Brokering Strategies in Electronic Commerce Markets

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ABSTRACT
Online brokers are inventing strategies as fast as they move online. Some strategies are being implemented already, such as the Yahoo! model of advertiser-supported brokerage, or the eBay model supported by commissions charged to sellers, but there is no theoretical backing for either of these two models compared to the wide variety of auction theory. The services offered by brokers are also evolving very rapidly. In this paper we first provide an overview of the evolving brokering practices and limitations of existing work. We then investigate in detail the effect of search costs on the performance of the broker's optimal strategy for the case of M buyers and N sellers where negotiation is on the price attribute of the product or service. The relation to the fees is also analyzed. A time dependent model is constructed and simulation results are reported.

Keywords
Electronic Commerce, Intermediation, Markets, Borkers, Internet.

1. INTRODUCTION
An electronic intermediary is a business entity that performs at least one intermediation function. Intermediation functions are those which help or completely enable a buyer and a seller to complete a transaction. Unmediated transactions require the buyer and seller to determine their needs, locate each other, negotiate, and settle directly between the two or more of them. Mediated transactions use an outside third party to give some assistance to at least one party (sometimes both) in at least one commercial function.

It has been argued that in the perfect electronic market, buyers and sellers will be able to contact each other in a direct, frictionless manner, thereby "eliminating the middleman." [2, 35]. However, evidence in the marketplace demonstrates that at least for some time to come, the role of intermediaries is becoming increasingly important. The role of intermediaries has been discussed extensively [5, 7, 19, 23, 28, 29], and the use of agents for this task is surveyed in [17]. One example of the many new Internet intermediaries is [3]. Some interesting case studies can be found in BusinessWeek [15], WebMaster [4] and Business 2.0 [18].

Following is an overview of major functions of an online intermediary:

Searching. One major function of an online intermediary is to facilitate searching in a marketspace. Some marketspaces are very large and help in sorting through the options is required; others offer very complex product offerings and help in matching product offerings and business needs is useful. The search function of the online intermediary has been widely recognized [5, 29, 31], and has been called either "making searching easier" or "reducing search costs."

Trust. Another major function is that of trust services. These services include escrow, security, authentication, and payment [5, 29].

Aggregation. It is often useful to aggregate buyer and seller demand and supply in the same place [5]. This is often done in financial markets, but happens online in the case of semiconductor parts [15] and miscellaneous merchandise [1] as well.

As an Infomediary. An infomediary is an intermediary that sells information about the product, rather than purely price information [18]. This separation of price information from the product information has been encouraged by [6]. In particular, analysis should be done on the cost of product information relative to the cost of the price information [7]. The recent surge in business-to-business markets and buying portals, however, combines the two (as well as many other value-added services). See [32] for an analysis of intermediary services in the context of B2B procurement.

Negotiation: Negotiation is a function that could be very useful if done properly by an online intermediary. Especially in multi-attribute bargaining, sometimes "win-win" solutions can be discovered more easily by an outside third party who has full information and neutral motives [27]. While full-blown automated bargaining has been widely recognized as an important function of an online intermediary [5, 16, 29, 31], it is very difficult to actually implement automated bargaining into an online intermediary for all the reasons it is very difficult to implement automated bargaining directly into buyers and sellers. However, single-attribute intermediation, over price alone, in marketspaces of many buyers and many sellers, is a form of an online auction, and can be implemented for all the same reasons online auctions are currently feasible and successful. Certain forms of multi-attribute bidding are both useful and feasible; see [12] for a multi-attribute scheme in the context of procurement.

Other intermediation functions. Several other intermediation functions have been identified as well. They include gateways,

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directories, malls, auditors, financial intermediaries and spot market makers [29, 32].

For the purposes of this paper, a broker is defined to be a mediator that performs the negotiation function. Of course, many real-life brokers can perform searching functions, delivery or payment services, and many other functions, which do not explicitly involve the negotiation function. Brokered transactions involve many buyers and many sellers, and often operate in a marketspace that changes with time.

Despite the various problems associated with automating complex intermediary functions, new intermediaries are springing up all over the Internet. They make product offerings more personal and customized, and aggregate and disaggregate products in new and useful ways [7]. There are some intermediaries for searching, such as Yahoo!, Excite, PersonaLogic, and Firefly. Tete-a-Tete is a beta-test version of software from Frictionless Commerce Inc., intended to assist with multi-attribute cooperative negotiation [3]. Intermediaries which recommend products include Jango, BargainFinder, Firefly, and Tete-a-Tete. There are also transportation inter-mediaries, such as FedEx, and payment/ security intermediaries, such as Visa, which do not operate exclusively over the Internet but which enable substantial portions of e-commerce.

This paper is concerned with brokering and negotiations on price only. For the purposes of this paper, a broker is defined to be a mediator that performs the negotiation function. Of course, many real-life brokers can perform searching functions, delivery or payment services, and many other functions, which do not explicitly involve the negotiation function. Brokered transactions involve many buyers and many sellers, and often operate in a marketspace that changes with time. While auction theory is well understood and well grounded, there is no coherent body of "broker theory" to provide the same base for brokers. The contribution of this work is the analytical analysis of a simple (to execute, yet difficult to analyze) model of online broker. Following an overview of online brokers, including limitations of existing work in Section 2, a mathematical model is presented in Section 3 and solved in Section 4. Simulation results based on the model are discussed in Section 5. The paper is concluded with a summary and future research directions.

2. ONLINE BROKERS

This section will outline the state of the art in online brokers. Some were around long before the Internet; others are using the Internet to overtake traditional intermediaries, and still others are using the Internet to offer mediation packages not available before.

The Web is disintermediating traditional brokers like real estate agents, stockbrokers , car dealers and travel agents. There is even an intermediary, Matchpoint, which helps customers sort out the 40,000 real estate brokers which have sprung up on the web [4]. HomeShark brokers mortgages; RoweCom brokers academic journal subscriptions; CompareNet brokers online price comparison for manufactured and consumer goods, and NECX is an 18-year-old business which has only newly taken its business to business computer sales online [18].

Online markets and online brokers were around long before the Internet. In the 1970's, securities dealers hooked computers together to make the system which was to become the NASDAQ trading exchange. As early as 1989, the trend towards electronic markets was underway, and electronic brokers for doctors, insurance services, cotton, automotive parts, and airline parts were available. "As electronic networks evolve, market activity will replace vertical integration." [25]. There are brokers which help with price comparisons for goods: BargainFinder, Pricewatch .com, computeresp, Jango, Onsale, eBay, and of course NASDAQ.

No tried-and-true brokerage strategy exists. Instead, online brokers are inventing strategies as fast as they move online. Some strategies are being implemented already, such as the Yahoo! model of advertiser-supported brokerage, or the eBay model supported by commissions charged to sellers, but there is no theoretical backing for either of these two models comparable to the wide variety of auction theory which backs online auctioneers.

This section will outline three major shortcomings in current brokerage strategy.

Traditional bargaining theory tools do not apply

Theoretical limitations of optimal brokerage strategy are substantial. There is no parallel to the coherent auction theory that underpins the online auction.

Some approaches begin with the same building blocks used (unsuccessfully) to try to solve the automated bargaining problem. These approaches run into trouble when assumptions such as perfect rationality do not hold in real life [8], and frequently also involve problems such as differential equations which are very difficult to solve for even simple negotiation problems [14]. Trying to design efficient brokerage schemes with these building blocks is also not very fruitful; there is the "Impossibility Result" showing no bilateral trading mechanism can be ex-post classical efficient [26] and that ex-ante efficiency is also unlikely [30].

Other attempts to analyze brokers look at the broker as part of a whole system. Attempts have been made to analyze the new role of brokers within Williamson's Transaction Cost Analysis (TCA) theory [36], in terms of principal/agent theory, and in terms of property rights theory, but no strong conclusions have been drawn yet. Some work has been done on a non-cooperative theory of large markets [30]. Even so, there is a large difference between two-person games, "few" person games (where few is from four to about 20), and "many person "games (from 20 to a few hundred) and then the large but finite games. As the number of participants increases, the game becomes much harder to study [33]. Hence, traditional bargaining tools do not easily transfer to this situation.

Tightly linked buyer-seller-broker strategies are complex

One major problem here is the closely linked nature of buyer, seller, and broker strategies. When solving unmediated buyer-seller negotiations, the buyer's strategy and the seller's strategy must only come to equilibrium with each other. Strategies are usually both individually rational (IR)[1] and incentive compatible (IC),[2] but little else can be assumed. Even with just one buyer and

[1] An IR strategy is one in which the participant's expected payoff is nonnegative. The party will not lose money by playing this strategy. It is assumed that a zero payoff is always available by "walking away."

[2] A strategy is IC if, for every possible set of conditions, it will give the party the highest expected payoff. Note this implies that the party will tell the truth only when truthtelling is the dominant strategy. Otherwise, the party will lie in a way

one seller, this interdependency gives rise to difficult solutions and often to complex equilibria [14, 26].

When a broker is included as part of the system, all three parties must come to equilibrium: buyer, seller, and broker. Some brokers are compensated by the number of deals they can enable. Others can be compensated as a function of the value of the deal, the quantity of goods sold, the timeliness of the deal, the buyer's utility, the seller's utility, or both the buyer's and seller's utilities. The broker's compensation structure will affect how it chooses to put together deals.[3] This, in turn, will affect the strategies employed by the buyer and seller, and these, in turn, will affect the broker's performance.

The tightly linked nature of this system makes optimal strategies and equilibrium behavior very difficult to calculate. What is the best way to set up a broker's compensation? How should buyers and sellers react? Given the buyer and seller reaction, is a strategy still optimal? Not only are the answers to these questions unknown, but they will be very difficult to answer in a manner parallel to the clean mathematical answers given by auction theory.

Dynamic nature of the system makes solution difficult

Another very difficult aspect of the online broker problem is the dynamic nature of the system. Frequently, brokers operate in a dynamic, not a static, environment. At the beginning of a time period, the buyers, sellers, and broker all see the state of the system. They each make their decisions, certain trades are executed, and the system is in another state, often different from its initial one. The process repeats: all parties see the new state of the new system, make (new) decisions, execute certain trades, and the system moves to yet another state.

One difficulty with analyzing such systems is the difference between **behavior**, which can be easily observed, and **strategies**, which are essentially unobservable.

This dynamic nature of the online broker system makes it exceedingly difficult to solve analytically. Many small, simple, dumb agents working together in even a simple environment can lead to complex system behavior [22]. One can take an otherwise simple bargaining situation for which there is a single, clear-cut equilibrium solution, and introduce the time dimension to it, thereby complicating the final solution considerably. Any reasonable examination of non-cooperative equilibria in multi-stage games shows an enormous proliferation of equilibria[4]" [33].

calculated to gain it the most expected utility. This makes it difficult to figure out what the party's true reservation price is.

[3] A broker could run a straightforward double auction to determine a clearing price, a k-auction in which the price is k-amount of the way between the buyer's and seller's offers, or could simply match up expensive sellers with rich buyers, and cheap sellers with poor buyers.

[4] An "enormous proliferation of equilibria" is nearly as useless as a complete lack of any equilibria. Which equilibrium state will the system end up choosing from its possibilities? Each equilibrium represents a very different state, which in a brokered marketspace could mean different equilibrium prices, different numbers of buyers and sellers joining the broker, and different system behavior.

More research on dynamic brokered marketspaces can be found in the Santa Fe Double Auction, a computer-programming contest in which programs bid to buy and sell tokens through an intermediary [33]. This empirical testbed looked at the dynamics of the double auction market, and investigated theories of price formation, design of efficient trading procedures, the behavior of computer programs in the marketspace testbed, and several other aspects of the subject. Their conclusions were that the double auction market was a very dynamic, nearly chaotic system, which did not necessarily correspond to neat predictions of auction or economic theory. There were no search or brokerage costs in this marketspace; it was purely to evaluate bids and asks, and the winning program was the simplest one.

To summarize, the dynamic nature of such problems makes them much more difficult to study and solve than similar static games. In some cases there are no equilibria, and in very few are there any solutions which can definitively tell where the system will be, what optimal strategies are, or what a broker should do.

There are two open research problems which will be covered here. The first is that of dynamic systems behavior; the second is the effect of search costs upon the brokered system.

Dynamic system behavior

One area for research in online brokers is the dynamic system behavior. Given the buyer, seller, and broker are all operating under a certain set of rules, and given they are using certain (possibly optimal) strategies, what will the system behavior over time be like? How many buyers and sellers will opt to use the broker? What prices will form? What supply and demand will be observed in the marketspace?

A parallel question in this area involves broker strategy. Given buyer and seller "demographics" and strategies, what is the effect of the broker's strategy upon system behavior? Is it possible to deduce dynamically optimal broker strategies?

Search vs. brokerage costs

The second open research problem lies in the effect of search costs upon the performance of the brokerage system.

There has been some work which studies the effect of search costs upon marketspaces without brokers. It has been widely argued that lower search costs promote price competition and reduce the market power of sellers because buyers can shop around more easily [6, 23]. Bakos [6] argues the electronic markets may benefit buyers (but not sellers), even when buyers must pay search costs to locate appropriate sellers.[5] Zink [37] establishes the existence and uniqueness of an equilibrium for a similar non-brokered marketspace with search costs.[6] In both of these papers, the search costs are the variable which drives different system behaviors, and

[5] He finds that at equilibrium, buyers will suffer inefficiencies because they spend some money searching. He also uses a multi-attribute negotiation setup, but hashes the multi-attributes into a single "position" along the unit circle for a seller's product, and finds sellers will maximally differentiate themselves along that circle.

[6] In Zink's model, buyers must pay search costs to locate products, and sellers may quote randomly drawn prices to buyers.

search costs which are too high will lead to complete market breakdown.

Research on search costs in brokered marketspaces, however, has been slim. Malone and Smith [24] find that if system reliability is the most important evaluation criterion, a decentralized market is the best structure. And, they find that if system performance (measured by production costs or average delay in processing) is the most important evaluation criterion, then the brokered marketspace is the best structure. Hence, if search costs are low enough, and if reliability is not such a key issue, the brokered marketspace may be a very efficient and effective market mechanism.

The open research question is: what is the effect of search costs upon the behavior of brokered marketspaces? What effect will search costs have upon the number of participants using the broker? What effect will search costs have upon the overall marketspace efficiency?

3. A MODEL OF A BROKERED MARKETSPACE

The problem analyzed here is the relationship between search costs and brokerage costs in a simple electronic marketspace. Several simplifying assumptions have been made so that this marketspace may be tractable, and to make the effects of the search and brokerage costs more evident.

There are several buyers $B_1 \ldots B_m$ and several sellers $S_1 \ldots S_n$, who each wish to trade in single units of a good. In this marketspace, there is also one broker Br who can (but does not have to) arrange buy/sell agreements between buyers and sellers. This broker performs only the price discovery function. Settlement takes place elsewhere. The negotiation is over price alone.

For each time period in which he has a demand of one unit, a buyer must decide whether to search privately for a seller or whether to place his order using the broker. For each time period in which a seller has a supply of one unit, he must also decide whether to wait privately for a buyer to come search him out, or whether to list his supply with the broker. The broker can match buy and sell orders within its possession. There is a time discounting factor, so all parties would like to make trades as soon as possible. The following is a summary of the model.

Problem characteristics:
Single attribute: negotiation is over price alone; Iterated bargaining with time discounting; M:Br:N marketspace: many-to-many brokered negotiation

Broker characteristics:
Two additional broker "hot spots" are the broker's reward function and the dealmaking mechanism. Here, the broker's reward is a flat fee for each deal executed, charged to the buyer, the seller, or both of them. This was chosen with the hope of encouraging the broker to make as many deals as possible. The dealmaking mechanism is taken to be a k=1/2 auction, in which the final price is halfway between the winning bid and ask prices, if the winning bid is larger than the winning ask. This is done to simplify the calculation of buyer and seller strategies, and to highlight the effect of search costs, rather than the effects of bid or ask strategy.[7]

Since, to the best of our knowledge, this research problem has not been solved, there are no known optimal equilibrium strategies for the buyer, the seller, or the broker. The following strategies have chosen because they are relatively simple and straightforward. The intent here is to focus on the effect of search vs. brokerage costs, not to analyze implications of different buyer, seller, and broker strategies.

Strategies of Buyers and Sellers:
Buyers must decide whether to place an order through a broker, in which case they expect to realize a price set by the broker, or whether to search for different sellers. Only buyers search for deals. When using a broker, the buyer tells the broker his truthful willingness to pay. When searching privately, buyers use a "satisficing" heuristic: the first seller whose asking price is affordable receives the deal.

Sellers must decide whether to place an order through a broker, or whether to wait for buyers to approach them. Sellers quote a fixed ask price *a* to brokers and to privately searching buyers alike.[8] The broker uses a k=1/2 auction to determine selling prices.

Search costs:
There are search costs for contacting a broker or for privately contacting other parties. Each message costs something, and the sender of a message pays for both the outgoing message cost and the "return the search costs. postage." In this problem setup, the buyer pays

Assumptions: Buyers and sellers will tell the truth to the broker about their reservation prices. Sellers will truthfully buyers their asking price. The broker will immediately execute all possible trades.

More specifically, the parties must follow the rules outlined below, and must make the decisions outlined:

Buyer
Realizes b, his willingness to pay for one unit of the good. The variable b is drawn from a common function: b~ F(). Sees the broker's state Br(M, N), which tells the price of the last successful deal, the number of buyers registered with the broker, and the number of sellers registered with the broker. He must decide whether to place his order with the broker or search privately for the unit. If he decides to use the broker, he sends a message to the broker with his bid b. This message costs m_b to send. The order remains with the broker until it is filled. If the order is filled, the broker charges a buyer's surcharge s_b.

[7] Although in many ways the k=1/2 double auction is a simple system, it is still too complex a system to calculate equilibrium strategies for buyer, seller, and broker.

[8] This is not necessarily the optimal decision for the seller. Again, this system is operating in a vacuum of theoretical knowledge of optimal strategies. In a first-price sealed-bid auction, for example, the seller's optimal strategy would be to shade his bid slightly above his absolute minimum ask price. However, in such a CDA, optimal strategies are not known.

If the buyer decides to search privately, He sends out an inquiry to a seller chosen at random from those who are not registered with the broker. Each inquiry message costs m_p to send. The seller will reply with his true asking price *a*. If the buyer can afford the asking price *a*, he will make the purchase at *a*. If the buyer cannot afford the asking price a, he will repeat the search in the next time period with a new seller. The buyer will not privately search with sellers who are listed with the broker. The buyer will choose to either use the broker or to search privately. He will not do both.

Seller

His asking price for one unit of the good drawn from a common function: *a*~ G(). (Note that this is not his private valuation of the item, nor does it reflect any costs to manufacture; this is his asking price.[9]). He Sees the broker's state Br(M, N), which tells the price of the last successful deal, the number of buyers registered with the broker, and the number of sellers registered with the broker. Must decide whether to place his order with the broker or wait until a buyer searching privately for the unit finds him. If he decides to use the broker, He sends a message to the broker with his true ask a. This message costs m_b to send. The order remains with the broker until it is filled. If the order is filled, the broker charges a seller surcharge s_s. If the seller decides to wait for a privately searching buyer, he waits until a buyer approaches him with an inquiry. The seller will reply with his asking price a. If the buyer makes the purchase at a, the seller will stop waiting. Otherwise, the seller must wait for the next buyer. The seller will choose to either use the broker or to be searched privately, not both.

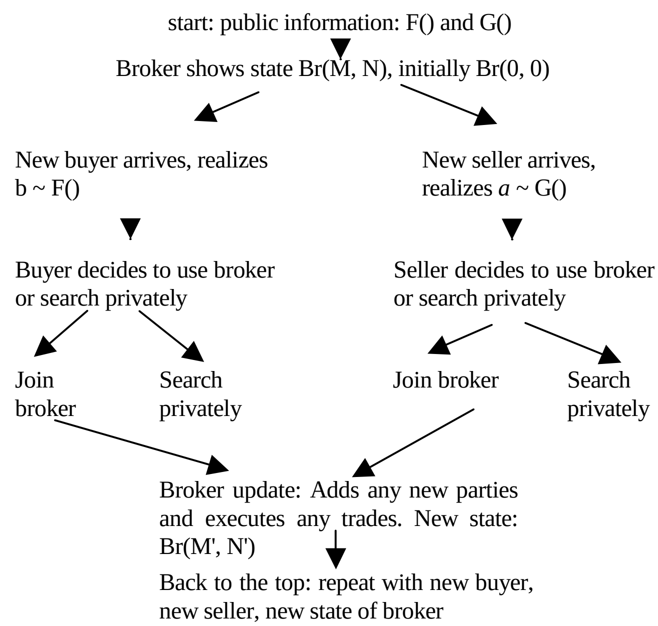

Figure 1: System dynamics of brokered marketspace

[9] We have simplified the seller's strategy here by making the final asking price the same for the broker and for private inquiries, and by taking it from a distribution G. Many game-theoretic models would instead choose the seller's private valuation of the good from a probability distribution, and from there calculate the seller's asking price using an equilibrium asking strategy.

Broker

Publishes the state Br(M, N), which tells the price of the last successful deal, the number of buyers registered with the broker, and the number of sellers registered with the broker. He keeps a list of all buyers who have registered with him and their bid prices. He keeps a list of all sellers who have registered with the broker and their ask prices. Since it makes a surcharge $s_b + s_s$ from each successful deal, its incentive is to make as many deals as possible. It uses a k=1/2 double auction to make deals. Once a buyer and a seller have been matched, they are both removed from the broker's list.

System

The system dynamics are what will determine interactions between buyers, sellers, and brokers. The system dynamics is shown in Figure 1 below.

The following decisions are analyzed in the next section: The buyer's decision whether to use a broker or search privately. The seller's decision whether to use a broker or search privately. The broker's calculation of the new clearing price.

4. MATHEMATICAL ANALYSIS

This section presents an analysis of the decisions.

Table 1 shows a listing of the variables that will be used for analysis.

Table 1: List of variables for broker analysis

Variable	Description
$B_1 \ldots B_m$	Buyer 1 through buyer m
$S_1 \ldots S_n$	Seller 1 through seller n
$b_1 \ldots b_m$: b ~ F()	Buyer bid price; iid
$a_1 \ldots a_n$: a ~ G()	Seller asking price; iid
M	Number of buyers registered with broker
N	Number of sellers registered with broker
k = ½	parameter of broker's deal making function. At k=1/2, deal price is halfway between winning bid and winning ask
m_b	Message cost to send message to broker (includes “return postage”)
m_p	Message cost to send message to private party (includes “return postage”)
s_b	Broker's surcharge which the buyer must pay upon successful sale
s_s	Broker's surcharge which the seller must pay upon successful sale
p	Clearing price of last transaction concluded by broker

4.1 Buyer's problem and solution

The buyer's problem can be stated as follows. **Given,**

- b, his private valuation
- Marketspace parameters F (uniformly distributed between F_{min} and F_{max}) and G (uniformly distributed between G_{min} and G_{max})
- Broker state (M, N)

- s_b, the broker's surcharge
- m_b and m_p, the messaging costs for broker and private messages, respectively

Assuming that the buyer will not revisit this decision in the future, the buyer will behave in an individually rational manner – he will not take part in a transaction which is expected to give him negative benefit.

Decide: Should he use the broker, search privately, or decline to participate?

The pseudocode for the solution is given in Figure 2 as follows:

```
The buyer's optimal decision is:
If E(benefit from search) < 0 and E(benefit from broker) < 0
    Decline to participate.
Otherwise,
    If E(buyer benefit from search) ≤ E(buyer benefit from broker), choose broker.
    Otherwise, choose private search.
```

Figure 2: Pseudocode for buyer's optimal decision

Using the broker will bring the buyer the following expected benefit. If the buyer's bid b is higher than the bids of all the M other bidders registered with the broker, the buyer can expect to pay the brokerage surcharge and receive a price which is halfway between his bid b and the lowest asking price a. Otherwise, the buyer does not expect a payoff:

Prob(b ≥ any of the M bids) = Pr (bid 1 ≤ b) Pr(bid 2 ≤ b) … Pr(bid M ≤ b) = F(b) F(b) … F(b) = F^M (b)

E(lowest ask of N asks) = expected value of the lowest order statistic = G_{min} + (1/N+1)(G_{max}-G_{min})

$$\text{E(buyer benefit from broker)} = -m_b + \left[-s_b + b - \frac{1}{2}\left(b + G_{\min} + \left(\frac{1}{N+1}\right)(G_{\max} - G_{\min})\right)\right]\left[F^M(b)\right]$$

Using a private search will bring the buyer the following expected benefit (derivation is omitted).The buyer's optimal decision can then be straightforwardly calculated from the pseudocode given in Figure 2.

$$\text{E(buyer benefit from search)} = \sum_{x=0}^{\infty}\left\{\left[\underbrace{-m_p\sum_{i=0}^{x}(1-r)^i}_{\substack{\text{search costs}\\ \text{of searching until x}}} + \underbrace{(b-E(a))(1-r)^x}_{\substack{\text{expected payoff}\\ \text{at x}}}\right]\underbrace{\left[(1-G(b))^x(G(b))\right]}_{\substack{\text{probability search will}\\ \text{terminate at exactly x}}}\right\}$$

$$\text{E(buyer benefit from search)} \le \frac{-m_p}{r} + \frac{(b-E(a))(G(b))}{1-(1-r)(1-G(b))}$$

A necessary approximation is the buyer's myopic decision-making with respect to the broker. Here, if the buyer thinks he cannot successfully win a brokered transaction this period, he expects no further payoffs from using the broker. In reality, the broker would be able to hold on to the unsuccessful bid and perhaps be able to fill it in the future. However, such prediction would require sophisticated beliefs about the broker's future ability to make trades. This, in turn, depends upon the current buyer's decision. The expected myopic benefit from using the broker ≤ the expected true benefit from using the broker, and so the inequalities used in making the decision are still quite valid. The full prediction is simply too complex for the current model, and so the buyer is reduced to his myopic decision-making here.

4.2 Seller's problem and solution

The seller's problem can be stated as follows. **Given,**

- *a*, his asking price
- Marketspace parameters F (uniformly distributed between F_{min} and F_{max}) and G (uniformly distributed between G_{min} and G_{max})
- Broker state (M, N)
- s_s, the broker's surcharge
- m_b and m_p, the messaging costs for broker and private messages, respectively

Assuming that the seller will accept the first transaction, from which he can realize his asking price, *a*.10 then **Decide**

- Should he use the broker or wait until a buyer seeks him out?

The seller's optimal decision is:

```
If E(seller benefit from search) ≤ E(seller benefit from broker), choose broker.
Otherwise, choose private search.
```

Figure 3: Pseudocode for seller's optimal decision

Using the broker will bring the seller the following expected benefit. If the seller's ask a is lower than the asks of all the N other sellers registered with the broker, the seller can expect to pay the brokerage surcharge and receive a price which is halfway between his ask *a* and the highest bid price b. Otherwise, the seller does not expect a payoff. Using a private search will bring the seller the following expected benefit (detailed derivation is omitted). Assuming the marketspace is large enough that the seller will receive at least one buyer visiting him per period. It is also assumed that the seller responds to only the first buyer he receives any period.

Prob(a ≤ any of the N asks) = Pr (ask1≥ a) Pr(ask 2 ≥ a) … Pr(ask N ≥ a) = (1-G(a)) (1-G(a)) … (1-G(a)) = $(1\text{-}G(a))^N$
E(highest of M bids) = exp. value of the highest order statistic = F_{min} + (M/M+1)(F_{max}-F_{min})

E(seller benefit from broker) =

$$-m_b + \left[-s_s + \frac{1}{2}\left(\begin{array}{l} F_{\min} \\ + \left(\frac{M}{M+1}\right)(F_{\max} - F_{\min}) \\ + a \end{array}\right)\right]\left[1 - G(a)\right]^N$$

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[10] This corresponds with a sunk-cost model, in which the seller has already produced the unit, and needs to recover an amount a to cover his costs. Having a seller behave in a profit-maximizing manner, in which he would try to receive the largest selling price possible, quoting different amounts to different buyers and brokers, is too complex to model here.

Expected Value (Seller benefits from search)=

$$\sum_{x=0}^{\infty} a\ (1-r)^x (F(a))^x (1-F(a))$$

$$= \frac{a\,(1-F(a))}{1-(1-r)(F(a))}$$

The seller's optimal decision can be straightforwardly calculated from the pseudocode given in Figure 3. The same assumptions and restrictions, which were necessary for the buyer's problem, apply to the seller's problem as well.

4.3 Broker's problem and solution

The broker's problem is different from that of the buyer or the seller. After the buyer and seller have made their decisions to use the broker or not, the broker must adjust the total number of buyers and sellers registered with it accordingly. If there was a trade possible, the broker needs to execute it and adjust the number of participants accordingly. Trade is possible whenever the highest b ≥ the lowest a. Keeping track of each past unfulfilled bid and ask would lead to an intractable explosion of possible state spaces for the broker. This is computationally not possible here, and hence approximations were made. In the individual buyer and seller analysis above, formulas were given for the E(highest of M bids) and the E(lowest of N asks). Building on this, Figure 4 gives the pseudocode for the broker's approximate updating function. These approximations to the broker's actions are necessary to predict and simulate the system dynamics as described in the next section.

If buyer chooses the broker, the broker needs to let M = M+1.
If seller chooses the broker, the broker needs to let N = N+1.
If E(highest of M bids) ≥ E(lowest of N asks), then the broker calculate a new price = 1/2 (highest bid + lowest ask), removes one seller and one buyer from its rosters: M = M-1; N=N-1.
Otherwise, the broker should do no further updating.

Figure 4: Pseudocode for updating broker

5. SIMULATION RESULTS

A simulation of this three-part dynamic broker system has been written, using Crystal Ball. The results are presented here.

5.1 Parameters

For this system, the following parameters were chosen. Some of them (the marketspace parameters F, G, M, and N) were fixed over the entire simulation. Others – the search cost variables m_p, m_b, s_s, and s_b -- were varied during the simulation to highlight the effect of search costs vs. brokerage costs upon the system. The two categories are shown in Figure 5 below. The constant parameters are as follows. The buyer's bid price b was drawn from F ~ U(0.5, 1.5). The seller's ask price a was drawn from G ~ U(0.0, 1.0). These were chosen to give a larger range of overlap, and hence more opportunity for trade to occur, than the usual setup of having both the buyer and seller have prices which were ~U(0.0, 1.0). Initially, the system had M=0 buyers registered with the broker and N=0 sellers registered with the broker. The time discounting rate was chosen to be r = 0.10.

Parameters which remained constant during simulation: Those not related to searching vs. brokerage fees
F: distribution of b, ~U(0.5, 1.5)
G: distribution of a, ~U(0.0, 1.0)
M: initial number of buyers registered with broker, set to 0
N: initial number of sellers registered with broker, set to 0
r: time discounting rate, set to 0.1
Parameters which changed during simulation:
Those related to searching vs. brokerage fees
$m_b = m_p$: cost of sending a message to the broker or a private party
s_b: surcharge charged to the buyer by the broker upon a successful transaction
s_s: surcharge charged to the seller by the broker upon a successful transaction

Figure 5: Parameters of the broker simulation

The parameters which changed are as follows. The messaging costs m_b and m_p were set equal to each other, to mimic a situation in which it cost the same amount to send a message, no matter who the recipient was. These costs were investigated over a range from "free" to "too expensive for the system to work," which for this system turned out to be $m_b = m_p \in \{0.0, 0.05, 0.10, 0.20. 0.30\}$. The brokerage surcharges for the buyer and seller, s_b and s_s, were chosen to vary independently from "free" to "too expensive for the system to work." In practice, for the buyer, s_b varied from 0.0 to 0.5, and s_s varied from 0.0 to 0.5 as well. Combinations of s_s and s_b, in which both the seller and buyer had to pay fees to the broker, were also investigated.

For lack of space, we include only a summary of the results. part of the results. One primary question of this research is: where does the broker attract business? What combination of search and brokerage costs make the broker the most attractive option? The "broker footprint" is defined as that combination of search costs (composed of m_p and m_b) and brokerage fees (composed of s_s and s_b) which makes the broker a feasible deal making mechanism. The broker is a feasible dealmaker when over the course the simulation, it was able to execute at least one trade between a buyer and a seller, else it is not a feasible dealmaker. When the search costs are too high or too low, the broker will not be used. And when the brokerage fees are too expensive, the broker will not be used. The broker footprint varies with search and brokerage fees, and is shown for a representative marketspace in Figure 7. When search costs are free (Figure 7, top left), the broker is relatively limited in what it can charge for its services. When search costs increase to low levels (top right), overall the broker has more latitude. When search costs are moderate (bottom left), the broker has the widest "footprint" of available revenue schemes. In this case, the broker does best if it charges buyers a hefty fee and lets sellers join cheaply – this situation will build up

Average broker trade price
No. of buyers (out of 100 possible) who chose to join broker
No. of sellers (out of 100 possible) who chose to join broker
No.r of trades executed
Total broker revenue

Figure 6: Variables measured with each run of broker simulation

a surplus of sellers and entice buyers to pay the registration fee and join. Alternatively, the broker could charge sellers a hefty fee and let buyers join cheaply – this situation will build up a surplus of buyers and entice sellers to pay the registration fee and join. Finally, when search costs are very expensive (bottom right), more parties opt to "stay home," limiting the options available to the broker.

6. CONCLUSIONS AND FUTURE WORK

Brokerage theory is less well developed than auction theory is, largely because brokered systems are much more complex than simple auctions. Brokered systems often involve competing strategies of three parties (buyer, seller, and broker) rather than the two (buyer and seller) of online auctions. Moreover, brokered systems often involve a dynamic time dimensions. Both of these differences considerably complicate brokered marketspaces. Moreover, Internet practice is currently fueled by experimentation rather than theory, leading to complex brokered markets where negotiation is only one aspect and business models are fast changing. Nevertheless, it is important to model the simpler situations in order to understand and predict the behavior and performance of emerging electronic markets. This analysis can be used as part of analyzing more complex situations.

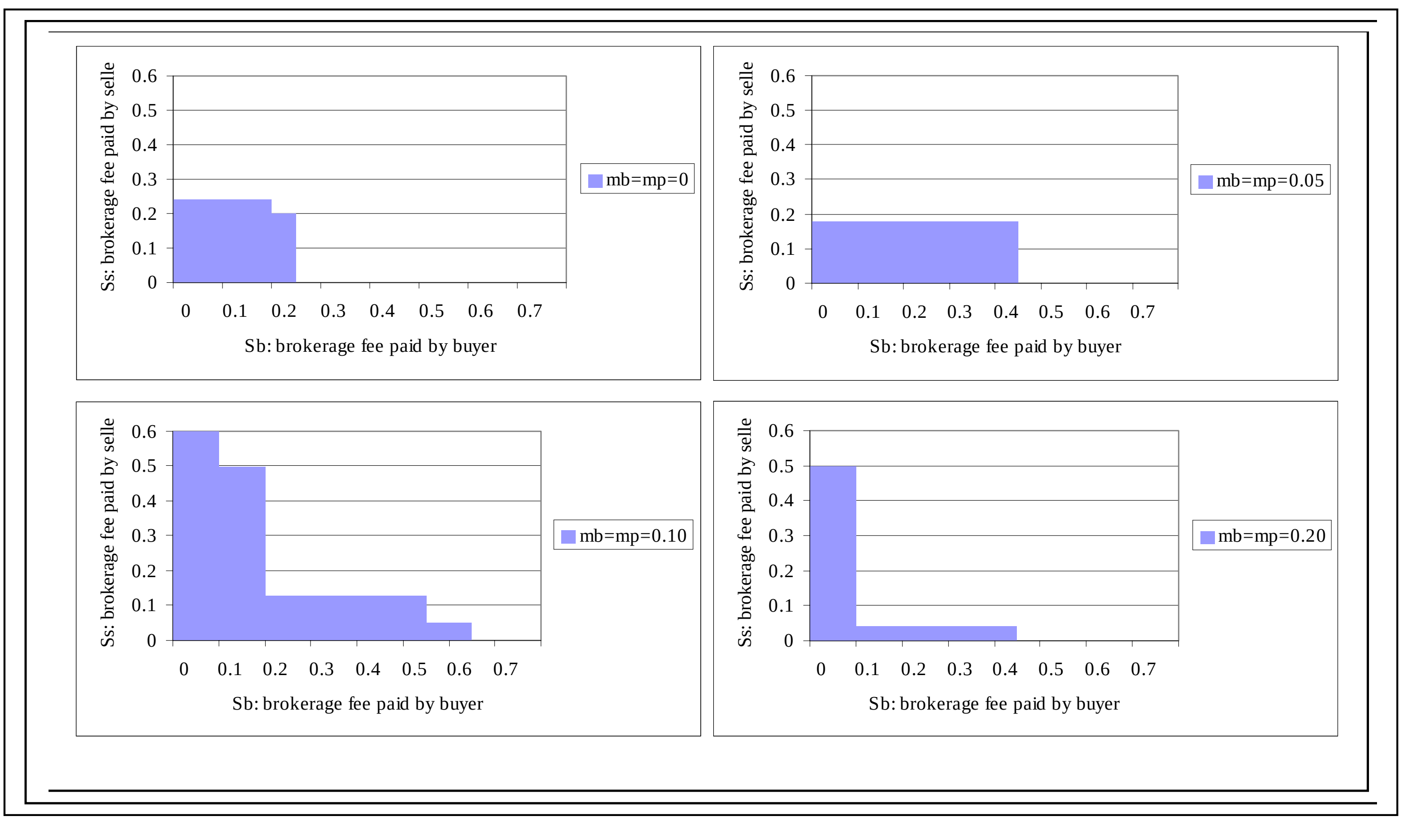
The contribution of this work is the analytical analysis of a simple (to execute, yet difficult to analyze) model of online broker. The results of the simulations based on the model validated intuitively expected results: when search costs are very low, the broker should choose to charge medium-high fees and plan on attracting only a small subgroup of buyers and sellers. As search costs increase to medium to medium-high, conditions for the broker improve. The broker can then afford to charge relatively high fees to buyers or sellers (but not to both) and still maintain a large volume of transactions and gather high revenues. When search costs become extremely high, the marketspace breaks down. The trading volume drastically decreases, and the broker's revenue with it. Current and future research work deals with the following extensions.

Vary the buyers' and sellers' reservation prices (the F and the G) to approximate some distributions, e.g., normal.

Vary the supply and demand quantities of the brokered marketspace. In this paper, the supply was assumed equal to the demand.

Vary the broker's strategy, the buyers' strategies, and the sellers' strategies. No known optimal strategies exist, but the broker could be made a buyer's broker or a seller's broker (by setting k=1 and k=0 respectively). Similarly, the buyers and sellers could adopt strategies other than truthtelling, such as the first-price sealed-bid auction strategy of shading a bid away from the true reservation price.

Investigate the agent and decision support functionality needed to support sellers, buyers, and brokers for different strategies implied by the models.



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