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ABSTRACT

Market transparency, in its most succint form, refers to the level of current trade information revealed to the public by market makers. We analyze the effect of market transparency on the outcomes of posted-offer style B2B markets under both stationary and non-stationary demand conditions. We find that sellers on average can extract significantly higher surplus than buyers, yet the difference decreases with increasing market transparency. Also, poor price-tracking ability of the posted-offer market after an external demand shock hurts buyers only. Seller profits are much less sensitive to the shock compared to buyer surpluses.

Keywords: *e-commerce, market transparency, experimental analysis, simulation*

INTRODUCTION

Proliferation of the Internet has led to development of many types of online markets, including electronic exchanges, net marketplaces, e-hubs, clearinghouses, and private industrial networks. The design and implementation of these markets require vital decisions about ownership, structure, and procedures. The transparency of a market, in this respect, is profoundly important and can by itself lead to market failure if not managed properly. The issue is more complicated for online markets because the main objective of these markets is to aggregate many buyers and sellers around the world. Since the level of transparency may deter one or both of the groups, market makers should find the optimal transparency level to maximize participation, liquidity, and revenues.

This paper investigates the effects of transparency on market outcomes within the context of a simulated posted-offer market framework. The primary objective is to gain insights regarding the impact of transparency on (*i*) the rents earned by buyers and sellers, (*ii*) mean prices, and (*iii*) market efficiency under both stationary and non-stationary demand conditions. The lack of definite analytical results in this topic reflects the complexity of interactions of the variables in electronic markets. Given this complexity, studying transparency with controlled experiments becomes a useful approach. In this study, we first propose an economic experiment, and detail the design and procedures to be followed. We, then, report the findings of a complementary simulation analysis we conducted by using proprietary software developed at the Krannert School of Management, Purdue University.

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THEORETICAL BACKGROUND

Laboratory markets: methodology and implementation

Two major advantages of experimental analysis are replicability and control. Replicability is the notion that any researcher can reproduce the conditions described by another researcher, and can expect to verify the reported phenomenon (Davis and Ramagopal 1998). Control is related with whether an observation in an environment can be attributed to nothing else but the induced incentives. In our proposed experiment, control is maintained by the abstract commodity, which has value only in the experiment. Therefore, outcome predictions arise only from the elements included in the design. Due to space restrictions, this proposal briefly describes our experimental design and procedures. The complete set of user instructions, algorithms, and derivation of supply and demand schedules are available upon request.

Buyer and seller behavior in posted-offer markets

Past research indicates that sellers have considerable strength over buyers in posted-offer markets (Ketcham et al. 1984). Ineffectiveness of strategic buyer behavior in posted-offer institutions is further illustrated by the results of Cason and Williams (1990). They show that buyers perform poorly in manipulating prices compared to sellers. In particular, whenever a buyer chooses not to make a profitable transaction, others that shop subsequently perform that transaction, eliminating any possible effect on the total quantity transacted. Sellers, on the other hand, engage in price signaling in a more successful manner. It is the strength of sellers as well as myopically optimal behavior of buyers that makes posted-offer institution more suited to analyzing seller behavior. In this research, therefore, we simulate buyer behavior and use human subjects for sellers. Simulating buyers may be further justified by the fact that buyers are many and dispersed in most markets.

EXPERIMENTAL DESIGN AND PROCEDURES

The market framework in this study comprises multiple sellers who repeatedly post prices for their undifferentiated homogeneous good. The number of buyers and sellers and their capacities are constant during the course of each simulation run, and there is no entry into or exit from the market. In what follows, a *cohort* is a group of four subjects who always trade together. A *market* is a sequence of trading rounds with a cohort in the same regime with the same parameters. A *session* is a 3-hour period during which a cohort participates in a series of market regimes.

Subjects and incentives

Each seller subject attends an initial training session and receives detailed instructions, a copy of which is available upon request. Sellers earn laboratory currency through their trading decisions, which is later converted to real dollars, and paid them at the end of the experiment. Such an incentive ensures that sellers behave rationally with the goal of maximizing their profits. There is no penalty for failing to sell, except that they make no profit in that session. At the start of each trading period, each seller is given an initial endowment of 3 units of a homogeneous good.

The institution

B2B exchanges have two dominant market mechanisms: buyer catalogs and dynamic pricing tools, such as auctions. Since our main focus is on the catalog sales where prices are posted for buyer search, the posted-offer institution is a suitable economic environment for our purposes. In order to observe how seller behavior changes under different levels of information revelation, trading rules of the institution are varied to generate Transparent, Opaque, and Semi-transparent markets (see the next section for details).

As in all posted-offer institutions, sellers in our setting post prices and buyers make 'take-it-or-leave-it' purchase decisions based on these posted prices. Each buyer (seller) has a marginal value (cost) representing the value (cost) of consuming (producing) that unit. These valuations and costs yield aggregate market demand and supply schedules as described in Ketcham et al. (1984). Sellers earn experimental cash rewards by selling a commodity at a price that is higher than its marginal cost. Induced valuation and cost assignments are kept strictly private in all sessions. Subjects are isolated at computer terminals, and no communication is allowed outside the rules imposed by the institution.

Each session consists of the following sequence of events. First, sellers learn their production costs, and decide on the price and quantity to produce at that price (limited by their capacities). Sellers are not restricted in their price choices, and production is made-to-order in the sense that cost is incurred only when a unit is sold. Buying sequence begins once all prices are posted. Simulated buyers accept offers as long as a product is priced below their valuations, and it is available. They purchase in a mechanic way, starting with the cheapest unit, and continue purchasing higher priced units.

Market treatments

The experiment employs the market treatments shown in Table 1. The treatment variable is transparency, that is, the level of information revealed to subjects. The variable is explored in three levels by varying information revelation rules of the institution.

In the transparent market, whenever a transaction is conducted in the market, trade details are presented in the public transaction history window of each seller. For each transaction listed in this window, the identities of the buyer and the seller are presented, along with the transaction size and the price at which the transaction is cleared. In addition, sellers' own transactions are also separately displayed in their private transaction history windows. In the opaque market, information about other sellers' prices or availability is not publicly available. The only information sellers see is the details of their own transactions, i.e., price, quantity, and trader identity. Semi-transparent market provides more information than opaque market but less information than transparent market. It is distinguished from transparent market with the unavailability of quantity information. Sellers still see all market transactions, but not the size of those transactions. Opaque treatment is intended to replicate the general market structure that is found in B2B catalog aggregators, while Transparent and Semi-transparent treatments are offered as potential *adjusted* market structures.

Opaque setting (O)	Semi-transparent setting (ST)	Transparent setting (T)
Sellers only see information about their own transactions.	Sellers see price and trader identity of every transaction.	Sellers see price, quantity, and trader identity of every transaction.

Table 1. Description of treatments

Experimental design

The experimental design shown in Table 2 aims to control differences in market parameters, differences across subjects, differences due to learning effects, and other unknown features of the experiment that stay constant across treatments. First, we control for differences across cohorts. Different subjects have different levels of intelligence, motivation, and familiarity with the experimental environment (Kagel and Roth 1997). If a cohort trades only in one of the three regimes that we design, the differences in their behavior may reflect the differences of the individuals, rather than what we intend to measure. We avoid this possible noise by having our cohorts trade in all of the three regimes, as shown in Table 2. Hence, we can observe the effect of transparency within a given cohort. Second, we control for learning effects. In laboratory experiments, even the same cohort can behave much differently when repeating a task. Therefore, learning effects gain dominance especially in complex games since subjects gain experience if they go through a predetermined sequence of events (Bloomfield and O'hara 1999). We control for such effects by having each cohort trade in the three settings in different orders.

Cohort number	Order of settings		
1	O	ST	T
2	ST	T	O
3	T	O	ST

Table 2. Experimental design

SIMULATION DESIGN

Design of stationary and non-stationary demand

We analyze market behavior under stationary and non-stationary demand conditions. In both cases, there are 5 sellers with 3 units of capacity and simulated buyers in each session. We have also run simulations with 10 sellers and varied the capacity constraints of the sellers. The number of sellers does not affect our findings. Variation of capacities across sellers also does not make much difference as long as sellers remain capacity constrained. Hence we report only the results pertaining to 5-seller case in which all sellers have 3 units of capacity. The supply and demand schedules of the stationary demand market are illustrated in Figure 1.

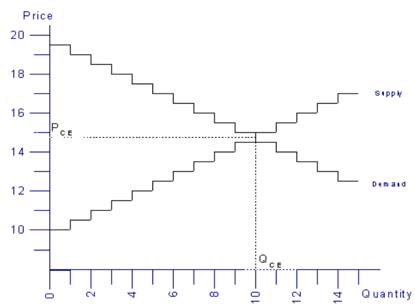

Figure 1. The design of stationary demand

The non-stationary demand design resembles that of Davis and Holt (1997). Several external factors may lead to non-stationary demand patterns, including changes in consumer taste, income, or interest rates. The first period starts with supply and demand schedules of the stationary demand treatment. The inflationary and then deflationary demand shifts are induced by altering unit values for the buyers. The demand curve shifts upward by a constant amount for 25 periods and then shifts downward by the same amount for the remaining 25 periods as illustrated in Figure 2. Hence, market demand ends up where it was at the first period.

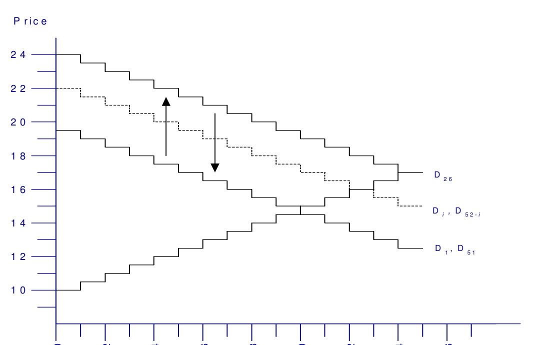

Figure 2. The design of non-stationary demand

Description of seller algorithms

Simulated buyer agents trade in Opaque, Semi-transparent and Transparent settings, each of which provides a different level of information available to sellers. Sellers in all settings can increase or decrease their prices independently. They can also undercut their competitors by ε, which is drawn from a uniform distribution in each period. Furthermore, sellers myopically assume that their competitors will post the same price in the next period in optimizing their posting decisions. Seller surplus in each session is calculated by multiplying her total quantity sold by the profit made from each unit sold (price-unit cost). Buyer surplus is the difference between the valuation of a unit by the buyer and its price paid, summed over all the units purchased by the buyer in a session.

Opaque seller has a two-period memory, thus it sets price according to the outcomes of the last two periods. It increases price as long as its profit increases by doing so. If buyers penalize such an action, opaque seller then starts decreasing the price by ε drawn in that period. Whenever profit increases after a price reduction, the agent tries to increase price again. A similar behavior is also used in the Semi-transparent setting, except that now sellers also see the prices of others' transaction. Hence, agents can judge whether they can earn more money if they undercut the lowest-priced seller and sell all their capacity or if they undercut the highest-priced seller and sell a single unit.

Transparent seller has the distinct advantage of being able to calculate its profit assuming that all others post the same price in the next period. Thus, it either sets the same price or undercuts the price of the seller at which its expected profit is maximized. This behavior results in early and continuous clustering of all prices in the market. However, transparent seller also tries higher prices whenever it sells above a predetermined number of units in two consecutive periods. This may be implemented to explore more profitable price ranges, which is especially useful in non-stationary demand conditions.

RESULTS

Result 1: *Increasing the transparency level of the market results in a higher efficiency. Semi-transparent market is almost as efficient as transparent market both in the case of stationary and nonstationary demands, i.e., revelation of quantity information is not very crucial.*

With more information revealed in the market, sellers find pricing close to the Competitive Equilibrium (CE) more profitable, see Table 3 below. Consequently, prices decrease and market efficiency increases as sellers try to optimize their earnings. An interesting point is that there is not much difference between Transparent and Semi-transparent settings in terms market efficiency. The efficiency differential between Transparent and Semi-transparent regimes is less than 3% in both stationary and nonstationary demand treatments, whereas the differential between Transparent and Opaque market settings is above 10%. Hence, revealing price information to sellers makes a difference, but additional information on quantity is not that effective.

	Stationary Demand		Nonstationary Demand	
	Avg. Efficiency	Avg. Price	Avg. Efficiency	Avg. Price
Opaque	74.2%	16.09	75.6%	17.54
Semi-Transparent	84.9%	15.59	86.3%	16.77
Transparent	86.6%	15.49	88.8%	16.60
CE Prediction	100%	14.75	100%	15.85

Table 3. Average market efficiencies in 6 treatments

Result 2: *Posted-offer markets favor sellers.However, increases in transparency level benefit buyers more. This is especially evident in non-stationary demand treatment where seller profits are nearly constant across all transparency settings.*

Sellers in our simulated markets can extract much more surplus than buyers can do (see Table 4 below). Interestingly, this bias towards sellers decreases as sellers get more information about each others' actions. This is because competition gets severe as they track each other, pushing prices down and increasing buyer surplus. Seller earnings increase very slightly despite decrease in prices.

	Stationary Demand		Nonstationary Demand	
	Average Buyer Surplus	Average Seller Surplus	Average Buyer Surplus	Average Seller Surplus
Opaque	13.4	23.7	20.6	37.6
Semi-Transparent	17.5	24.9	27.9	37.9
Transparent	18.3	25.0	29.6	38.2

Table 4. Average surpluses in 6 treatments

Result 3: *Posted-offer market responds poorly to demand shocks. Sellers in all settings go off the track when demand changes its trend, which is more pronounced in Opaque setting. Buyers suffer most from the demand shock.*

Sellers in all settings get closer to the CE prediction during successive trading periods until the demand shock arrives at the 27th period. Then onward, sellers poorly track the CE price level. Tables 5 and 6 below illustrate the effect of the demand shock on the market participants. The interesting point here is that poor price tracking of sellers do not affect their earnings, but significantly hurts buyer surpluses. Sellers are initially indifferent between maintaining high price levels and tracking the shift in demand because selling more at a lower price is identical to selling less at a higher price. Only when the shift in demand starts to hurt them, do they respond and start decreasing prices. On the other hand, buyer earnings almost rock bottom as soon as market demand starts its downward movement. Here, we see another stark example of seller dominance in posted-offer markets.

	First 26 periods	Last 25 Periods	% Change
Opaque	24.4	16.6	-32%
Semi-transparent	30.6	25.2	-18%
Transparent	32.2	26.8	-17%

Table 5. Average buyer surplus in nonstationary demand before and after the demand shock

	First 26 periods	Last 25 Periods	% Change
Opaque	37.9	37.3	-1%
Semi-transparent	37.9	38.0	0%
Transparent	38.4	37.9	-1%

Table 6. Average seller surplus in nonstationary demand before and after the demand shock

CONCLUSION

Our results have important implications on the design of B2B marketplaces. Assuming that sellers are not allowed to collude, buyers strictly prefer a higher level of transparency. Therefore, sellers can attract more buyers when setting up a market if they announce that their market will reveal information that would foster competition. The usefulness of revealing information on transaction quantity, however, remains as an open question. Since the levels of profits are almost identical, sellers may prefer Semi-transparent design over Transparent one, which may lead to a collusion and a potential investigation by the Federal Trade Commission. Buyers may also prefer Semi-transparent design if they fear that sellers can collude when quantity information is available. Thus, we conjecture that catalog sales activity in B2B markets can accelerate if their design is switched from the widely accepted Opaque form to Semi-transparent regime.

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