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Seller Strategies on eBay: Does Size Matter?

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Running head: Seller strategies on eBay

Abstract

We examine seller strategies in 1177 Internet auctions on eBay, to understand the diversity of strategies used, and their impacts. Dimensions of strategic choice include the use of a ‘Buy it Now’ option, the level of the starting price, and the use of a secret reserve price. A major focus of our analysis is on differences across sellers with different volumes of sales. The largest volume sellers (termed “retailers”) in our sample employ uniform selling strategies, but lower volume sellers exhibit a wide variety of strategic choices. While some components of sellers’ strategies appear important in raising seller revenue, including starting the auction with a ‘Buy it Now’ offer, the overall impact of seller strategy choices on the outcome appears to be quite small. We interpret this as evidence for the competitiveness of the online auction market for frequently traded items with conventional retail alternatives. An exception is provided by the use of a secret reserve price, which raises the winning bid conditional on a sale, but reduces the probability of a sale. Depending on sellers’ risk aversion and impatience, this may also be an efficient outcome.

Keywords: Internet auctions, posted prices, market institutions

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1. Introduction

By the end of the year 2001, eBay had become a fixture of the e-commerce sector, and it has continued to thrive where many other e-businesses failed. The business plan of eBay has constantly included actions to attract the largest number of heterogeneous sellers and buyers, who trade not just collectibles, but an increasingly wide variety of common retail products. A considerable amount of data on seller characteristics, selling strategies, and outcomes can be gleaned from these online transactions. As a consequence, auctions on eBay provide an emerging opportunity to compare selling strategies across individuals, small businesses, and larger retailers, something that has not been possible to investigate systematically prior to the advent of e-commerce. This paper focuses on the seller side of this market and provides insight into how the observable characteristics of heterogeneous sellers correlate with their selling strategies in eBay auctions, and with the outcomes of these auctions. We document the prevalence of a wide variety of seller strategies, even in the presence of a well-honed strategy used by high-volume sellers on eBay. At the same time, the competitiveness of the market is illustrated by our analysis.

Online sales in the United States accounted for 2.8 percent of retail transactions in 2006, or \$108.7 billion out of over \$3.9 trillion in total US retail sales,¹ And continue to grow rapidly. These numbers, while still relatively small, represent substantial growth. While auctions have not been used for traditional, brick-and-mortar retail transactions, they may be better suited for online buying and selling, because of the automation of the

¹ These estimates are from the US Census Bureau (2007): “A stratified simple random sampling method is used to select approximately 11,000 retail firms whose sales are then weighted and benchmarked to represent the complete universe of over two million retail firms... Coverage includes all retailers whether or not they are engaged in e-commerce. Online travel services, financial brokers and dealers, and ticket

auction process and the consequent reduction in some kinds of transaction costs. In 2003, eBay's net sales, from transaction fees on \$15 billion in gross revenues, reached \$1.2 billion (Hof, 2003). This growth mainly involved displacing individual transactions conducted through traditional and less structured bargaining methods, but also some conventional retailing, as new and existing businesses also began to use eBay as a sales channel. Thus, online auctions have expanded beyond web-based garage sales or swap meets, focusing on collectibles or unique items, to including entrepreneurs seeking to launch or enhance 'e-tail' businesses in direct competition with traditional retail markets. Established retailers, such as Sears Roebuck, and other firms that have moved into retailing, such as Walt Disney, have responded to this threat by selling on eBay as well, capitalizing on their existing brand names (Hof, 2003).

In order to achieve the objective of widespread use of its online marketplace, eBay has provided easily accessible tools for new and inexperienced sellers to get started, and to establish and maintain seller ratings, based upon buyer feedback. Although these tools could conceivably allow less frequent sellers to represent themselves better, and even mimic larger volume retailers, we find that heterogeneous seller characteristics do result in different seller choices, even while selling basically the same item as a retailer. At the same time, the openness of the online marketplace tends to even out the consequences of these heterogeneous seller choices.

The variety of options available on eBay gives sellers considerable latitude in how they set the initial conditions for any auction and seller choices in our sample exhibited a wide range of strategic combinations. Examples of such choices include the length of the

sales agencies are not classified as retail and are not included in either the total retail or retail e-commerce sales estimates. Nonemployers are represented in the estimates through benchmarking.”

auction, information provided about the product, payment options, the starting price, and whether to use a private reserve price. EBay auctions also allow the seller to include the option for buyers to purchase immediately at a pre-specified ‘Buy it Now’ price. This option therefore allows sellers to offer a hybrid of an auction format and a posted price format, as well as pure versions of each market institution.

The side-by-side competition among sellers with widely differing degrees of experience in our sample, and the availability of data on selling strategies, transaction outcomes, and some seller characteristics on eBay, permits a new kind of analysis of selling strategies, particularly the possible impact of experience.² The use of the auction format also permits us to compare our data with some predictions of the economic theory of auctions, especially what aspects of those theoretical predictions still hold in online auctions with multiple sellers.

In this paper we seek to understand how sellers’ characteristics, such as reputation and frequency of selling, affect their choices about the initial conditions of the auction that are under their control. In order to examine these questions, we chose a relatively homogeneous, ‘mature’ product at the time of our data gathering (August-September, 2001): the Palm Pilot Vx.

A key result of our analysis is that price dispersion is quite low, relative to the degree of heterogeneity in seller strategies. We interpret this as evidence for the competitiveness of the eBay market place for such products, even in a relatively early period (2001) of the online auction institution. Thus, even though high-volume sellers with successful strategies do not function as ‘leaders’ in the eBay marketplace, the lack

of this knowledge spillover is outweighed by the robustness of competition in online auctions.

Part of the explanation for differences in strategy choices between retailers and lower volume sellers (and among lower volume sellers themselves) comes from observed differences in characteristics among sellers. We also find evidence for learning and experimentation among different sellers, indicating that sellers are able to adjust their strategy combinations in a short period of time.

The rest of the paper is structured as follows. Section 2 reviews some of the most relevant literature on Internet auctions, other types of Internet markets, and eBay auctions with the ‘Buy it Now’ option in particular. Section 3 summarizes the data, obtained from 1177 eBay auctions for the Palm Pilot Vx, over a period of five weeks. We document the range of different strategic approaches, and summarize market patterns. Section 4 examines the relationships between observable characteristics of products and sellers, and the relationship between sellers’ characteristics and their choices with respect to the format of the auction. In particular, we show that there is no monotonic relationship between frequency of selling and various seller strategic choices.

Section 5 considers auctions that did not result in a sale, and discusses differences from successful auctions. Having a high starting price (over \$100) and/or a secret reserve price appear to be the two main reasons for failure to sell, though this ‘failure’ would typically just represent a delay in selling, since an initial failure to sell allows the seller to re-list the item without charge. Section 6 concludes with a summary of our analysis, a discussion of implications, and suggestions for future research.

² The focus on experience makes our analysis distinct from studies such as Zhuang et al. (2006), which examines established retailers’ strategies in the context of Porter’s overarching classification of generic

2. Research on Internet Auctions

This paper attempts to understand the diversity of seller strategies for eBay auctions, and the effect of strategies on outcomes. Thus, the general theoretical literature on optimal auction design is relevant; it addresses connections between auction structure, efficiency, and value maximization. For instance, Riley and Samuelson (1981) evaluate the appropriate choice of minimum bid or reserve price for maximization of a single seller's revenue, given an environment of private bidder values. The optimal minimum bid maximizes revenue but introduces the possibility of failure to sell the item. Auction design in an environment with many sellers is explored by Peters and Severinov (2006). The authors identify equilibrium seller behavior regarding auction structure and reserve prices. They verify the result of McAfee and Vincent (1993) that sellers set a reserve price equal to cost in equilibrium. Their primary focus, however, is on bidder response to such design and the resulting efficiency properties. Their environment incorporates neither heterogeneity in seller and product characteristics nor the potential to offer a posted price. In general, much of this theoretical literature does not fully capture the institutional features of Internet auctions.

A key, novel feature of Internet auctions, represented in our data, is the 'Buy it Now' option. This gives bidders the option of bypassing the auction and purchasing immediately at a price set by the seller. Reynolds and Wooders (2004) construct a theoretical model of auctions with 'Buy it Now' offers. The model assumes all bidders have some risk aversion and the main results are that (1) a seller increases his revenue through making a 'Buy it Now' offer, whether it is accepted or not, and (2) bidders

strategies (low cost vs. differentiation). This is discussed further in Section 2.

should have “no regret” in turning down such an offer, as long as it is not below their reservation value for the item and is not being used to effectively post a price by setting a minimum price equal to the ‘Buy it Now’ offer price. Hidvegi et al. (2006) develop a model of auctions where a ‘Buy it Now’ option can raise seller profit by exploiting the risk aversion of buyers. An alternative motive for use of ‘Buy it Now’ pricing put forth by Qiu et al. (2006) suggests that sellers might use such prices as a signal to impact bidder valuation of items.

The range of strategic choices available for sellers in e-commerce has attracted substantial interest in research into the relationship between seller choices and different e-tail environments. Zhuang et al. (2006) examine survey data from Business-to-Consumer sites to investigate this question. They find evidence that sellers’ e-commerce strategies vary with seller characteristics but each of the strategies they identify allow sellers to enhance profits. Unlike our paper, which examines the details of sellers’ strategy choices, Zhuang et al. focus on the larger consequences of overall strategic stances (i.e., low cost vs. differentiation) in the tradition of Michael Porter.

More specifically, empirical studies of the conduct of online auctions address a wide range of issues. Pioneering work by David Lucking-Reiley (1999) focuses on testing classical results from auction theory, such as revenue equivalence using field experiments. In another field experiment, Katkar and Lucking-Reiley (2000), comparing public and private (also called ‘secret’) reserve prices, show that the use of a secret

reserve (where the seller's reserve price is not revealed to bidders) reduces both the probability of a sale and the transaction price.³

Reputation is an important aspect of e-commerce, due to the need for trust between buyers and sellers in a virtual environment. While an imperfect measure of seller trustworthiness (Malaga, 2001) and subject to manipulation by sellers (Brown and Morgan, 2006), reputation mechanisms such as that of eBay represent the primary source of information regarding sellers for potential bidders. Resnick et al. (2003) find that the effects of seller reputation, often unclear in field data, are as predicted, with a positive impact on seller revenues when proper experimental controls are imposed. However, Livingston (2005) provides evidence of rapidly diminishing returns to higher reputation scores on eBay. Zhang and Li (2006) consider connections between reputation measures and seller choices regarding payment acceptance. They find a positive relation between seller reputation and wider acceptance of payment options.

Our work belongs to the approach that collects and analyzes transactions data from Internet sites, rather than conducting field experiments.⁴ Using this method, for example, Morgan and Baye (2001) analyze persistent price dispersion in posted price markets on the Internet. Also, Houser and Wooders (2006) examine the effect of bidder and seller reputation on auction outcomes, concluding that seller reputations are correlated with auction success in *Pentium III* microprocessor auctions on eBay. Roth and Ockenfels (2002) study the timing of bids, and the impact of different methods of

³ One caveat to these results is that the authors found some informal evidence that sellers were using the secret reserve to circumvent eBay's fee structure by contacting high bidders on the side in unsuccessful auctions.

⁴ While field experiments allow for greater control, they are limited, for cost reasons, in the kinds of goods they can use. A third empirical approach has been to use laboratory experiments, e.g., Ariely, Ockenfels and Roth (2003)

specifying auction deadlines.⁵ Lucking-Reiley et al. (2000) use data collected from eBay auctions of one-cent coins to study determinants of price. They find evidence that seller feedback ratings have a significant impact on prices, that minimum bids and secret reserve prices raise the auction price, and that the length of an auction has a significant and positive effect on price in these auctions.

Anderson et al. (2007) examine a sub-sample of the eBay auctions considered in this paper, and use regression analysis to analyze auction outcomes. For example they find that less experienced sellers received lower prices, on average, unless they effectively posted a price, but seller reputation, as measured by eBay's feedback ratings, did not significantly affect the final price. Milam (2002) also examines the issue of posted prices versus auctions, contrasting the working of eBay and Yahoo auctions in this respect. A major difference is that Yahoo allowed a 'Buy it Now' price to be available even after bidding starts (eBay switched to this format subsequent to our data collection period), and this flexibility led to the 'Buy it Now' option being used by a greater proportion of Yahoo sellers, with more auctions also ending with a buyer accepting the 'Buy it Now' price.

3. Data Overview

Seller behavior on an online auction site is best examined with a reasonably large sample of auctions involving a homogeneous good, and over a short period of time. Therefore we chose to gather data for a homogeneous item with a high sales volume during our sample period (August-September 2001): the Palm Vx handheld computer.

⁵ See also Bajari and Hortaçsu (2003) and Ockenfels and Roth (2006) on this and related issues.

The data was taken from eBay, the largest Internet auction site, using a web-crawling ‘spider’ program, similar to that described in Lucking-Reiley *et al* (2000).

EBay Auction Rules

Before presenting the data, we review eBay’s basic rules during our sample period. The seller provides information on the item, such as a description and picture, terms of payment and shipping, and chooses the duration of the auction, either 3, 5, 7, or 10 days. The seller also chooses a minimum first bid, or starting price, and whether to enter a secret reserve price. Potential buyers know when a secret reserve price exists but do not know its value until someone bids above it. Sellers may also provide links to their own “home pages” on the web, which can be a source of further information for buyers.

Potential buyers can bid on any item they find on eBay’s web site and current, but abbreviated, bid histories are available to them. That is, a potential buyer can observe the history of bid increments since the beginning of the auction but they cannot observe how high the current, winning bidder is willing to bid (maximum bid) or other, exact bid amounts in the bid history. The auction ends at the pre-specified time (i.e., a “hard” close to the auction – see Ariely, Ockenfels and Roth, 2003), and the item goes to the highest bidder for the minimum bid increment above the second highest bidder. This represents a fairly standard second-price auction. Details of shipping and payment are left up to the buyer and seller, although eBay provides services for these aspects of the transaction, for an additional fee. Finally, eBay also provides a record of comments about buyers and sellers, so that sellers have the potential to develop and maintain reputations. Potential buyers have access to these comments, as well as all seller-provided information.

The seller also can specify a ‘Buy it Now’ price, whereby s/he commits to sell the item immediately to any buyer who accepts that specified price, thus ending the auction early. The ‘Buy it Now’ option is extinguished (and disappears from the item’s auction site) when any buyer enters a bid that is at least as great as the minimum first bid, even if the first bid is lower than the ‘Buy it Now’ price.⁶ The seller can prevent this from happening by specifying a starting price (or a secret reserve price) at or above the ‘Buy it Now’ price. Such price combinations are equivalent to the seller having a posted price (by far the dominant method of pricing in developed countries prior to the use of Internet auctions), since bidding is rendered irrelevant. A scan of buyer comments on eBay suggested that they found the practice of using a high secret reserve price annoying and might avoid such auctions. Using a high starting price is just as effective and more transparent. Used by itself, the ‘Buy it Now’ option creates a hybrid institution, a mix of an auction and a posted price.

The Data

We collected complete data on 1177 Palm Vx auctions on eBay from August 6 to September 11, 2001.⁷ The Palm Vx was available at that time, new, in many different types of conventional, “bricks-and-mortar”, retail outlets and was also available, used, in

⁶ As noted in the last section, this feature has now changed, to allow the ‘Buy it Now’ offer to persist.

⁷ Data gathering was interrupted by the events of ‘9-11;’ however, we believe we have sufficient data to make our main point of robust competition. Subsequent revisiting of eBay’s auction sites, to buy and sell many different items, and ‘checking-in’ on the evolution of eBay’s institutions, including ‘Buy it Now’, has led us to remain confident in still being able to use this dataset in order to understand eBay seller behavior. Options regarding the “Buy it Now” feature have expanded to allow sellers to offer items under the “Buy it Now” price exclusively, equivalent to the posted price practice we observed using a first bid equal to buy price. Other changes since our sample period have chiefly been improvements in access technology that have increased the frequency with which bidders can bid, and the turnover and numbers of infrequent sellers. Even in 2006, the consistency of strategies amongst retailers using eBay to sell an increasing variety of goods and the heterogeneity of strategies of less-frequent sellers appear to remain as we have

traditional resale outlets, such as pawn shops, during our sample period. Of all the auctions in our sample, 1008 resulted in a sale, while 169 were unsuccessful. Section 4 focuses more (though not exclusively) on these 1008 successful auctions. Section 5 provides an analysis of the differences between auctions that resulted in a sale and those that did not, and examines all of the 1177 auctions.

A list of all the variables used in the analysis is provided in Table A of the Appendix. The observable product characteristics are coded as 0-1 variables, with our categorization of the characteristic being present relying on a definitive indication in the accompanying product description. Most important to our analysis is the frequency with which the seller's auctions appear and the feedback rating of the seller. We categorize the number of auctions conducted by an individual during the sample period as follows: SINGLSLR codes 1 auction, MULTSLR codes 2-10 auctions, FREQSLR codes 11-50, and RETAILER codes over 50. Seller ratings, measuring reputation, are derived from a simple accounting of the string of unique positive and negative comments, accrued by the eBay member through his/her past behavior as either a buyer or as a seller. We use two alternative measures: NEGRATIO is the ratio of negative to total comments and LNSLRTNG is the natural log of the difference between the number of positive and negative comments. Thus lower NEGRATIO and higher LNSLRTNG indicate two aspects of better seller reputation.

The two rating variables are not highly negatively correlated (Table 3), suggesting they capture different aspects of reputation. Even if old, possibly irrelevant, negative comments on a seller do matter to a potential buyer, one should expect them to eventually

identified them in this paper. This is not surprising, given that we argue that the robustness of competition with online auction institutions allows them to support heterogeneous seller strategies.

be swamped by mostly positive feedback if the seller continues to be able to sell on eBay. That is, for an experienced eBay seller/buyer mistakes of the past are not likely to be reflected in the rating, nor easily discovered by the potential buyer, although the negative feedback remains on the seller's permanent record. Due to this limited variation in number of negative comments amongst sellers and small number of negative comments, NEGRATIO may be a superior reputation measure.

The focus in this paper is on seller characteristics and strategies. In general, the observed characteristics of the good were not strongly correlated with seller characteristics, choices, or auction outcomes. The correlations are all reported in Table B of the Appendix. Some correlations are noteworthy. For example, 'frequent' sellers were more likely to put a new item up for sale. Other correlations, such as the relatively strong positive correlation between DAMAGE and NEGRATIO when 'Buy it Now' was accepted, are unsurprising.

Table 1 presents the mean values of the variables for the 1008 successful auctions, where these means represent proportions for the 0-1 variables. The first column reports on the full sample of completed transactions, the second and third report the subsamples for which the seller did not or did use the 'Buy it Now' option, and the last two divide the previous subsample according to whether the 'Buy it Now' option was exercised. For example, row one of the table indicates that the 'Buy it Now' option is less likely to be offered, but more likely to be accepted, on new items, which constitute 28.3% of the entire sample.⁸ The QUANTITY variable refers to the number of units offered in a

⁸ The proportion of new items could be understated, since items that were not factory "sealed" in the original box may not have been explicitly described as "new." In particular, the two retailers in the sample did not sell "new" items according to this classification. The 'spider' program used had to focus on certain key words and qualifiers in the title and text describing the item. Since the sellers are likely to shade the

particular auction; the modal value is always one, since single item sales are by far the most common⁹ DAYS806 is the time trend; auctions starting later would tend to yield lower prices due to economic obsolescence. We also use the DAYS806 variable to track experimentation by sellers who sold multiple times during our sample period.

[Table 1 about here]

Turning to seller characteristics, it is noteworthy that the two retailers in our sample accounted for more than half of the ‘Buy it Now’ offers but only 1% of ‘Buy it Now’ transactions. Seller ratings are better on average in the ‘Buy it Now’ subsamples. Seller choices are summarized in the next section of the table: starting prices, the use of a secret reserve, whether or not to make a ‘Buy it Now offer, and whether or not to use that ‘Buy it Now’ offer to effectively post a price are the ones that matter most in the following analysis. Starting prices average about \$60, but diverge for accepted and not accepted ‘Buy it Now,’ reflecting the fact that this option was accepted almost exclusively when it was a posted price (POSTDPRC = 1). Secret reserve prices were used in 18.3% of all auctions, and more frequently when a ‘Buy it Now’ price was accepted. 47.1% of auctions in our sample offer the ‘Buy it Now’ option; of these 19.2% actually are posted price.¹⁰

truth as much in their favor as possible, our specifications for the script search had to be very strict. Similar issues arose with the presence of “extras.”

⁹ Only two sellers (not retailers per our classification) sold significantly large quantities per auction. In looking at seller choices, their strategies were basically the same, though quite different from the retailers. They did not use a secret reserve price but they did set their starting prices very high. Such auctions are termed “Dutch Auctions” on eBay and usually result in the seller receiving a lower price in order to move a larger quantity of items more quickly. We define “retailers” to exclude such sellers, whose choices might consistently be affected by extraordinary time constraints.

¹⁰ The low number of sellers posting a price in our sample may indicate that sellers interested in posting a price preferred to use alternative posted price sites, such as Half.com, rather than working within the eBay framework, where most buyers expect to find auctions. We also noted by inspection that eBay allowed sellers to post links to their storefronts at Half.com in order to sell the same item at a posted price.

The last part of the table contains data on the auction outcomes, including average duration, the number of bids, number of unique bidders, and the winning bid. Part of the attraction of offering the ‘Buy it Now’ option, for sellers who wish to increase the pace of sales, is apparent from the decrease in average duration from 5 days, for auctions without the ‘Buy it Now’ option to about 2 days, when ‘Buy it Now’ was accepted.

Market Patterns

To understand the market conditions underlying the means in Table 1, we also examined statistics on the actual number of sellers and key seller choices on a typical day, including sellers who were unsuccessful that day. On average, about 29 unique sellers were selling the item on any given day and they held about 34 auctions in attempting to sell about 58 individual items per day. About 29 of the 34 auctions per day resulted in a sale, and about 3 of these ended with acceptance of a posted price offer, on average. Each day during our sample period, at least 1 auction received no bids, and a maximum number of 5 auctions received no bids on some days. Including unsuccessful auctions (omitted in Table 1), there was an average of about 9 unique bidders per auction and they averaged about 16 bids per auction (including no bids on some auctions). These statistics describe a very competitive market for the sellers during our sample period.

The data includes a large number of apparently inexperienced sellers with heterogeneous characteristics, as one would expect. These sellers tried a wide range of strategies. They did not follow the strategies of retailers, even when they had similar high seller ratings. Interestingly, out of 441 unique sellers, only 63 decided to post a price, but they were all successful at selling at that price. Posted prices were very close to the prevailing “market” price for the item. Since the ‘Buy it Now’ price remained visible for

the entire duration of the auction only if it was somehow protected on eBay, and posting a price in this way appears to have been less annoying to buyers than holding a secret reserve price, this seems to have been an attractive strategic option. Since very few sellers felt confident enough to post a price on eBay, it may not be straightforward for new sellers to identify and copy successful auction strategies, in particular those of experienced, high-volume retailers.

The data suggest that buyers and sellers in the auctions are generally well aware of outside alternatives, including other auctions for the same product: this is a relatively “thick” market with good information.¹¹ For example, the 62 sellers who posted prices chose very similar price levels. Interestingly, 69 sellers in this sample made ‘Buy it Now’ offers that were about \$25 higher than the “equilibrium” price. It is possible that this strategy was intended to catch any highly risk-averse or impatient buyer, who would be willing to pay such a premium. In practice, this never happened in the sample period. Also surprising was the fact that the majority of sellers did not make a ‘Buy it Now’ offer, even though it was costless to do so.¹² A possible explanation may be lack of experience. From Table 1, sellers who offered the ‘Buy it Now’ option earned about an extra \$6 per transaction, on average, but differences in characteristics of the good or auction (e.g. multiple units) seem to explain the difference.

Additional insight into the data comes from identifying individual sellers through the unique email addresses they provided to eBay. Sellers could have used different email aliases, but our sample period was short enough that this should have been rare. We then

¹¹ Borle et al. (2006) document the prevalence of multiple bidding across auctions that are running simultaneously. This practice is certainly present in our sample, and contributes to the competitiveness of the market.

¹² There is no evidence that offering a ‘Buy it Now’ price annoys buyers, as can happen with secret reserve prices. EBay has since instituted a nominal charge of \$0.05 – 0.25 for use of ‘Buy It Now.’

tracked the timing of the day they started each of their auctions as well as changes in strategies of the more frequent sellers. These changes can be interpreted as experimentation by sellers.

During our entire sample period, 441 unique sellers sold the item at least 1 time, and 86 individuals attempted (unsuccessfully) to sell the item.

- Of the 441 sellers, 132 sold after making a ‘Buy it Now’ offer and 63 of these sellers used this offer in tandem with an equivalent starting price to effectively post a price.
- Of the 132 ‘Buy it Now’ sellers, 11 sold with both posted price offers and with “regular” ‘Buy it Now’ offers; of these, 6 made their first sale with a posted price and then followed that with their first regular ‘Buy it Now’ sale. The other 5 sold with a regular ‘Buy it Now’ offer before successfully using a posted price offer. Nine ‘Buy it Now’ sellers also successfully tried non-‘Buy it Now’ auctions, with 5 selling first with a non-‘Buy it Now’ auction and 4 selling following the opposite sequence.
- 18 of the 132 ‘Buy it Now’ sellers also had auctions that resulted in “no sale”. Of these, 10 failed to sell for the first time before being successful with a ‘Buy it Now’ auction, and the other 8 had already successfully made a sale in an auction with a ‘Buy it Now’ offer before their first unsuccessful auction (during our sample period).

To provide an example of experimentation during our sample period, our lower volume retailer (100 auctions during the period) successfully experimented on the 17th day of the period with a posted price of \$209 and ended up raising the ‘Buy it Now’ offers on her subsequent auctions to \$209 (after all of her previous auctions in our sample

had been started with a ‘Buy it Now’ offer of \$199). Although no ‘Buy it Now’ offer by this seller, outside of the lone posted price offer, was accepted either before or after this experiment, the seller did not again post a price during our snapshot. For the two retailers, the final sales prices appear to have been high enough, on average, to repeatedly adopt the same strategy, which included making a high, unprotected ‘Buy it Now’ offer, in order to sell multiple items every day.

4. Seller Characteristics and Choices in Successful Auctions

Table 1 indicated that seller ratings were better on average for the sellers that made ‘Buy it Now’ offers, and final sale prices were higher in such cases, even when the ‘Buy it Now’ option was not used. Reputation has been one of the important seller characteristics to be analyzed in research on Internet auctions. The issue is how to judge the quality of the seller in the absence of familiar visual signals (storefront, location, and so on). As noted in hedonic studies of seller rating, surveyed by Bajari and Hortascu (2004), feedback may underrepresent buyer satisfaction due to reluctance to leave negative comments for fear of retaliation. Our alternative measures of reputation are designed to overcome this shortcoming, which may affect eBay’s own rating measure.

Correlations between seller characteristics, seller choices, and outcomes are reported in Table 2. One might expect selling frequency and rating to be positively correlated. An exception to this in our sample is the existence of sellers who repeatedly sell very “well used” or damaged goods on eBay, and have a large number of negative comments. This fact surfaces in the positive correlations between the ratio of negative comments and being a ‘multiple’ seller (with 2-10 auctions in our sample) for both ‘Buy

it Now' sub-samples. This higher proportion of negative feedback may be a function of product heterogeneity associated with used goods.

[Table 2 about here]

In the relationship between seller reputations and seller choices regarding auction conduct, causality is difficult to establish. However, the observed correlations of the starting bid variables and use of secret reserve are consistent with the conjecture that greater flexibility in accepting bids compensates for deficient seller characteristics, and may be preferred by potential bidders. This is reflected in the positive correlations of NEGRATIO with starting price, use of a secret reserve and auction duration. These correlations are strongest for the auctions that started with a 'Buy it Now' offer. The ratio of negative comments is not strongly correlated with most of the other seller choices.

Sellers who started their auctions with 'Buy it Now' and have a higher ratio of negative feedback, tend to set lower 'Buy it Now' prices (Table 2). This likely reflects the negative impact of negative comments on price in general, as seen in the negative correlations with WINBID. In fact, auction outcomes, duration, number of bids, number of bidders, and the final price are all negatively correlated (in this subsample) with negative feedback on these sellers.¹³

Selling Frequencies and Strategies

We next examine how the choice of starting an auction with a 'Buy it Now' offer, other seller choices regarding conduct of the auctions, and outcomes vary across selling

frequency groups. Figures 1-6 chart mean values of auction characteristics in our sample, according to the different selling frequencies, in order to better identify patterns in auction strategy across seller types. Figure 1 demonstrates how, on average, a seller's net rating (LNSLRTNG) increases with increased frequency of selling. Thus, more frequent selling of Palm Pilot Vx's during our sample may be indicative of more experience with eBay overall. In interpreting the selling strategies of less frequent sellers we might envision them as more in a process of experimentation, although we were best able to track experimentation for only the more frequent sellers during our snapshot.

[Figure 1 about here]

However, results for the alternative rating measure are somewhat different. Figure 2 illustrates the differences in NEGRATIO across seller categories. Note that for the sellers in our retailer category this proportion is very small. The remaining types show an increasing proportion of negatives with selling frequency during the sample period.

[Figure 2 about here]

Figure 3 presents average seller choices involving whether to protect price, either through a posted price or a secret reserve price, and whether to start the auction with a 'Buy it Now' offer. Starting the auction with 'Buy it Now' may signal impatience, or that the seller has some idea of what the equilibrium price should be. Alternatively, it can be a strategy to capture impatient buyers. It might, therefore be more prevalent amongst more frequent sellers. However, the mean proportion of auctions that start with 'Buy it Now'

¹³ One detail about our sample period that should be noted here is that seller ratings were updated once during our sample period, at the beginning of September, and no seller's rating appeared to decrease at that

varies little, and unsystematically for all the groups excluding retailers. The averages in Table 1 suggested that making a ‘Buy it Now’ offer might leave a positive impression on bidders, even after it was erased by the first bid. However, sellers other than the retailers were inclined to forgo any potential signaling effects of a ‘Buy it Now’ offer, in favor of more direct strategies to attempt to boost the sales price of the item, such as posting a price, requiring bidders to match a secret reserve or starting the auction at a higher initial price.

[Figure 3 about here]

Protecting a price with either a secret reserve price or by posting a price is not a favored strategy by either retailer, but the proportion of these choices is also not monotonically decreasing with increased selling frequency for our less-frequent sellers. Therefore, these choices do not appear to be predictably tied to the volume of sales by sellers. Of course, these choices are often combined in different ways by the different sellers. Single sellers were the most likely to protect their price with a secret reserve price. Posting of fixed prices using a ‘Buy it Now’ price in conjunction with an equal starting price or secret reserve was most popular with the ‘multiple’ and ‘frequent’ categories of sellers.

The last method of protecting a price is to simply set a higher starting price, with a tradeoff between attracting fewer bidders and bids vs. forcing bids to higher levels earlier in the bidding process. Average starting prices and corresponding sales prices are depicted in Figure 4. On average, by group, single sellers started with slightly lower

time.

prices than multiple sellers but frequent sellers favored even lower starting prices, but no group was anywhere near the starting price of \$0.01 used by the retailers.

[Figure 4 about here]

One can see from Figure 4 that retailers did sell their products for higher average prices, although they started the auctions without posting a price, no secret reserve, and the lowest possible starting price. The frequent sellers in our sample held as many as 20-33 auctions during our sample, yet still did not consistently adopt the same strategies as our retailers or do as well in the end, on average. Multiple sellers held as many as 10 auctions during our sample period yet their final sales prices were the worst of all, on average. There is a big jump in the number of auctions held by retailers versus other categories, and inventories, as well as other unobserved characteristics, are likely to differ substantially between retailers and all of the other seller categories. Still, it is noteworthy that even multiple sellers appeared to still be experimenting with their sales strategies during the sample period.

The consequences of seller choices on the conduct of their auctions are shown in Figure 5. Briefly, single sellers attracted the lowest number of bids and unique bidders even though their auctions lasted the longest period of time. We must therefore look to seller characteristics, rather than seller choices, to explain how this group of sellers managed to do better on average than ‘multiple’ sellers (Figure 4).

[Figure 5 about here]

Multiple sellers appear to have attracted only slightly more bids and bidders than single sellers, while frequent sellers were substantially better, as a group, at encouraging

more excitement surrounding their auctions. Retailers did not attract that many more unique bidders than frequent sellers but the bidding appears to have been allowed to carry on for a bit longer, which may help explain the slightly higher sales prices that the two retailers received, on average, relative to frequent sellers.

We also checked for how the mean quality of the product varied across these groups of sellers. It is apparent from the Figure 6 that selling more frequently meant dealing less and less with damaged merchandise. It also meant offering fewer extras as part of the product package. It should be noted that sales of new items on eBay appear more prevalent with greater selling frequency of the seller. Note that the two retailers were selling new but repackaged items, probably returned items from some other retail outlets. However, these items were not classified as “new” using our criteria.

[Figure 6 about here]

To test statistical significance across different levels of sellers, we first conducted t-tests of differences in means across seller frequencies for several conduct and outcome variables. These results are presented in Table 3, and confirm that the differences in strategies and reputations across pairs of seller frequencies identified visually above were typically statistically significant.

[Table 3 about here]

A further test of differences across seller frequencies was performed with one-way analysis of variance (ANOVA). The null hypothesis in this case is that there is jointly no significant difference across categories. We tested this with and without retailers in the set of seller categories. The results are presented in Table 4, where F-

statistics and significance levels are given. It is clear that, with the exception of the decision to use the ‘Buy it Now’ option for the case where retailers are excluded, the null of no difference in mean choices across seller categories is rejected in every case.

[Table 4 about here]

Further insight into the differences across seller frequencies is obtained through two-way ANOVA.¹⁴ Table 5 presents results for an analysis of factors affecting the choice of whether a secret reserve is used or not. For this analysis, seller ratings are simplified to a binary variable (above average or not). While the use of a low starting price has no significant impact, seller ratings do matter for the use of a secret reserve price. In particular, for the sample excluding retailers, the difference across frequency categories is no longer significant, except as an interaction effect with the rating variable. In other words, the impact of rating on the choice of a secret reserve price differs across selling frequencies.

[Table 5 about here]

The results in Table 5 are complemented by a two-way ANOVA of factors affecting the choice of a starting price, now considered as the actual starting price, rather than a high-low variable. These results are presented in Table 6. In this case, differences across seller groups are always significant, while the seller rating has a significant impact only through its interaction with the frequency of selling. An important feature of Table 6 is in the comparison of all auctions with successful auctions. In particular, the impact of the choice of a secret reserve price on the choice of the starting price is no longer

significant when only successful auctions are considered. This is related to a point we develop in the next section, that a key driver of differences in the sample auctions was the use of a secret reserve price.

[Table 6 about here]

5. Sale Probabilities, Seller Characteristics and Strategies

In this section, we analyze the impact of the use of a secret reserve price on the probability of successful completion of an auction. Table 7 illustrates systematic differences between auctions that resulted in a sale and those that did not. In particular, potential sellers who used a secret reserve price were much more likely to fail to sell the item. Furthermore, a higher proportion of the auctions that did end in a sale started with the ‘Buy it Now’ option. Sellers in our sample rarely chose to use ‘Buy it Now’ to effectively post a price, but all posted prices resulted in a sale.

[Table 7 about here]

As reported in section 3, we were able to track individual sellers, and insights into selling strategies and success can be gained from that information. There were 124 unique potential sellers who failed to sell in at least one auction during the sample period. Of these, 70 required the bidders to meet a secret reserve price to win the auction. 51 of the unsuccessful sellers made ‘Buy it Now’ offers, and these offers averaged about \$240. For auctions that ended in a sale, the average seller rating was higher for unsuccessful sellers that offered ‘Buy it Now’ compared to those that did not. 39 of these 124 potential sellers who failed to sell in at least one auction were successful in selling at least one item

¹⁴ We are indebted to a referee for suggesting this analysis.

in a different auction. Many components of these sellers' strategies were altered between successful and unsuccessful auctions for these sellers, but one that went largely unchanged was the choice of whether or not to set a secret reserve price. 16 sellers failed to sell with a secret reserve price, and at least one switched to holding no secret reserve price after failing to sell. At least one other switched to holding a secret reserve price after successfully selling without one and subsequently failed to sell the second item during our sample period. Observation of the eventual sales prices for these 16 sellers indicates that they typically lowered their secret reserve price in order to sell the item.

The most common strategic error of the other 23 (i.e., 39 – 16) eventual sellers in their unsuccessful auctions was to set a starting price that was too high, receiving no bids as a result. Unlike secret reserve auctions, we could directly observe that most of these sellers lowered their starting prices, and that this usually led to final bids lower than their previous starting prices. To manage this possibility, 13 of these unsuccessful 23 sellers proceeded to make posted price offers, which were accepted. In some cases, potential sellers received no bids even with a low starting price, because there were so many sellers of the item. In one extreme example, a seller failed to sell in an auction that started on the 9th day of our sample period, with a starting price of \$1, no secret reserve, and a 'Buy it Now' offer of \$149. This seller was successful with this same strategy in 5 other auctions that started on the same day, and the average sales price in those auctions was about \$175. After gaining this experience, this same seller relisted the unsold item on the 14th day of our sample period for a posted price of \$200, and it sold for that amount.

To summarize, the main reasons for failure to sell were having a secret reserve price, a high starting price, or both. About 85 sellers never did succeed during our snapshot, and 9 of these 85 failed to sell in multiple auctions. Of these 9, 5 failed to sell

twice, and 4 failed to sell thrice each. All of these 9 consistently required potential bidders to meet a secret reserve price. Our sample period was too short to observe if more of these potential sellers would eventually succeed in selling the item.

[Table 8 about here]

Table 8 elucidates the impact of choosing a secret reserve price. The proportion (likelihood) of auctions without a secret reserve price that resulted in “no sale” was only $74/898 = 0.082$. By comparison, the proportion of secret reserve auctions that resulted in “no sale” was $95/279 = 0.341$. However, this does not imply that using the secret reserve was futile. Successful secret reserve auctions in this sample resulted in higher prices, *ceteris paribus*, consistent with the findings of Katkar and Lucking-Reiley (2000). Within our sample of successful auctions (1008 observations), the mean sales price for all sellers who held a secret reserve price was \$207.20 while that for the sellers who did not hold a secret reserve was only \$199.22. A t-test comparing these two average sales prices indicated that the difference between them was significant at the 1% level. Also, sellers had the option of relisting and selling with a different strategy, so the true cost of the secret reserve was delay rather failure in selling. Thus, the cost of the average \$8 gain in the sale price would have been significantly less than the difference in probabilities of sale for individual auctions (0.918 vs. 0.659).

[Table 9 about here]

In Table 9, we consider differences between strategies and seller characteristics for auctions that resulted in a sale or not, broken down by frequency of selling. There are some variations across the non-retailer categories, but the main difference is between

these sellers and retailers. This view of the data highlights the distinctiveness of the retailer strategy. The unanimous application of the ‘Buy it Now’ option with a low starting price, but not as a posted price in the vast majority of cases stands in contrast to the variety seen on the strategies of others. The negative influence of secret reserve prices on probability of a sale can be seen here. This probably explains the observed avoidance of such reserve prices on the part of retailers.

Finally, we carried out a two-way ANOVA with respect to the outcomes of whether the auction concluded with a sale, and the winning bid in successful auctions. These results are reported in Table 10. Overall, the results are consistent with earlier conclusions that selling frequency does matter: here, for outcomes rather than for seller choices. However, the key result in Table 10 is with respect to successful auctions, once the retailers were excluded. In this case, once the use of a secret reserve price is accounted for, selling frequency has no significant explanatory power. This indicates that this strategic dimension was the main determinant of differences across frequency groups, in terms of the level of the winning bid. In other words, the observed heterogeneity of strategies did not significantly affect this key outcome, consistent with the market being highly competitive.

[Table 10 about here]

6. Conclusions

A major conclusion of our analysis is that the common eBay selling strategy of the retailers in the sample did not serve as a template which less frequent sellers of the same product followed. This difference in strategy was not explained by any one observed characteristic of the sellers themselves, including their eBay reputations, nor

was it only due to differences in product characteristics. The pattern of strategy choices was a combination of observable characteristics and different levels of experience amongst the sellers in the sample. Some sellers were clearly still in a process of experimentation with the various components of their selling strategies.

Despite the variation in strategies, the competitiveness of the online market came through in the fact that there was much greater dispersion in seller choices than in the mean final sales price, especially conditional on selling frequency. This can be tied in to observations with respect to differences between less frequent sellers and retailers: only the latter would have an incentive to fine tune their selling strategies, while less frequent sellers would make do with slightly lower returns, in exchange for avoiding learning costs.

A priori, we expected negative comments in a seller's ratings to have a detrimental effect on a seller's eBay reputation and, therefore, on the seller's choices and the outcomes of these auctions. However, in Table 2 we observed that the ratio of negative comments was not highly correlated with either sellers' choices or the conduct/outcomes of their auctions. It is possible that negative comments are not easily observed by buyers, being effectively buried on a separate seller's feedback page, which allowed sellers to avoid any significant negative effect on reputation. The retailers in our sample were clearly in a different reputational category

If some auctions include the 'Buy it Now' option, and others involve straight auctions, then in a separating equilibrium, more risk averse and/or impatient buyers will go for the 'Buy it Now' price (Reynolds and Wooders, 2004). However, the market for our homogeneous item was sufficiently thick that the 'Buy it Now' option, when used, was mostly not availed of by buyers. Nevertheless, the winning bid in auctions where

'Buy it Now' was offered was slightly higher, which may be due to product quality differences, multiple items being sold, or a signaling effect of the 'Buy it Now' offer, rather than impatience or risk aversion.

The features of the specific strategy adopted by the retailers are also of interest, namely, that (i) seller ratings are higher for retailers than for the rest of the sample, which relates to our discussion of how eBay's seller ratings favor more frequent sellers; (ii) both of the retailers in our sample started their auctions by making a 'Buy it Now' option available but they did not post a price (except for in one experimental auction) by setting the starting price to equal the 'Buy it Now' price; (iii) retailers did not rely on a secret reserve price to protect their 'Buy it Now' price and the starting prices that they selected were all the lowest possible (\$0.01), to encourage a larger volume of bidding. Thus, all retailers in our sample took full advantage of the hybrid, 'Buy it Now' institution by using it to provide a quick sale to impatient buyers, yet encouraging as much bidding up of the price as possible, if no impatient buyer happened to be shopping at the time. This retailer strategy illustrates the appeal of 'Buy it Now' for larger volume sellers on eBay.

Many lower volume sellers were experimenting with different selling strategies during our entire sample period and some held multiple unsuccessful auctions. Future work may be able to explore the possibility that information technology accelerates processes of evolution of strategies in markets. On the other hand, high turnover and heterogeneity among sellers on eBay will continue to make convergence of strategies difficult. In a broader perspective, one can view eBay and other online auctions as a type of 'lab' for studying the evolution of markets, where both larger corporations and individual entrepreneurs may be represented.

Finally, our analysis of unsuccessful auctions clearly illustrated the importance of a secret reserve price, leading to a trade-off between selling price and probability of sale. Our analysis is limited to a single item, and single time period. Hence, there is scope for significant further analysis with additional data sets. Future work that is more concerned with the dynamics surrounding experimentation and re-entry can build upon our observations here, and attempt to follow sellers who failed to sell, in order to determine how their strategies evolve in future attempts.

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Table 1: Sample and Sub-sample Means

Variable	All Sales	“Buy it Now” not Offered	“Buy it Now” Offered	“Buy it Now” not Accepted	“Buy it Now” Accepted
Product Characteristics					
NEW	0.283	0.368	0.187	0.157	0.312
DAMAGE	0.019	0.023	0.015	0.005	0.054
EXTRAS	0.316	0.400	0.223	0.168	0.452
QUANTITY	1.793	2.480	1.021	1.026	1
DAYS806	18	18	17	17	18
Seller Characteristics					
SINGLSLR	0.316	0.445	0.173	0.131	0.344
MULTSLR	0.216	0.270	0.156	0.089	0.430
FREQSLR	0.208	0.285	0.122	0.099	0.215
RETAILER	0.259	0	0.549	0.681	0.011
NEGRATIO	0.019	0.030	0.007	0.005	0.017
LNSLRTNG	4.132	3.313	5.052	5.155	4.627
Seller Choices					
SLRHOME	0.210	0.141	0.288	0.309	0.204
STARTPRC	\$62.56	\$63.91	\$61.05	\$26.20	\$204.20
LOWSTPRC	0.541	0.435	0.659	0.819	0
PRIVTRES	0.183	0.225	0.135	0.086	0.333
FEATURED	0.020	0.038	0	0	0
DSCLNGTH	9618	4485	15378	18126	4090
IMAGE	0.794	0.675	0.926	0.953	0.817
SCRPYDUM	0.800	0.705	0.905	0.937	0.774
POSTDPRC	0.090		0.192	0.003	0.968
STRTBYNW	0.471		1	1	1
BYNOWPRC	\$224.34		\$224.34	\$229.03	\$205.08
Auction Outcomes					
DURATION	5.030	5.164	4.880	5.516	2.269
ENDBYNOW	0.101		0.196	0	1
NUMBIDS	17.299	18.317	16.156	19.500	2.419
UNIQBIDR	9.771	10.424	9.038	10.804	1.785
WINBID	\$200.83	\$197.94	\$204.07	\$204.04	\$204.20
Sample Size	1008	533	475	382	93

Table 2: Correlations of Seller Choices and Auction Outcomes with Seller Reputational Characteristics

Variable	All Sales		No “Buy it Now”		Only “Buy it Now”		“Buy it Now” not Accepted		“Buy it Now” Accepted	
	NEGS.	RTNG	NEGS.	RTNG	NEGS.	RTNG	NEGS.	RTNG	NEGS.	RTNG
Seller Choices										
SLRHOME	-0.03	0.45	-0.00	0.40	0.09	0.48	0.03	0.59	0.32	0.13
STARTPRC	0.06	-0.17	0.00	-0.09	0.24	-0.29	0.26	-0.38	-0.36	0.06
LOWSTPRC	-0.27	0.32	-0.24	0.17	-0.33	0.38	-0.34	0.46	0	0
POSTDPRC	-0.01	0.08			0.26	-0.16	0.09	-0.01	0.06	-0.09
STRTBYNW	-0.24	0.46								
BYNOWPRC					-0.34	-0.19	-0.24	-0.37	-0.37	0.05
PRIVTRES	0.02	-0.27	-0.03	-0.19	0.09	-0.34	0.16	-0.41	-0.12	-0.16
FEATURED	-0.05	0.05	-0.09	0.15	0	0	0	0	0	0
DSCLNGTH	-0.05	0.57	0.38	0.31	-0.22	0.65	-0.21	0.78	0.03	0.21
IMAGE	0.00	0.42	0.11	0.35	-0.06	0.30	-0.14	0.30	0.11	0.25
SCRPYDUM	-0.01	0.29	0.08	0.19	-0.10	0.25	-0.20	0.21	0.122	0.25
Auction Outcomes										
ENDBYNOW	-0.02	0.08			0.25	-0.15				
DURATION	-0.18	-0.08	-0.27	0.00	-0.18	-0.14	-0.08	-0.34	-0.11	0.12
NUMBIDS	-0.04	0.11	-0.02	0.15	-0.26	0.20	-0.20	0.15	-0.04	0.10
UNIQBIDR	-0.04	0.12	-0.02	0.17	-0.32	0.21	-0.30	0.18	-0.06	0.11
WINBID	-0.07	-0.04	-0.00	-0.08	-0.23	-0.12	-0.14	-0.22	-0.36	0.06
Sample Size	1008		533		475		382		93	

Table 3: T-tests for Differences in Means across Seller Frequencies

Variable	Single vs. Multiple	Single vs. Frequent	Single vs. Retailer	Multiple vs. Frequent	Multiple vs. Retailer	Frequent vs. Retailer
Seller Reputation						
NEGRATIO	-2.397*	-6.379*	5.121*	-4.035*	6.585*	9.929*
LNSLRTNG	-4.427*	-11.292*	-23.778*	-5.679*	-15.017*	-9.872*
Seller Choices						
STARTPRC	-1.454	4.397*	19.567*	5.220*	16.869*	11.012*
POSTDPRC	-2.904*	-22.072*	-7.517*	-16.165*	-4.134*	11.204*
STRTBYNW	-2.038*	-0.485	-30.317*	1.418	-20.549*	-23.404*
PRIVTRES	4.028*	2.520*	12.138*	-1.287	6.660*	7.656*
Auction Outcomes						
DURATION	4.255*	7.423*	0.472	2.389*	-3.359*	-5.968*
NUMBIDS	-0.667	-4.387*	-12.014*	-2.599*	-5.771*	-3.054*
UNIQBIDR	-1.408	-5.678*	-15.352*	-2.938*	-4.873*	-1.169
WINBID	2.371*	-1.261	-1.753	-3.926*	-4.070*	-0.908

Note: * denotes significance at 5% level

Table 4: One-Way ANOVA

Variable	Including Retailers	Excluding Retailers
Seller Reputation		
NEGRATIO	41.668***	25.181***
LNSLRTNG	160.846***	55.359***
Seller Choices		
STARTPRC	105.428***	15.042***
POSTDPRC	18.009***	6.426***
STRTBYNW	219.128***	2.230
PRIVTRES	36.378***	8.257***
Auction Outcomes		
DURATION	18.290***	25.492***
NUMBIDS	25.805***	8.734***
UNIQBIDR	26.614***	15.108***
WINBID	6.966***	6.310***

Note: *** denoted significance at 1% level.

Table 5: Two-Way ANOVA – Choice of Secret Reserve

Factor	All Auctions		Sales Only	
	Incl. Retailers (1177 obs.)	No Retailers (912 obs.)	Incl. Retailers (1008 obs.)	No Retailers (747 obs.)
LOWSTPRC ¹	0.01	0.27	0.15	2.16
Frequency Group ²	5.26***	5.22***	7.93***	8.18***
LOWSTPRC*Frequency	0.64	0.74	0.71	0.78
	R ² = 0.1020	R ² = 0.0128	R ² = 0.1021	R ² = 0.0261
HIRATING ³	20.03***	17.32***	16.95***	12.46***
Frequency Group	13.76***	0.74	12.70***	3.70**
HIRATING*Frequency	N/A	4.93***	N/A	6.27***
	R ² = 0.1151	R ² = 0.0378	R ² = 0.1130	R ² = 0.0540

Notes: (1) LOWSTPRC = 1 if the initial bid price is set by the seller to be \leq \$20; = 0, Otherwise.
(2) Frequency Groups are defined as Single Sellers, Multiple Sellers, Frequent Sellers, and Retailers.
(3) HIRATING = 1 if the eBay seller rating is above the median for the entire sample (N = 1177); = 0, Otherwise.
Significant at the 1% level = ***, at the 5% level = **, and at the 10% level = *.

Table 6: Two-Way ANOVA – Choice of Starting Price

Factor	All Auctions		Sales Only	
	Incl. Retailers (1177 obs.)	No Retailers (912 obs.)	Incl. Retailers (1008 obs.)	No Retailers (747 obs.)
PrivtRes	20.48***	13.63***	0.69	0.00
Frequency Group ²	118.22***	13.99***	100.69***	15.04***
PrivtRes*Frequency	N/A	0.13	N/A	3.61**
	R ² = 0.2331	R ² = 0.0530	R ² = 0.2401	R ² = 0.0488
HIRATING ³	0.04	0.08	0.18	0.11
Frequency Group	72.08***	14.22***	70.98***	13.08***
HIRATING*Frequency	N/A	9.59***	N/A	9.82***
	R ² = 0.2197	R ² = 0.0561	R ² = 0.2397	R ² = 0.0639

- Notes: (1) The outcome variable for this ANOVA (“Starting Price”) is not equal to the factor variable LOWSTPRC, rather it is the initial starting bid price, as chosen by sellers at the beginning of each auction.
(2) Frequency Groups are defined as Single Sellers, Multiple Sellers, Frequent Sellers, and Retailers.
(3) HIRATING = 1 if the eBay seller rating is above the median for the entire sample (N = 1177); = 0, Otherwise.
Significant at the 1% level = ***, at the 5% level = **, and at the 10% level = *.

Table 7: Differences between Auctions that Resulted in a Sale or Not

Selected Seller Choices and Characteristics	Sale	No Sale
Seller had a Secret Reserve Price	0.183	0.562
Seller Chose to Make a ‘Buy it Now’ Option Available	0.471	0.302
Seller Chose to use “Buy it Now” to Effectively Post a Price	0.090	0
Seller only Held 1 Auction During the Sample period	0.316	0.396
Seller Held 2-10 Auctions During the Sample Period	0.216	0.450
Seller Held 10-50 Auctions During the Sample Period	0.208	0.130
Seller Held over 50 Auctions During the Sample Period	0.259	0.024
Number of Unique Negative Comments on Seller	2.77	2.04
Number of Unique Positive Comments on Seller	230	116
Seller Rating	228	115
Sample Size	1008	169

Table 8: Numbers of Auctions Resulting in a Sale with Use of Secret Reserve

	No Secret Reserve	Secret Reserve	Total
Auction Resulted in No Sale	74	95	169
Auction Resulted in Sale	824	184	1008
Total	898	279	1177

Table 9: Differences between Auctions that Resulted in a Sale or Not, by Seller Type

Selected Seller Choices and Characteristics	Single Sellers		Multiple Sellers		Frequent Sellers		Retailers	
	Sale	No Sale	Sale	No Sale	Sale	No Sale	Sale	No Sale
Seller had a Secret Reserve Price	0.317	0.567	0.170	0.592	0.219	0.545	0	0
Sellers' Choice of a Starting Price (Mean)	89.534	119.746	100.220	92.841	59.249	65.564	0.811	0.010
Seller Chose to Make a 'Buy it Now' Option Available	0.257	0.179	0.339	0.368	0.276	0.318	1	1
Seller Chose to use "Buy it Now" to Effectively Post a Price	0.097	0	0.188	0	0.090	0	0.004	0
Number of Unique Negative Comments on Seller	1.022	0.179	1.959	1.382	8.767	10.318	0.743	0
Number of Unique Positive Comments on Seller	112.40	25.79	155.82	105.58	264.30	424.41	409.38	146.00
Seller Rating	112	26	154	104	257	417	409	146
Sample Size	319	67	218	76	210	22	261	4

Table 10: Two-Way ANOVA – Auction Outcomes

Factor	Proportion of Sales		Mean Level of Winning Bid	
	Incl. Retailers (1177 obs.)	No Retailers (912 obs.)	Incl. Retailers (1008 obs.)	No Retailers (747 obs.)
LOWSTPRC ¹	0.00	0.03	0.00	0.13
Frequency Group ²	9.90 ^{***}	11.47 ^{***}	4.33 ^{***}	6.02 ^{***}
LOWSTPRC*Frequency	0.32	0.38	1.13	1.60
	R ² = 0.0641	R ² = 0.0269	R ² = 0.0238	R ² = 0.0210
PrivtRes	95.21 ^{***}	74.66 ^{***}	9.40 ^{***}	8.64 ^{***}
Frequency Group	16.09 ^{***}	20.39 ^{***}	8.19 ^{***}	1.98
PrivtRes*Frequency	N/A	9.64 ^{***}	N/A	0.49
	R ² = 0.1336	R ² = 0.1201	R ² = 0.0295	R ² = 0.0296
HIRATING ³	1.68	1.24	4.20 ^{**}	3.94 ^{**}
Frequency Group	17.02 ^{***}	11.81 ^{***}	8.39 ^{***}	6.24 ^{***}
HIRATING*Frequency	N/A	5.03 ^{***}	N/A	0.22
	R ² = 0.0646	R ² = 0.0381	R ² = 0.0245	R ² = 0.0225
LOWSTPRC	0.22	0.55	0.08	0.08
PrivtRes	134.97 ^{***}	90.14 ^{***}	4.74 ^{**}	6.77 ^{***}
LOWSTPRC*PrivtRes	29.20 ^{***}	17.99 ^{***}	5.60 ^{**}	2.78 [*]
	R ² = 0.1261	R ² = 0.0946	R ² = 0.0172	R ² = 0.0182

Notes: (1) LOWSTPRC = 1 if the initial bid price is set by the seller to be ≤ \$20; = 0, Otherwise.
(2) Frequency Groups are defined as Single Sellers, Multiple Sellers, Frequent Sellers, and Retailers.
(3) HIRATING = 1 if the eBay seller rating is above the median for the entire sample (N = 1177); = 0, Otherwise.
Significant at the 1% level = ***, at the 5% level = **, and at the 10% level = *.

Figure 1: Mean Seller Rating for Each Group of Sellers in Sample
(Sellers Grouped According to Sample Selling Frequency)

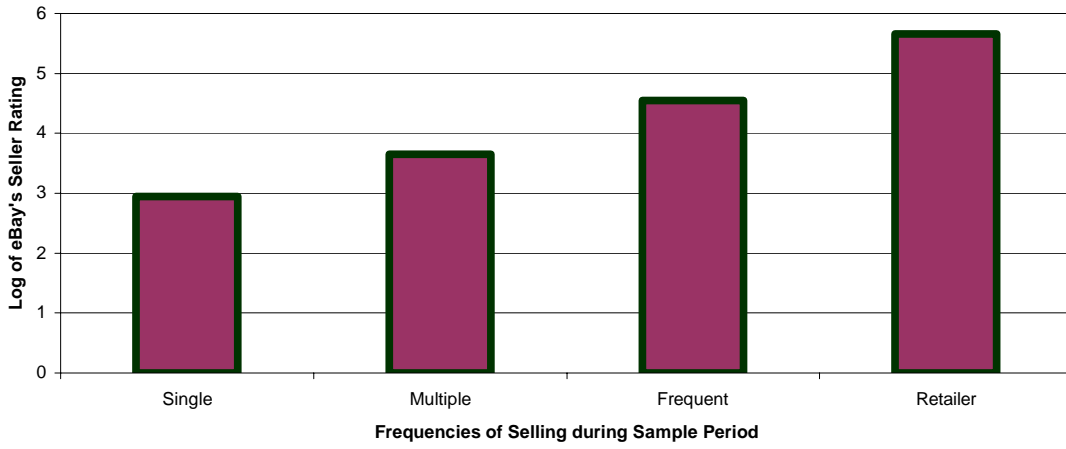


Figure 2: Fraction of Unique Negative Comments

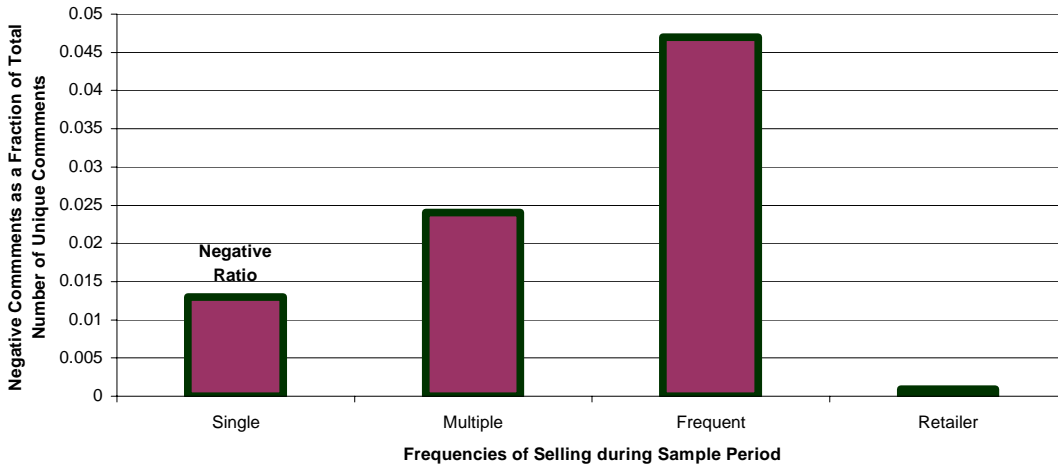


Figure 3: Selected Seller Choices

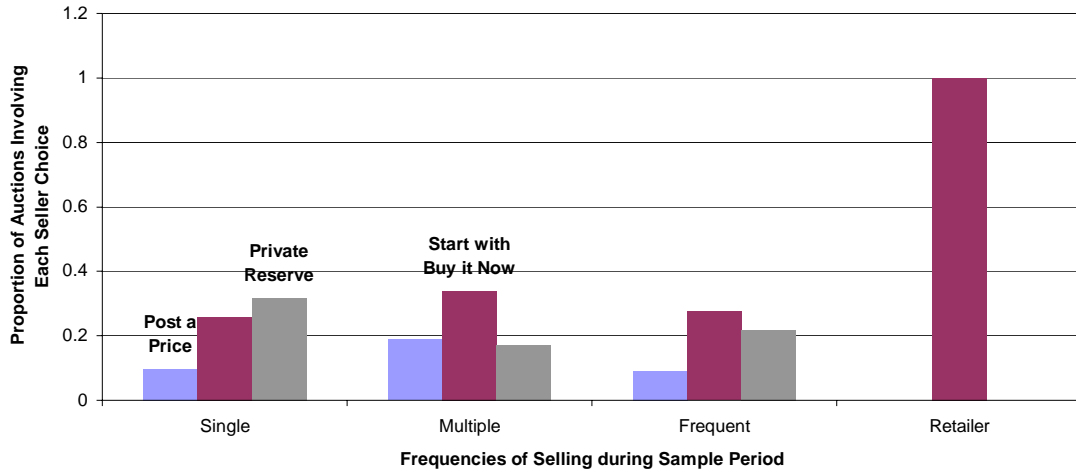


Figure 4: Mean Starting Prices and Winning Bids by Seller Group

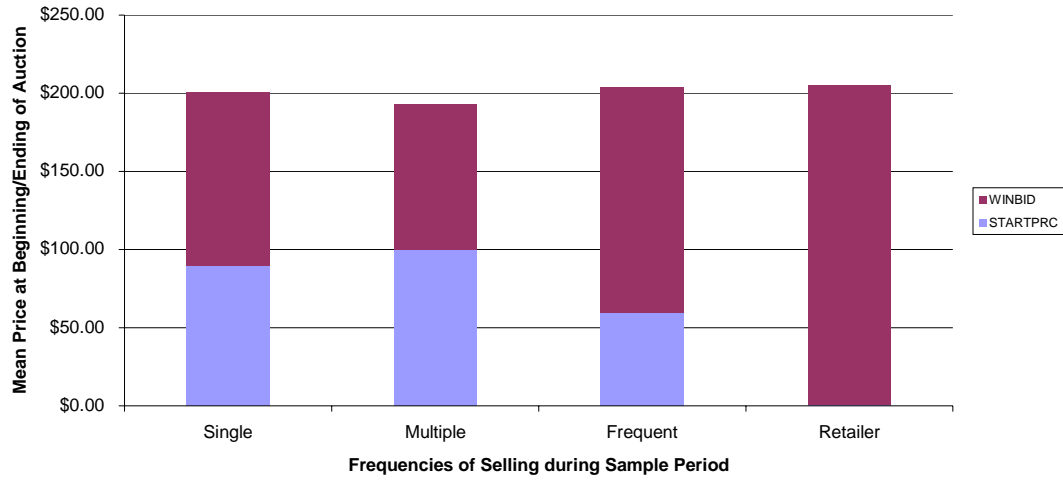


Figure 5: Mean Auction Conduct Indicators, Conditional on Seller Group

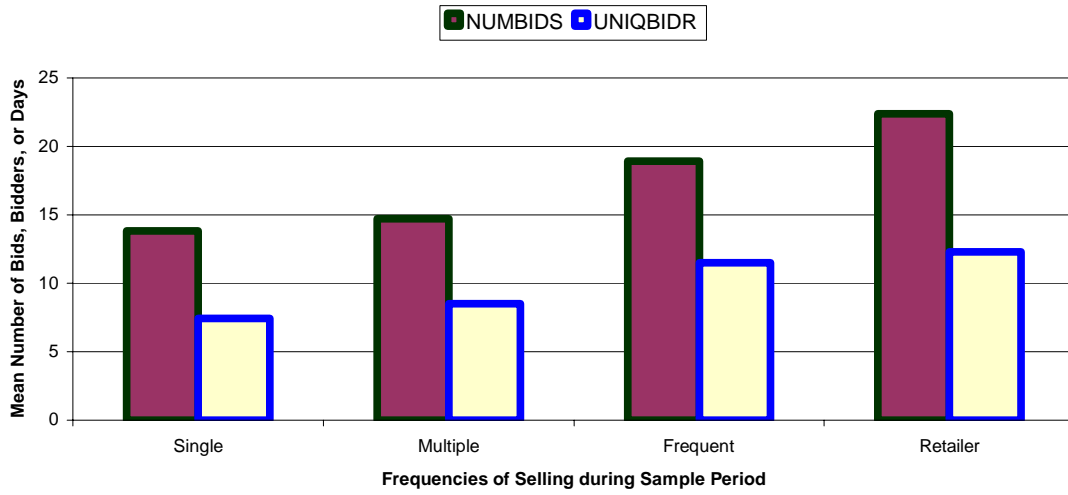
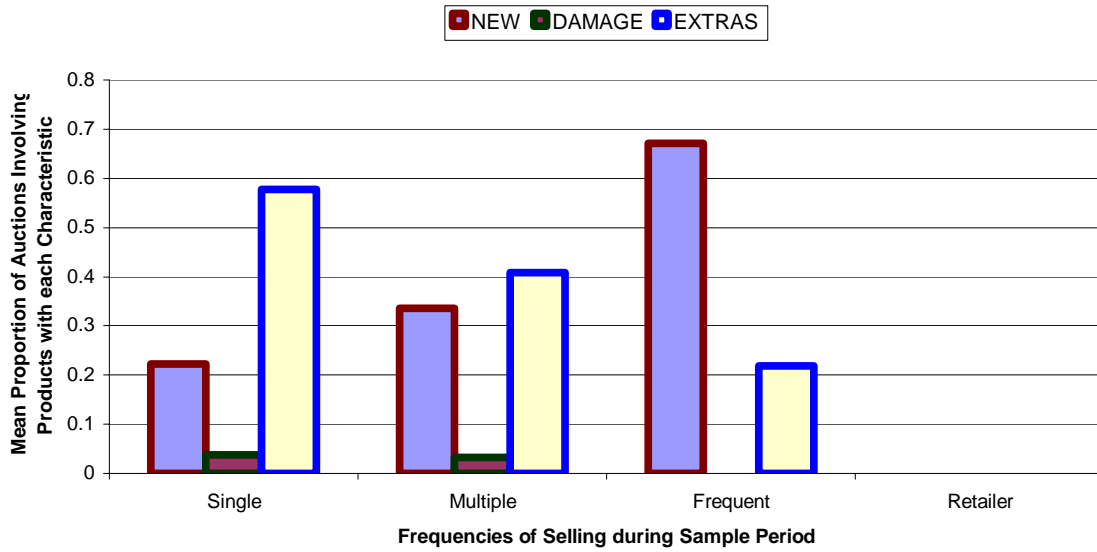


Figure 6: Mean Proportion of Auctions for Product with each Characteristic



Appendix

Table A: Variable Names and Definitions

Variable	Description
NEW	Equal to one, if the item is definitively described to be “sealed, in the box, and new” in either the title of the auction listing or in the description text (zero otherwise)
DAMAGE	Equal to one, if any significant damage to the item is mentioned in either the title or the description text.
EXTRAS	Equal to one, if the item is being offered with significant accessories, mentioned in either the title or the description text.
QUANTITY	Number of items sold in a single, particular auction.
DAYS806	Number of days between the start of the auction and the date of the first auction in the sample (8/6/01).
SINGLSR	Equal to one, if the seller only held one auction during our sample.
MULTSLR	Equal to one, if the seller held more than one auction but no more than ten auctions during our sample.
FREQSLR	Equal to one, if the seller held more than ten auctions but no more than fifty auctions during our sample.
RETAILER	Equal to one, if the seller held more than fifty auctions during our sample.
LNSLRTNG	Natural logarithm of the difference between the number of unique, positive comments about the seller and the number of unique, negative comments.
NEGRATIO	Ratio of the number of unique, negative comments to the total number of unique comments listed in the seller's feedback page.
SLRHOME	Equal to one, if the seller posts a link to his website in the description text of the auction listing.
STARTPRC	Initial price to start the bidding, posted by the seller at the beginning of the auction.
SQRSTPRC	Square of the seller's starting price.
LOWSTPRC	Equal to one, if the seller posts an initial price below twenty dollars.
POSTDPRC	Equal to one, if the seller sets the initial price equal to a displayed, ‘Buy it Now’ price.
STRTBYNW	Equal to one, if the seller offers buyers the option to buy the item immediately at a displayed, ‘Buy it Now’ price.
BYNOWPRC	Seller's price if displayed at the beginning of the auction as a ‘Buy it Now’ offer.
PRIVTRES	Equal to one, if the seller displays a notice that actual sale is subject to a buyer at least bidding as high as some unknown, secret, reserve price.
FEATURED	Equal to one, if the seller paid extra to have the item(s) listed at the top of the listings, no matter what the potential buyer's search criteria was.
DSCLENGTH	Number of text characters in the description of the item, composed by the seller for the auction listing page, minus the number of HTML tags.
IMAGE	Equal to one, if the seller included at least one image in the description of the item.
SCRPYDUM	Equal to one, if the seller accepts credit cards, PayPal, or eBay Online Payments.
DURATION	Duration of the auction, initially set by the seller to a maximum of 3, 5, 7, or 10 days.
ENDBYNOW	Equal to one, if the auction ends with a buyer accepting a seller's ‘Buy it Now’ option.
NUMBIDS	Number of bids on the item(s) in a particular auction.
UNIQBIDR	Number of unique bidders for the item(s) in a particular auction.
WINBID	Dollar value of the final bid in an auction that resulted in a sale.

Table B: Correlations Between Product and Seller Characteristics

Non-‘Buy it Now’ Sub-sample (533 Observations)											
Variable	NEW	DAMG.	EXTS.	QUNT.	DAYS.	SINGL.	MULT.	FREQ.	RET.	NEGS.	LRTNG
NEW	1	-0.06	-0.23	-0.02	0.02	-0.29	-0.02	0.34	0	0.27	0.08
DAMAGE		1	-0.05	-0.04	0.06	0.09	-0.01	-0.10	0	-0.06	0.04
EXTRAS			1	-0.12	0.02	0.36	0.04	-0.43	0	-0.21	-0.14
QUANTITY				1	0.09	-0.23	-0.01	0.27	0	0.01	0.27
DAYS806					1	0.01	0.08	-0.09	0	0.04	-0.06
SINGLSLR						1	-0.54	-0.57	0	-0.22	-0.33
MULTSLR							1	-0.38	0	-0.06	0.04
FREQSLR								1	0	0.31	0.32
RETAILER									1	0	0
NEGRATIO										1	0.04
LNSLRTNG											1
‘Buy it Now’ not Accepted Sub-sample (382 Observations)											
Variable	NEW	DAMG.	EXTS.	QUNT.	DAYS.	SINGL.	MULT.	FREQ.	RET.	NEGS.	LRTNG
NEW	1	-0.03	0.27	0.10	0.02	0.15	0.27	0.55	-0.63	0.17	-0.23
DAMAGE		1	0.16	-0.01	0.04	0.08	0.10	-0.02	-0.11	-0.02	-0.15
EXTRAS			1	-0.05	0.01	0.41	0.18	0.39	-0.65	0.22	-0.41
QUANTITY				1	-0.04	-0.04	0.32	-0.03	-0.15	0.12	-0.10
DAYS806					1	0.01	-0.05	0.12	-0.06	-0.07	-0.14
SINGLSLR						1	-0.12	-0.13	-0.57	0.14	-0.36
MULTSLR							1	-0.10	-0.46	0.40	-0.35
FREQSLR								1	-0.49	0.07	-0.14
RETAILER									1	-0.38	0.56
NEGRATIO										1	-0.20
LNSLRTNG											1
‘Buy it Now’–Accepted Sub-sample (93 Observations)											
Variable	NEW	DAMG.	EXTS.	QUNT.	DAYS.	SINGL.	MULT.	FREQ.	RET.	NEGS.	LRTNG
NEW	1	-0.16	-0.10	0	0.02	-0.19	-0.30	0.61	-0.07	-0.02	0.37
DAMAGE		1	-0.12	0	0.12	0.03	0.08	-0.12	-0.02	0.45	-0.12
EXTRAS			1	0	-0.06	0.02	-0.18	0.21	-0.09	-0.19	-0.10
QUANTITY				0	0	0	0	0	0	0	0
DAYS806					1	-0.07	0.02	0.07	-0.02	-0.02	0.05
SINGLSLR						1	-0.63	-0.38	-0.08	-0.20	-0.42
MULTSLR							1	-0.45	-0.09	0.19	-0.11
FREQSLR								1	-0.05	0.02	0.59
RETAILER									1	-0.05	0.12
NEGRATIO										1	-0.15
LNSLRTNG											1