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A COMPUTATIONAL APPROACH TO COMPARE INFORMATION REVELATION POLICIES

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Abstract

Revelation policies in an electronic marketplace differ in terms of the level of competitive information disseminated to participating sellers. Since sellers who repeatedly compete against one another learn based on the information revealed and alter their future bidding behavior, revelation policies affect welfare parameters—consumer surplus, producer surplus, and social welfare—of the market. Although different revelation policies are adopted in several traditional and Web-based marketplaces, prior work has not studied the implications of these policies on the performance of a market.

In this paper, we study and compare a set of revelation policies using a computational marketplace. Specifically, we study this in the context of a reverse-market where each seller's decision problem of choosing an optimal bid is modeled as an MDP (Markov decision process). Results and analysis presented in this paper are based on market sessions executed using the computational marketplace.

The computational model, which employs a machine-learning technique proposed in this paper, ties the simulation results to the model developed using the game-theoretic models. In addition to this, the computational model allows us to relax assumptions of the game-theoretic models and study the problem under a more realistic scenario. Insights gained from this paper will be useful in guiding the buyer in choosing the appropriate policy.

Introduction

The motivation for this paper comes from a real-life electronic marketplace. FreeMarkets (**http://www.freemarkets.com**), a Web-based reverse marketplace, initiates *market sessions* or *periods* at the request of buyers. The marketplace includes geographically distributed sellers that face uncertainty both about the number of competitors (referred to as *market structure uncertainty*) and their opponents' cost structure. Their ability to overcome these uncertainties is dependent on the market transparency scheme, or the *information revelation policy*, a choice made by the buyer.

An information revelation policy dictates the information about bids—winning bids, number of bidders, etc.—that are revealed to geographically dispersed sellers at the beginning, in the middle, and at the end of a market session. At one end of the spectrum of available policies, the buyer can choose to accept sealed bids and notify its decision to each seller individually. Under this policy, no other competitive information is revealed to the sellers. At the other end, the buyer can choose a revelation policy that allows sellers to observe all bids submitted by their opponents in real-time. Under this policy, all competitive information is revealed. Over the course of multiple market sessions, the revelation policy affects what sellers learn, how they bid in the future, and the overall performance of the market. To our knowledge, this important problem—the impact of revelation policies on buyer surplus—has not been studied in any prior work. This leaves little guidance for the buyer to choose the appropriate policy.

To investigate the problem, we consider the following two of the many policies[1] available to a buyer in reverse-markets hosted by FreeMarkets.

1. Complete Information Setting (CIS): At the end of a reverse-auction, all quotes are revealed to all bidding sellers.

2. Incomplete Information Setting (IIS): At the end of a reverse-auction, only the winner's bid is revealed to all bidding sellers.

We chose to study these specific policies because they are commonly adopted in both traditional marketplaces and electronic marketplaces (Thomas 1996). The impact of these policies is explained for each type of uncertainty while describing the problem context in the next section.

As a first step, we began attacking the relevant subproblems game-theoretically. Arora et al. (2002) analytically compare CIS and IIS using a framework where identical sellers are uncertain only about their market structure. Based on the analysis, we found that CIS is preferred by the buyer to IIS under market structure uncertainty. However, the results were different in Kannan and Krishnan (2003), which uses a framework where sellers are uncertain only about their opponent's cost structure. Under certain conditions, CIS was found to be better than IIS and vice-versa. In real-life marketplaces since both types of uncertainties exist, the key question that arises is: Which effect dominates the other when both types of uncertainties are considered together?

As we will argue later, combining both types of uncertainties—market structure uncertainty and cost structure uncertainty—makes the comparison between CIS and IIS analytically intractable, forcing us to seek alternate methodologies. In light of this, our present paper employs a computational model to study the effect of revelation policies in a framework where both types of uncertainties can be combined. Knowledge gained from this analysis are intended to guide the buyer in choosing the appropriate policy. Although our work is motivated by a real-world electronic marketplace hosted by FreeMarkets, results generated in this paper are applicable to any reverse-market setting that can create these different information regimes.

Our paper is organized in the following manner. Following the problem context description in the next section, we review the literature most relevant to this topic in Section 3. Following that, we motivate the need for a computational model and describe the model itself. Results from executing market sessions on the computational marketplace are presented. In the final sectoin, we present conclusions.

Problem Context

We begin this section by describing a typical reverse-marketplace for coal. Buyers sequentially arrive at the electronic reverse-marketplace and initiate market sessions. For each market session convened at its request, the buyer has the liberty of choosing its desired revelation policy. On the seller side, there are a certain number of geographically distributed sellers who can offer coal. Only a subset of them bid in each market session. For example, in each auction conducted by FreeMarkets, a maximum of three or four coal sellers participate. Exogenous factors such as the type of coal the buyer wants or the distance between the coal mine and the buyer site limit seller participation. Participating sellers are unaware of their market structure (number of competitors) and cost structure, which they learn about across market sessions. At the beginning of a market session, each participating seller submits a multidimensional bid which includes coal content, ash content, and water content of its coal, and the price quote. After reviewing all bids, the buyer chooses the best bid and awards the contract to the winner. At the end of the market session, submitted bids are revealed according to the information revelation policy chosen by the buyer.

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[1]Other examples: (1) A policy where only the rank information is provided to the sellers as feedback. (2) A policy where all bids with names are revealed. (3) A policy where all bids with the names are revealed. (4) A policy where the only feedback provided is whether the seller won or lost the market session.

In our paper, we model the following three types of participants: buyers, the broker (the market-maker), and sellers. The broker acts as an intermediary for the marketplace with N_l number of low-cost sellers and N_h number of high-cost sellers. A low-cost seller incurs $c_l = 0$ marginal cost of production whereas a high-cost seller incurs an exogenous c_h. Only a subset of all of these sellers bid in each market session. Participation is assumed to be a random process determined by an exogenous parameter, θ_l or θ_h. θ_l is the exogenous *participation probability*[2] for the low-cost type and θ_h is that for the high-cost type. In this computational marketplace, the task of deciding about seller participation is delegated to the broker. The broker samples a uniform distribution for each seller for each market session and decides about the participation for that seller. Although sellers know the values of θ_l and θ_h, the *realized values of the participation probabilities* are not known.[3] In this manner, we capture the uncertainty faced by each seller. At the end of this process, let there be M sellers participating in the market session.

Each participating seller, i, submits a price, $p_i \in [0,100]$, which is assumed to represent multiple attributes of the bid. The price bid is dependent on the following: the information revelation policy adopted in the marketplace, its belief about being a monopolist, and its belief about being the only seller of its cost-type in the reverse-market. After receiving all bids, the buyer chooses the lowest priced seller as the winner (ties are broken randomly) and awards the contract.

While developing the product, the winner incurs a cost corresponding to its cost type. The built product is delivered to the buyer who, in turn, remunerates the winner. This point corresponds to the end of one market session. At the end of this market session, information about the bids submitted is revealed, according to the revelation policy adopted in the marketplace. The information revealed allows sellers to learn about the nature of their competition for future market sessions. Table 1 describes CIS and IIS policies in detail. The table also provides a descriptive explanation of the impact of these policies on each type of uncertainty.

Table 1. Information Revealed Under Each Policy

	Complete Information Setting (CIS)	Incomplete Information Setting (IIS)
Beginning of a market session	Uncertain	Uncertain
At the end of a market session	All bids are revealed	Only winner's bid revealed.
Beginning of the next market session	All sellers are aware of market structure	• Losing seller is aware of the market structure. • Winner from the first market session continues to be uncertain.
Impact on market structure uncertainty	• When no other price bid is observed, seller learns that it is a monopolist • Otherwise, it learns about its competitor	• When a seller loses, it learns about the existence of competition. • But if it wins, it learns nothing about market structure.
Impact on cost structure uncertainty	• When a price lower than c_h is bid by an opponent, a seller learns about the low-cost opponent • Otherwise, it is not sure; it could be that the low-cost opponent faked	• When a seller loses and observes a price lower than c_h bid by the winner, it learns about the winner's cost structure. If it observes the winner's bid price to be greater than c_h, it is not sure if any of its opponents is a low-cost type. • But if it wins, it learns nothing about cost structure.

[2]An exogenous participation probability value is assumed for simplicity. Typically, the market-maker sends invitations to sellers. The set of sellers invited to participate may vary depending on what the incentives are for the market-maker. Incentives for some market-makers may be aligned with consumer surplus (e.g., FreeMarkets). Other market-makers may have an incentive to maximize social welfare (e.g., marketplaces such as Transora or ForestExpress, where the marketplace is owned by consortia of both buyers and sellers). After receiving the invitation, a seller may choose to accept or reject the invitation. Its decision could be based on production capacity constraints, expected profits from participation, etc.

[3]For example, when θ_h = ½, sellers know that nature tosses a coin for each low-cost seller and allows that seller to participate only if the outcome is heads. But sellers do not know if the outcome was heads or tails when nature tossed a coin to decide whether or not to permit one of the low-cost opponents to participate in that market session.

A similar process is repeated when the next buyer initiates a new market session. The key difference between the first and the second market sessions is that with a certain exogenous probability k, the same set of sellers that participated in the first market session bid in the second market session also. With a probability of $1 - k$, a new set of sellers bid in the second market session. The value of k determines *participation correlation across market sessions, ρ.*[4] When $\rho = 0$, each market session is entirely independent of the other and there is no value for the sellers to learn across market sessions. But when $\rho = 1$, the value from learning about the competitive nature is very high. Anecdotal evidence from FreeMarkets suggest that ρ is neither 0 nor 1 but somewhere in between. We intend to study the impact of these revelation policies for different values of ρ by controlling k.

The reverse-auction process is iterated T times, i.e., we simulate the arrival of T buyers to the e-marketplace. We are interested in studying the impact of varying T on the expected prices paid by each of the T buyers. As noted by Engelbrecht-Wiggans (2001), analyzing the impact of the number of periods is important in a multi-period game (or a multi-period reverse-auction setting). The impacts of parameters ρ and T are studied by using the computational marketplace described later. The need for such a computational model is explained after we review the relevant literature.

Literature Review

Revelation policies in financial markets are referred to as trade-transparencies by the market micro-structure literature. Depending on whether information about outstanding orders or completed orders is revealed, these policies are respectively called *pre-trade transparency* or *post-trade transparency*. Information revealed under these transparency schemes include details of the limit order such as the number of securities purchased or sought and price. A number of papers have studied the impact of these trade transparencies (e.g., Bloomfield and O'Hara 1999; Flood et al. 1999; Madhavan et al. forthcoming). In the interest of space, we skip the details of these papers, but focus on structural differences between electronic reverse-markets and financial markets. Typically, financial exchanges are double-sided auctions[5] whereas electronic reverse-markets are single-sided auctions. Information revealed in a double-sided auction not only affects the behavior of sellers but also that of buyers. In a single-sided reverse-auction, information revealed affects the behavior of sellers only. These differences make revelation-policy-comparisons in our procurement e-marketplace context different from that in financial markets.

To our knowledge, revelation policies in single-sided auctions have been studied only by Arora et al. (2002), Kannan and Krishnan (2003), Koppius and van Heck (2003), and Thomas (1996). Thomas compares CIS and IIS in a framework with two sellers, where each seller is certain about the presence of its opponent but uncertain about its opponents' cost structure. The model assumes that each seller faces an opponent that is a high-cost type with a probability of ½. Using this, he demonstrates that CIS generates higher savings for the buyer than IIS. This model is further generalized in Kannan and Krishnan, which is discussed in the next section.

Koppius and van Heck use experimental data to compare revelation policies on bidders' profits in a multi-attribute auction setting. They show that the setting that creates the least level of uncertainty for bidders generates the highest profit for them. In their paper, bidders face the following types of uncertainties: uncertainty about the valuation that the buyer places on each attribute and uncertainty about their opponents' cost structure. Our paper is different from both Koppius and van Heck and Thomas in its focus. In our present paper, we study the effect of information revelation policies in a framework where sellers face uncertainty both about the market structure as well as opponent's cost structure. Arora et al. and Kannan and Krishnan are reviewed in detail while motivating the computational model.

Need for a Computational Model

Recall that Arora et al. (2002) deal with the effect of revelation policies under just the market-structure uncertainty while Kannan and Krishnan (2003) deal with the same issue but under cost-structure uncertainty. Both papers employ two-period game-theoretic

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[4] $\rho = \frac{k^2}{(k^2+(1-k)^2)}$.

[5] The only financial market that operates as a single-sided auction is the primary bond market (e.g., U.S. Treasury Bills). Even in the bond markets, the standard policy is to reveal the winner's bid and the quantity.

models. In the model, each reverse-auction period is initiated by a buyer arriving at the e-marketplace. Participating sellers simultaneously bid prices and the lowest price wins. For the simplicity of the analytical model, it is assumed that the same set of sellers participate in both periods, i.e., participation is perfectly correlated across market sessions. The model in Arora et al. corresponds to the setting $T = 2$, $k = 1$, $N_l = 2$, and $N_h = 0$ and the model in Kannan and Krishnan corresponds to $T = 2$, $k = 1$, and $N_l = 2$. Using these models, the expected prices paid by the buyer in CIS and IIS are compared.

Under the framework with just market structure uncertainty, we demonstrate that CIS generates higher savings for the buyer than IIS. The intuition for this result is as follows. Since only the winner's bid is revealed at the end of the first period in IIS, the information asymmetry disfavors the first-period winner in the second period game. In order to avoid this uncertainty in the second period, sellers are willing to lose the first period. They do so by bidding a higher first period price, thus leading to a higher expected price paid by the buyer in IIS than in CIS. In contrast to this, the comparison under cost-structure uncertainty, which is executed numerically, demonstrates that IIS is better than CIS under certain conditions and vice-versa. Since all bids are revealed in CIS, low-cost sellers may have an incentive to fake their cost structure under certain conditions. This faking behavior leads to a higher expected price paid by the buyer in CIS than in IIS.

Note that the game-theoretic framework under the cost-structure uncertainty framework involves no uncertainty about market-structure, i.e., a known fixed number of sellers are assumed to participate. Even in this setting the analysis is analytically intractable, forcing us to execute numerical comparisons. When uncertainty about the number of sellers is also introduced into the framework (which is our final goal), the equilibrium computations become complex thus, making a case for the computational model (Kannan and Krishnan 2003). Additionally, in the computational approach, one can relax the following restrictive assumptions that a game-theoretic model requires:

- The number of periods: Only a two period game is studied in game-theoretic models. In reality, buyers arrive at the reverse-auction sequentially, initiating each period. So, the game is a multi-period game.

- Participation correlation: Participation correlation across the two periods was assumed to be unity in the game-theoretic models. Stated differently, the same set of sellers that participated in the first period are assumed to continue in future periods. Based on the anecdotal evidence from FreeMarkets, we find that, although the correlation is high, it is not unity.

The computational model adopted in this paper is described next.

Computational Model

In this computational marketplace, software agents are used to mimic the broker, buyers, and sellers. From the problem context description presented earlier, it is straightforward to design software agents that mimic the behavior of buyers and the broker. But the optimal bidding behavior of sellers is unknown and so, instead of modeling the bidding behavior, we provide a framework for the "seller-agents" to learn.

Learning Model

The task for any seller, *i*, is to choose an optimal bid and, based on the outcome of the bid, learn to bid in future market sessions. For this decision problem, if we know the relationships between the different parameters, we can employ naïve learning models such as regression, ID3, and KNN (k-nearest neighbor) and allow the sellers to learn the weights for the decision variables. In our case, however, the model cannot be completely specified and so there is a need for a model-free approach, e.g., Markov decision process (MDP) and partially observable Markov decision process (POMDP).

The factors (or *states* of the Markov model) that drive the bidding behavior in our model are the realized probability value[6] of being a monopolist, the realized probability value of being the only seller of its cost type, and the current period (one of the T periods). By design, these states are unobservable and the framework corresponds to a POMDP model (Kaelbling et al. 1996). However, the learning techniques for POMDP are still in the preliminary stages of research and, therefore, we mold this process as an MDP.

[6]Outcome of the coin toss is described in footnote 3.

The state space for our POMDP framework are belief about being the only seller of its own cost type (discretized for finiteness of the state space), belief about being the only seller in the market (discretized for the finiteness of the state space), the current period (one of the *T* periods), and, finally, whether or not it acted like a low-cost type by bidding a price lower than c_h, the high-cost type's cost, in the earlier period. The last dimension accounts for the knowledge gained by the seller while it fakes its cost-structure. The action chosen by the seller—the price bid— affects how the state space transitions. If the price bid is p_i and the state space transitions from S to S', the reward (profit or loss) function is

$$R^{p_i}_{S\to S'} = \begin{cases} p_i - c_i & \text{if } i \text{ wins} \\ 0 & \text{if } i \text{ loses} \end{cases} \tag{1}$$

In our model, sellers can bid discrete prices only, i.e., $p_i \in$ {10,20…,100]. The optimization model used by the seller, given that the seller is in state S, is

$$\max_{p_i} Q(S, p_i) \tag{2}$$

where

$$Q(S, p_i) = \sum_{S'} \Omega_{S\to S'} \left[R^{p_i}_{S\to S'} + \max_{p'_i} Q(S', p'_i) \right] \tag{3}$$

$\Omega_{S\to S'}$ is the transition probability from state S to S' that the environment controls. The beliefs which are a component of the state-space are computed by each seller based on the observation. If b_{mono} represents the belief held by a low-cost seller about being a monopolist, b_{cost} represents the belief held by the same seller about being the only low-cost seller in the reverse-market, and M represents the number of market sessions in which it participated, then beliefs are computed by that seller in the following manner:

- Independent of CIS or IIS, if it is the first market session or if the seller participates in a particular market session but did not participate in the previous market session, then

$$b_{mono} = (1-\theta_l)^{(N_l-1)}(1-\theta_h)^{(N_h-1)} \tag{4}$$

$$b_{cost} = (1-\theta_l)^{(N_l-1)} \tag{5}$$

- Among all the bid prices revealed in CIS, let p_j be the lowest bid in the reverse-market excluding its own bid.

    - if $p_j < c_h$

$$b_{mono} = 0 \tag{6}$$

$$b_{cost} = 0 \tag{7}$$

    - if $p_j > c_h$

$$b_{mono} = (1-\theta_l)^{(N_l-1)}(1-\theta_h)^{(N_h-1)}\left((1-k) + k\frac{M}{M_{hi}}\right) \tag{8}$$

$$b_{cost} = (1-\theta_l)^{(N_l-1)}\left((1-k) + k\frac{M}{M_{hi}}\right) \tag{9}$$

where M_{hi} is the number of previous market sessions, the seller observed a price $p_j > c_h$.

- But if the seller did not observe any other bid in the reverse-market, then

$$b_{mono} = (1-\theta_l)^{(N_l-1)}(1-\theta_h)^{(N_h-1)}(1-k) + k \tag{10}$$

$$b_{cost} = (1-\theta_l)^{(N_l-1)}(1-k) + k \tag{11}$$

- In IIS, let p_j be the best price bid that is revealed to all sellers and p_i be the bid submitted by that particular seller.
  - If that seller won the market session, then $p_j = p_i$, then,

$$b_{mono} = (1-\theta_l)^{(N_l-1)}(1-\theta_h)^{(N_h-1)}\left((1-k) + k\frac{M}{W_{p_i}}\right) \tag{12}$$

$$b_{cost} = (1-\theta_l)^{(N_l-1)}\left((1-k) + k\frac{M}{W_{p_i}}\right) \tag{13}$$

where W_{p_j} is the number of previous market sessions, the seller won by bidding p_j.

  - If it lost the market session and $p_j < c_h$, then

$$b_{mono} = 0 \tag{14}$$

$$b_{cost} = 0 \tag{15}$$

  - If it lost the market session but observes $p_j > c_h$, then

$$b_{mono} = (1-\theta_l)^{(N_l-1)}(1-\theta_h)^{(N_h-1)}\left((1-k) + k\frac{M}{L_{p_i}}\right) \tag{16}$$

$$b_{cost} = (1-\theta_l)^{(N_l-1)}\left((1-k) + k\frac{M}{L_{p_i}}\right) \tag{17}$$

where L_{p_i} is the number of previous market sessions the seller lost by bidding p_i.

In a similar manner, each high-cost seller computes its beliefs.

In this framework, the recursive optimization function in equation 2 can be solved analytically if the expression for the transition probabilities, $\Omega_{S\rightarrow S'}$, is known. In fact, one can derive the expression for $\Omega_{S\rightarrow S'}$ for $\rho = 1$ and $T = 2$ when each type of uncertainty—uncertainty about market structure or uncertainty about their opponents' cost structure—is considered separately. Such solutions correspond to the game-theoretic models of Arora et al. (2002) and Kannan and Krishnan (2003).

For different values of ρ or T or when both types of uncertainties are combined, however, computing transition probabilities become analytically intractable. In such a case, reinforcement-learning algorithms similar to those described in Sutton and Barto (1998) need to be used for solving the recursive equation. The only constraint that the learning algorithm has is that it should be able to identify mixed-strategy equilibria. This is important because results from Arora et al. and Kannan and Krishnan, although for a specific setting, indicate the existence of such mixed strategy equilibria in this framework (in the interest of space, the functional form of the equilibria are not shown). Standard Q-learning algorithm fails to identify them well. In contrast, a variant of the Q-learning algorithm that we developed, *ratio-Q* (the algorithm is shown in Figure 1), performs very well. We compare the closeness between the predicted distribution and the empirical bid distribution identified by sellers adopting the algorithm for a specific setting.

Input: Cost c; $c = c_h$, if seller is high cost type. Similarly $c = 0$, if low-cost type.
Initialize $Q(S, p_i) = p_i - c \forall S \forall p_i$; Stores Q-values
Initialize $N(S, p_i) = 10 \forall S \forall p_i$; Keeps track of the number of iterations
Repeat (for each market session)
Initialize S
    Choose action p_i from S using Ratio-Q policy
    Take action p_i , observe R, S

$$Q(S,p_i) \leftarrow Q(S,p_i) + \frac{[R - c + \max_{p_i'}(Q(S',p'_i) - Q(S,p_i))]}{N(S,p_i)}$$

    $N(S, p_i) \leftarrow N(S, p_i) + 1$
    $S \leftarrow S'$
Until End of Market sessions

Ratio-Q policy: Given state S
$Q_{min} = min\ Q(S, p) \forall p$
$Q_{max} = max\ Q(S, p) \forall p$

Choose action p_i with probability $\dfrac{e^{\frac{Q(S,p_i)-Q_{\min}}{Q_{\max}-Q_{\min}}}}{\sum_k e^{\frac{Q(S,p_k)-Q_{\min}}{Q_{\max}-Q_{\min}}}}$

Figure 1. Ratio-Q Algorithm

Specifically, we set $N_l = 2$, $\theta_l = 0.35$, $N_h = 0$, and $T = 1$ and in our problem context description, i.e., we consider a single-period game with two low-cost sellers where each seller is uncertain about the participation of its opponent. The probability that each seller observes its opponent is the θ_l . In this game, the bidding behavior of the sellers can be computed game-theoretically. The equilibrium is a mixed strategy one, whose cumulative density function (cdf) is

$$F(p) = 1 - \frac{\theta_l(1-p)}{(1-\theta_l)p} \tag{18}$$

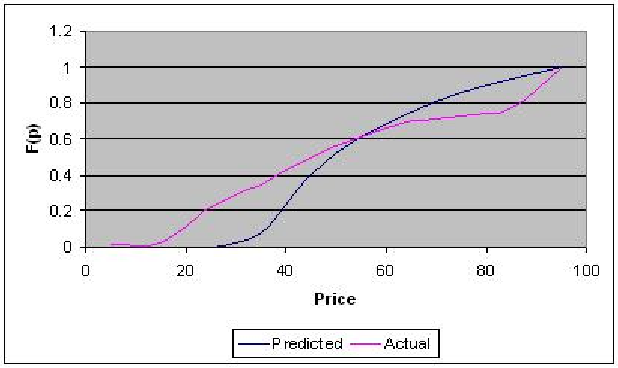

Figure 2. Comparing the Empirical Bid Distribution of Sellers Using Q-Learning Algorithm and the Predicted Distribution

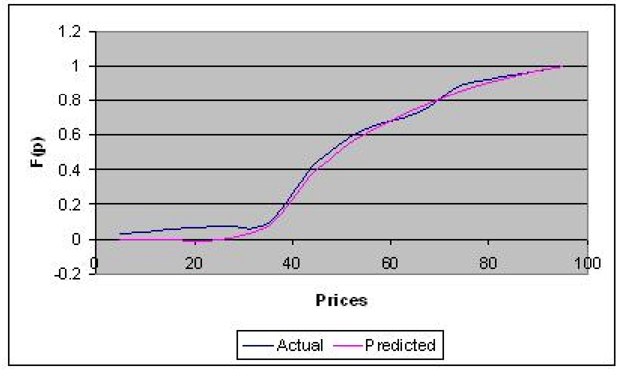

Figure 3. Comparing the Empirical Bid Distribution of Sellers Using Ratio-Q Algorithm and the Predicted Distribution

To compare the closeness of the empirical bid distributions to the predicted distribution, we set up these parameters in our computational marketplace and execute two sets of 100,000 market sessions. In the first set, the sellers were embedded with the standard Q-learning algorithm. In the second set, sellers were embedded with the ratio-Q algorithm. Figure 2 shows the empirical bid distributions of sellers using Q-learning algorithm, and the predicted bid distribution from the game-theoretic model. Similarly, Figure 3 shows the bid distribution for ratio-Q algorithm and the predicted result. The closeness of each distribution to the predicted values is evaluated using a simple nonparametric test metric: Kolmogorov-Smirnov (K-S) distance. This distance measure is about 0.35 between the empirical distribution with Q-learning algorithm and the predicted values. In contrast, the distance measure is about 0.05 between the empirical distribution with ratio-Q and the predicted values. Observe that ratio-Q performs significantly better than the standard Q-learning algorithm.[7] We employ this ratio-Q algorithm in our computational marketplace to execute market sessions. Results based on data collected from these market sessions are presented next.

Results

Recall that we are interested in understanding how the expected prices paid by the buyer in CIS and IIS are affected by variations in ρ and T when each type of uncertainty is considered separately. Further, we are also interested in understanding how CIS and IIS compare when both types of uncertainties are considered together. First, we present our hypotheses. We then validate those hypotheses using data collected from market sessions executed on our computational marketplace.

Hypothesis

Participation correlation, ρ, is an important factor that determines how much sellers value learning across market sessions. The value that sellers obtain from learning is the highest when $\rho = 1$ (i.e., the exact same set of sellers repeatedly participates across market sessions). At the other extreme, when $\rho = 0$ (i.e., each market session is independent of the other), there is no value in learning. We know that the expected price paid by the buyer in CIS is lower than in IIS when $\rho = 1$ under market-structure uncertainty (Arora et al. 2002). As ρ decreases, the value of learning decreases. This implies that sellers in IIS have lesser incentives to increase their first period price in order to learn their market-structure. So,

> **Hypothesis 1.** As correlation decreases, the performances of CIS and IIS will tend to be similar when sellers face uncertainty about market structure.

[7]We also compared these performance under the settings corresponding to Arora et al. (2002) and Kannan and Krishnan (2003) and observed that ratio-Q performs significantly better than standard Q-learning.

Similarly, results presented in Kannan and Krishnan (2003) are valid when uncertainty about opponents' cost structure is considered separately at $\rho = 1$. For reasons similar to that presented in the previous hypothesis, we expect the following:

> **Hypothesis 2.** When sellers face uncertainty about their opponents' cost structure, the expected price paid by the buyer in CIS and IIS will tend to be similar as correlation decreases.

In multi-period games (reverse-auctions), the number of periods is an important factor dictating the bidding behavior (Engelbrecht-Wiggans 2001). Under market structure uncertainty, sellers in CIS learn about their market structure at the end of each market session. Since their learning is independent of the outcome of the market session, their bidding behavior is not altered. But in IIS, only the winner's bid is revealed to all participating sellers, so the value that sellers obtain from losing initial market sessions is higher as T increases and therefore, we expect the following:

> **Hypothesis 3.** When sellers face uncertainty about market-structure, the difference between the expected prices paid by the buyer in IIS and CIS will increase as T increases.

For similar reasons, we hypothesize a similar behavior under cost uncertainty.

> **Hypothesis 4.** When sellers face uncertainty about their opponents' cost-structure, the difference between the expected prices paid by the buyer in IIS and CIS will increase as T increases.

Now let us focus on combining both these types of uncertainties. It is interesting to observe whether or not CIS is better than IIS. We hypothesize the following:

> **Hypothesis 5.** When sellers face both types of uncertainties, the expected price paid by the buyer will be higher in IIS than in CIS.

The intuition for this result is that the expected price paid by the buyer is lower in CIS than in IIS (Arora et al. 2002) when market structure uncertainty is considered separately. Under cost-structure uncertainty, the expected prices are higher in CIS than in IIS but only for very high values of θ_l (Kannan and Krishnan (2003). So when combining both types of uncertainties, we expect the effect of market structure uncertainty to override the effect of uncertainty about opponents' cost structure.

Hypothesis Validation

We intend to validate these hypotheses by using data collected from market sessions executed on the computational marketplace. Parameters for this computational model are set to be similar to a coal reverse-marketplace. Typically, there are 12 to 15 sellers who can provide coal and, out of these, 3 or 4 participate in each market session.[8] We replicate this by setting $N_l = 5$, $N_h = 6$, $\theta_l = 0.3$, $\theta_h = 0.3$, and $c_h = 100$ in our computational model. When we deal with just market-structure uncertainty, participating sellers are of the same type and no uncertainty about opponents' cost is assumed to exist. Specifically, only the low-cost sellers were assumed to participate. When we model uncertainty about opponents' cost structure, it is assumed that the uncertainty about the number of competitors does not exist and we retain the total number of competitors $M = 10$. For each (ρ, T) pair, we simulated 200,000 executions on the computational marketplace and the results based on the data collected are summarized below.

Testing Hypothesis 1

For this analysis, we set $T = 2$ and executed market sessions for different values of ρ. Table 2 shows the variation of the expected price paid by the buyer as ρ changes under market structure uncertainty. First, notice that the expected price paid by the buyer is significantly (statistically significant at the 5 percent level) higher in IIS than in CIS when $\rho = 1$. This matches the result demonstrated by Arora et al. (2002). Second, we observe that the difference between the expected prices of CIS and IIS decreases with decreasing ρ as hypothesized.

[8]Based on personal communication with FreeMarkets Inc.

Table 2. The Effect of Variation of ρ on the Expected Price Paid by the Buyer When Sellers Are Uncertain About Their Market Structure
(Standard Deviation shown in parenthesis)

	Complete Information Setting (CIS)		Incomplete Information Setting (IIS)	
	First Buyer	**Second Buyer**	**First Buyer**	**Second Buyer**
$\rho = 1.0$	29.92 (0.16)	45.35 (0.21)	65.12 (0.17)	47.86 (0.28)
$\rho = 0.75$	30.12 (0.14)	40.66 (0.18)	57.35 (0.15)	42.29 (0.25)
$\rho = 0.5$	30.03 (0.16)	37.26 (0.15)	48.92 (0.19)	38.06 (0.21)

Testing Hypothesis 2

Similar to the earlier section, we set $T = 2$ and vary ρ. Table 3 shows the effect of variation of the expected price with ρ when sellers face uncertainty about their opponents' cost structure. Based on the results, we observe the following: First, notice that the expected price paid by the buyer in CIS is higher than that in IIS (statistically significant at the 5 percent level). Second, when comparing Table 2 and Table 3 corresponding to $\rho = 1$, we observe that the expected price paid by the buyer in CIS under cost-structure uncertainty is significantly higher (at the 5 percent level) than that market-structure uncertainty. This can be attributed to low-cost sellers' faking their cost structure and bidding as high-cost sellers and this serves to increase the expected price paid by the buyer. Third, observe that hypothesis 2 is valid. Note that the difference in the expected prices paid by the buyer decreases as ρ decreases.

Table 3. The Effect of Variation of ρ on the Expected Price Paid by the Buyer When Sellers Face Uncertainty About Their Opponent's Cost Structure
(Standard Deviation shown in parenthesis)

	Complete Information Setting (CIS)		Incomplete Information Setting (IIS)	
	First Buyer	**Second Buyer**	**First Buyer**	**Second Buyer**
$\rho = 1.0$	61.62 (0.26)	48.75 (0.24)	63.27 (0.13)	46.01 (0.28)
$\rho = 0.75$	55.24 (0.27)	43.28 (0.21)	56.54 (0.14)	42.87 (0.27)
$\rho = 0.5$	47.53 (0.15)	37.26 (0.22)	49.10 (0.13)	38.38 (0.27)

Testing Hypothesis 3

For this analysis, we set $\rho = 0.75$ and vary T. Table 4 shows the effect of T on the expected price paid by the buyer when sellers are uncertain about their market structure. Observe that the difference between the expected price paid by the buyer increases with T, thus, validating hypothesis 3.

Table 4. The Effect of Variation of T on the Expected Price Paid by Each Buyer When Sellers Are Uncertain About Market Structure

	Time	First Buyer	Second Buyer	Third Buyer	Fourth Buyer
Complete Information Setting (CIS)	$T = 2$	30.12 (0.14)	40.66 (0.18)		
	$T = 3$	32.24 (0.28)	36.25 (0.32)	38.61 (0.22)	
	$T = 4$	31.28 (0.32)	34.54 (0.29)	37.21 (0.31)	36.63 (0.27)
Incomplete Information Setting (IIS)	$T = 2$	57.35 (0.15)	42.29 (0.25)		
	$T = 3$	61.33 (0.32)	60.97 (0.42)	39.22 (0.31)	
	$T = 4$	65.49 (0.43)	63.21 (0.39)	61.29 (0.25)	40.26 (0.37)

Testing Hypothesis 4

Similar to the earlier section, we set $\rho = 0.75$ and vary T. Table 5 shows the effect of varying T on the expected price paid by the buyer when sellers are uncertain about their opponents' cost structure. Note that although we observe results as hypothesized, we did not take into account the following observation: as T increases, the value that the low-cost sellers obtain from faking their cost-structure is also higher. Thus, we observe that the expected price paid by the first buyer in CIS increases with T, but the increase in the expected price paid by the buyer in CIS is lower than that in IIS.

Table 5. The Effect of Variation of *T* on the Expected Price Paid by Each Buyer When Sellers Face Uncertainty About Their Opponents' Cost Structure

	Time	First Buyer	Second Buyer	Third Buyer	Fourth Buyer
Complete Information Setting (CIS)		55.24 (0.27)	43.28 (0.21)		
		57.62 (0.34)	51.82 (0.42)	41.71 (0.44)	
	$T = 4$	59.02 (0.37)	54.27 (0.32)	48.67 (0.29)	38.67 (0.41)
Incomplete Information Setting (IIS)	$T = 2$	56.54 (0.14)	42.87 (0.27)		
	$T = 3$	60.36 (0.32)	58.31 (0.34)	43.51 (0.39)	
	$T = 4$	62.40 (0.35)	59.26 (0.38)	55.23 (0.27)	42.17 (0.41)

Testing Hypothesis 5

Table 6 shows the variation of the expected prices paid by the buyer when sellers face both types of uncertainties. Based on this result, we validate our hypothesis. The difference between IIS and CIS is statistically higher (at the 5 percent level) and the difference increases with increasing T. This also implies that the effect of numbers uncertainty overrides the effect of faking behavior.

Table 6. The Effect of Variation of *T* on the Expected Price Paid by the Buyer When Sellers Face Both Types of Uncertainty

	Time	First Buyer	Second Buyer	Third Buyer
Complete Information Setting (CIS)	$T = 2$	52.93 (0.22)	55.36 (0.31)	
	$T = 3$	54.29 (0.32)	50.26 (0.34)	51.74 (0.32)
Incomplete Information Setting (IIS)	$T = 2$	59.04 (0.26)	58.97 (0.31)	
	$T = 3$	61.86 (0.34)	59.19 (0.39)	57.84 (0.36)

Conclusion

In conclusion, this paper addresses an important IT-enabled real-world problem. A buyer arriving at an electronic reverse-marketplace needs guidance to choose the appropriate information revelation policy. In line with this motivation, our paper studies the effect of information revelation policies using a framework that is closer to reality—where sellers face uncertainty about both their market structure and their opponents' cost-structure. Specifically, we compare the expected price paid by the buyer in CIS and IIS, two of the many policies available to a buyer in a reverse-market hosted by FreeMarkets.

We execute these comparisons computationally. Similar economic problems have been studied using computational models in other contexts (e.g., Das et al. 2001; Kephart and Greenwald 2002). Our set-up is unique in being very closely tied to the analytical framework while at the same time providing opportunities to extend beyond the limitations of the analytical model. As described earlier, the ratio-Q algorithm is able to identify the analytically optimal bidding behavior for each seller under the same assumptions of the analytical model. However, when extending the game-theoretic framework, i.e., when combining both types of uncertainties or when relaxing the assumptions of the game-theoretic model, we are not aware of what the optimal bidding behavior of the sellers would be. Given that our machine learning algorithm traces the true optimal behavior under the assumptions of the analytical model, we believe that it does so even when the assumptions are relaxed.

Using market sessions executed on the computational framework, we learned that the effect of numbers uncertainty dominates the effect of faking. In addition to this, our analysis provides valuable insights into how participation correlation across market sessions affects the expected price paid by the buyer. For example, consider a reverse-marketplace for metal castings. There are about 2,000 U.S.-based metal-casting suppliers registered with FreeMarkets.[9] In a typical reverse-auction for metal castings, about 20 of them are invited to participate. The participation correlation across market sessions for these sellers is observed to be low. In this case, our results suggest that sellers in CIS and IIS behave identically and the buyer will be indifferent between the two settings. On the other hand, in a marketplace for coal, there are very few sellers and only a subset of them participate. The correlation across market sessions is higher and suppliers value learning. In this case, the buyer is better off choosing CIS over IIS. This example illustrates the applicability of our results.

Summing up, the computational model described in our paper has provisions to combine both types of uncertainty, to alter the time period or the participation correlation across market sessions. These were not feasible game-theoretically. In that sense, the computational approach acts as a bridge between theoretical and experimental study, an important benefit as argued by Simon (1990) and Geoffrion and Krishnan (2001). However, the primary limitation of our computational model is our inability to endogenize participation probability. This is because sellers attempting to learn by trying different prices cannot learn if the change in outcome they observe—say the win or the loss—is due to the change in the bid price or due to the change in the opponent's participation probability. We are interested in investigating this problem further as a part of the future work. Other possible extensions follow.

- Note that this paper compares only a few of the many policies facilitated in reverse-marketplaces. We intend to extend this work to study other policies facilitated in electronic reverse-marketplaces.

- This framework exogenizes the participation decision but one can extend this model to study the effect of revelation policies in a framework where sellers decide about their participation endogenously.

- Other factors such as reputation effects can also be studied.

- In addition to these extensions, we also intend to focus on ratio-Q algorithm and study its properties.

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