Quality information and market segmentation in auctions for reducing nonpoint source pollution: A laboratory experiment

Nobuyuki Ito

Associate Professor, Faculty of Economic Sciences, Niigata University

nobuyuki.ito@econ.niigata-u.ac.jp

Abstract

Auctions have the potential to improve the cost-effectiveness of nonpoint source pollution abatement to which applying the polluter pays principle is difficult. Laboratory experiments have shown that revealing the environmental impacts of reducing polluting inputs to nonpoint sources (potential sellers) leads to the deterioration of auction performance. The auction mechanism that simultaneously achieves cost-effectiveness and transparency for reducing nonpoint source pollution remains unclear. Through a laboratory experiment, I find that although the disclosure of information on environmental impacts deteriorates auction performance, contrary to theoretical predictions, market segmentation improves performance and cancels out these impacts. (JEL Q15, Q53)

1. Introduction

Regulations and investments to reduce water pollution from point sources such as industrial facilities and wastewater treatment plants have substantially contributed to water pollution mitigation (OECD 2017). However, the abatement of pollution from nonpoint sources (or diffuse sources), as typified by agricultural land and urban runoff, remains challenging. Nitrogen and phosphorus fertilizers and livestock manure from the agricultural sector are major causes of eutrophication and toxic algal blooms in freshwater systems in many countries (OECD 2017).

The level of emissions from individual nonpoint sources cannot be observed and measured at

doi:10.3368/le.102.4.060225-0044R1

sufficiently low costs. Standard emission-based economic instruments such as emission taxes and emissions trading can hardly be applied to internalize the externality of nonpoint source pollution. Starting with Griffin and Bromley (1982), environmental economists have developed economic instruments based on polluting inputs or ambient environmental quality levels to address this problem (Segerson 1988; Xepapadeas 1992; Shortle et al. 1998; Xepapadeas 2011).

The imposition of input- or ambient-based taxes or other economic instruments in which the polluter pays principle (PPP) is applied can improve the cost-effectiveness of water pollution abatement. The laboratory experimental results of Cochard et al. (2005) revealed that implementing input- and ambient-based taxes enhances social welfare. However, the technological barrier of monitoring and measuring the amounts of pollutants discharged from nonpoint sources renders the application of PPP to nonpoint source pollution abatement difficult in many countries (OECD 2012).

Auctions could improve the cost-effectiveness of policies for nonpoint source pollution even when PPP application is difficult. Emissions trading programs for water pollution control (water quality trading programs) have been established to improve the cost-effectiveness of pollution abatement, mostly in the United States and Australia (Selman et al. 2009). Water quality trading programs can apply to trades not only between regulated point sources but also between regulated point sources and unregulated nonpoint sources. For example, the Great Miami Trading Program (GMTP) in Ohio, in which trades are introduced via reverse (or procurement) auctions, has amassed numerous farming participants and funded various best management practices (Newburn and Woodward 2012). In water quality trading auctions, a buyer can purchase credit from a seller who can reduce water pollutants at a lower cost than they can and offset emissions by the amount specified by the credit. Usually, regulated point sources and unregulated nonpoint sources (or regulated point sources) participate as buyers and sellers, respectively, during auctions (OECD 2017). Unregulated nonpoint sources (such as farmers) can sell credits, whereas regulated point sources can reduce their pollution abatement costs for regulatory compliance. Although transactions between buyers and sellers via auctions could reduce water pollution abatement costs, water quality trading programs have not yet expanded globally (OECD 2012; Fisher-Vanden and Olmstead 2013).

Pollutants from nonpoint sources flow along complex underground pathways. The environmental burden of pollutant emissions from each nonpoint source on water quality at the monitoring point in the targeted water body varies depending on site-specific characteristics such as the soil type and climatic and topographic conditions (Segerson 1988; Shortle et al. 1998). This property can produce asymmetry among nonpoint sources in abatement cost distributions, which are evaluated in terms of water quality improvement at the monitoring point, thus making it difficult to obtain theoretical evaluations for different auction mechanisms (Cason et al. 2003). Thus, auction performance under different auction formats, price rules, and environmental impact information has been examined in laboratory experiments with general parameters and testbed experiments with field parameters.

In the laboratory testbed experiment of Cason et al. (2003), field parameters from the BushTender program were employed to examine the impact of revealing land use change pollution abatement information to sellers (quality information) on auction performance. The program was operated by the Department of Natural Resources and Environment in Victoria, Australia, which faced budget constraints and employed multiple rounds of sealed bids and discriminative price auctions. Moreover, the abovementioned auction formats were employed. In the experiment, although the sellers could offer bids for three land use change projects, a successful bid could occur for a maximum of only one project per seller. The experimental results indicated that although revealing quality information did not influence auction performance during early periods, as measured by the ratio of the realized pollution abatement to the maximum pollution abatement and the ratio of the realized pollution abatement cost-effectiveness to the maximum pollution abatement cost-effectiveness, it deteriorated these performance measures during later periods. Quality information revelation also increased sellers' profits regardless of the period.

Conte and Griffin (2017), via a laboratory experiment, examined the effects of revealing information on the ranking of the environmental qualities of project options on auction performance. As with Cason et al. (2003), although the sellers could choose among three project options, they were asked to choose only one option to bid on; notably, one auction round was conducted for each trading opportunity. Their experimental results indicated that the revelation of ranking information did not influence auction performance, whereas the revelation of quality information improved auction performance when sellers could only bid on one of multiple project options.

In the laboratory testbed experiment of Cason and Gangadharan (2005), the auction performance for reducing nitrogen and salt pollution from the agricultural sector under discriminative and uniform price rules was examined. Under the discriminative price rule, each successful seller traded credit at the price offered by the seller. Sellers faced uncertainty regarding whether their offers would be accepted by the buyer but not regarding prices. Similar to the experiment of Cason et al. (2003), field parameters from Victoria, Australia, were adopted. However, in this experiment, quality information was not disclosed to the sellers; the sellers offered bids during only one round per trading opportunity. Under the uniform price rule, successful sellers trade at a uniform price that is determined by the market. The results of the experiment suggest that discriminative price rules perform better than uniform price rules.

In a laboratory experiment, Conte and Griffin (2019) investigated the effects of landowners' onsite private benefits from erosion reduction on auction performance for conservation practices. The existence of onsite private benefits from conservation practices could decrease the expected value of the net opportunity costs of these practices and impact landowners' bidding behaviors. The experimental results of Conte and Griffin (2019) revealed that the existence of onsite private benefits from conservation practices reduced the average net opportunity costs of these practices and increased the environmental quality achieved by the auction more than that obtained in the absence of onsite private benefits. However, the results also revealed that this could increase landowners' rent-seeking behavior and deteriorate auction cost-effectiveness, as measured by the ratio of the cost-effectiveness realized by the auction to the maximum cost-effectiveness of optimal practices when the agency knew the net opportunity costs of all landowners.

In the simulation analysis of Palm-Forster et al. (2016), the effects of the perceived transaction costs of bid application on landowners' participation decisions in conservation auctions and uniform payment (fixed price) programs and their cost-effectiveness were examined. The results suggested that when transaction costs are sufficiently high, the cost-effectiveness of conservation auctions can be inferior to that of uniform payment programs.

Several challenges remain for studies on water quality trading auctions: the reduction in transaction costs for participation (entry) and the improvement of program cost-effectiveness. Revealing information on transfer coefficients or the environmental impacts of conservation projects could improve auction transparency and fairness (Cason et al. 2003) and contribute to reducing the transaction costs for auction participation. However, it remains unclear what auction mechanism is cost effective when quality information is revealed to sellers.

In this study, I consider a water quality trading auction in which a buyer and multiple sellers of nonpoint sources exist. This study aims to theoretically and experimentally examine the effects of market segmentation on bidding behavior and auction performance. When the market is segmented by the seller's transfer coefficients (marginal impacts on pollution abatement at the monitoring point), each segmented market encompasses sellers with identical transfer coefficients. In the segmented market, sellers with high transfer coefficients may lose their advantage of high-quality credits to those with low transfer coefficients. To my knowledge, no study has aimed to examine the effect of market segmentation on auction performance, except for Ito (2023), who considered ambient-based emissions trading for nonpoint source pollution. I also experimentally reexamine the impact of revealing information on the transfer coefficients of sellers on auction performance and bidding behavior when each seller has a single project option to bid on. In a laboratory experiment, I found that although revealing environmental quality information deteriorates the performance of water quality trading auctions, contrary to theoretical predictions, market segmentation improves auction performance and predominates over these impacts.

2. Optimal bidding model

I consider an enclosed water body with a watershed that contains N nonpoint sources with heterogeneous transfer coefficients a_L or a_H ($a_L < a_H$). A nonpoint source with a transfer coefficient of zero is not eligible to participate in emissions trading. Furthermore, because not all of a unit of pollutant discharged from nonpoint sources reaches the monitoring point in the water body[1] (U.S. EPA 2007), I assume $0 < a_k < 1$ for $k \in \{L, H\}$.

The water quality of the water body deteriorates due to pollutants such as nitrogen and phosphorus from nonpoint sources. To address this, a regulatory agency conducts a reverse auction in which pollution reduction credits can be traded. The agency and nonpoint sources participate in the auction as the buyer and potential sellers of credits, respectively. The agency faces a budget constraint Z and aims to cost-effectively reduce water pollution.

I consider a sealed-bid and multiunit reverse auction under the discriminative price rule and budget constraint, which was also experimentally studied by Cason et al. (2003), Cason and Gangadharan (2005), and Conte and Griffin (2017; 2019). In the auction, seller i ($i = 1, 2, \ldots, N$) submits a bid of b_i for credit of y_i to be traded. When a successful bid is made, seller i receives b_i as the price of the credit but is obliged to reduce polluting inputs by y_i, at an opportunity cost of c_i. The amount of y_i is measured on the basis of the pollutant reduction at the source (input- or emission-based credit). Here, I assume that each seller *i* can trade only one credit with the buyer. When the successful seller with transfer coefficient $a_i \in \{a_L, a_H\}$ reduces the polluting inputs by y_i, pollution at the monitoring point is reduced by $a_i y_i$. Then, the cost-effectiveness of bid b_i can be measured as $b_i/(a_i y_i)$. For ease of analysis, the amount of polluting inputs to be reduced is assumed to be identical between farmers, such that $y = y_i$ for all i.

The farmer (nonpoint source) possesses private information on the opportunity costs to reduce the polluting inputs by y to generate credit of y. In contrast, the agency possesses private information on the budget and transfer coefficients of nonpoint sources. Suppose that the agency considers disclosing information on transfer coefficients (qualities of credits) a_i to increase auction transparency. Then, compared with seller *j* with quality a_L (low-type seller *j*), seller *i* with quality a_H (high-type seller *i*) exhibits a cost-effectiveness advantage for the same bid amount b, i.e., $b/(a_L y) > b/(a_H y)$ for $b = b_i = b_j$. Even if the high-type seller increases the bid amount (more than b), the cost-effectiveness of the bid is superior to that of the low-type seller's bid b until the equality holds. As experimentally shown by Cason et al. (2003), revealing quality information can deteriorate the cost-effectiveness of pollution abatement. In this study, I consider market segmentation, in which each segmented market encompasses sellers of identical quality (RS treatment). Although the sellers possess quality information in the segmented market, high-type sellers with quality a_H lose advantages because of quality differences from low-type sellers with quality a_L. To examine the effects of market segmentation and quality information dissemination, I also consider an integrated market (the market is not segmented) in which quality information is revealed to the sellers (RI treatment) and an integrated market in which quality information is not revealed to the sellers (UI treatment).

To demonstrate the impact of market segmentation on the optimal bidding behavior of farmers (sellers), I apply an optimal bidding model (conservation auction model)[2], which was developed by Latacz-Lohmann and Van der Hamsvoort (1997). I omit the subscript *i* below to simplify the notation unless needed for clarity.

A seller knows that bid b for credit y with transfer coefficient a of farmland (quality of the credit) will be evaluated by the buyer with a bid score of $b/(ay)$ in terms of cost-effectiveness. I set $y=1$ below for simplification since the emission abatement to be achieved by a successful seller is identical, so that $b/(ay)=b/a$. I assume that the seller forms an expectation regarding the maximum acceptable bid score ϕ, which is a random variable with cumulative distribution function F and density f on support $[0,\bar{\phi}]$, where $\bar{\phi}$ denotes the bid score cap[3]. Bid b submitted by the seller with quality a is accepted if the bid score does not exceed the maximum acceptable bid score, i.e., $b/a \leq \phi$, and rejected otherwise. The acceptance probability of the bid (the survival function) G is then defined as follows:

$$G\left(\frac{b}{a}\right)=\Pr\left(\phi \geq \frac{b}{a}\right)=\int_{\frac{b}{a}}^{\bar{\phi}} f(v)dv=1-F\left(\frac{b}{a}\right). \quad [1]$$

It is plausible to assume that a zero bid ($b=0$) will be accepted with certainty, i.e., $G(0)=1$, because the buyer can purchase credit and improve the water quality without a cost burden. I assume that the seller's expectations regarding the probability of bid acceptance G are continuous and decreasing on $[0,\bar{\phi}]$.

The seller obtains utility $u(\pi_0+b-c)$ if the bid is accepted by the buyer where u is assumed to be increasing and twice differentiable von Neumann–Morgenstern utility function, and π_0 denotes the farmer's profit from not participating in the auction. For ease of analysis, I normalize the seller's profit from not participating in the auction to zero, i.e., $\pi_0=0$, and assume that there is no transaction cost for the bidding process (bid preparation and submission). I further normalize the utility of not participating in the auction or not winning the auction to zero, i.e., $u(0)=0$. The expected utility of the seller participating in the auction can be thus expressed as follows:

$$u(b-c)\left[1-F\left(\frac{b}{a}\right)\right]. \qquad [2]$$

Moreover, I assume that the seller is risk averse so that $u'=du(x)/dx>0$ and $u''=d^2u(x)/dx^2<0$.

A higher bid increases the utility that can be received by the seller if the bid is accepted but reduces the bid acceptance probability. The seller's optimal bid b^* maximizes the expected utility given by equation [2]. Then, the first-order condition of the interior solution is as follows:

$$\frac{u'(b^*-c)}{u(b^*-c)}=\frac{f(b^*/a)}{a\left[1-F(b^*/a)\right]}. \qquad [3]$$

Equation [3] indicates that the marginal rate of a change in the utility, when increasing the bid, equals the marginal rate of a change in the probability of rejection (the hazard rate) at the optimal bid b^*.

I can demonstrate the impact of an increase in the seller's opportunity cost on the optimal bidding by applying the implicit function theorem:

$$\frac{\partial b^*}{\partial c}=-\frac{u'\{-(u''/u')(1-F)+f/a\}}{-u'\left\{-(u''/u')(1-F)+2f/a+uf'/(a^2u')\right\}}, \qquad [4]$$

where $u=u(x^*)$, $u'=du(x^*)/dx^*$, $u''=d^2u(x^*)/dx^{*2}$, $F=F(v^*)$, $f=f(v^*)$, and $f'=df(v^*)/dv^*$ for $x^*=b^*-c$ and $v^*=b^*/a$. According to the assumption of a risk-averse seller, the numerator of the right-hand side of equation [4] is positive. The denominator is negative because the optimal bid b^* is the solution of the maximization problem of equation [2]. Thus, I can obtain $\partial b^* / \partial c > 0$, indicating that a risk-averse seller increases the optimal bid as the opportunity cost increases[4].

Similarly, the impact of a quality difference on the optimal bids is as follows:

$$\frac{\partial b^*}{\partial a} = -\frac{(b^* uf / a^2)\left\{u'/u + f'/(af) + 1/b^*\right\}}{-u'\left\{-(u''/u')(1-F) + 2f/a + uf'/(a^2 u')\right\}}. \qquad [5]$$

The sign of equation [5] is generally indeterminate. An increase in quality increases the optimal bid if and only if $u'/u + f'/(af) + 1/b^* > 0$. I will examine this aspect by specifying the distribution of ϕ below.

Integrated market

The buyer faces a limited budget Z. The buyer accepts seller *i*'s bid b_i in increasing order of the bid scores of cost-effectiveness $v_i = b_i / a_i$. Let $v = (v_1, v_2, \ldots, v_N)$ denote a vector of the bid scores sorted in increasing order such that $v_1 \le v_2 \le \ldots \le v_N$ and W denote the number of accepted sellers ($W \ge 1$). Then, the buyer accepts bids until the total expenditure for the accepted bids equals the budget ($\sum_{i=1}^{W} b_i = Z$) or until the total expenditure after accepting an additional bid b_{W+1} exceeds the budget ($\sum_{i=1}^{W} b_i < Z$ and $\sum_{i=1}^{W+1} b_i > Z$), i.e., $\sum_{i=1}^{W} b_i \le Z$.

For a competitive auction market, it is plausible to assume that even if all the sellers' bid scores equal the expected value of the maximum acceptable bid score, $\mathrm{E}[\phi^I]$, some bids are rejected; i.e., $\sum_{i=1}^{N} a_i \mathrm{E}[\phi^I] > Z$, where ϕ^I denotes the maximum acceptable bid score in an integrated market. If a low-type seller i and a high-type seller j ($i \ne j$) both submit bids with score $\mathrm{E}[\phi^I]$, then $b_i = a_L \mathrm{E}[\phi^I]$ and $b_j = a_H \mathrm{E}[\phi^I]$. Although the buyer's payments for these bids differ ($b_i < b_j$), their evaluations are indifferent for the buyer. Thus, if all the sellers submit bids with score $\mathrm{E}[\phi^I]$, the expected number of successful sellers is $\Pr(\phi^I \geq \mathrm{E}[\phi^I])N$. A seller would believe that an increase in the number of sellers or a decrease in the buyer's budget renders the auction market more competitive and decreases expectations regarding $\mathrm{E}[\phi^I]$. Therefore, it would be plausible to assume that if the seller knew the buyer's budget *Z*, the sellers would form expectations regarding $\mathrm{E}[\phi^I]$ such that:

$$\Pr(\phi^I \geq \mathrm{E}[\phi^I])\left\{a_L \mathrm{E}[\phi^I]n_L + a_H \mathrm{E}[\phi^I]n_H\right\} = Z, \qquad [6]$$

where $\Pr(\phi^I \geq \mathrm{E}[\phi^I])a_k \mathrm{E}[\phi^I]n_k$ is the buyer's expected payment for all sellers with quality a_k, for $k \in \{L, H\}$, when all n_k sellers bid with score $\mathrm{E}[\phi^I]$. Then, $\sum_{i=1}^{N} a_i \mathrm{E}[\phi^I] > Z$ holds if $\Pr(\phi^I \geq E[\phi^I]) < 1$.

Because bids with score $\mathrm{E}[\phi^I]$ are indifferent for the buyer regardless of seller type, the share of accepted sellers for each type is assumed to be identical. Assuming that the seller knows the buyer's budget, I use the seller's expectation of $\mathrm{E}[\phi^I]$ given by equation [6] as a benchmark for the comparative static analysis of the optimal bidding behavior in an integrated market.

Segmented market

In a segmented market, the buyer's budget is divided into two markets for different qualities. Let z_k denote the allocated (type-by-type) budget for the market for quality a_k (for $k \in \{L, H\}$). Then, the sum of the type-by-type budgets equals Z; i.e., $Z = z_L + z_H$. As in the integrated market, the buyer accepts seller *i*'s bid b_i in increasing order of the bid scores of cost-effectiveness $v_i = b_i / a_i$ in each of the segmented markets. Then, $\sum_{i=1}^{W_k} b_i \leq z_k$ holds, where W_k ($W_k \geq 1$) denotes the number of accepted sellers with quality a_k.

I assume that a seller participating in an auction market for quality a_k forms an expectation of $\mathrm{E}[\phi_k^S]$, where ϕ_k^S denotes the maximum acceptable bid score of a seller with quality a_k in the segmented market such that:

$$\Pr(\phi_k^S \geq \mathrm{E}[\phi_k^S]) a_k \mathrm{E}[\phi_k^S] n_k = z_k, \quad k \in \{L, H\}. \qquad [7]$$

Assuming that the seller knows the buyer's budget, I use the seller's expectation of $\mathrm{E}[\phi_k^S]$ given by equation [7] as a benchmark for the comparative static analysis of the optimal bidding behavior in a segmented market.

To obtain theoretical predictions for the experiment, I assume the distributions of ϕ^I and ϕ_k^S below.

Assumption: The seller expects that the maximum acceptable bid scores in an integrated market and segmented market are uniformly distributed, with a mean of $\overline{\phi}^I/2$ on $[0, \overline{\phi}^I]$ and a mean of $\overline{\phi}_k^S/2$ on $[0, \overline{\phi}_k^S]$, respectively, for $\overline{\phi}^I > 0$ and $\overline{\phi}_k^S > 0$ for $k \in \{L, H\}$.

For example, assume that ϕ^I is uniformly distributed, $F^I(v) = v/\overline{\phi}^I$ and $f^I(v) = 1/\overline{\phi}^I$ for $0 \leq v \leq \overline{\phi}^I$, and $\Pr(\phi^I \geq \mathrm{E}[\phi^I]) = 1/2$, where F^I and f^I denote the cumulative distribution and the density in an integrated market, respectively. The Assumption indicates that when all the sellers submit bids with an identical score v greater than $\mathrm{E}[\phi^I]$, i.e., $v > \mathrm{E}[\phi^I]$, the number of successful sellers is expected to be less than $N/2$.

Proposition 1: *Suppose that the Assumption holds. Then, the optimal bid increases with increasing seller quality.*

Proof: All proofs are provided in the Proofs section in the Appendix.

According to Proposition 1, the optimal bid of a high-type seller is greater than that of a low-type seller in an auction market where quality information is revealed. In contrast, if quality information is not revealed to the sellers, high-type sellers cannot directly recognize their advantage and therefore are unlikely to bid higher than low-type sellers in early periods. However, feedback from the auction results may allow them to infer quality information, potentially leading to higher bids in later periods, as in the quality-revealed market.

Proposition 2: *If the Assumption holds, market segmentation does not influence the low- and high-type sellers' optimal bids if and only if the buyer allocates the budget Z to each segmented market for sellers with quality* a_k *according to:*

$$z_k = Z \frac{a_k n_k}{\sum_t a_t n_t}, \quad k \in \{L, H\}. \tag{8}$$

The buyer has information on the quality and number of low- and high-type sellers. Proposition 2 indicates that market segmentation does not influence the optimal bids of either seller type. Equation [6] implies that if $\Pr(\phi^I \geq \mathrm{E}[\phi^I])$ does not depend on $\mathrm{E}[\phi^I]$, a decrease in the number of low- or high-type sellers raises the seller's expectation of $\mathrm{E}[\phi^I]$, whereas a decrease in the buyer's budget Z lowers it. Holding the total number of sellers and the buyer's budget constant, an increase in the share of high-type sellers—i.e., an increase in the number of high-type sellers, accompanied by a corresponding decrease in the number of low-type sellers—lowers the seller's expectation of $\mathrm{E}[\phi^I]$. Since higher $\mathrm{E}[\phi^I]$ increases the seller's optimal bid regardless of quality, Proposition 2 implies that, under the budget allocation rule in equation [8], the effect of a reduction in the number of sellers balances the effect of a decrease in the buyer's budget.

Similar results hold even when ϕ^I and ϕ_k^S are exponentially distributed. For example, suppose that ϕ^I is exponentially distributed on $[0,\infty)$ with distribution parameter $\lambda > 0$, such that $F^I(v) = 1 - e^{-\lambda v}$ and $f^I(v) = \lambda e^{-\lambda v}$ for $v \geq 0$, $\mathrm{E}[\phi^I] = 1/\lambda$, and $\Pr(\phi^I \geq \mathrm{E}[\phi^I]) = 1/e \approx 0.368$. Then, if all sellers submit identical bid scores $v > \mathrm{E}[\phi^I]$, the expected number of successful sellers is less than N/e.

3. Experimental design

I designed a laboratory experiment to examine auction performance under three treatments: integrated market treatment under the condition of unrevealed quality information (UI treatment), integrated market treatment under the condition of revealed quality information (RI treatment), and segmented market treatment under the condition of revealed quality information (RS treatment). These treatments were randomly assigned to participants via a between-participant design.

Table 1 presents example bids for the RI and RS treatments. The rule for determining successful bidders under the UI treatment is identical to that under the RI treatment.

<< Table 1 about here>>

In an integrated market (UI and RI treatments), successful bidders are determined via the following procedures: First, a successful bidder during the auction is determined by the rank of the bid amounts per quality (Rank2 in Table 1). The buyer's budget less the bid amount of the successful bidder is the remaining budget (Surplus2). This process is repeated until the remaining budget decreases to the bid amount with the lowest bid score (bid per quality) among the remaining sellers. The remaining budget of 90 was less than the bid amount of 118 of seller 202 for the RI treatment. Thus, this bid was unsuccessful. Since this rule is based on the rank of the bid amounts per quality, there can exist an unsuccessful bid that is lower than the remaining budget. Thus, in this study, I introduce the following second evaluation criterion. In the second step, a successful bidder is determined by the rank of the bid amounts (not per quality) that have not yet been successful (Rank3) until the remaining budget decreases to the lowest bid amount among unsuccessful sellers at the time[5]. Seller 199 did not win because their remaining budget of 11 (after seller 208 won) was lower than the bid amount of 84.

In the segmented market (RS treatment), although successful bidders during the auction are determined via two decision rules on the basis of the ranks of the bid amounts per quality and the bid amounts themselves, the rules comprise the following three steps. First, a successful bidder is determined by the rank of the bid amounts per quality within each segmented market where there are sellers with identical qualities (Rank1L or Rank1H in Table 1). Under the RS treatment, the buyer's type-by-type budgets for markets with low- and high-type sellers were 36 and 214, respectively. The buyer's type-by-type budget less the bid amount of the winner is the remaining type-by-type budget. This process is repeated until the remaining type-by-type budget decreases to the bid amount of an unsuccessful seller with the lowest bid amount per quality within each segmented market. In the second step, the type-by-type budgets are summed, and similar to the first step in the integrated market, winners are determined on the basis of the ranks of the bid amounts per quality among all unsuccessful sellers at the time (Rank2). This process is repeated until the remaining budget (Surplus1) decreases to the bid amount of an unsuccessful seller with the lowest bid amount per quality. The remaining budget of 72 was less than the bid amount of 73 of seller 351 for the RS treatment. Thus, this bid was unsuccessful. In the third step, a successful bidder is determined by the rank of the bid amounts (not per quality) offered by the remaining unsuccessful sellers (Rank3) until the remaining budget decreases to the lowest bid amount of an unsuccessful seller at the time. Seller 340 did not win because the remaining budget of 32 (after seller 345 won) was lower than the bid amount of 60.

A summary of the experimental sessions is provided in Table 2. I recruited 192 undergraduate students from the participant pool at Niigata University in September and November 2022. Each individual participated in one of twelve sessions. In each session, sixteen individuals participated in the experiment. Upon arrival at the laboratory, the participants sat in seats at desks separated by partitions and completed an informed consent form prior to the experiment. No communication among participants was allowed during the session.

<<Table 2 about here>>

Each session comprised four stages of the auction experiment followed by a stage of the lottery choice experiment to elicit participants' risk aversion (Holt and Laury 2002). The participants completed six periods of auctions at every stage (i.e., 24 periods in total). The auction engaged eight sellers. I also assigned a series of parameter settings for the share of high-type sellers in the market, at 25% or 75%, using a within-participant design to examine the robustness of the treatment effects to seller heterogeneity in the market. I also implemented treatments in which the order of auction stages with different shares of high-type sellers in the market was rearranged to examine the order effects of the condition regarding sellers' heterogeneity on auction performance and bidding behavior via a between-participant design (Table 2).

As in common laboratory experiments of experimental economics, neutral terminology was adopted in the experiment. Notably, the terms "item", "blue-type (yellow-type) seller", and “quality” were employed instead of water quality credit, a low-type (high-type) seller, and the amount of pollution abatement at the monitoring point, respectively.

Verbal instructions (recorded in advance) for the auction experiment were provided to the participants[6]. Printed presentation slides containing instructions were distributed among the participants. In the instructions, the rule for determining successful bidders was illustrated through numerical examples.

The participants completed three practice periods to facilitate their understanding of the price rule and the method of determining their profits during the auction after which instructions for the experimental stages were provided. During all the sessions, the participants completed auctions of integrated markets at the practice stage.

During the first period of each stage, the participants were divided into two groups. Seller types were then assigned to the members of each group. Both the group assignments and seller types were determined anonymously and randomly, in accordance with the treatment condition on the share of high-type sellers at each stage. The sellers were provided with an explanation clarifying that their types would remain the same across all periods at each stage. The sellers were informed of their own qualities and the number of high- and low-type sellers before they submitted bids only under the RI and RS treatments.

The units of costs and bid amounts were expressed as experimental points. These values were defined as integers. The sellers were informed that their costs of producing an item were independently and uniformly distributed on [1, 100] and could vary across periods. I chose narrower support of the cost distribution than Cason et al. (2003), Cason and Gangadharan (2005), and Conte and Griffin (2017) did to reduce participants’ decision costs and enhance the dominance condition of the experiment (Smith and Walker 1993). The sellers were informed of their own costs before submitting bids but were not informed of the other sellers’ costs, either before or after bidding. The sellers were asked to determine their bid amounts as an integer between 0 and 1,000 points to reduce outliers and make the buyer's budget difficult for them to guess.

In all the treatments, I set the parameters of the qualities of the items produced by low- and high-type sellers such that $a_L y = 1$ and $a_H y = 2$, respectively. These quality values were revealed to the sellers only under the RI and RS treatments.

The participants were informed of the rules for determining successful bidders on the basis of two evaluation criteria: the ranks of their bid amounts per quality and the ranks of the bid amounts themselves. The sellers were not provided information on the buyer's budget except that the buyer purchased items within a certain budget amount and that the buyer possessed type-by-type budgets only under the RS treatment. For each of the segmented markets under the RS treatment, the budget allocation rule expressed in equation [8] was applied. I set the parameter of the budget such that $Z = 250$ in all the treatments (Table 2). When a successful bid is made, the successful seller sells the item at the price of the bid amount submitted (discriminative price rule). Because the seller must also bear the costs to produce the item, the profits are determined as the bid amounts (price) less the costs.

During each auction, each seller submitted a bid for an item to be sold on a PC programmed with z-Tree software (Fischbacher 2007). The buyer decisions described above were also programmed. Although the results for each seller were provided individually, the results for the other sellers were not provided. The sellers could view the results of their previous periods at the current stage on their PC screens.

Verbal instructions (recorded in advance) for the lottery choice experiment were provided after the auction experiment. There was no practice period for the lottery choice experiment. After the lottery choice experiment, the participants were asked to respond to a brief questionnaire (mainly concerning demographic characteristics).

The participants received a show-up fee of $7.00 (¥1,000) and experimental rewards depending on their decisions during the auction and lottery choice experiments. At the end of each session, two out of six periods at each auction experiment stage were randomly drawn to determine the rewards for the auction experiment. The experimental points earned during those eight periods, including losses (negative profits), were converted at the rate of $4.20 (¥600) per 100 points under the UI treatment. To enhance the dominance condition, I set different conversion rates of $5.60 (¥800) yen per 100 points for low-type sellers and $2.80 (¥400) per 100 points for high-type sellers under both the RI and RS treatments in which quality information was disclosed to the participants (Smith 1982; Cason et al. 2003). When the monetary rewards of a given participant were negative, the participant paid losses from the reserve for losses of $0.70 (¥100). For positive rewards, the participant received the full amount of the reserve in addition to the show-up fee and monetary rewards from the auction experiment. One lottery pair out of ten decision tasks was also randomly drawn to determine the prize in the lottery choice experiment. The rewards were placed in an envelope and privately paid to each participant. The average experimental rewards during the auction and lottery experiments were approximately $3.70 (¥528.4) and $3.09 (¥441.1), respectively. The average time spent on a session excluding (including) questionnaire completion and reward payment was approximately 55 (71) minutes.

4. Results

Table 3 presents descriptions of the independent variables used in the econometric analysis of auction performance and sellers' bidding behaviors.

<<Table 3 about here>>

4.1. Auction performance

Auction performance was measured by three indices: the percentage of the realized and maximum abatement ratio (PMAR), the percentage of the realized and maximum cost-effectiveness ratio (PCER), and the sellers' profits to abatement ratio (SPRA). Let W^R and W^M denote the number of accepted sellers during an auction and the number of sellers with which the buyer would trade if they knew the opportunity costs of all the sellers, respectively. I defined the PMAR as the percentage of the ratio of the pollution abatement realized at the monitoring point, $q^R = \sum_{i=1}^{W^R} a_i y$ (where i denotes the increasing order of bid scores $v_i = b_i / a_i$), to the maximum abatement that could be achieved if there was no private information on potential sellers' abatement costs and no market segmentation, $q^M = \sum_{j=1}^{W^M} a_j y$ (where j denotes the increasing order of c_j / a_j), i.e., PMAR = $100 \times q^R / q^M$. The PCER represents the relative cost-effectiveness, which is defined as the percentage of the ratio of the costs per unit of abatement realized, p^R / q^R ($p^R = \sum_{i=1}^{W^R} b_i$ denotes the total costs, which are the sum of successful bids, of the abatement realized), to the cost per unit of the maximum abatement, c^M / q^M ($c^M = \sum_{j=1}^{W^M} c_j$ denotes the total costs of maximum abatement). This value is expressed as PCER = $100 \times (p^R / q^R)/(c^M / q^M) = 100 \times (p^R / c^M) \times (\text{PMAR})^{-1}$. Furthermore, I define the SPRA as the total sellers' profits (prices less opportunity costs) earned, $x^R = \sum_{i=1}^{W^R} (b_i - c_i)$, per unit of abatement realized, i.e., SPRA = x^R / q^R. As sellers' profits increase even when they lower their bids and pollution abatement increases, the total sellers' profits would not be appropriate as an index of undesirable performance. Thus, I use the SPRA instead of the total sellers' profits. According to these definitions, an increase in the PMAR or a decrease in the PCER or SPRA indicates an improvement in auction performance.

Summary statistics of the variables in the auction performance models are provided in Table 4. The kernel densities of those auction performance measures by treatment and share of high-type sellers are shown in Figure 1. According to Figure 1, for a 25% share of high-type sellers, although the density of the PMAR under the RS treatment seems close to that under the RI treatment, the densities of the PCER and SPRA under the RS treatment are located on the left side of those under the RI treatment. For a 75% share of the high-type sellers, the densities of the PMAR, PCER, and SPRA under the RS treatment are located on the right side of that of the PMAR and on the left side of those of the PCER and SPRA under the RI treatment.

<<Table 4 about here>>

<<Figure 1 about here>>

The variations in the time series of the average auction performance across groups (auction markets) during each period are shown in Figure A.1 in the Appendix. The PMAR, PCER, and SPRA curves for the UI treatment are close to those under the RI treatment during later periods for both the 25% and 75% shares of high-type sellers.

I estimated random effects (RE) models with the dependent variables PMAR, PCER, and SPRA to investigate the average treatment effects of market segmentation and the revelation of quality information. The RE model allows one to estimate the coefficients of time-invariant variables such as treatment variables and the average risk aversion of the group. Table 5 provides the estimation results of the RE models for auction performance.

<<Table 5 about here>>

Revealing quality information causes a reduction in auction performance. The estimated coefficients of *Revealed* are significantly positive in all the specifications for the PCER and SPRA regardless of the share of high-type sellers (Table 5). The results indicate that revelation of quality information, *ceteris paribus*, deteriorates the PCER and the SPRA for the 25% share of high-type sellers and deteriorates the PCER and the SPRA for the 75% share of high-type sellers (panels C, D, E, and F, respectively, of Figure 1). In contrast, for the PMAR, although it is insignificant for the 25% share of high-type sellers (panel A of Figure 1), it is significantly negative for the 75% share of high-type sellers (panel B of Figure 1). Given the 75% share of high-type sellers, revealing quality information deteriorates the PMAR.

In contrast to the predictions of the optimal bidding model, market segmentation improves auction performance. The estimated coefficients of *Segment* are significant in all specifications except the PMAR for the 25% share of high-type sellers (Table 5). The results indicate that, compared with the integrated market, where quality information is revealed, market segmentation improves the PCER and the SPRA for the 25% share of high-type sellers (panels C and E, respectively, of Figure 1) and improves the PMAR, the PCER, and the SPRA for the 75% share of high-type sellers (panels B, D, and F, respectively, of Figure 1).

Furthermore, market segmentation predominates over the effects of revealing quality information. All the sums of the estimated coefficients of *Segment* and *Revealed* are insignificant in two-sided tests except the SPRA for the 25% share of high-type sellers (panels B, C, D, E, and F of Figure 1). The sum of *Segment* and *Revealed* for the SPRA for the 25% share of high-type sellers is significantly negative (panel A of Figure 1), indicating that market segmentation improves the SPRA more than not revealing quality information. These results indicate that market segmentation completely predominates over the impact of revealing quality information on all auction performance measures.

The estimates of the control variable of *GrpAvgCost* are significant in all specifications (Table 5). As indicated in Table 4, the sample mean of *GrpAvgRskAvs* for each treatment indicates that the participants are categorized into risk-averse bidders on average (Holt and Laury 2002). Although sellers are expected to increase their bids as costs increase, the magnitude of the marginal effects can be determined empirically. An increase in bid amounts due to an increase in sellers' opportunity costs decreases the pollution abatement realized (in the numerator of the PMAR) and decreases the PMAR. In contrast, an increase in sellers' opportunity costs also decreases the maximum pollution abatement (the denominator of the PMAR) and increases the PMAR. These impacts cancel each other out. Suppose that increases in sellers' costs raise their bid amounts in the market. Higher bid amounts can reduce the number of successful sellers. If the last successful seller under the pollution abatement realized (seller W^R) and maximum abatement scenarios (seller W^M) is not accepted by the increases in bids, then pollution abatement under these scenarios decreases to $\sum_{i=1}^{W^R} a_i y - a_{W^R} y$ and $\sum_{j=1}^{W^M} a_j y - a_{W^M} y$, respectively. If, for example, the marginal effect of an increase in a seller's opportunity costs on the bid amount is constant and less than one, the marginal effect of the increase in the group-averaged costs on the buyer's expenditures under the pollution abatement realized scenario ($\sum_{i=1}^{W^R} b_i$) is less than that on the buyer's expenditures under the maximum abatement scenario ($\sum_{j=1}^{W^M} c_j$). Thus, the increase in the sellers' opportunity costs improves the PMAR and PCER if $a_{W^R} < a_{W^M}$. Moreover, if the marginal effect of the increase in the seller's cost on the bids is less than one and the number of successful sellers under both scenarios is unchanged (so that the PMAR does not change), then the PCER improves. In contrast, if the marginal effect of the increase in the seller's cost on the bids is less than one, the group-averaged costs are always expected to improve the SPRA. I will examine these impacts in detail in the following analysis of the bidding behavior.

The estimates of the control variable of *GrpAvgRskAvs* are significant in all specifications except for the PMAR (Table 5). The results indicate that auction performance, as measured by the PCER and SPRA, improves as the degree of the sellers' risk aversion in the group increases.

The estimates of the control variable ln*Period* are insignificant in all specifications. The results indicate that repeating auctions does not influence any of the auction performance measures.

I subsequently examined two types of order effects: the effect of participating in a stage of auctions with a 75% share of high-type sellers after they participated in a stage with a 25% share of high-type sellers (*AfterHigh*25) and the effect of participating in a stage with a 25% share of high-type sellers after they participated in a stage with a 75% share of high-type sellers (*AfterHigh*75). The base group comprises the first and third stages. The estimates of the order effects are insignificant in all specifications except specification (4), in which it is significant at the 10% level. Since the results are not structural, I believe that there are no order effects of the shares of high-type sellers assigned to participants via a within-participant design.

As noted by Palm-Forster et al. (2016), complex buyer decision rules may increase the transaction costs of potential participants in auctions for water quality improvement and decrease the number of participants and cost-effectiveness. I examined the effects of market segmentation using the samples that excluded observations in which the buyer's second evaluation criterion—where bids themselves (rather than bids per quality) were directly evaluated—was applied. The results can be found in Table A.1 in the Appendix. Even after the auction periods with successful bids determined by the buyer's second evaluation criterion were excluded, the results remained similar. Market segmentation completely predominates over the impacts of revealing quality information on auction performance, except for the SPRA for the 75% share of high-type sellers.

4.2. Bidding behavior

In the empirical analyses of bidding behavior, I focus on the effects of market segmentation and the revelation of quality information and split the sample by the share of high-type sellers in the market. Scatter plots of low- and high-type sellers' costs and bids for the RI and RS treatments by the share of high-type sellers in the market are shown in Figure 2. With few exceptions, all the bids lie above the 45-degree lines in which the sellers' bids equal their costs. According to Figure 2, market segmentation tends to decrease the bid amounts submitted by high-type sellers (panels C and D), but not those submitted by low-type sellers (panels A and B), regardless of the share of high-type sellers in the market. The mean of the maximum accepted bid score by treatment and seller type is shown in Table A.2 in the Appendix. For the UI and RI treatments, the maximum accepted bid scores tend to decrease as the share of high-type sellers increases. For the RS treatment, the maximum accepted bid scores for the low-type sellers also tend to decrease with an increase in the share of high-type sellers. These results are consistent with the assumptions in equations [6] and [7], respectively. In contrast, those for high-type sellers, for the RS treatment, tend to increase slightly.

<<Figure 2 about here>>

The submitted bids range from two to one thousand experimental points across all the treatments; there are several extremely high bid amounts in the samples. I define an outlier of seller *i*'s bid amount, Bid_i, such that $|Bid_i - \text{med}(Bid_i)|/\text{MAD} > 3$, where $\text{med}(Bid_i)$ denotes the median of Bid_i and MAD denotes the median absolute deviation, which is defined as $\text{MAD} = b \times \text{med}(|Bid_i - \text{M}|)$, with b = 1.4826 (assuming a normal distribution for Bid) and $\text{M} = \text{med}(Bid_i)$ (Rousseeuw and Croux 1993; Rousseeuw and Hubert 2011; Leys et al. 2013). I estimate models including outlier dummies and models using samples in which outliers are eliminated[7]. The estimation results of the RE models with the dependent variable *Bid* are provided in Table 6. The results of the empirical analysis of bidding behaviors are consistent with the results obtained for auction performance.

<<Table 6 about here>>

The estimated coefficients of *RskAvs* and *RskAvs*×*HighType* are insignificant in specifications (1), (2), (4), and (5), as listed in Table 6, indicating that the degree of risk aversion of participants measured in the lottery choice experiment, *ceteris paribus*, does not influence the bid amount at the individual level, regardless of the seller type. Thus, I eliminate them in specifications (3) and (6). The estimated coefficients of *Outlier* are significantly positive in both specifications (1) and (4). Because they are larger than the maximum values of the accepted bids (110, 118, and 108 for the UI, RI, and RS treatments, respectively), the outliers do not affect auction performance. I then provide interpretations of the results of specifications (3) and (6). The estimated coefficients of *AfterHigh*75 and *AfterHigh*25 are insignificant in specifications (3) and (6), respectively, indicating that there is no order effect at the individual level.

The estimated coefficients of *Cost* are significant in specifications (3) and (6), as expected (Table 6). The coefficients of *Cost* are also significantly different from one in both (3) and (6) in two-sided tests (p=0.000 for both). The results indicate that the marginal effect of an increase in a seller's opportunity cost on bid amounts are less than one regardless of the share of high-type sellers. The results are also consistent with the finding that the average seller costs of the group significantly improve auction performance.

Even when quality information is not revealed, although there is no difference in bids between high- and low-type sellers during the first few periods, the high-type sellers' bids become higher than those of the low-type sellers during the later periods. The estimated coefficient of *HighType* is insignificant in both specifications (3) and (6), indicating that, at any cost and regardless of the share of high-type sellers, there is no difference in the bid amounts between seller types during the first period of the UI treatment (Table 6). There is an opportunity to learn the seller's type by repeating the bidding process and receiving the result in the UI treatment. The difference in bids between seller types changes across periods under the UI treatment. These changes can be estimated by the sum of the estimated coefficient of *HighType* and the product of the estimated coefficient of ln*Period*× (1−*Revealed*)×*HighType* and the logarithm of the period number. The estimated results are listed in Table 7A. The results indicate that under the UI treatment high-type sellers bid higher than low-type sellers after the first period when the share of high-type sellers is 25% and after the second period when the share of high-type sellers is 75%. The results suggest that via auction repetition, the sellers can learn their expectation of the maximum acceptable bid scores that would be obtained if they possessed quality information.

<<Table 7 about here>>

When quality information is revealed, high-type sellers bid higher than low-type sellers in both integrated and segmented markets. The difference in bids between high- and low-type sellers under the RI treatment can be estimated by the sum of the estimated coefficients of *HighType* and *Revealed*×*HighType*. The estimation results are provided in Table 8. The estimates are significantly positive for the 25% and 75% shares of high-type sellers in the market for specifications (3) and (6), respectively. The results indicate that for the RI treatment, the bid amounts of the high-type sellers are greater than those of the low-type sellers regardless of the share of high-type sellers in the market. The difference in bids between high- and low-type sellers under the RS treatment can be estimated by the sum of the estimated coefficients of *HighType*, *Segment*×*HighType*, and *Revealed*×*HighType* (Table 8). The estimates are significantly positive for the 25% and 75% shares of high-type sellers in the market for specifications (3) and (6), respectively. The results indicate that the bid amounts of the high-type sellers exceed those of the low-type sellers under the RS treatment, regardless of the share of high-type sellers in the market.

<<Table 8 about here>>

When quality information is revealed, both low- and high-type sellers decrease their bids with repeated auctions in both integrated and segmented markets. In specifications (3) and (6), three variables capture the effects of repeating auctions on bids: ln*Period* and its interaction terms with (1−*Revealed*) or (1−*Revealed*)×*HighType* (Table 6). Thus, the base group for ln*Period* comprises low- and high-type sellers under the RI and RS treatments. The estimated coefficients of ln*Period* are significantly negative in both specifications (3) and (6). The results indicate that both seller types decrease their bids with repeated biddings under the RI and RS treatments.

Although revealing quality information decreases the bid amounts of low-type sellers in integrated markets, it increases those of high-type sellers. Compared with markets in which quality information is not revealed, the effects of revealing quality information on high-type sellers compete with those of auction repetition, since under the RI treatment high-type sellers decrease their bid amounts through repeated auctions (Table 6). Furthermore, under the UI treatment, high-type sellers increase their bid amounts through repeated auctions (Table 7A). Consequently, in markets with a 25% share of high-type sellers, the difference in high-type sellers' bids between the RI and UI treatments disappears after the second period, whereas in markets with a 75% share of high-type sellers, the difference persists even after the second period (Table 7B). The estimated coefficients of *Revealed* are significantly negative in both specifications (3) and (6). The results indicate that revealing quality information decreases the low-type sellers' bid amounts regardless of the share of high-type sellers in the market. Furthermore, the effects of revealing quality information on the high-type sellers' bids change across periods. These changes can be estimated by the difference between the sum of the estimated coefficients of *Revealed* and *Revealed*×*HighType* and the product of the estimated coefficient of ln*Period*×(1−*Revealed*) ×*HighType* and the logarithm of the period number (Table 7B). The results indicate that revealing quality information increases the high-type sellers' bid amounts and generates significant differences in their bids between the markets with and without revealing quality information. However, there is no difference after the second period for the 25% share of high-type sellers. In contrast, when the share is 75%, the effects of revealing quality information overtake those of bidding repetition so that the difference persists during later periods.

When quality information is revealed, although market segmentation does not influence low-type sellers' bids as predicted, it decreases high-type sellers' bids contrary to predictions. As indicated in Table 6, the estimated coefficients of *Segment* are insignificant in both specifications (3) and (6). The results indicate that regardless of the share of high-type sellers in the market, market segmentation does not influence the low-type sellers' bid amounts (panels A and B of Figure 2), which decrease because the quality information is revealed. In contrast, the estimated coefficients of *Segment*×*HighType* are significantly negative in both specifications. The effects of market segmentation on high-type sellers' bids when quality information is revealed can be estimated by the sum of the estimated coefficients of *Segment* and *Segment*×*HighType* (Table 8). The estimates are significantly negative for specifications (3) and (6) regardless of the share of high-type sellers. The results indicate that regardless of the share of high-type sellers in the market, market segmentation decreases high-type sellers' bid amounts (panels C and D of Figure 2).

Market segmentation decreases low-type sellers' bids and cancels out the effects of revealing quality information on high-type sellers' bids by decreasing their bids. I investigated these phenomena by setting the UI treatment as the reference point. The effects of market segmentation on low-type sellers' bids can be estimated by the sum of the estimated coefficients of *Segment* and

Revealed (Table 8). The estimates are significantly negative for specifications (3) and (6) for the 25% and 75% shares of high-type sellers in the market, respectively. The results indicate that the bid amounts of low-type sellers in segmented markets are lower than those in integrated markets where quality information is not revealed. Similarly, the canceling effects of market segmentation on high-type sellers' bids can be estimated by the difference between the sum of the estimated coefficients of *Segment*, *Revealed*, *Segment*×*HighType*, and *Revealed*×*HighType* and the product of the estimated coefficient of ln*Period*×(1−*Revealed*)×*HighType* and the logarithm of the period number. These estimates are listed in Table 7C. The results indicate that market segmentation completely cancels out the effects of revealing quality information on high-type sellers' bids after the second period when their market share is 75% and during all periods when their share is 25%. As demonstrated above, the high-type sellers' bid amounts decrease as the number of periods increases under the RS treatment regardless of their share in the market (Table 6). When the share is 25%, the high-type sellers' bid amounts in segmented markets after the second period are lower than those of sellers of the same type in integrated markets where quality information is not revealed (Table 7C).

5. Conclusion

The application of the PPP to nonpoint source pollution abatement has not yet been adopted in many countries (OECD 2017). Auctions have potential as cost-effective policy instruments even when PPP application is difficult. In this study, I theoretically and experimentally examined the effects of market segmentation on auction performance when, to enhance auction transparency, information on the environmental impacts of polluting input abatement was disclosed to sellers. Applying the optimal bidding model, I generate theoretical predictions by assuming that the sellers' expectations of the maximum acceptable bid scores are uniformly or exponentially distributed.

As shown in the experiment of Cason et al. (2003) and theoretically predicted, I found that revealing quality information caused deterioration in all three auction performance measures (PMAR, PCER, and SPRA), regardless of the share of high-type sellers except the PMAR for the 25% share of high-type sellers in the market. With respect to sellers' bidding behaviors, I found that revealing quality information decreases low-type sellers' bid amounts but increases high-type sellers' bid amounts, regardless of the share of high-type sellers. In contrast, even when quality information is not revealed, repeating auctions increases high-type sellers' bids. Compared with markets with and without quality information, although there is a significant difference in the high-type sellers' bids during early periods, the difference disappears during later periods for the 25% share of high-type sellers. In contrast, for the 75% share of high-type sellers, the difference persists even during later periods.

However, contrary to theoretical predictions, I found that market segmentation improved all auction performance measures regardless of the share of high-type sellers. With respect to the sellers' bidding behaviors, I found that market segmentation does not influence the low-type sellers' bid amounts but decreases the high-type sellers' bid amounts regardless of the share of high-type sellers. The results suggest that decreasing high-type sellers' bids is the major factor in the improvement in auction performance caused by market segmentation. I further showed that market segmentation completely predominated over the impacts of revealing quality information. For sellers' bidding behaviors, I found that market segmentation completely cancels out the impacts of revealing quality information on high-type sellers' bids even during later periods when the sellers are considered to have learned their expectations of the maximum acceptable bid scores that they would otherwise have obtained if they were provided with quality information.

Although Ito (2023) reported, through a laboratory experiment, that market segmentation can improve the performance of water quality trading auctions in which ambient-based credits are traded, its success depends on the configuration of sellers' cost distributions (which are determined by the share of high-type sellers). The results of this study, in which emissions trading of input-based (emission-based) credits was assumed, were clearer than those of Ito (2023). The optimal bidding model can also be applied to auctions for ambient-based credits. In the optimal bidding model, qualities (environmental impacts) do not influence the expectation of the distribution or the expected value of the maximum acceptable bids since the quality of ambient-based credits is identical. Thus, quality information is unlikely to influence sellers' bidding behavior. This would be a major cause of the unclear effects of market segmentation on auction performance.

Regulatory agencies may consider disclosing information on transfer coefficients to increase transparency and decrease the transaction costs of water quality trading programs (Cason et al. 2003) or to encourage the participation of farmlands with high transfer coefficients. The experimental results suggest that market segmentation can cancel out the effects of revealing quality information on auction performance and can improve both transparency and cost-effectiveness. These results may depend on the experimental parameters. I considered two levels of transfer coefficients and eight potential sellers in the market. This experiment could be extended to settings with more heterogeneous transfer coefficients or a larger number of sellers in future research. Furthermore, although seller costs were uniformly distributed in this experiment, alternative cost distributions may yield different results. It is also unclear whether the experimental results can be generalized to other auction designs, such as those involving bidding for multiple items, item selection by sellers, or multiple bidding rounds. Addressing these extensions would help to assess the robustness of the findings.

Acknowledgment

I appreciate the two anonymous reviewers for their contributions to improving the manuscript. Any remaining errors are solely my responsibility. This work was supported by JSPS KAKENHI Grant Numbers JP18K12766 and JP25K15554. The author would like to thank American Journal Experts for their English proofreading of this manuscript.

References

Cason, T.N., and Gangadharan, L., 2005. A laboratory comparison of uniform and discriminative price auctions for reducing non-point source pollution. *Land Economics* 81, 51–70. https://doi.org/10.3368/le.81.1.51

Cason, T.N., Gangadharan, L., Duke, C., 2003. A laboratory study of auctions for reducing non-point source pollution. *Journal of Environmental Economics and Management* 46, 446–471. https://doi.org/10.1016/S0095-0696(03)00026-3

Cochard, F., Willinger, M., Xepapadeas, A.P., 2005. Efficiency of nonpoint source pollution instruments: an experimental study. *Environmental and Resource Economics* 30, 393–422. https://doi.org/10.1007/s10640-004-5986-y

Commonwealth of Pennsylvania, Nutrient Credit Trading. https://www.pa.gov/agencies/dep/programs-and-services/water/clean-water/nutrient-credit-trading.html#accordion-1483f8dd6e-item-e423136192 (accessed 7 Jan. 2026)

Conte, M.N., Griffin, R.M., 2017. Quality information and procurement auction outcomes: Evidence from a payment for ecosystem services laboratory experiment. *American Journal of Agricultural Economics* 99, 571–591. https://doi.org/10.1093/ajae/aaw096

Conte, M. N., Griffin, R. 2019. Private benefits of conservation and procurement auction performance. *Environmental and Resource Economics* 73, 759-790. https://doi.org/10.1007/s10640-019-00333-y

Fischbacher, U., 2007. z-Tree: Zurich toolbox for ready-made economic experiments. *Experimental Economics* 10, 171–178. https://doi.org/10.1007/s10683-006-9159-4

Fisher-Vanden, K., Olmstead, S., 2013. Moving pollution trading from air to water: potential, problems, and prognosis. *Journal of Economic Perspectives* 27, 147–72. https://doi.org/10.1257/jep.27.1.147

Griffin, R.C., Bromley, D.W., 1982. Agricultural runoff as a nonpoint externality: a theoretical development. *American Journal of Agricultural Economics* 64, 547–552. https://doi.org/10.2307/1240648

Holt, C. A., Laury, S. K., 2002. Risk aversion and incentive effects. *American Economic Review* 92(5), 1644-1655. https://doi.org/10.1257/000282802762024700

Ito, N., 2023. Can market segmentation improve the performance of water quality trading auction? A laboratory experiment. *Ecological Economics* 213, 107934. https://doi.org/10.1016/j.ecolecon.2023.107934

Latacz-Lohmann, U., Van der Hamsvoort, C., 1997. Auctioning conservation contracts: a theoretical analysis and an application. *American Journal of Agricultural Economics* 79(2), 407–418. https://doi.org/10.2307/1244139

Leys, C., Ley, C., Klein, O., Bernard, P., Licata, L., 2013. Detecting outliers: Do not use standard deviation around the mean, use absolute deviation around the median. *Journal of Experimental Social Psychology* 49, 764–766. https://doi.org/10.1016/j.jesp.2013.03.013

Newburn, D.A., Woodward, R.T., 2012. An ex post evaluation of Ohio's Great Miami Water Quality Trading Program. *Journal of the American Water Resources Association* 48, 156–169. https://doi.org/10.1111/j.1752-1688.2011.00601.x

OECD. 2012. Water Quality and Agriculture: Meeting the Policy Challenge. Paris: OECD Publishing. https://doi.org/10.1787/9789264168060-en

OECD. 2017. Diffuse Pollution, Degraded Waters: Emerging Policy Solutions. Paris: OECD Publishing. https://doi.org/10.1787/9789264269064-en

Palm-Forster, L.H., Swinton, S.M., Lupi, F., Shupp, R.S., 2016. Too Burdensome to Bid: Transaction Costs and Pay-for-Performance Conservation. *American Journal of Agricultural Economics* 98, 1314–1333. https://doi.org/10.1093/ajae/aaw071

Rousseeuw, P.J., Croux, C., 1993. Alternatives to the median absolute deviation. *Journal of the American Statistical Association* 88, 1273–1283. https://doi.org/10.1080/01621459.1993.10476408

Rousseeuw, P.J., Hubert, M., 2011. Robust statistics for outlier detection. *WIREs Data Mining and Knowledge Discovery* 1, 73–79. https://doi.org/10.1002/widm.2

Segerson, K., 1988. Uncertainty and incentives for nonpoint pollution control. *Journal of Environmental Economics and Management* 15, 87–98. https://doi.org/10.1016/0095-0696(88)90030-7

Shortle, J.S., Abler, D.G., Horan, R.D., 1998. Research issues in nonpoint pollution control. *Environmental and Resource Economics* 11, 571–585. https://doi.org/10.1023/A:1008276202889

Smith, V.L., 1982. Microeconomic systems as an experimental science. *American Economic Review* 72, 923–955. https://www.jstor.org/stable/1812014

Smith, V.L., Walker, J.M., 1993. Monetary rewards and decision cost in experimental economics. *Economic Inquiry* 31, 245–261. https://doi.org/10.1111/j.1465-7295.1993.tb00881.x

U.S. Environmental Protection Agency (U.S. EPA). 2007. Water Quality Trading Toolkit for Permit Writers (Updated June 2009). Washington, DC. https://www.epa.gov/sites/default/files/2016-04/documents/wqtradingtoolkit.pdf (accessed 7 Jan. 2026)

Vukina, T., Zheng, X., Marra, M., Levy, A., 2008. Do farmers value the environment? Evidence from a conservation reserve program auction. *International Journal of Industrial Organization* 26(6), 1323–1332. https://doi.org/10.1016/j.ijindorg.2008.01.001

Selman, M., Greenhalgh, S., Branosky, E., Jones, C., Guiling, J., 2009. Water quality trading programs: An international overview. WRI Issue Brief, Washington, DC.

http://pdf.wri.org/water_trading_quality_programs_international_overview.pdf (accessed 7 Jan. 2026)

Wichmann, B., Boxall, P., Wilson, S., Pergery, O., 2017. Auctioning risky conservation contracts. *Environmental and Resource Economics* 68, 1111–1144. https://doi.org/10.1007/s10640-016-0063-x

Xepapadeas, A.P., 2011. The economics of non-point-source pollution. *Annual Review of Resource Economics* 3 (1): 355–373. https://doi.org/10.1146/annurev-resource-083110-115945

Xepapadeas, A.P., 1992. Environmental policy design and dynamic nonpoint-source pollution. *Journal of Environmental Economics and Management* 23, 22–39. https://doi.org/10.1016/0095-0696(92)90039-Y

Table 1. Example bids and transaction results in markets for the RI and RS treatments

Seller	Cost	Bid	Bid/Quality	Rank1L	Rank1H	Traded1	Surplus1	Rank2	Traded2	Surplus2	Rank3	Traded3
A. *RI treatment* (*integrated market where quality information is revealed to the sellers*)												
193	75	76	38					2	1	90		
196	84	85	85					7	0	90	3	0
199	83	84	84					6	0	90	2	0
202	48	118	59					4	0	90	5	0
205	94	95	95					8	0	90	4	0
206	44	55	55					3	1	90		
207	25	29	29					1	1	90		
208	76	79	79					5	0	90	1	1
B. *RS treatment* (*segmented market where quality information is revealed to the sellers*)												
340	56	60	60	2		0	72	5	0	72	2	0
342	6	68	34		3	1	72		0	72		
344	87	91	46		6	0	72	4	0	72	5	0
345	31	40	40	1		0	72	2	0	72	1	1
346	32	43	22		1	1	72		0	72		
347	80	81	41		5	0	72	3	0	72	4	0
348	65	67	34		2	1	72		0	72		
351	45	73	37		4	0	72	1	0	72	3	0

Note. The type-by-type budgets of the low- and high-type sellers in the RS treatment of panel B were 36 and 214, respectively. Rank1L, Rank1H, Traded1, and Surplus1 are used under the RS treatment only. Rank1L and Rank1H denote the ranks of the bid amounts per quality for each seller type. The value of Traded1 is 1 if the item of the seller is purchased based on Rank1L or Rank1H by the buyer with type-by-type budgets. Surplus1 denotes the sum of the remaining type-by-type budgets. Rank2 denotes the rank of the bid amounts per quality for the RI treatment or those which had not yet been successful for the RS treatment. The value of Traded2 is 1 if the item of the seller is purchased based on Rank2. The purchases based on Rank2 are subtracted from Surplus1. Surplus2 and Rank3 denote the remaining budget and the rank of the bid amounts (not per quality) that had not yet been successful after the transactions based on Rank2, respectively. The value of Traded3 is 1 if the item of the seller is purchased by the buyer based on Rank3 with the remaining budget of Surplus2.

Table 2. Summary of the experimental sessions

Session	Treatment	Number of high-type sellers n_H at each stage	Budget allocated to high-type seller's market z_H
1, 9	UI	(6,2,2,6)	No budget allocation
2, 12	UI	(2,6,6,2)	No budget allocation
3, 8	RI	(6,2,2,6)	No budget allocation
4, 11	RI	(2,6,6,2)	No budget allocation
5, 7	RS	(6,2,2,6)	$z_H = 100$ for $n_H = 2$; $z_H = 214$ for $n_H = 6$
6, 10	RS	(2,6,6,2)	$z_H = 100$ for $n_H = 2$; $z_H = 214$ for $n_H = 6$

Note. UI, RI, and RS denote the treatment of an integrated market where quality information is unknown to the sellers, the treatment of an integrated market where quality information is revealed to the sellers, and the treatment of a segmented market where quality information is revealed to the sellers, respectively. The number of high-type sellers is expressed as $(n_H^1, n_H^2, n_H^3, n_H^4)$, where n_H^T denotes the *T*th stage in the experiment. The distributions of sellers' costs (uniform with support [1, 100]), the parameters of item qualities for low- and high-type sellers ($a_L y$=1 and $a_H y$=2), and the buyer's budget (Z=250) were identical across all treatments. Under the RS treatment, $Z = z_L + z_H$. Sellers' realized costs could vary across periods. Sellers' assigned types could vary across stages but not across periods within a given stage.

Table 3. Descriptions of the independent variables

Variable	Description
GrpAvgCost	The average costs of the potential sellers within the group during the period
GrpAvgRskAvs	The average number of safe choices of potential sellers (participants) within the group in the lottery choice experiment
Segment	A dummy variable that takes a value of one if the market is segmented, with a value of zero otherwise
Revealed	A dummy variable that takes a value of one if quality information is revealed to potential sellers (i.e., RI or RS treatment), with a value of zero otherwise
ln*Period*	The natural logarithm of the number of periods, with a value between one and six
*AfterHigh*75	A dummy variable that takes a value of one if the share of high-type sellers at the previous stage is 75%, with a value of zero otherwise
*AfterHigh*25	A dummy variable that takes a value of one if the share of high-type sellers at the previous stage is 25%, with a value of zero otherwise
Cost	The costs of a seller to produce an item
RskAvs	The number of safe choices of a seller (participant) in the lottery choice experiment
HighType	A dummy variable that takes a value of one if the seller is a high-type seller, with a value of zero otherwise

Table 4. Summary statistics for the variables in the auction performance models

Variable	Treatment	Mean	Std. Dev.	Min.	Max.
The number of accepted bids	UI	3.979	0.647	3	6
	RI	4.016	0.712	3	6
	RS	4.391	0.772	3	7
Pollution abatement realized	UI	6.563	1.383	4	11
	RI	6.354	1.184	4	10
	RS	6.875	1.554	3	11
Maximum pollution abatement	UI	8.703	1.845	6	13
	RI	8.984	1.962	5	14
	RS	9.125	1.986	6	14
PMAR (%)	UI	76.07	10.06	50.00	114.3
	RI	71.99	10.64	46.15	100.0
	RS	75.80	10.01	50.00	100.0
PCER (%)	UI	134.0	17.00	100.9	195.2
	RI	144.8	22.22	99.59	218.5
	RS	134.0	18.26	96.97	190.7
SPRA	UI	11.49	5.515	2.143	35.80
	RI	14.03	5.861	0.400	36.75
	RS	11.24	4.850	1.400	26.00
GrpAvgRskAvs	UI	5.797	0.433	4.375	6.375
	RI	5.313	0.766	3.875	6.750
	RS	5.844	0.712	4.375	7.625

Note. The number of observations for each variable by treatment is 192 (2 groups × 6 periods× 4 stages×2 conditions×2 sessions).

Table 5. Estimated random effects models for auction performance

Variable	Condition/dependent variable					
	25% share of high-type sellers			75% share of high-type sellers		
	PMAR	PCER	SPRA	PMAR	PCER	SPRA
	(1)	(2)	(3)	(4)	(5)	(6)
Segment	2.265	−10.257***	−3.954***	7.771***	−17.868***	−3.250***
	(1.973)	(3.572)	(1.229)	(1.731)	(3.653)	(0.631)
Revealed	−0.226	5.620*	1.921*	−8.430***	18.190***	3.993***
	(1.852)	(3.032)	(1.080)	(1.724)	(3.263)	(0.614)
GrpAvgCost	0.227***	−0.683***	−0.172***	0.387***	−0.792***	−0.125***
	(0.085)	(0.103)	(0.035)	(0.059)	(0.106)	(0.024)
GrpAvgRskAvs	−2.050*	4.949***	1.624**	−0.564	2.957*	0.566
	(1.169)	(1.616)	(0.649)	(0.924)	(1.652)	(0.350)
ln*Period*	−0.875	3.266**	0.488	0.127	−1.080	0.242
	(0.985)	(1.660)	(0.506)	(0.940)	(1.764)	(0.415)
*AfterHigh*75	−0.933	0.421	0.540			
	(1.602)	(2.637)	(0.941)			
*AfterHigh*25				−2.093*	1.787	0.673
				(1.272)	(2.306)	(0.482)
Constant	76.654***	136.599***	12.159***	60.624***	159.441***	12.202***
	(7.776)	(10.939)	(3.999)	(6.331)	(9.176)	(1.917)
Sum of the estimates of *Segment* and *Revealed*	2.039	−4.636	−2.033	−0.659	0.322	0.743
p value (two-sided test)	0.318	0.155	0.058	0.675	0.881	0.196
Observations	288	288	288	288	288	288
R^2-within	0.062	0.171	0.087	0.147	0.154	0.072

Note. The total number of observations is 288 (2 groups×6 periods×2 stages×12 sessions). The numbers in parentheses are standard errors clustered at the group level by stage. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. An increase in the PMAR or a decrease in the PCER or SPRA indicates an improvement in auction performance.

Table 6. Estimated random effects model of the bid amounts

Variable	25% share of high-type sellers			75% share of high-type sellers		
	(1)	(2)	(3)	(4)	(5)	(6)
Cost	0.702***	0.751***	0.751***	0.667***	0.716***	0.716***
	(0.035)	(0.017)	(0.017)	(0.025)	(0.019)	(0.019)
HighType	14.369	2.211	−1.185	2.985	−4.049	−1.313
	(10.222)	(6.036)	(2.734)	(5.289)	(4.215)	(2.283)
RskAvs	1.562	0.147		−0.256	−0.134	
	(1.296)	(0.223)		(0.323)	(0.320)	
RskAvs×*HighType*	−2.411	−0.748		0.411	−0.061	
	(1.934)	(0.894)		(0.869)	(0.467)	
Segment	−0.883	1.283	1.378	−0.445	0.750	0.722
	(1.699)	(1.073)	(1.063)	(1.844)	(1.323)	(1.332)
Revealed	−6.777*	−6.319***	−4.935***	−6.996*	−8.047**	−4.546**
	(3.775)	(1.801)	(1.178)	(3.784)	(3.311)	(1.883)
Segment×*HighType*	−8.328	−13.606***	−13.848***	−8.758***	−7.452***	−7.544***
	(5.489)	(3.608)	(3.644)	(3.126)	(2.175)	(2.163)
Revealed×*HighType*	10.532*	21.819***	21.184***	11.378*	22.092***	19.032***
	(6.046)	(3.983)	(3.806)	(6.730)	(3.710)	(2.825)
ln*Period*	−0.345	−1.094**	−1.449***	−1.848	−3.338***	−3.687***
	(1.121)	(0.537)	(0.464)	(1.287)	(0.721)	(0.683)
ln*Period*×(1−*Revealed*)	3.108	−1.328		−0.383	−3.093	
	(2.969)	(1.075)		(3.541)	(2.194)	
ln*Period*×(1−*Revealed*) ×*HighType*	1.664	10.616***	9.660***	−0.840	8.138***	5.391***
	(4.318)	(2.155)	(2.002)	(4.586)	(2.274)	(1.159)
Outlier	247.035***			188.397***		
	(41.132)			(30.364)		
*AfterHigh*75	−5.352**	−1.648	−1.570			
	(2.410)	(1.031)	(1.025)			
*AfterHigh*25				0.076	0.503	0.500
				(1.721)	(1.046)	(1.042)
Constant	28.997***	32.062***	31.783***	38.486***	37.234***	33.391***
	(4.224)	(2.188)	(1.581)	(4.156)	(3.759)	(2.193)
Observations	2,304	2,248	2,248	2,304	2,251	2,251
R^2-within	0.528	0.754	0.754	0.535	0.671	0.671

Note. The dependent variable for all specifications is *Bid*. The total number of observations is 2,304 (16 participants×6 periods×2 stages×12 sessions). Outlier dummies are included in specifications (1) and (4). The samples of outliers are dropped in specifications (2), (3), (5), and (6). The numbers in parentheses are standard errors clustered at the seller level by stage. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 7. Estimates of the differences in bids between seller types and treatments by period

High-type sellers' share in the market	Estimate/ p value	Period number 1	2	3	4	5	6
A. *Differences in bids between high- and low-type sellers when quality information is not revealed*:							
25%	Estimate[i]	−1.185	5.510	9.427	12.206	14.362	16.123
	p value	0.665	0.037	0.001	0.000	0.000	0.000
75%	Estimate[i]	−1.313	2.424	4.609	6.160	7.363	8.346
	p value	0.565	0.215	0.015	0.001	0.000	0.000
B. *Impacts of revealing quality information on high-type sellers' bids*:							
25%	Estimate[ii]	16.249	9.553	5.637	2.858	0.702	−1.059
	p value	0.000	0.008	0.138	0.481	0.870	0.814
75%	Estimate[ii]	14.486	10.750	8.564	7.013	5.810	4.827
	p value	0.000	0.000	0.000	0.000	0.001	0.006
C. *Canceling-out effects of market segmentation on high-type sellers' bids*:							
25%	Estimate[iii]	3.779	−2.916	−6.833	−9.612	−11.768	−13.529
	p value	0.275	0.388	0.057	0.012	0.004	0.002
75%	Estimate[iii]	7.664	3.928	1.742	0.191	−1.012	−1.994
	p value	0.000	0.014	0.248	0.901	0.528	0.237

Note. Specifications (3) and (6) in Table 6 are used for the estimations. All p values are for two-sided tests. (i) The estimated sum of the coefficient of *HighType* and that of ln*Period*× (1−*Revealed*)×*HighType* multiplied by the logarithm of the period number. (ii) The estimated difference between the sum of the coefficients of *Revealed* and *Revealed*×*HighType* and the coefficient of ln*Period*×(1−*Revealed*)×*HighType* multiplied by the logarithm of the period number. (iii) The estimated difference between the sum of the coefficients of *Segment*, *Revealed*, *Segment*×*HighType*, and *Revealed*×*HighType* and the coefficient of ln*Period*×(1−*Revealed*)×*HighType* multiplied by the logarithm of the period number.

Table 8. Estimates of the differences in bids between seller types and treatments

Estimates	25% share of high-type sellers	75% share of high-type sellers
High- vs. low-type seller bids for the RI treatment(i)	19.998	17.719
p value	0.000	0.000
High- vs. low-type seller bids for the RS treatment(ii)	6.151	10.175
p value	0.012	0.000
RS treatment vs. RI treatment for high-type seller bids(iii)	−12.470	−6.822
p value	0.000	0.000
RS treatment vs. UI treatment for low-type seller bids(iv)	−3.557	−3.824
p value	0.005	0.042

Note: Specifications (3) and (6) in Table 6 are employed for the estimations. All *p* values are for two-sided tests. (i) Sums of the estimated coefficients of *HighType* and *Revealed*×*HighType*. (ii) Sums of the estimated coefficients of *HighType*, *Segment*×*HighType*, and *Revealed*×*HighType*. (iii) Sums of the estimated coefficients of *Segment* and *Segment*×*HighType*. (iv) Sums of the estimated coefficients of *Segment* and *Revealed*. Quality information is revealed to the sellers, but the market is not segmented under the RI treatment. Quality information is revealed to the sellers, and the market is segmented under the RS treatment. Quality information is not revealed to the sellers, and the market is not segmented under the UI treatment.

Figure 1. Kernel densities of the auction performance by treatment and share of high-type sellers

Figure 2. Sellers' costs and bids by type, treatment and share of high-type sellers in the market

Note. In panel A, the observations with (*Cost*, *Bid*) = (100, 1,000) and (95, 500) are dropped from the RI treatment sample to clarify the differences in bids between the treatments. In panel B, the observation with (93, 500) is dropped from the RI treatment sample. In panel C, the observation with (23, 700) is dropped from the RI treatment sample. In panel D, the observations with (94, 1,000) and (95, 900) are also dropped from the RI treatment sample.

[1] For example, in Pennsylvania's Nutrient Trading Program, the nutrient reductions from nonpoint sources are converted to credits using a delivery ratio based on the watershed segment and distance from the Chesapeake Bay, as determined by the Chesapeake Bay Watershed Model. Delivery ratios in segments close to the Bay are near 1.0, while those in segments farther from the Bay are lower (Commonwealth of Pennsylvania).

[2] The approach in the optimal bidding model differs from that of the game-theoretic reverse auction model of standard auction theory in which the optimal bidding strategy is endogenously determined from the sellers' cost distributions (Latacz-Lohmann and Van der Hamsvoort 1997; Wichmann et al. 2017). Similar models were also applied by Vukina et al. (2008) and Wichmann et al. (2017) in conservation auctions.

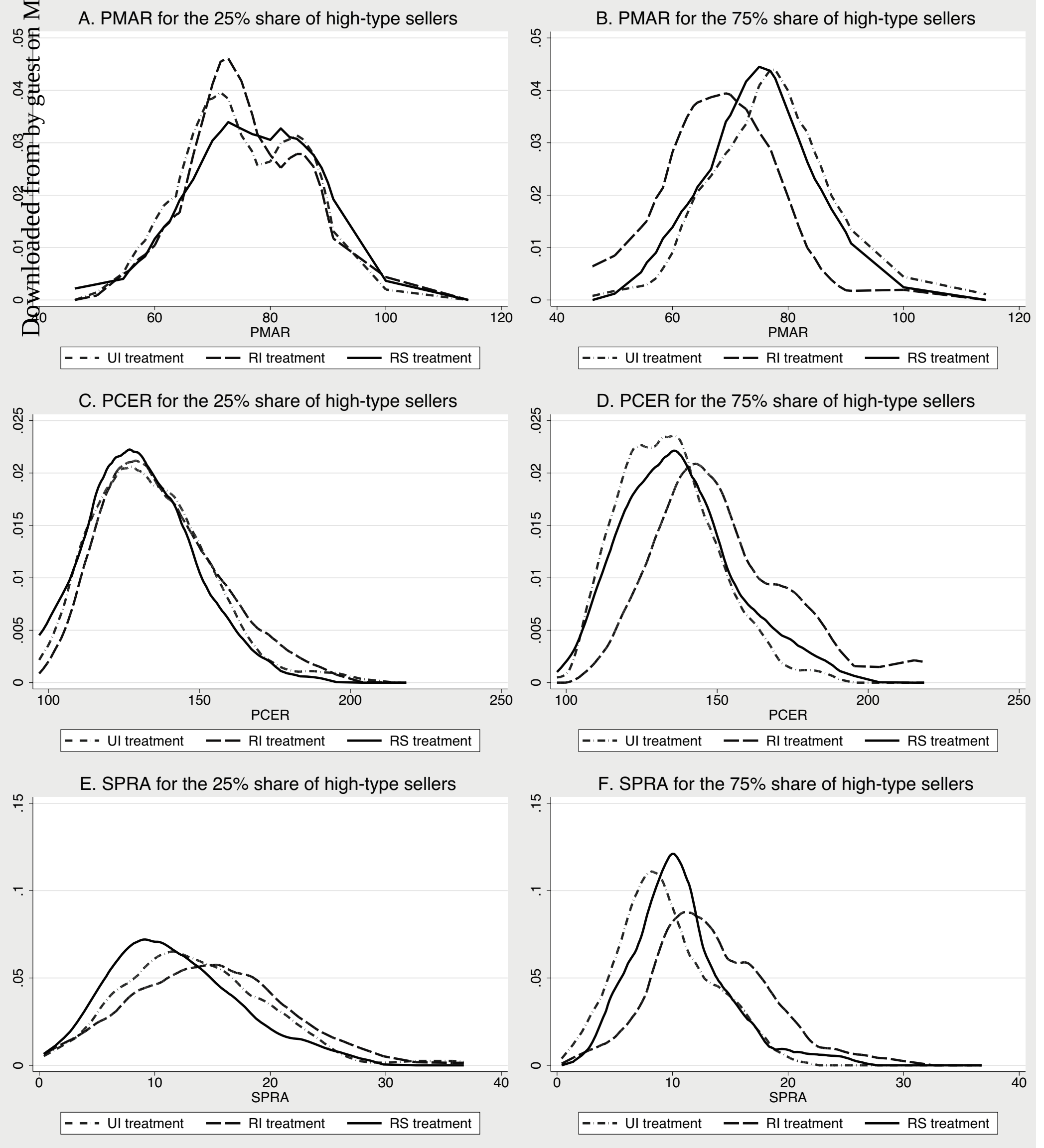
[3] For example, if the sellers expect the maximum acceptable bid score to follow a uniform distribution, the support is bounded (i.e., the bid score cap is finite). In contrast, if they expect it to follow an exponential distribution, the support is unbounded (i.e., the bid score cap is infinite).

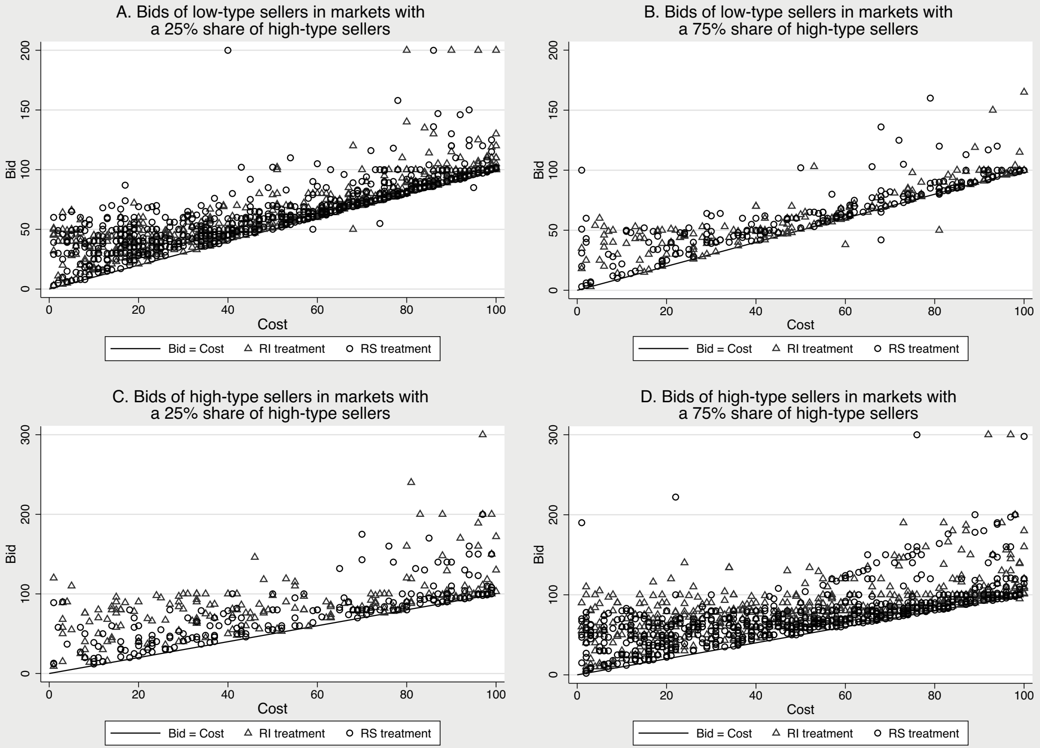
[4] Equation [4] is derived from $\frac{\partial b^*}{\partial c} = -\frac{\partial EU' / \partial c}{\partial EU' / \partial b^*}$, where EU' denotes the first derivative of the expected utility in equation [2].

[5] The rule in the second step involves the assumption that the buyer's budget is insufficient to achieve the water quality goal even through emissions trading. Although this rule does not aim to evaluate sellers' transfer coefficients, it allows the buyer to reduce pollution in a cost-effective manner within the feasible options at the time.

[6] The experimental instructions can be found in the Appendix.

[7] Although 0.564% and 0.043% of the bids from low- and high-type sellers, respectively, are lower than the costs, they do not satisfy the outlier condition.


A. PMAR for the 25% share of high-type sellers
B. PMAR for the 75% share of high-type sellers
C. PCER for the 25% share of high-type sellers
D. PCER for the 75% share of high-type sellers
E. SPRA for the 25% share of high-type sellers
F. SPRA for the 75% share of high-type sellers
PMAR
PCER
SPRA
UI treatment
RI treatment
RS treatment


A. Bids of low-type sellers in markets with a 25% share of high-type sellers
B. Bids of low-type sellers in markets with a 75% share of high-type sellers
C. Bids of high-type sellers in markets with a 25% share of high-type sellers
D. Bids of high-type sellers in markets with a 75% share of high-type sellers
Bid
Cost
0
20
40
60
80
100
50
150
200
300
Bid = Cost
RI treatment
RS treatment