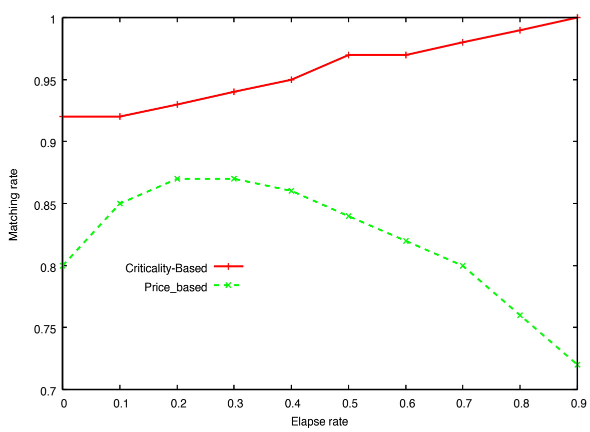

Figure 4: Matching rates in the high-risk market

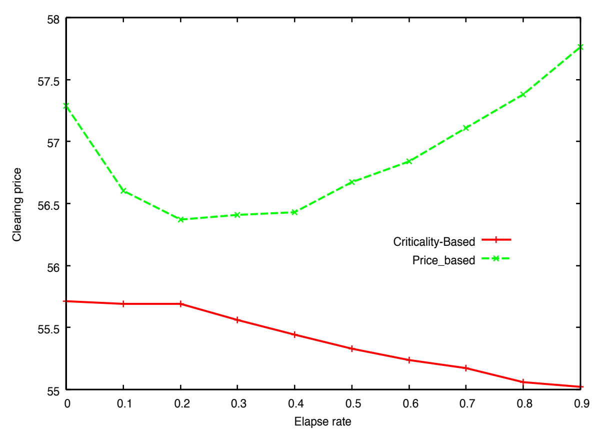

Figure 5: Clearing prices in the high-risk market

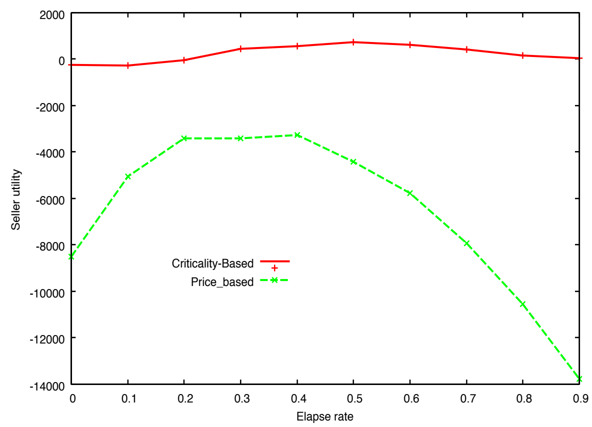

Figure 6: Utility of sellers in the high-risk market

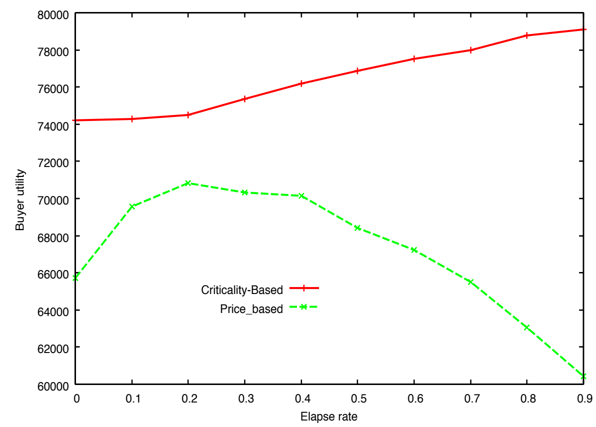

Figure 7: Utility of buyers in the high-risk market

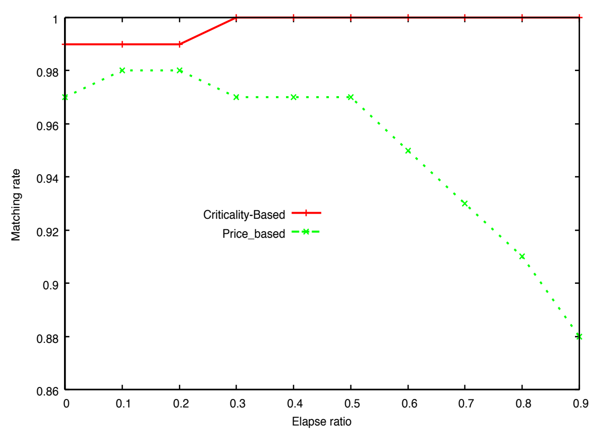

Figure 8: Matching rates in the low-risk market

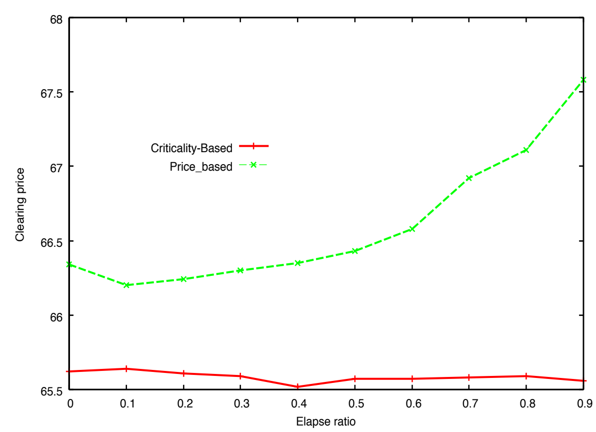

Figure 9: Clearing prices in the low-risk market

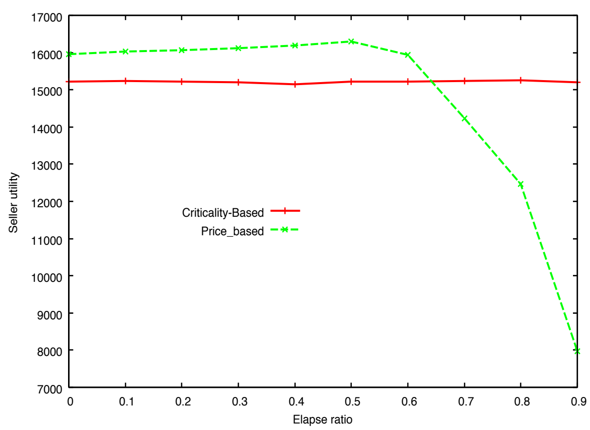

Figure 10: Utility of sellers in the low-risk market

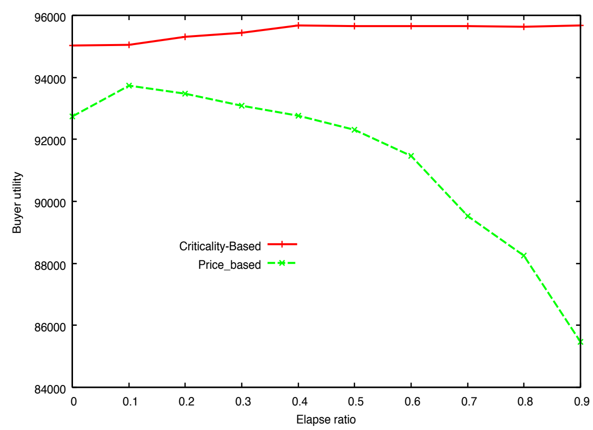

Figure 11: Utility of buyers in the low-risk market

Table 2: Payoff matrix in the high-risk market

Seller\Buyer	MONO	TT	ZIA
MOD	100%, 53.2	100%, 54.2	100%, 40.7
	81,730.8 (399.5) -2,530.8 (399.5)	80,290.8 (399.5) -1,090.8 (399.5)	99,734.4 (1,161.8) -20,534.4 (1,161.8)
MONO	98%, 54.1	98%, 55.0	95%, 43.5
	79,448.4 (677.9) -1,402.0 (256.4)	78,260.8 (708.2) -14.8 (264.1)	91,538.2 (1,507.6) -15,619.7 (1,210.2)
TT	80%, 56.0	100%, 55.0	58%, 53.1
	66,286.1 (644.8) -11,315.6 (777.7)	79,092.0 (324.0) 42.0 (127.4)	53,844.9 (2,633.4) -25,866.4 (2,792.1)
ZIA	100%, 53.7	100%, 54.7	99%, 41.5
	81,061.8 (298.9) -1,915.8 (260.7)	79,496.0 (579.2) -500.0 (368.3)	97,940.3 (1,353.3) -18,341.1 (1,181.5)

Table 3: Payoff matrix in the low-risk market

Seller\Buyer	MONO	TT	ZIA
MOD	100%, 64.1 97,788.9 (479.4) 13,091.1 (479.4)	100%, 65.1 96,348.9 (479.4) 14,531.1 (479.4)	100%, 48.7 119,928.3 (1,435.0) -9,048.3 (1,435.0)
MONO	100%, 64.7 96,861.3 (281.5) 14,018.7 (281.5)	100%, 65.7 95,455.2 (289.6) 15,424.8 (289.6)	97%, 51.8 113,289.8 (1,538.5) -4,562.4 (1,387.1)
TT	100%, 64.7 96,938.4 (260.9) 13,941.6 (260.9)	100%, 65.6 95,670.0 (324.2) 15,210.0 (324.2)	86%, 57.8 94,997.1 (2,634.7) -2,100.9 (2,444.9)
ZIA	100%, 64.6 96,881.7 (594.7) 13,874.1 (416.3)	100%, 65.7 95,417.4 (565.3) 15,367.8 (302.0)	100%, 49.5 118,684.1 (2,243.7) -7,968.5 (2,198.9)

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