Behavioral Effects of Using Proxy Traders

Roumen Vragov
City University of New York, roumen_vragov@baruch.cuny.edu

Follow this and additional works at: http://aisel.aisnet.org/amcis2005

Recommended Citation
http://aisel.aisnet.org/amcis2005/286
Behavioral Effects of Using Proxy Traders

Roumen Vragov
Department of Computer Information Systems
Zicklin School of Business
Baruch College
City University of New York
Roumen_Vragov@baruch.cuny.edu

ABSTRACT

The advances in communication technology have allowed us to create fully automated markets that can function twenty-four hours a day using software agents as proxies to decrease transaction costs and increase efficiency. In this paper I examine the short-term and long-term behavioral effects of these agents on human market participants using experiments with economically-motivated human subjects. Findings indicate that humans try to outsmart the less flexible agents, which leads to lower efficiency levels initially. This behavior disappears towards the end of the experiment, and superior efficiency levels are reached.

Keywords

Electronic markets, electronic market design, software agents, experimental methods, Internet auctions, behavioral economics

INTRODUCTION

In the last three years our society has made a decisive leap towards automating many repeated tasks so that the creative efforts of people may be directed to other more profitable/productive activities. The advent of the Internet and the appearance of automated online exchanges has been an important part of this development. It is now possible for companies and people around the world to trade goods and services 24 hours a day in a seamlessly integrated fashion. Unfortunately, the number of E-commerce sites has exploded, and the simple buying and selling of goods on the Internet has become a nontrivial task. For example, there are presently at least twenty different web sites where one could purchase a plane ticket for travel between the same two cities. Each of these sites sells tickets in different ways. They require different user information and apply different restrictions. Navigating through this maze of information is still challenging. Search engines like google.com simplify this task, but it is still up to the user to choose which on-line exchange will better serve her purpose and what her optimal strategy will be given the rules of the chosen sites. To deal with this issue people have come up with another technical innovation; They have started creating software programs to assist the user in her interactions on-line. These programs have been called robots, auctionbots, software agents, etc. Such a feature is presently available on one of the most successful consumer-to-consumer E-commerce sites, eBay, under the name of proxy bidding (Roth and Ockenfels, 2002). After a buyer has decided to participate in an auction, she can give a limit price to her proxy. eBay keeps this information private. The proxy then bids in the auction. Every time the proxy is outbid but the current price remains below the limit price provided by the buyer, the proxy bids a minimum increment over the current bid. Meanwhile the buyer does not have to follow the auction. She can devote her time to more important activities. The robots could possess different levels of sophistication including but not limited to: searching for items to buy/sell; searching for the best web sites for buying/selling items; and devising strategies. Interesting and optimistic results from simulations involving the use of trading robots are reported in Greenwald, 1999 and Kephart, 1998. Agent research in E-commerce has flourished at different Universities in the US and abroad (Go to http://www.multiagent.com/Laboratories/Market-oriented/ for a list of related initiatives). However, there have been no studies that address how humans respond behaviorally to the various types of agents.

This paper uses a simple behavioral model to predict the human behavioral response to the introduction of a relatively simple prototype of trading robots. Hypotheses are then tested in an experimental setting using humans as subjects. The results of the tests have two important design implications: (1) Adding even simple ad-hoc automated strategies in the design of complex
trading environments can increase efficiency and decrease price volatility; (2) Humans have a tendency to try to outsmart the software agents; they often try to buy/sell at unacceptable levels, thinking they're going to trick the robot into accepting their bid or reservation price. This causes lower efficiency levels shortly after initiation of the trading process.

METHODOLOGY

The experiment consists of two basic treatments: a No-Agent treatment and an Agent treatment that will be described in detail below. There are twenty-six subjects in each treatment (13 buyers and 13 sellers). None of the subjects participated in both treatments. Each buyer has values for ten units and each seller has costs for ten units. If all sellers start auctions for all of their items, the buyers can participate in as many as 130 auctions. Sellers' costs are independently drawn from a uniform distribution with support [$0.00, $4.00]; buyers' values are drawn independently from a uniform distribution with support [$4.00, $8.00]. This guarantees that all units present on the market might be exchanged without loss if time costs (described later) are disregarded.

Buyers can buy up to ten items. Buying more than ten items does not add value. Sellers can start up to ten auctions and can sell only up to ten items. A subject's profit from buying an item is $v_i - p$ (value minus price) and from selling an item, $p - c_i$. Values are used in the following way: if Buyer 1 buys one unit for $4.00 and his value for the first unit is 8.00, his/her profit would be $8.00 - 4.00 = 4.00$. If Buyer 1 buys three units for $4.00 each and his/her values for the first three units are 8.00, 7.41, and 6.22, then his profit is $8.00 + 7.41 + 6.22 - 3 \times 4.00 = 9.63$. Costs are used in the following way: if Seller 1 sells one unit at $4.00 and the cost of his/her first unit is 1.58, his/her profit would be $4.00 - 1.58 = 2.42$. If Seller 1 sells three units at $5.00 and his/her costs are 1.58, 1.95, his/her profit would be $3 \times 5.00 - 1.58 - 1.95 = 11.88$. Every minute during the experiment subjects incur two types of costs: The first is a monitoring cost that depends on the time they need to buy/sell 10 units. Every buyer is randomly assigned a monitoring cost from the following set {0.00, 0.01, 0.02, 0.03, 0.04, 0.05, 0.06, 0.07, 0.08, 0.09, 0.1, 0.11, 0.12}. The same procedure is performed for the sellers. The second cost is an inventory cost per unsold item from the initial allocation. This charge is applied only to the sellers. For every seller a number is randomly chosen from the set {0.00, 0.01, 0.02, 0.03} to represent his/her inventory charge. These time costs are introduced in the experiment as a more direct way of measuring how the speed of transactions affects efficiency. The intent is to create some level of urgency while still giving subjects the chance to earn a reasonable amount of money for their effort.

During the course of one experimental session a buyer could incur total time costs somewhere between $0.00 and $2.40, which is approximately between 0% and 13% of the possible attainable individual profit. For the sellers the corresponding figures are much larger. Their monitoring cost is in the same range as the buyers, but inventory costs can pile up quickly. They can be between $0.00 and $6.00, or approximately between 0% and 33% of the possible attainable individual profit per market participant. The maximum cost of $6.00 is incurred only if a seller has not been able to sell anything throughout the duration of an experimental session.

Each treatment consists of three sessions, and each session is terminated at a specified time (20 minutes after start). Sellers can choose to start an auction at any time during the 20 minutes, and buyers can choose to participate in any of the active auctions. The cost and value parameters are the same for all sessions and treatments. All subjects went through a training session that explained the rules of all trading institutions, described below, and gave the subjects the chance to participate in each one of them separately. Subjects also had a chance to participate in two short training sessions using agents as proxies. Subjects were paid $5.00 for showing up for the experiment on time, and they kept all profits ($18.00 on average) that they made from all sessions.

No-Agent Treatment (NA)

In the No-Agent treatment four institutions of exchange are offered to the participants. These institutions are described in the following section. (Note that no subject participated in both experiments) These four specific auction type have been chosen because of their popularity both in economic science circles and in practice.

First Price Sealed Bid Auction

This auction type has been theoretically analyzed in Elyakim (1994) and experimentally tested in Cox et. al. (1988). If a seller chooses this auction type, she has to specify a reserve price for each auction. Every buyer who wants to participate in auctions of this type is required to submit a sealed bid. The auction is completed when five bids from different buyers are
entered. In order to win the auction, a buyer has to have submitted the highest bid, and her bid should be greater than or equal to the seller’s reserve price. At the end of the auction, the highest buyer pays her bid.

Second Price Sealed Bid Auction

This auction type has been theoretically analyzed by Vickrey (1961), and experimentally tested in Coppinger et. al., 1980. When starting an auction of this type, the seller specifies a reserve price for the item to be sold. Every buyer who wants to participate in an auction is required to submit a sealed bid. The auction is completed when five bids are entered. In order to win an auction, a subject has to have the highest bid, and the price that he pays for the item should be greater than or equal to the seller’s reserve price. The price that the buyer pays is equal to the second highest bid.

English Clock (EC) Auction

This is a version of the English auction tested experimentally in McCabe et. al. (1991) In this type of auction, the seller has to specify a reserve price. The auction starts when five subjects express willingness to participate. The price starts going up by an increment of $0.25 every 10 seconds. At every increment bidders indicate whether they are willing to buy the item at the clock price. If a bidder drops out of the auction once, he is not allowed to come back. The auction stops when there is only one active bidder. The winner pays a price equal to the current clock price.

eBay auction

At this auction web site the seller has to specify a reserve price, and a length for the auction. There are only four possible lengths that are predetermined - so the seller has to choose one of these four options: 5, 8, 11, or 14 minutes. These lengths were chosen to imitate the four different options that sellers face on the eBay.com website. They are equally spaced and since the entire session lasts twenty minutes, even the longest auction can take place. Each auction is then opened to everyone who wishes to participate. Bidders can start submitting bids, with the only requirement that every new bid satisfy a minimum increment rule. Buyers are not told the reserve price, but they are informed if their bid is below or above it. When the end is reached and the highest bid is greater than or equal to the reserve price, the auction is successful. The seller receives the price and the buyer receives the value of the item.

During the three sessions of the NA treatment subjects are not given the opportunity to use an agent. In trying to discover how to design the agent strategies, I turn to classical economic theory and game theory.

Equilibrium Predictions

The induced demand and supply curves in the experiment cross at $4.00. This price is the competitive equilibrium at the beginning of each session. The equilibrium quantity is 130, and the total surplus is $481.22. However, as the session goes on, buyers and sellers start incurring time costs. Since the sellers’ time-related costs are higher than the buyers’, the supply curve starts shifting up faster than the demand curve shifts down. Therefore, equilibrium quantity will be less than 130 and equilibrium price greater than $4.00. Given this situation, classical economic theory gives us no clues as to what an optimal strategy should look like. However, it tells us that there is no need to choose between auction types because the end result should be the same. Modern game theoretic approaches and experiments have shown that institutions of exchange do matter, and strategies, prices, and final allocations might depend on the institutions used. Modern game theory, however, is not yet sophisticated enough to derive the optimal strategies for this experimental set-up where costs and values are not linear in quantity, decisions are not made simultaneously and only once, and time costs are not linear in time.

Agent strategies

I use the following three basic principles to design a software agent strategy:

Partial Autonomy, i.e. the agents do not act completely autonomously. They require their users to provide them with limit prices at the beginning of each session in the experiment.

Minimization of losses, i.e. the agents strictly abide by the limit prices provided by the buyers and sellers. An agent should never sell below a seller’s reservation price and never buy above a buyer’s limit price.
Opportunity for learning and updating: This is mostly concerning the buyer-agent’s strategy. Buyers should be trying to buy items at the lowest limit price first, and then go up to a higher limit price after a certain number of failed bids.

**Agent Treatment**

In the Agent treatment all experimental parameters are kept exactly the same as in the No-Agent treatment. The only difference is the fact that both buyers and sellers are given the option of choosing a software agent to represent them in the experimental market environment (this is like choosing proxy bidding on eBay although the automated strategy there is quite simple). Both the buyer and seller software agents implement a fixed sub-optimal strategy. They work according to the following algorithms:

**Seller agent**

At the beginning of every experiment the seller agent starts an auction with every limit price provided by the seller as the reservation price. Auction types are chosen randomly with equal probability, and if eBay is chosen, auction lengths are chosen randomly with equal probability.

**Buyer agent**

The buyer agent receives and processes information about all available auctions. Initially, it randomly chooses to participate in ten auctions comprised of Second price sealed bid-auctions, First price sealed bid-auctions and English clock auctions. It also stores information about the closing times of all eBay auctions. If an eBay auction reaches its end, the buyer-agent drops out of the EC auction. If there is no English clock auction available, the buyer agent waits for a result from the other auctions before proceeding. In case of failure, the buyer agent tries another eBay auction as soon as one is available. After a certain number of failures, the lowest limit price is raised to the second-lowest limit price. The buyer agent makes sure that a certain ratio of active bids to units for which limit values are provided is kept constant throughout the experiment.

Subjects were not informed about these specifics. Instead, they were given a chance to experiment with the agent in two 10-minute test-runs before the actual experiment started. Here is the part of the instructions that pertains to the usage of the agents. For sellers: “… In this experiment you will be provided with robot assistants. You can choose to participate in the round yourself or to let a robot participate instead of you. The robot will automatically search all auction sites, trying to find the best deal for you, given the information available. Some of the robot actions are random, so different results might occur at different times. The only thing that you know for sure is that the robot will never sell below your limit prices…” For buyers: “… In this experiment you will be provided with robot assistants. You can choose to participate in the round yourself or to let a robot participate instead of you. The robot will automatically search all auction sites, trying to find the best deal for you, given the information available. Some of the robot actions are random, so different results might occur at different times. The only thing that you know for sure is that the robot will never buy above your limit prices…”

**Behavioral response theory**

Let us suppose that in our experimental environment seller j’s equilibrium strategy is $EP_j (r^*, \mu^*)$. Where $r^*$ is the set of all equilibrium reservation prices for seller $j$ and $\mu^*$ is the equilibrium number of auctions started. It usually takes some time for humans to achieve equilibrium. Therefore we will introduce into the model the possibility that a human might have a choice between engaging in an exploratory activity towards discovering the optimal strategy, or can costlessly choose a fixed and non-optimal strategy readily provided to her. We assume that there is some cognitive cost, $w_j$, involved into the discovery of the optimal strategy and $(r_j, \mu_j)$ is the provided fixed strategy in the face of a software agent. If $(r_j, \mu_j)$ is not an equilibrium strategy, then $EP_j(r^*, \mu^*) < EP_j(r^*, \mu)$ or the equilibrium payoff, however, if a person has chosen to be represented by an agent then $EP_j(r^*, \mu^*) - EP_j(r_j, \mu_j) \leq w_j$. From the definition of equilibrium strategy we can also infer that people who choose not to use agents can unilaterally improve their pay off using some strategy, which is a best response to $(r_j, \mu_j)$. To conclude this theoretical discussion, we can say that the act of introducing the possibility of a person choosing a software agent will result in higher efficiency levels because of two reasons. First, humans will self-select
themselves into two groups depending on the value of $w_j$ thus saving on effort. This increase in efficiency would be
difficult to measure in experimental setting, however the act of self-selection can be witnessed clearly. Second, there would
be gains in efficiency because some time costs are forfeited. This can clearly be tested in an experimental setting. Another
conclusion that follows from this discussion is that humans not using agents will act more “aggressively” in the market place
in the initial stages— i.e. they will be looking for strategies, which are best responses to the agent’s fixed strategy, and could
therefore be more profitable. This is because humans, who have not chosen to be represented by agents, are more flexible
during every session, while humans, who have chosen to be represented by agents, can update their limit prices only before
the beginning of the next session. Since total surplus is fixed, this aggressiveness will be demonstrated by an initial increase
in human sellers’ reservation prices and a decrease in the human buyers’ bids. These issues are examined in the experiment,
and the results are described in one of the following sections.

Hypotheses

Keeping in mind the design and the theoretical discussion in the previous section, we can test the following hypotheses,
which compare the two treatments:

H1
A certain number of humans will choose to be represented by agents suggesting that cognitive (or effort) costs are greater
than zero in the specific experimental environment, i. e. we will be able to witness the process of self-selection.

H2
Human sellers should increase their reserve prices in the first session of the Agent treatment compared to the NA treatment.

H3
Human buyers should decrease their bids in the first session of the Agent treatment compared to the NA treatment.

H4
Human sellers should choose more eBay auctions with shorter lengths in the Agent treatment compared to the No-Agent
treatment. This happens because both buyers and sellers will know that automated proxies will be able to find and aggregate
faster in a given auction. If the same task were performed by humans, it would obviously take a longer period of time.

H5
There should be measurable gains to efficiency in the Agent compared to the No-Agent treatment.
RESULTS AND ANALYSIS

I first discuss the results related to H1. As mentioned earlier, the experiment involves 26 human subjects. Agents were used by seven buyers and eight sellers in the first session, five buyers and seven sellers in the second session, and five buyers and eight sellers in the third session. The average rate of agent-usage is 51%. This shows that for half of the subjects the cognitive cost of finding the optimal strategy was above their respective cognitive (or effort) costs.

Reservation prices in the two treatments are shown in Table 1 and Figure 1. As stated in H2, the average reservation prices of the human sellers in the Agent treatment are lower than the corresponding figures for the No-Agent treatment. The difference is statistically significant in the first two sessions, but not in the third one ($t_1 = 6.31$, $t_2 = 3.75$, $t_3 = 0.84$). This is a clear indication that human sellers initially underestimate either their agent competitors or the automated buyers.

As shown on Table 2 and Figure 2, this happens to be true for the human buyers as well. The bids in the Agent treatment are lower for the first two sessions, and the difference is statistically significant for the initial session ($t_1 = 2.21$, $t_2 = 0.93$, $t_3 = -0.77$). So both H2 and H3 are supported by the data gathered.

There is a sharp drop in limit prices that the buyers provided to their agents in the second session of the agent treatment. This phenomenon was not anticipated by any of our hypotheses. A possible explanation could be the fact that one or more buyers tried to test the robustness of their agent strategies and pushed them farther from the equilibrium bids. Clearly more modeling and experiments are required to completely understand this phenomenon.

### Table 1. Reservation prices

<table>
<thead>
<tr>
<th></th>
<th>Session 1</th>
<th>Session 2</th>
<th>Session 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>NA</td>
<td>2.19 (1.22)</td>
<td>2.63 (1.01)</td>
<td>2.79 (0.82)</td>
</tr>
<tr>
<td>Agent/Human Sellers</td>
<td>3.43 (1.88)</td>
<td>3.22 (1.48)</td>
<td>2.78 (1.08)</td>
</tr>
<tr>
<td>Agent/Agent Sellers</td>
<td>2.05 (1.44)</td>
<td>2.45 (1.36)</td>
<td>2.28 (1.46)</td>
</tr>
</tbody>
</table>

![Figure 2. Bids](image)
The support for H4 is shown in Table 3. There is a tendency of increase in the number of short auctions in the Agent compared to the No-Agent treatment. Looking at the last session, we see that only 11% of all eBay auctions started are five minutes in length. The corresponding number for the Agent treatment is 29% which is higher, and statistically significantly so (t = 4.10).

Looking at the figures showing the realized reservation prices and bids in the two treatments, we can clearly say that the behavioral effects mentioned above are only a short-term phenomenon, which quickly disappears. Both the reservation prices and bids seem to be converging to the same point in the third session towards the end of the experiment. This leads us to believe that maybe the only long-term benefit of the adoption of similar agent strategies is the overall expediency of the transactions.

Lastly I would like to comment on the efficiencies of the treatments conducted. The results are plotted in Figure 3. Efficiency in this setting is measured as a percentage of $481.22, which is the total surplus at the time that the experimental sessions are started or the area between the initial demand and supply curves. We see that in sessions one and three, the Agent treatment is more efficient. About 73% of the gains in efficiency are due to less time-cost incurred. Notice the dip in the efficiency level of the second session in the Agent treatment. This is the session in which the buyers who used agents were trying to get better deals by entering bids far below equilibrium. Overall, however, the Agent treatment dominates the No-Agent treatment when we take into consideration all sessions. Comparing the distribution of prices in Figure 5 suggests that agents decrease price volatility and increase the number of transactions, which happen around the neighborhood of the initial equilibrium price of $4.00.
DISCUSSION

The results of the experiment show that software agents can successfully become an integral part of a new electronic market environment, and their adoption could potentially lead to higher efficiency. Real world trading places are complex, but the introduction of even simple ad-hoc automated strategies based on the three principles mentioned above increases efficiency levels. This result confirms previous findings in the field. In addition this paper documents a result that has not been reported in previous research. It is easy to see that human market participants have a tendency to try to outsmart the software agents - a phenomenon that can lead to lower efficiency levels in initial periods. Clearly, this is only a short-term phenomenon. Toward the third session we see a tendency of convergence between the reservation prices and bids across treatments, and efficiency levels rise again.

CONCLUSION

A major obstacle in front of the wider usage of trading robots is the view that human traders share about their automated counterparts. It seems that humans need some time to adjust to the idea that simple trading tasks can be performed well by automated algorithms. That is why we have to keep in mind that we cannot use only simulations to evaluate software agent
system designs because we must find a way to evaluate the impact that they would have on human behavior. Laboratory experiments could prove very useful in this aspect.

REFERENCES


