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Robert J. Kauffman
University of Minnesota, RKauffman@csom.umn.edu

Charles A. Wood
University of Minnesota, cwood@umn.edu

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Robert J. Kauffman
rkauffman@csom.umn.edu
Charles A. Wood
cwood@umn.edu
Information and Decision Sciences Department, Carlson School of Management, University of Minnesota

Abstract

Although the Internet is great for transferring information, transactions in Internet auctions have a greater *information asymmetry* than corresponding transactions in traditional environments because current auction market mechanisms allow the seller to remain anonymous and to easily change identities. Buyers must rely on the seller's description of a product and ability to deliver the product as promised. Internet auction environments make opportunistic behavior more attractive to sellers because the chance of detection and punishment is decreased. In this research, we examine auction data to see the effect of opportunism in the online auction environment.

Introduction

E-commerce (**EC**) offers a variety of new business models, such as long-lasting auctions or 24-hour per day automated order taking. These new models are designed to generate and sustain revenue by taking advantage of the unique characteristics of the World Wide Web. Though the trade media has viewed EC as "the next big thing," its growth has been below expectations. Most companies have Web sites to provide information, but only 4% of organizations currently generate revenue using EC technology, up from 3% in 1998 (Littlewood 1999), implying low customer demand for EC services from most customers. Many media analysts attribute the lower-than-expected EC growth to low levels of trust among consumers (Rankin 1999). Many observers have written about how EC benefits the consumer because of reduced search costs (Bakos 1997; Choudhury 1998). However, what needs to be better recognized by the research literature is how EC opportunism is facilitated by an increase in information asymmetry between the online buyer and the online seller.

Economics defines *information asymmetries* as instances in which there is knowledge that one party has and that another other party lacks in a variety of decision-making settings (e.g., production, investment, resource allocation, contracting, and so on). Information asymmetries often lead to various kinds of problems in these settings, including inappropriate decisions and outcomes, unfair exchanges of value, and loss of social welfare. They also can occur in sales transactions, where buyers and sellers are involved. The asymmetry in information can occur with respect to knowledge about product quality or knowledge about behavior that may occur even after the sale. As a result, information asymmetries can lead to transactions in which only one side benefits. They can also lead to fraud, cheating, misrepresentation of self or product, or other *moral hazards* benefiting one party in a transaction at the expense of another (Tirole 1988).

Although EC buyer behavior has been investigated (Lee 1998), less work has been done to investigate changes in seller behavior, especially in Internet auctions. In this research, we propose and test a model that shows how sellers in Internet auctions behave in the absence of identification, personal contact, and a higher uncertainty on the part of the buyer about the product. We explore the following research questions:

- Why and how does the increase in information asymmetry brought about by Internet auction transactions change seller behavior?
- How does the buyer in an Internet auction respond to this increase in information asymmetry?
- How does information asymmetry affect prices in online auctions, and social welfare, more generally?

We employ a software agent to gather data from online auctions, extending prior work by Kauffman, March, and Wood (1999). We analyze this data to show how Internet auction sellers react to the customer when information asymmetry increases.

Literature

We examined two areas in the literature that offer useful insights for modeling and understanding information asymmetry problems in buyer-seller interaction on the World Wide Web. The economics literature has a stream of research that investigates problems involving *information asymmetries*. This work analyzes the effects of one-sided information in a transaction. In addition, there are a number of recent articles in the information systems literature that discuss *online auctions*, as well as a larger body of literature on the economics of auctions that are worthwhile in this context. See Milgrom (1989) for an overview.

Economic Perspectives on Information Asymmetries. Many authors have investigated how information asymmetries can lead to a reduction of promised product quality. Akerloff (1970) discussed how markets with high information asymmetry such as the used car market eliminate potential transactions because buyers cannot believe sellers will not act opportunistically. As a result, buyers will not pay for any quality car above the lowest quality. Hence, high quality sellers will not be able to sell their products for what they are worth, and therefore will not transact. Klein and Leffler (1981) developed an analytical model that shows how opportunistic behavior will occur when the profit from misleading customers is greater than the profit from lost sales due to reputation effects. Shapiro (1982) discussed how, when sellers control a market (as with a monopoly), product quality is reduced if buyers cannot be fully and accurately evaluated before the purchase. In related work, Shapiro (1983) extended Klein and Leffler's model and relaxed their assumption of perfect communication between customers. We apply Shapiro's model as a theoretical basis for the ideas presented in this paper.

IS Perspectives on Online Auctions. Although the current body of online auction literature has ignored seller behavior in online auctions, there have been many recent studies examining item characteristics and bidder behavior in Internet auctions. Bapna, Goes and Gupta (2000a) discuss how bid increment can affect revenue generated in a multi-item auction. They also discuss lot size, opening bid amount, the magnitude of closing bids and the specified bid increment all affect the revenue generated by an Internet multi-item auction. A related paper (Bapna, Goes and Gupta, 2000b) uses online auction data to explore and refute some common assumptions about online auction behavior found in the economics literature (e.g., Milgrom, 1989). Both of these papers delve into types of bidders found on multi-item auctions. We extend their results in this research by comparing seller behavior to bidder behavior, and by investigating bidder response to seller behavior.

Seidmann and Vakrat (1999) compared online catalog prices with online auction prices. They obtained data from 473 online auctions, such as SurplusAuction (www.surplusauction.com) and OnSale.Com (www.onsale.com). They compared prices received in these auctions with prices from Internet catalog sellers, such as Egghead (www.egghead.com) and PriceScan.Com (www.pricescan.com). Their data analysis revealed that consumers expect greater discounts for more expensive items. A second study by Vakrat and Seidmann (2000) analyzed bidder arrivals in 324 online auctions and found that about 70% of bidders arrive during the first half of the auction and that high required starting bids tends to result in fewer bidders. In their studies, Seidmann and Vakrat employed Internet agents as a data collection tool. Although they compared online catalog prices to Internet auction prices, we will be comparing online auction prices to traditional, "real-world" shops. We extend their work to investigate why researchers can expect information asymmetries to cause a difference in prices between traditional and online sources. Also, although Vakrat and Seidmann concentrated on timing of bidder entry into an auction, we concentrate on timing of bidder exit from an auction.

Modeling Opportunistic Behavior Among Sellers in Internet Auctions

Our proposed model is based on a model by Shapiro (1983). He defined, in general terms, how price premia from good reputations cause sellers to avoid selling low-quality goods in markets where the buyer cannot inspect a good before buying. Shapiro's model shows that there is a price premium for acting *reputably*. Moreover, buyers will penalize opportunistic players, and no longer pay a premium for their products.

Although Shapiro concentrated only on a seller's misrepresentation of quality, we generalize his model to describe *any* opportunistic behavior. Shapiro made two simplifying assumptions. *First*, he assumed perfect competition where sellers can only sell for marginal cost. We relax that assumption to allow all sellers to profit, thereby showing the motivation for the sale for both opportunistic and non-opportunistic sellers. *Second*, sellers were easily identified and distinguishable from each other. By this assumption, he assumed that sellers would be punished for acting opportunistically by experiencing reduced demand and lower profits.

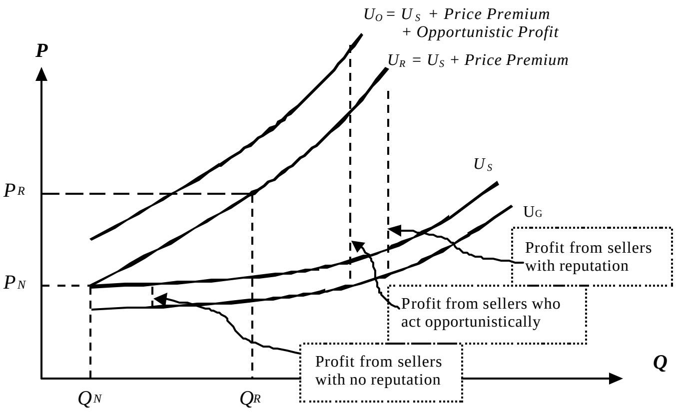
We assume that products are sold at price P_R by perceived *reputable sellers* (R), resulting in a quantity sold of Q_R. Goods sold by *non-reputable sellers* (N) are sold at price P_N with quantity Q_N. We assume that the non-reputable sellers are new sellers who are untested, and thus do not have a reputation yet. They also *may* be inclined to profit from opportunistic behavior. Rational buyers demand fewer goods from non-reputable sellers and will penalize their lack of reputation by paying less (P_N) until their reputation can be established. A reputable seller can demand a higher price for his products since buyers rely on his reputation. The economics literature shows that rational sellers will act opportunistically unless buyers not only pay more by absorbing the higher cost of production, but also reward non-reputable sellers with a *price premium* for acting non-opportunistically (Klein and Leffler 1981; Shapiro, 1983).

Figure 1, based on the model presented by Shapiro (1983), shows how the price charged by an opportunistic seller in a purely competitive environment, P_R, is the price that leads to normal profits plus the price premium that consumers are willing to pay that acts as an incentive to sellers to avoid opportunism. U_G is the *utility of not selling*. For some sellers in an Internet auction, U_G will be the cost of production.[1] For others, such as collectors on eBay, U_G will be the utility the seller receives from keeping the product, if he is unable to sell at or above his *reserve price*. Once utility of selling the item (e.g., the revenue from the sale, U_S) exceeds U_G, the seller will sell the item. Reputable sellers gain additional utility, U_R, in the form of a price premium for acting reputably. The utility that opportunistic sellers (O) receive, U_O, is from the profit from the sale as well as the opportunistic action, but if detected, the seller would forego future sales.

By changing behavior and acting opportunistically, an opportunistic seller will increase profit because the

[1] This is not an unreasonable assumption, because some crafts and collectibles are made for direct sale via the Internet in auctions such as eBay's, when seller-producers don't have the capability to sell in another channel.

Figure 1 -- Profit Based on Reputation



seller not only profits from opportunistic behavior but also receives a price premium for being perceived as a reputable seller. In the first period, buyers will not know that the opportunistic seller acted opportunistically and would still be willing to pay more for products from this seller. Equation 1 shows that the Period 1 profits for acting opportunistically is a product of the number of units sold and the difference between revenue gained by the opportunistic action and the price premium of a reputable seller.

Single-Period Profit for Opportunistic Seller:

$$\pi_1 = \int_{QN}^{QR} (U_O - U_R)\,dq \qquad \textbf{(1)}$$

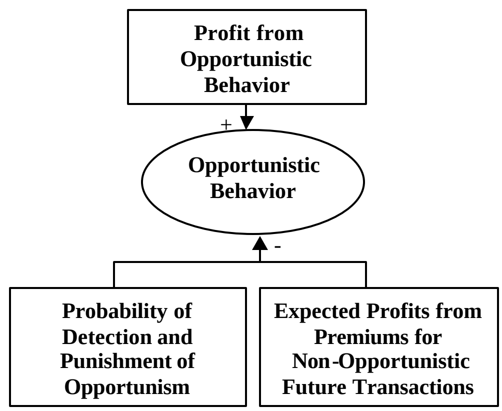
Assuming perfect detection and perfect customer-to-customer communication, in periods that follow Period 1, the opportunistic seller will achieve lower sales; consumers will now consider the seller to be opportunistic, and will avoid buying from that seller. Shapiro (1983) went further to describe situations where the opportunism would not be detected. For instance, in a new car, safety features (such as air bag equipment) can be left off, and the consumer might never find out. He introduced a variable, λ, to indicate the *probability of detection of opportunistic behavior.* For the purposes of our model, we expand Shapiro's definition by defining λ as the *probability of being detected and punished for opportunistic behavior.* Opportunistic sellers do not consider whether they will be detected, but rather they concentrate on the probability of future losses because of their current behavior. Future losses can be expressed as $1-\lambda$ adjusted by the *annuity discount rate*, *r*, multiplied by future profits for non-opportunistic behavior, as shown in Equation 2.

***Future Lost Profit for Current Opportunistic Seller*:**

$$\pi_f = \frac{1-\lambda}{r} \int_{QN}^{QR} (U_R - U_G)\,dq \qquad \textbf{(2)}$$

When $\pi_f \geq \pi_1$, the reputable seller will not act opportunistically. This is because it will not be in his best interest to do so. Only if $\pi_f < \pi_1$ will the seller act opportunistically. In Equation 2, the lower the probability of detection and punishment, the greater the likelihood of an opportunistic seller emerging in the market. Therefore, not only does there need to be a reasonable profit for *not* acting opportunistically, but there also needs to be a reasonable chance of punishment if a seller starts acting opportunistically. This is shown in the conceptual framework in Figure 2. As the chance of detection and punishment approaches zero, buyers will assume that opportunistic behavior will occur no matter what, and will force prices down across the entire market as a result (Akerloff 1970). More generally, we believe that increases in information asymmetry in a variety of buyer-seller interaction settings on the Internet (even with straightforward marketing and selling websites, for example) can make opportunistic behavior more attractive to online sellers. Their chances of being punished are slight, since anonymity is so easy to obtain on the Internet.

Figure 2 -- Incentives for Opportunistic Behavior



Analysis

Testing seller opportunism is difficult for three reasons. *First*, non-reputable sellers try to remain anonymous. Because they are attempting to hide their identity, it is difficult to identify them. *Second*, it is difficult to track multiple Internet auction identities and tie them together. *Third*, opportunistic behavior often needs to be viewed in total rather than in isolation. For instance, if a seller leaves himself a good comment or bids on his own item to run the price up, such behavior needs to be viewed in context of other behavior before the opportunistic seller can be identified.

Based on the proposed model, we expect sellers in Internet auctions to be likely to be opportunistic. From anecdotal evidence in discussions with eBay buyers, we know that sellers can easily set up multiple identities and sell through the same channel. Sellers are also anonymous. Finally, sellers can easily perform opportunistic behavior that is difficult to detect. Sellers either establish new handles or work in collusion with certain buyers to bid on their own items and also may leave themselves good reputation scores. As a result of the reduction in the chances of detection, the Internet auction seller's benefit from opportunistic behavior may be greater than the chance of loss of profit from future transactions since changing a handle can mask a seller's identity and eliminate reputation effects.

Rational buyers in Internet auctions recognize that sellers have several avenues of opportunistic behavior open to them. As a result, we hypothesize that rational bidders pay little, if any, attention to a seller reputation score reported by the auction because of possible opportunistic action by the seller to leave themselves good comments. In addition, online auctions should command lower prices than identical items sold in traditional markets where the information asymmetry is less prominent. This is because, as Akerloff (1970) suggests, the high chance of opportunism decreases the amount sellers can charge. Buyers will expect some level of opportunism because of the increase in information asymmetry and will adjust their prices downward.

Data and Hypotheses. Using the methodologies described by Kauffman, March, and Wood (1999), we developed a data-collecting Internet agent to gather data from an online auction. With the information gathered by this agent, we explored bid timing and amounts, and gauged the effects of an auction and item characteristics on what a bidder is willing to bid. The exhaustive nature of this data collection would have been impossible using traditional data-collection methodologies.

Our focus in this study is the rare coin collection market on eBay. We classified coins using an artificial intellegence algorithm that we developed for this purpose. The algorithm uses a classification scheme that consists of identifying the *coin year* (e.g., 1888, etc.), the *coin denomination* (e.g., penny, 2-cent piece, etc.), the *coin type* (e.g., Philadelphia mint, double die, feather between the "C" and the "A", etc.), and the condition, or *coin grade* (e.g., very good, extremely fine, etc.). Coin grade is communicated using a special language known to coin collectors. It allows coin collectors to communicate the grade of a coin. For example, collectors know the difference between *fine* and *very fine*, and that *fine+* and *fine/very fine* and *f15* are the same grade for a coin. Only rare coins from the 1800s were considered, to eliminate the likelihood that "flea market" buyers and sellers would be considered. Coin types and book values for these coins were obtained from *Coin World* (Gibbs 1999), the "industry bible" for coin collectors. These book values are typically what is charged by coin dealers at coin stores, like the *Blue Book* of used car prices, and represent pricing in the traditional market for coin collectors. We collected 38,714 bids from 6,798 different bidders on 14,528 items from eBay during May 1999 and February 2000. Any bid that came in later than a previous bid but was for a lesser amount was not placed in the data set.

We define *questionable bidder behavior* (**QBB**) as bidding on an item when the same or a lower bid could have been made on the exact same item in a concurrent auction ending before the bid-upon auction. We consider QBB to be irrational, since the buyer has a greater level of utility if she were to bid on another item for the same or lower cost. We feel it is reasonable to assume that eBay sellers have identical reputations, since they are typically small dealers who do not have much brand equity. Bakos (1997) showed that, for commodity items, rational buyers will buy the lowest priced item when the search price is low. There are three possible explanations for QBB. *First*, bidders are only *boundedly rational* and do not search the auction for similar items before bidding. We reject this logic for two reasons: (a) auctions that end early appear towards the top in the eBay screen display and therefore should be found first, and (b) most auctions allow easy searching for items. *Second*, bidders are *irrational* and bid on an item that is listed that gives other bidders greater time to bid against their bid. While irrational behavior may be exhibited by some bidders some of the time, we reject the idea that bidders in aggregate will bid on an item when the same or lower bid can be offered on an item whose sale is ending sooner. *Third*, bidders have a vested interest in making sure a high price is received for a particular item, either because of collusion with the seller or because the buyer handle is used by the seller as a second identity to *run up the bid*. We believe that this is the case. We found QBB in 987 bids in 713 auctions.
We next investigate three hypotheses using our data:

Low Revenue Hypothesis: Online coin auctions will generate significantly lower prices than Coin World's book value, which is used to sell coins in traditional coin shops. Akerloff (1970) and Leland (1979) showed that, when faced with an asymmetric information situation, buyers will be forced to assume that the value of what they are buying is not worth what the seller is stating. This is because the seller may act opportunistically and mislead the buyer about the condition of the good. Although Akerloff concentrated on the used car market, the same dynamics should also apply to online auctions where the buyer cannot inspect the good before the transaction. We hypothesize that goods purchased in an EC environment must sell for less than corresponding goods sold from a traditional store. Of the 10,000 coins listed, 8,011were sold to bidders and had an entry in *Coin World* (Gibbs 1999). Our findings support the hypothesis with a high level of significance. Coins transacted in online auctions sold at only 47% of the price suggested by *Coin World*. These results confirm Akerloff's (1970) and Leland's (1979) research: buyers expect to pay less for coins sold in online auctions because of the increased risk of opportunism.

Effective Comments Hypothesis: eBay's reputation score will have an insignificant impact on seller price and bids, and negative comments will have a significant, negative effect on seller price. Akerloff (1970) describes how buyers, when faced with asymmetric information, will act rationally and will assume that sellers will take advantage of the information asymmetry to act opportunistically. Based on conversations that we had with eBay bidders and our personal experiences, we learned that some sellers may offer a discount after the auction if the buyer leaves a good comment. Additionally, we found that some sellers can leave themselves good comments using another handle or work in conjunction with other sellers to leave each other good comments. Hence, we believe that rational bidders will realize the ineffectiveness of comments and ignore the eBay reputation score when making buying decisions. Conversely, since buyers can leave bad comments for sellers but sellers would have no incentive to leave themselves bad comments, we hypothesized that negative comments will have a significant, negative effect on price.

For this test, we conducted a within-subjects quasi-experiment. Since collectibles can change in value over time, we first separated bids collected in March 1999 from bids collected in February 2000. We then identified buyers who bid multiple times on the same item (same year, denomination, type, grade) from different sellers during the same time period, and calculated the average price for each bidder. We identified 774 distinct bidders/item combinations. From these, we identified 1,822 final bids from bidders for items and calculated the percentage difference between the final bid for each specific item and seller and the average for that item among all sellers. We then compared the percentage to eBay's reported reputation *overall score* and to the number of negative comments left by other bidders. Our analysis showed an extremely slight correlation (r=4%) between reputation score and price that was only modestly significant (p-value=.076). We expected a significant negative relationship between the number of negative comments and price. Instead, we found a positive (r=1.1%) but insignificant (p-value = .63) correlation between negative comments and price. When the percentage of negative comments to overall comments is considered instead of the raw negative score, we see the predictive negative effect (r=-3.0%), but not at a significant level (p-value = .20). Finally, the relationship between number of bids and the reputation is *significantly negative* (r=-0.1 with a p-value extremely close to zero).

We explain these results by noting that higher overall reputation scores and many negative comments indicate a seller who has sold much on eBay and is somewhat established. Therefore, buyers may feel safer with more established players than with the fly-by-night sellers who do not stand to gain much from a good reputation. Non-established bidders tend to set starting bids that are too low, and therefore invite a larger number of bidders. In other words, eBay's reputation score can be a proxy for seller experience rather than the actual reputation of the seller.

Run Up the Bid Hypothesis: Bidders that exhibit QBB will bid on items from fewer sellers, have a lesser probability of winning an auction than average, tend to complete bidding earlier in an auction compared to other bidders, and, bid in higher increments than average increments between bids. Detecting multiple handles in online auctions is especially difficult. Sellers who run up the bid will try to remain anonymous, and the online auction environment facilitates their anonymity. Since it is unlikely to find bidders who will divulge their opportunistic actions, instead we investigated recorded behavior that is intrinsic to running up the bid. Specifically, those who run up the bid:

(a) are agents of the seller, and therefore not necessarily buyers and will tend to limit their bids to a single seller or perhaps a few seller Ids;
(b) do not want to win the auction, but rather want the winner to pay more;
(c) want to avoid bidding near the end of the auction where the chance of winning is greater; and,
(d) bid in increments higher than average in an effort to quickly run up the bid.

Table 1. Results of Hypothesis Tests

Hypothesis	t-statistic	N (Group1/ Group 2)
Low Revenue:		
Auction Price for Coins Will Be Less Than Coin Store Price	13.2***	8,011 / 8,011
Effective Comments:		
(a) Overall Score Will Be Significant on Final Price	1.8*	1,822 / 1,822
(b) Negative Comments Will Be Negative and Significant on Final Price	0.5	1,822 / 1,822
(c) Percentage Ratio of Negative Comments to Overall Score Will Be Negative and Significant on Final Price	-1.3	1820
(d) Overall Score Will Be Significant and Positive on the Number of bids	-11.2***	14,156
Run Up the Bid: QBs who we hypothesize are in actuality running up the bid have:		
(a) Fewer Sellers	3.8***	643 / 6,155
(b) Fewer Winners	7.5***	1,260 / 26,425
(c) More Early Bidders	39.3***	1,260 / 26,425
(d) Higher Bid Increments	3.9***	588 / 18,648

Legend: * = significant at the 10% level;
*** = significant at the 1% level

We examine these by studying the behavior of those bidders who exhibited QBB. We then compare their behavior to other bidders' behavior to see if there is evidence of collusion or multiple seller handles used to run up the bid.We identified 643 bidders from the 6,798 different bidders that have shown QBB. To test the number of sellers, we derived a ratio between the number bids and the number of sellers. A non-parametric two-tailed t-test was used to test the ratios to see if there was a difference. "Questionable bidders" (**QBs**) had more bids per seller than other bidders (***m***=1.45 vs. ***m***=1.25), indicating that QBs are concentrating on specific sellers. Our analysis shows that QBs only win 26% of the time, compared to bids from other bidders who win 35% of the time. QBs also tend to drop out sooner than other bidders. They drop out an average of 5.1 days before the auction ends, compared with 1.8 days before the auction ends for other bidders. Finally, QBs tend to bid 200% above the previous bid, if there is one. Other bidders, on the other hand, only bid 65% above the previous bid. These tests show that results consistent with "running up the bid" behavior exist in online auctions, and that sellers are running up the bid to try to falsely signal more interest in an item or to get the current bidders to bid higher amounts.

Contribution

This is one of the first examinations of Internet auction seller behavior. Opportunistic seller behavior is extremely difficult to research because of the guile exhibited by opportunistic sellers. We addressed this by determining what the end result of opportunistic behavior would be, how that would be different if there were no opportunistic behavior, and then tested to see if there is evidence of the results of opportunistic behavior. With the rate of EC consumer fraud increasing at record levels, especially in online auctions, such an examination is needed. Armed with our results, online auction bidders can be better prepared for an online environment where information asymmetry gives sellers an advantage.

Buyers' reaction to the increase in opportunism was also examined in this research. Buyers will not pay as much as they do in traditional markets, and we feel buyers tend to ignore the reputation score in eBay, but base their evaluation of reputation on their own observations of which sellers are interested in long-term relationships with the eBay channel.

One possible limitation of this study is the existence of *automatic bidding* technologies. Embedded in some auction Web sites, these technologies automatically lodge bids for a bidder by the exact bid increment over the current bid. We reject that QBB is a result of automatic bidding because of the differences in the other tests. While Automatic Bidders will have earlier bids because the technology allows them to enter an auction early, they also will have *lower* not higher bid increments, as shown by our tests. Furthermore, there is no reason to assume that automatic bidders will bid on fewer sellers or generate fewer winners.

Another possible limitation of this analysis is the documented existence of *evaluators* by Bapna, Goes, and Gupta (2000a; 2000b). They showed how evaluators in multi-item auctions bid early at an amount higher than the bid increment. We reject that QBs are evaluators because of three reasons. *First*, the authors indicated that evaluators would be rare in traditional auctions like eBay. *Second*, the authors also never indicated that QBs could have bid on other items in auctions that ended earlier. *Third*, evaluators in their work usually won their auctions compared with QBs who typically lost their auctions, indicating a difference in motivation between evaluators and QBs.

Researchers will be able to build on the exploratory results that we report here. The framework presented in this paper is based on a relatively simple model that needs to be expanded to show why an equilibrium price premium for reputable sellers should exist that will deter opportunistic behavior. Additionally, researchers need to further delve into seller behavior both inside auctions and in EC in general to generate a more complete picture of seller strategies and behavior.

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