How much is a dollar worth? Arbitrage on eBay and Yahoo

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Abstract

This paper uses field experiments to identify substantial and persistent arbitrage opportunities on online auctions sites. Auction and two-sided market theory require price disparity to be small for competing sites of different sizes to coexist in equilibrium. Yet, statistical evidence suggests a violation of this no arbitrage condition in eBay and Yahoo coin markets. Buyers on eBay pay 20 to 60 percent more than those on Yahoo, despite buyer and seller mobility between sites. The magnitude of the revenue difference is striking, overwhelming possible rationales relating to information availability, the value of reputation and trustworthiness of site users. The price disparity may signal unexploited opportunities or represent a market in transition.

1 Introduction

With 95 million users selling more than 970 million items per year, eBay dominates the online auction industry (eBay, 2003). In 2001, it held 64.3 percent of the U.S. market share by revenue (Nielsen/NetRatings, 2001). eBay dwarfs its most notable rival, Yahoo, which maintains an auction service with less than 3 percent of the market share.[1] However, Yahoo is still an active player in online auctions with hundreds of thousands of sale items and users. Both sites bring online users together to buy and sell a wide range of goods, from the unusual to the mundane, in what has been called a 'vast electronic garagesale'.

Online auctions sites have spread worldwide and, while relatively young, competition appears aggressive. In 2001, Yahoo overwhelmed eBay in the Japanese auction market and, in 2002, eBay's

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[1] ubid.com and egghead.com had 15 and 4 percent of online auction market share in 2001, respectively. Both of these sites differ from eBay and Yahoo auction platforms. The ubid site provides business-to-buyer auction services only. The egghead site, which auctioned computers and computing accessories, was acquired by Amazon.com in December, 2001 and is currently operated as a retail site.

dominance forced the closure of Yahoo auctions in Europe. Yet, in the U.S., eBay and Yahoo auctions have operated simultaneously since 1998. From the marked difference in eBay and Yahoo market shares emerges several interesting economic questions: Is the online auction market in the process of 'tipping' to the point where all business falls to eBay? Or, is this an equilibrium phenomenon where two very unequal-sized markets can coexist? And, in either case, how do the firms' services and organization affect the outcome?

Ellison, Fudenberg and Möbius (2004) suggest that the latter case of coexistence is theoretically possible, and illustrate this with a model of competing online auction sites. Of course, in an equilibrium setting, both buyers and sellers should be close to indifferent between the sites, and price disparity between the venues should be minimal. To investigate, I study eBay and Yahoo through a series of field experiments with collectible coins.

This paper uses Yahoo and eBay field experiment data to compare the two auction sites. Revenue comparisons consistently indicate that buyers on eBay pay 20 to 60 percent more than their Yahoo counterparts for identical items. Further statistical tests strengthen the case for persistent and substantial revenue disparity.

In addition, the field experiment data permit the empirical testing of auction style-related effects, including ending rule and reserve value. As expected, positive reserve values lead to later bid submissions on both sites, while reserve effects on revenue are ambiguous. Interestingly, no significant differences in revenues or bid timing are found between hard-close and automatic extension ending rules on Yahoo, a departure from theory developed by Ockenfels and Roth (2001) suggesting that bidder behavior varies by ending rule. Specifically, their work suggests that late bidding may be a best response in hard-close auctions, while relatively early bidding is consistent with optimal bid timing in auctions with the automatic-extension ending rule. Yet, data gathered in these field experiments show no significant variation in timing or revenue across ending rules.

While the failure to identify effects of ending rule variation represents a significant challenge of Ockenfels and Roth's (2001) theoretical prediction, the most surprising result remains the presence of substantial arbitrage opportunities between the sites. The revenue disparity and the apparent violation of the Ellison, Fudenberg and Möbius (2004) no arbitrage condition make the existence of these competing auction sites remarkable indeed.

The remainder of this section highlights some related work, both theoretical and experimental.

Section 2 describes the simple independent private values auction model that underlies the hypotheses tested with the field experiment data. Section 3 outlines the experimental design, motivated by the testable model predictions, while the fourth section describes key results of the statistical analysis. Finally, section 5 revisits the research questions, providing some possible rationale for the findings and stepping back to relate the results to the current state of online auctions.

1.1 Related Literature

1.1.1 Theory

Online auction sites are examples of what Rochet and Tirole (2002) call "two-sided markets", characterized by two groups of users who benefit from interactions through a common platform. In their work on two-sided competing markets, Rochet and Tirole (2002) conclude that both monopoly and competitive platforms design their price structure to engage both sides of the market. They define 'multihoming' where users may be affiliated with several platforms. The degree of multihoming on one side of the market impacts the competitiveness of prices on the other side of the market, as platforms compete for exclusive user relationships. For example, Yahoo and eBay aim to attract buyers and sellers, and users can readily 'multihome' with simultaneous browsing.

Extending this conclusion, Caillaud and Jullien (2003) model intermediaries in markets with network externalities and examine the role of exclusivity in service provision. 'Exclusive' implies that users cannot register on several platforms. They conclude that intermediaries may propose non-exclusive services to moderate competition and exert market power; exclusivity promotes competition between intermediaries, and forces profits to zero. In contrast, non-exclusivity allows a range of strictly profitable equilibria. For online auctions, the Caillaud-Jullien model implies that a site need not restrict users to select a single service, since the lack of competition for exclusive users permits each firm to set user fees for positive profits. They find that, in equilibria with multihoming, intermediaries may differentiate through both transaction and registration fees; in particular, dominant firms are better off charging transaction fees rather than registration fees. In fact, neither eBay nor Yahoo charge users to register for their services. While Yahoo initially provided the listing service free of charge, both sites now charge sellers fees to post item advertisements.[2]

[2] eBay has charged user fees since its inception. In 2001, eBay raised its sellers fees after Yahoo announced that it would start charging sellers for item postings.

Ellison, Fudenberg and Möbius (2004) examine auction markets explicitly, introducing a tipping model to develop conditions under which unequally-sized auction sites can coexist. They define two effects in the market. A 'scale effect', where larger markets provide greater expected surplus per participant, makes concentration efficient. A 'market impact effect', where a user considers his impact on a market before entering, favors site multiplicity. The relative magnitude of these offsetting forces determines whether smaller markets survive. To illustrate the critical conditions for coexistence, the authors model a market with uniformly-distributed bidder valuations. They report that the smaller auction site must attract approximately $(\frac{1}{4})(1\text{-}\frac{S}{B})$ of the buyers to be viable. That is, when $\frac{S}{B}$ is small, a site needs $\frac{1}{4}$ of the buyers to survive. When the seller-buyer ratio is large, the small site need only attract a tiny fraction of participants. Without assumption, Ellison, Fudenberg and Möbius also predict that sites may coexist even when site-specific fees vary widely.

Ockenfels and Roth (2001) present a theoretical framework styled after the eBay mechanism to examine late and multiple bidding behavior in second-price online auctions. They model two ending rules: a hard-close rule where the auction end is fixed, and an automatic extension rule where the auction close is delayed by five minutes if a bid is placed within 10 minutes of the scheduled end. The authors conclude that bidders in a hard-close, second-price auction have no dominant bidding strategy, in contrast to the conventional sealed-bid, second-price auction where the dominant strategy is to bid is one's maximum willingness-to-pay.[3] In particular, they suggest that the lack of dominant strategy implies that late bidding may be a best response to the behavior of other bidders. Incremental bidding occurs when a bidder, when he is not the highest-bidder, submits minimum increment bids until he regains his highest-bidder position or reaches his maximum willingness-to-pay. Ockenfels and Roth show that late bid submission may be a best response to incremental bidding, since early bidding may induce bidding wars that raise prices. Furthermore, they conclude that equilibria exist where bidders may want to bid both early and late, despite the risk that last-minute bids may not be successfully transmitted. That is, multiple bidding may not necessarily indicate bidder irrationality or inexperience. Ockenfels and Roth suggest that the benefits of late-bidding may be eliminated with automatic extension auctions since incremental bidders have time to respond to late bidding. In addition, they prove that in any subgame perfect equilibrium with

[3] Informally, a bid lower than one's true valuation may result in a failure to win the item at an attractive price and a missed opportunity to earn a profit. If one bids higher than one's true valuation, one may win but incur a loss. According to this reasoning, only one true-valuation bid is required in a second-price, sealed-bid auction.

the automatic extension ending rule the auction is not extended. Little is known, however, about the theoretical impact of ending rule on revenues and allocative efficiency.

1.1.2 Experimental Results

As the theory relating to competing auction services and strategies builds, popular online auction sites provide environments in which to test the theory empirically. Following their theoretical presentation described above, Ockenfels and Roth (2001) gather information from eBay and Amazon auctions of computers and antiques to test their predictions about timing and ending rules. Ending rule effects on timing are significant, with significantly more last-minute bidding on eBay with the hard close, than with Amazon's automatic extension. Furthermore, differences between the timing strategies appear to increase with experience. However, their work fails to control for differences between eBay and Amazon user and item counts, bidder characteristics and valuations. Ariely, Ockenfels and Roth (2003) correct for this source of ambiguity in a series of controlled laboratory experiments using eBay- and Amazon-styled auction rules. They find that the difference in auction ending rules is sufficient to produce the differences in late bidding observed in the field data. In addition, they conclude that Amazon's automatic extension rule leads to higher revenues, perhaps because time extensions provide bidders the opportunity to learn more about their valuations.

Roth and Ockenfels (2002) also relate bid timing to experience, with field results suggesting that bidders' late-bidding is due to incremental bidding by relatively less experienced users. Examining a sample of eBay auctions, Wilcox (2000) concludes that bidders learn optimal bidding strategies (*e.g.* last-minute bidding in a hard-close auction) as they gain experience.

While Riley and Samuelson (1981) provide an early theoretical treatment of the effects of reserve price, Lucking-Reiley (2000) uses the online first-price auction of *Magic* cards to show that increased reserve prices decreases the number of the bids received, decreases the probability of sale, and increases auction revenues. Furthermore, Ariely and Simonson (2003) auctioned electronics and found that, while low starting prices draw more bidders, participants bid relatively low due to the anchoring effect.

1.1.3 Relation to the literature

While the work of Ellison, Fudenberg and Möbius (2004), Ockenfels and Roth (2001), and others provide a strong theoretical foundation for auction-related hypotheses, and experimental work has begun to test the real-world implication of such theories, the current research make three important contributions to the existing literature.

First, the field experiment analysis represent a unique test of the stable site coexistence vs. transitional tipping hypothesis. While past work suggests the theoretically-necessary conditions for eBay and Yahoo's coexistence, this paper uses carefully-designed experimental field data to test for this real-world phenomenon. The work's second major contribution is a test of auction ending rule. Past empirical tests have used data gathered from the Internet where sale conditions were not controlled by the investigators. That is, item descriptions, starting values, auction timing, seller reputation, and other auction variables could vary subtly (or widely) across the dataset. This field experiment's matched-pair design allows for precise control over the sale environment. As detailed in section 3, all aspects of the auction, except bidding itself, was attentively managed to ensure the comparability of results. Finally, through careful experimental design, this research strengthens claims about the effects of reserve values on auction revenues and bid timing. The opportunities for future online auction research are broad, yet this work represents significant advancements in our understanding of auction characteristics and the online auction industry.

2 Theory

2.1 A Simple Auction Model

To guide the hypotheses and experimental design, it is useful to consider a simple independent private values auction model. The subscript s indexes auction sites, where $s \in \{y$ for Yahoo, e for eBay$\}$. Let there be a single seller with one good facing N_s potential bidders with independent valuations, $v_{is}, i = 1, ...N_s$, drawn from some common bounded distribution, $F_s(v)$. A player can submit a bid at any time $t \in [0, T]$, where T is the hard-close auction deadline.[4] Let the current price, p_s, be equal to the second highest accepted bid plus a small increment, k.[5] Each subsequent

[4] For an automatic extension end rule with x-minute extensions, *potential* $t \in [0, T] \cup (T, T + x] \cup (T + x, T + 2x] \cup ...$

[5] For simplicity, assume a trivially-small k.

accepted bid must exceed p_s. If a bidder attempts to submit a bid equal to or less than p_s,the bid is neither accepted nor posted. Define n_s as the number of actual bidders where $n_s \leq N_s$ and n_s is endogenous to the model. The highest bid is never revealed, since the second-highest bid is publicly posted as the standing price. Overall, (N_s-n_s-1) bids are censored from the auction history.

Suppose now that $F_s(v)$ is a uniform distribution on the interval $[a_s, b_s]$. Auction revenue, in this case, can be defined as

$$rev_s = \frac{N_s - 1}{N_s + 1}[b_s - a_s] \tag{1}$$

To illustrate the censoring, consider the example where $N = 5$, $a = 0$ and $b = 1$. Assume that bids are distributed uniformly along the $[0, 1]$ interval, submitted in the following order: $\frac{1}{3}, \frac{1}{2}, \frac{1}{6}, \frac{5}{6}, \frac{2}{3}$. After the second bidder, the standing price is $\frac{1}{3}$. The third potential bidder's attempt to bid lower than the standing price is refused. The fourth bid exceeds the standing price and is accepted, leading to a new price of $\frac{1}{2}$. The final bid is higher than the standing price and is accepted. That is, the price history is: $\frac{1}{3}, \frac{1}{2}, \frac{2}{3}$. The highest bidder, who submitted a bid of $\frac{5}{6}$, pays the second-highest bid and auction revenue is $\frac{2}{3}$. Note that the highest bidder's bid does not enter the history of prices. Censoring of bids leads to the inequality $n < N$.

Consider now the effect of a nontrivial reserve price, r, where the seller-determined reserve value is greater than the lower-bound of the distribution of valuations (*i.e.* $r > a$). Clearly, the truncation of accepted bid results in fewer actual bidders, $n_{reserve,s}$, by screening out bidders with valuations below r. Recall that, since valuations are developed independently, the increased reserve value has no impact on players' bids. Except where the chosen r results in the screening of $(N_s - 1)$ bidders, revenue remains equal to the zero-reserve auction revenue. In this case of optimal reserve choice, revenue equals the reserve value which is strictly greater than the zero-reserve revenue since the would-be second-highest bid fell below r.

A more complex theoretical model is required to describe the effects of ending rules on bids and revenues. As described in more detail in section 1.1, Ockenfels and Roth (2001) present a model supporting the claim that late-bidding may be equilibrium behavior in auctions with set closing times. Their work also suggests that an automatic extension end rule, which delays the auction for close by x minutes if a bid is placed within m minutes of the auction end, makes late bidding more difficult to achieve in equilibrium. In other words, while last-minute bidding may

be an optimal strategy in hard-close auctions with incremental bidding, automatic time extensions allow incremental bidders to respond to a bid submitted at $t = T$. These varying optimal strategies suggest that a seller's choice of ending rule may affect the timing of submitted and accepted bids.

2.2 Hypotheses

The simple theoretical model motivates the tests of site, reserve and ending rule effects. The three auction hypotheses are outlined in the discussion below and are tested empirically in section 4.2.

H1: Site effect

To compare revenue from competing auction venues, we must recall that both n_s and the distribution $F_s(v)$ may vary between sites. The interaction of the number of bidders, n_s, and the distribution of values, $[b_s - a_s]$, as in equation (1), make site-related hypotheses difficult to develop. Since reserve value choice is hypothesized to affect participation, and the site effect absorbs the effect of bidder count variation between the venues, the number of bidders is considered endogenous in the auction mechanism. Ellison, Fudenberg and Möbius (2004) suggest that the two sites' co-existence relies on prices being approximately equal between the sites and, controlling for auction characteristics, I expect no difference to exist between auctions on Yahoo and eBay.

H2: Reserve effect

A non-trivial reserve value truncates the history of accepted bids by screening out low-bidding participants, yet has no theoretical impact on auction revenues when at least two bids are received. That is, positive reserve values are expected to have no effect on revenue when more than one actual bid is received. When examining bid timing, reserve effect expectations are ambiguous. While high reserve values screen out low-bidding participants who might place bids early in the auction, there is no theoretically-supported hypothesis about reserve effects on timing.

H3: Ending rule effect

Ending-rule choice is expected to affect both auction revenue and bid timing. While the direction of the effect is ambiguous for ending rule effects on revenue, use of the automatic extension ending rule is expected to result in earlier bidding. In other words, when the auction has a firm closing

time, bidders are expected to delay submission until close to the deadline either to protect their information about the value of the item, or to avoid incremental bidding.

Explained in the following section, the experimental design permits empirical testing of these three hypotheses. Careful selection of ending rule and reserve treatments allow me to isolate the impact of these auction characteristics, and the use of both eBay and Yahoo permits site comparison.

3 Experimental Design

Empirical tests of the hypotheses described above are facilitated by the provision of auction services by eBay and Yahoo. It is reasonable to argue that eBay is familiar to most internet-users, and the brand name 'Yahoo' is certainly well-known.[6] Yet, Yahoo Auctions may be much less-recognized, lacking the household-name status of its rival. While small relative to eBay, trade on Yahoo auctions is not insignificant. To illustrate, searches of the "Morgan Dollars (1878-1921)" product category on eBay and Yahoo, performed November 5, 2004, revealed 12,559 and 1,209 items for sale, respectively. One-tenth the size of eBay, the coin market on Yahoo is still thick and active.[7]

Online auctions provided accessible and user-friendly means for individuals and firms to buy and sell a wide variety of items, from common goods to collectibles. Lists of sale items can be searched by keywords, broad categories and price-levels. Internet visitors may search without logging in, but bidders and sellers must register a username and password for future identification. Sellers may post product descriptions, digital images and other information on the product page. Sellers on eBay and Yahoo pay fees for listings and selected options.[8] Neither site charges bidders for market participation. Registered bidders may submit single bids, or use a proxy-bidding feature. With a proxy-bid, buyers submit their maximum willingness-to-pay value and, as price increases, bids are

[6] The main Yahoo website is the most trafficked Internet site worldwide (Yahoo, 2004).

[7] Many items available on eBay are not listed on Yahoo. Moreover, the Yahoo-eBay listing ratio for collectible coins does not hold across all common item categories; on March 12, 2005, Yahoo-eBay ratios were approximately 1:3, 1:6 and 1:20 for antique books, antique firearms and collectible beanie babies, respectively. Note that the quality of many collectibles is not systematically established as it is with graded coins, making direct product and price comparisons between the sites difficult. While suggesting that relative market thickness is not consistent across product categories, these overall differences between the sites do not detract from the remarkable results outlined below.

[8] Yahoo fees are two-part; listing fees are based on starting price, ranging from \$0.05 to \$0.75, and the final value fee is 2 percent of the final value up to \$25 and 1 percent of the remaining closing price. Reserve fees are \$0.40 or \$0.75 depending on chosen value. eBay fees are higher than Yahoo's fees. eBay listing fees range from \$0.30 to \$4.80, and the final value fee is 5.75 percent of the initial \$25 and 2.75 percent of the remaining value up to \$1,000. Reserve fees are \$1 or \$2 depending on the chosen reserve. eBay also charges for displaying more than one photo and other display options.

automatically submitted on their behalf up to their indicated maximum. Once the maximum value is reached, they can drop from the auction or adjust their maximum willingness-to-pay.

Both eBay and Yahoo use a second-price auction mechanism with sequential bidding and a private maximum bid. Participants submit a bid indicating their willingness to pay for the item, and the auction is won by the bidder who submits the highest bid. Current price is set at the second-highest bidder's maximum bid plus some small increment, and is updated as new high bids are received.[9] When a nontrivial opening bid is specified, the first bidder's standing price is the seller-specified opening value. The next bidder to bid higher than the first bidder's maximum bid faces the standing price of the first bidder's maximum bid. The auction continues similarly until time elapses, or the ending criterion is reached. Yahoo auctions allow sellers to also choose the auction ending rule. The hard-close ending rule specifies an exact time at which the auction will end. The 'going-going-gone' ending rule allows for the automatic extension of the auction by five minutes if a bid is placed close to the auction end. On the Yahoo item description screen, a small ending rule indicator appears under "Notes".[10] All eBay auctions have a fixed ending time.

3.1 The Field Experiments

The online experiments conducted on eBay and Yahoo were designed to address the three previously-outlined hypotheses. Experiments took place between August, 2003 and November, 2004. Eight types of coins from the Morgan and Peace Dollar series, described in Table 1, were purchased from a coin dealer in Southern California. Prior to purchase, the coins were professionally graded and sealed by the Numismatic Guaranty Corporation of America. Each encapsulated coin was marked with the coin's date, denomination, grade, and identification number. The choice of coins for these experiments was strategic; the coins are popular, yet not particularly rare, collectibles. That is, the market is thick enough to limit the effect of these auctions on market prices. Furthermore, the relative common nature of the auctions was unlikely to reveal these auctions as field experiments.[11] Coin experts may have more insight into valuations than non-experts, but not to the extent that

[9] On both sites, increments depend on current price, ranging from less than $1 for items valued below $100 and $100 for items valued over $5000.

[10] For the hard close ending rule, the text states: "This auction does not get automatically extended." For the automatic extension rule, the text states: "Auction may get automatically extended."

[11] This migitates any behavior changes that could arise as a consequence of bidders' awareness of the experimental aspect of the auctions.

casual buyers cannot establish their own valuations for the objects.

We created the online auctions by first logging into the sites with a username and password. Selecting the option to "Sell", we entered the sellers' interface to create the item description pages.[12] All coins were sold with nearly identical descriptions, varying only by coin age and rating, with three detailed digital photographs of the encapsulated coin.[13] All auctions were seven days in length. Both eBay and Yahoo auction websites allow sellers to choose the opening bid value as well as a secret reserve price for an item. No secret reserve price was selected. Instead, opening bid values were modified to create the reserve treatment. Shipping and handling charges (approximately $1.30 for U.S. addresses) were free to buyers in all auctions.

Eighty-eight auctions, divided into 11 batch of eight coins, were conducted in total.[14] Selected to test the hypotheses described above, the three auction treatments are: (a) Yahoo vs. eBay auction sites; (b) no-reserve vs. positive-reserve; and (c) hard-close vs. automatic extension ending rules.

Table 1: Auctioned Coins

item #	item description	PCGS book value	bulk purchase price
1	1878-S Morgan Dollar NGC Slab MS-64	105	73
2	1885-O Morgan Dollar NGC Slab MS-63	42	35
3	1898-O Morgan Dollar NGC Slab MS-65	145	89
4	1902-O Morgan Dollar NGC Slab MS-65	145	98
5	1904-O Morgan Dollar NGC Slab MS-64	60	41
6	1922-P Peace Dollar NGC Slab MS-63	32	25
7	1923-P Peace Dollar NGC Slab MS-64	55	30
8	1923-P Peace Dollar NGC Slab MS-65	165	79

Notes: Professional Coin Grading Service (PCGS) book values available online at pcgs.com. Above values listed 8/1/04. Bulk purchase price was our cost from a coin dealer in Southern CA.

Since eBay does not allow users to select the automatic extension ending rule, ending rule effects are examined for Yahoo auctions only. Positive-reserve values were set at 70 percent of the purchase price of the coins from the dealer. The no-reserve treatment used a reserve of $1, a trivial price relative to the actual value of the coins.

Specifying the hard-close auction rule, two batches of no-reserve and one batch of positive reserve

[12] Seller's accounts on eBay and Yahoo, through which payments are exchanged, had already been established for previous transactions.

[13] The text below the photographs was: "The coin shown is the exact coin you will receive. Sealed in NGC slab. Free shipping and handling with USPS first class. Picture cannot capture all details, please go with grading. Payments can be made via with paydirect, paypal, cash and money order only."

[14] I define a 'batch' as a group of eight auctions conducted simultaneously online.

auctions were conducted on Yahoo. Three batches of no-reserve and two batches of positive reserve auctions were held on eBay. This paired-design allows for comparison both between sites holding reserve value constant, and within sites varying reserve price. In addition, to examine the effect of ending rule, two batches of no-reserve and one batch of positive-reserve auctions were conducted on Yahoo with the automatic extension rule. These replications permit the isolation of ending rule effects holding reserve constant, and also the effects of reserve values in the automatic extension ending rule setting.

Both Yahoo and eBay sites maintain reputation ratings for registered users. Reputation values reflect users' reviews from previous transactions; positive feedback increases a user's rating by one point, while negative feedback reduces the rating. Since previous studies have identified reputation effects on sales (Resnick and Zeckhauser, 2002), the seller's name and reputation rating was identical for all items auctions on each site. Seller reputation values were reasonably high on both sites at 87 and 245 for Yahoo and eBay, respectively. The dataset was constructed from information gathered from auctions' bidding history files. Both Yahoo and eBay sites allow users to view summaries of auction activities, including bids, bidders' usernames and, on eBay only, all bidders' reputation ratings. Yahoo lists only winning bidders' reputation ratings. In addition, Yahoo tracks the number of pageviews.[15]

The auctions were posted online on Tuesday, Wednesday or Thursday evenings. Yahoo and eBay's planning feature allows sellers to schedule auction starts in advance, allowing all auctions in a batch to be posted at approximately the same time. The field experiments were monitored only through the seller's portal to ensure that pageview counts were not affected. Upon completion, the item information page and the bidding history page were saved electronically to preserve the results. All items were promptly shipped to the winners.

Unlike field data retrieved from online auctions (*e.g.*, Roth and Ockenfels, 2002), this experiment ensures the consistency of product quality and online descriptions, shipping fees, seller's name and reputation value, and auction length. The matched-pair design allows for direct comparison between the treatment groups, exploiting the homogeneity of the auctioned item pairs and directly addressing the testable hypotheses outlined above. The following section describes the dataset generated by

[15] Although this count does not necessarily reflect the number of unique interested users, it provides an upper bound on the number of potential bidders.

the field experiments, and highlights the important results of the statistical analysis.

4 Results

4.1 Overview of Data

The dataset consists of posted bid values and times, bidder names and reputation, and other auction attributes from 88 auctions. Five Yahoo auctions finished without a sale and were dropped from the dataset.[16] Table 2 summarizes some results. Average Yahoo revenues are lower than eBay revenues for all items; Yahoo-eBay price spreads range from approximately 20 to 65 percent. Averaging across all auctions, eBay buyers paid 35 percent more than Yahoo buyers for identical items. This disparity and its potential causes are explored more thoroughly in sections that follow.

Table 2: Descriptive Statistics - Bid Values

		item							
		1	2	3	4	5	6	7	8
revenue ($)	*Yahoo*	58.66	25.06	77.81	83.33	37.36	16.75	19.66	54.37
		(5.14)	(2.93)	(4.31)	(6.22)	(4.76)	(0.96)	(4.27)	(6.23)
	eBay	71.54	32.80	97.13	110.52	44.73	23.91	33.33	85.96
		(3.98)	(2.16)	(15.02)	(15.98)	(4.28)	(3.03)	(4.85)	(11.12)
Yahoo!-eBay price spread (%)		21.95	30.88	24.83	32.63	19.73	42.72	69.52	58.11
all bids ($)	*Yahoo*	31.26	14.84	52.34	51.95	19.10	9.04	11.41	27.71
		(18.86)	(8.30)	(26.84)	(29.08)	(12.84)	(6.84)	(7.52)	(18.63)
	eBay	54.93	25.84	66.08	75.38	31.78	18.44	25.07	60.22
		(17.34)	(7.77)	(30.52)	(33.13)	(11.67)	(6.30)	(7.87)	(23.56)
last bids only ($)	*Yahoo*	38.52	18.54	48.81	55.84	24.16	10.25	14.00	27.33
		(17.90)	(7.77)	(28.49)	(29.49)	(12.21)	(6.70)	(7.82)	(18.55)
	eBay	56.20	26.57	69.12	81.20	33.58	19.22	26.74	66.81
		(17.92)	(8.02)	(32.70)	(33.55)	(11.60)	(6.56)	(8.92)	(22.29)
# of bidders / auction	*Yahoo*	4.17	2.83	5.17	5.50	4.83	2.33	2.67	4.50
		(2.64)	(1.47)	(3.06)	(2.59)	(3.37)	(2.16)	(2.42)	(4.28)
	eBay	5.60	4.60	7.20	7.60	6.40	5.20	4.60	7.60
		(2.97)	(2.70)	(1.92)	(2.41)	(3.36)	(1.48)	(1.82)	(1.52)
# of bids / auction	*Yahoo*	8.50	7.00	9.00	11.33	10.50	3.50	6.00	7.17
		(7.82)	(6.75)	(4.43)	(6.62)	(9.05)	(3.27)	(6.39)	(7.31)
	eBay	10.00	6.40	11.00	11.20	8.00	7.40	8.00	13.00
		(6.40)	(3.05)	(5.39)	(5.36)	(4.74)	(2.61)	(2.74)	(5.43)

Notes: Standard deviations in parentheses.Yahoo!-eBay price spread is the price difference of eBay and Yahoo! as a percentage of the average price on Yahoo!

Conventional second-price auction theory rejects the idea of multiple bids, since bidding one's true valuation is a dominant strategy, yet theory presented by Ockenfels and Roth (2001) suggests that multiple bids may result from strategic responses to incremental bidding. In practice, it appears that multiple bids are not uncommon; on average, Yahoo and eBay bidders placed 1.968 and

[16] Failure to sell is not simply a case of censoring of revenue. While an unsuccessful seller loses the fees paid to the site, he may attempt to sell the item again in a subsequent auction. That is, revenue from a failed posting is not zero; it is simply delayed and eroded by additional fees.

1.588 bids each, respectively. Average values for all bids placed in the auctions by item, as well as the average of bidders' final bids, are also presented in Table 2.[17] Similar to the pattern observed in revenues, Yahoo bid values are consistently lower than those on eBay. Before reviewing results of the regression analysis, inspection of eBay and Yahoo last bids in Figure 1 reveals remarkably different distributions; Mann-Whitney tests for equality fails to suggest similarity of bid distributions (z=−3.929, p-value=0.0001). Figure 2 displays the distribution of Yahoo last bids by ending rules. The histograms appear similarly distributed and Mann-Whitney tests for equality of distributions fail to reject the hypothesis of equality (z=−0.100, p-value=0.9201). Both of these informal observations are confirmed in the results discussion below.

Figure 1: Yahoo! *vs.* eBay bids (Hard-close Auctions Only)

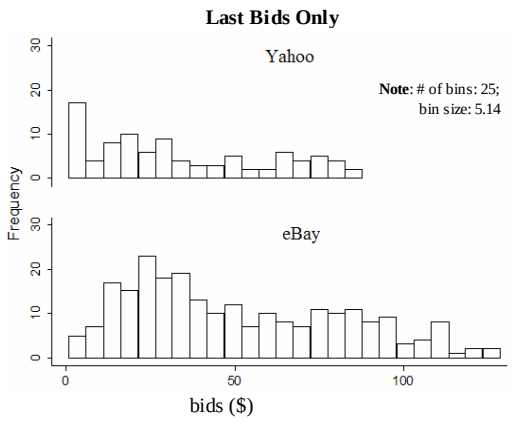

Figure 2: Yahoo Bids by Ending Rule

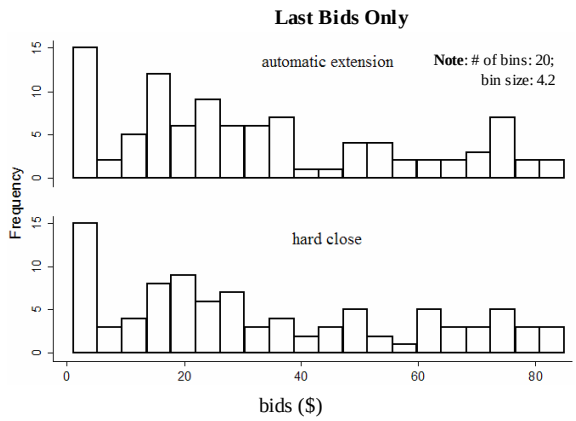

Figure includes all last bids except winners' final bids, unavailable due to the second-price nature of the auctions.

Table 3 summarizes several bid timing values from the field experiments. As expected, bids in auctions with positive reserve values tend to be closer to auction ends on both sites. Further statistical analysis presented below strengthens this informal result.

4.2 Statistical Analysis

Censoring is a central concern in the analysis of auction datasets. While online auction sites maintain records of bids, bidders, timing and page 'hits', no mechanism exists to track *potential* bidders and bids. In particular, neither Yahoo nor eBay register bids lower than the current highest bid in an auction. Therefore, the number of active bidders represents a lower bound on the true number of auction participants. Furthermore, the second-price nature of eBay and Yahoo auctions results in

[17] To separate multiple bids, I distinguish between "all bids" and "last bids", describing the collection of every bid from all bidders and only the final bid from all bidders, respectively.

the upper censoring of bid values. That is, the highest bidder's bid remains unposted in any auction and little can be done to recover this information. Despite this limitation, however, the dataset consists of all accepted bid and bidder information.

Table 3: Descriptive Statistics - Average Minutes from Auction End

		item							
		1	2	3	4	5	6	7	8
All bids									
Yahoo	no reserve	5671.87	4015.92	2711.29	4143.54	5307.70	3094.35	2475.47	3431.70
		(3718.88)	(2822.67)	(2936.82)	(3365.43)	(3476.04)	(3064.94)	(2919.77)	(3410.33)
	reserve	1494.50	401.00	3006.46	4054.64	1394.78	79.00	7.00	-
		(2943.18)	(692.37)	(2974.21)	(2793.04)	(2810.27)	-	(5.66)	-
eBay	no reserve	2637.27	2853.67	4283.16	4542.79	2836.01	2620.17	2660.80	4861.00
		(3938.41)	(3527.75)	(3674.91)	(3737.78)	(2917.70)	(2844.55)	(2728.67)	(3337.63)
	reserve	222.69	851.38	942.15	203.66	1264.58	809.31	1176.39	1367.70
		(543.16)	(1369.96)	(1524.50)	(405.32)	(1906.99)	(1499.58)	(1533.26)	(1811.55)
Last Bids Only									
Yahoo	no reserve	4652.29	3132.53	2970.52	3362.04	4465.48	2709.54	1875.2	3557.96
		(3607.34)	(3193.68)	(3058.02)	(3377.69)	(3736.00)	(3145.15)	(2312.79)	(3324.22)
	reserve	1494.5	9.66667	2177.13	3054.29	1345.33	79	7	-
		(2943.18)	(8.33)	(2775.86)	(2765.15)	(3158.64)	-	(5.66)	-
eBay	no reserve	2526.74	2479.73	4271.95	4052.86	2542.62	1873.42	2249.69	3828.32
		(3655.08)	(3596.41)	(4221.70)	(4134.76)	(3039.44)	(2438.03)	(2514.06)	(3572.30)
	reserve	296.16	737.98	1145.46	232.82	1264.58	205.44	1442.50	1395.43
		(647.02)	(1589.02)	(1671.91)	(458.98)	(1906.99)	(550.23)	(1698.00)	(1815.68)

Note: Standard deviations in parentheses. Average Minutes from End describes the number of minutes between the bid placement and the auction's end. Last Bids includes the final bid summitted by each bidder.

Twenty sets of regressions are described in Tables 4 to 8. Designed to test the hypotheses developed in section 2.2, the general form of the empirical model is

$$dep = \alpha + \gamma item + \beta_1 site + \beta_2 reserve + \beta_3 close + \varepsilon, \tag{2}$$

where *item* is an item-specific effect, *site*={1 if eBay, 0 otherwise}, *reserve*={1 if positive-reserve, 0 otherwise} and *close*={1 if hard-close, 0 otherwise}.

Following this linear regression model, the tables are organized by dependent variable: revenue, all bids, last bids and minutes between bids and auction close. Whenever possible, regressions were performed both on data from the individual sites, and data from the sites pooled. Since ending rule does not vary in eBay auctions, '*close*' is omitted from eBay-specific regressions. To control for heteroskedasticity, robust standard errors are reported.[18] Table 4 presents four sets of regressions of revenue on auction characteristics. To allow for nonlinearities in item-specific variables, wholesale price or appraisal values and appraised values-squared are included in regressions (4.3) and (4.4)

[18] White's general test for heteroskedasticity was conducted for all regressions. The null hypothesis of constant variance is rejected in all cases.

instead of item dummy variables.[19] R^2-values in Table 4 are high, ranging from 0.85 to 0.97, suggesting that these covariates explain a large amount of the variation in revenue.

Table 4: Revenue Regression Results

Dependent variable: revenue

	(4.1)		(4.2)			(4.3)			(4.4)		
	all auctions	Yahoo	all auctions	Yahoo	eBay	all auctions	Yahoo	eBay	all auctions	Yahoo	eBay
item effects	yes	yes	yes	yes		no	no		no	no	
site effect	**15.679**		**15.053**			**14.842**			**14.551**		
	(1.87)		(1.86)			(1.94)			(2.86)		
ending rule effect	0.215	0.027	0.508	0.117		0.416	0.155		0.738	0.488	
	(1.96)	(1.46)	(2.01)	(1.50)		(2.18)	(1.97)		(3.28)	(3.22)	
reserve effect			**4.666**	1.365	**6.528**	**4.893**	2.853	**6.528**	**5.633**	3.816	6.528
			(1.77)	(1.55)	(2.58)	(1.79)	(1.78)	(2.65)	(2.53)	(3.33)	(3.84)
wholesale price						**1.006**	**0.887**	**1.133**			
						(0.03)	(0.03)	(0.06)			
book value									**1.256**	**1.292**	**1.238**
									(0.17)	(0.23)	(0.21)
(book value)²									**-0.004**	**-0.004**	**-0.003**
									(0.00)	(0.00)	(0.00)
constant	**57.228**	**58.616**	**55.602**	**58.027**	**68.925**	**-13.855**	**-5.967**	**-6.669**	**-31.183**	**-28.109**	**-19.225**
	(2.08)	(2.74)	(2.33)	(3.10)	(1.63)	(2.95)	(2.67)	(2.68)	(7.65)	(9.35)	(8.05)
# of observations	83	43	83	43	40	83	43	40	83	43	40
R^2	0.93	0.97	0.94	0.97	0.94	0.93	0.94	0.93	0.86	0.85	0.87

Notes: Robust standard errors in parentheses. Values in bold are statistically significant at a 5 percent level. "Item effects" indicates whether item dummy variables were included in the regression."Site effect" equals 1 if auction site was eBay. "Ending rule effect" equals 1 if auction end was fixed. "Reserve effect" equals 1 if reserve value is non-zero. Wholesale prices are for a bulk coin purchase in Southern CA. Book values are the PCGS book values available online at pcgs.com.

Tables 5 and 6 report results for similar sets of regressions on all submitted bids and final bids, respectively. R^2-values are approximately 0.5, suggesting that the linear model explains revenues better than it explains all participants' bids.

Table 5: All Bids Regression Results

Dependent variable: all bids

	(5.1)		(5.2)			(5.3)			(5.4)		
	all auctions	Yahoo	all auctions	Yahoo	eBay	all auctions	Yahoo	eBay	all auctions	Yahoo	eBay
item effects	yes	yes	yes	yes	yes	no	no	no	no	no	no
site effect	**17.532**		**14.539**			**14.207**			**14.640**		
	(1.81)		(1.71)			(1.71)			(1.80)		
ending rule effect	2.180	2.720	2.852	3.232		2.620	2.512		1.147	1.293	
	(2.06)	(2.04)	(1.95)	(1.93)		(1.96)	(1.95)		(2.05)	(2.04)	
reserve effect			**21.716**	**20.053**	**22.833**	**21.976**	**22.343**	**22.432**	**22.710**	**23.594**	**22.808**
			(1.44)	(1.93)	(1.88)	(1.41)	(1.77)	(1.84)	(1.55)	(2.02)	(2.09)
wholesale price						**0.659**	**0.553**	**0.764**			
						(0.03)	(0.04)	(0.04)			
book value									**1.019**	**0.830**	**1.179**
									(0.09)	(0.14)	(0.12)
(book value)²									**-0.003**	**-0.003**	**-0.004**
									(0.00)	(0.00)	(0.00)
constant	**32.701**	**29.981**	**31.325**	**28.167**	**51.731**	**-15.551**	**-8.767**	**-5.598**	**-33.014**	**-22.410**	**-26.676**
	(2.23)	(2.81)	(2.11)	(2.71)	(2.28)	(1.76)	(1.96)	(1.75)	(3.85)	(5.33)	(4.64)
# of observations	753	378	753	378	375	753	378	375	753	378	375
R^2	0.49	0.41	0.56	0.47	0.58	0.56	0.45	0.57	0.52	0.40	0.54

Notes: Robust standard errors in parentheses. Values in bold are statistically significant at a 5 percent level. "Item effects" indicates whether item dummy variables were included in the regression."Site effect" equals 1 if auction site was eBay. "Ending rule effect" equals 1 if auction end was fixed. "Reserve effect" equals 1 if reserve value is non-zero. Wholesale prices are for a bulk coin purchase in Southern CA.

[19] Wholesale price-squared is not statistically-significant and, therefore, was omitted from the reported regressions.

Table 6: Last Bids Regression Results

Dependent variable: last bids

	(6.1)		(6.2)			(6.3)			(6.4)		
	all auctions	Yahoo	all auctions	Yahoo	eBay	all auctions	Yahoo	eBay	all auctions	Yahoo	eBay
item effects	yes	yes	yes	yes	yes	no	no	no	no	no	no
site effect	**18.604**		**15.717**			**15.644**			**16.193**		
	(2.55)		(2.41)			(2.38)			(2.47)		
ending rule effect	1.152	1.705	1.676	2.030		1.374	1.295		0.213	0.518	
	(3.04)	(3.01)	(2.85)	(2.82)		(2.83)	(2.78)		(2.95)	(2.90)	
reserve effect			**20.498**	**18.850**	**20.726**	**20.460**	**21.002**	**20.610**	**20.699**	**21.123**	**20.074**
			(1.81)	(2.65)	(2.33)	(1.77)	(2.45)	(2.25)	(1.97)	(2.93)	(2.56)
wholesale price						**0.690**	**0.527**	**0.817**			
						(0.04)	(0.05)	(0.05)			
book value									**1.093**	**1.062**	**1.082**
									(0.12)	(0.19)	(0.15)
(book value)²									**-0.004**	**-0.004**	**-0.003**
									(0.00)	(0.00)	(0.00)
constant	**37.171**	**37.773**	**34.918**	**34.614**	**52.626**	**-15.393**	-4.777	**-6.453**	**-34.393**	**-27.042**	**-22.077**
	(3.03)	(3.80)	(2.84)	(3.75)	(3.05)	(2.58)	(2.75)	(2.19)	(5.14)	(6.98)	(5.63)
# of observations	436	195	436	195	241	436	195	241	436	195	241
R^2	0.48	0.38	0.56	0.45	0.60	0.56	0.42	0.60	0.52	0.38	0.57

Notes: Robust standard errors in parentheses. Values in bold are statistically significant at a 5 percent level. "Item effects" indicates whether item dummy variables were included in the regression."Site effect" equals 1 if auction site was eBay. "Ending rule effect" equals 1 if auction end was fixed. "Reserve effect" equals 1 if reserve value is non-zero. Wholesale prices are for a bulk coin purchase in Southern CA.

Tables 7 and 8 examine the timing of bid submission. The dependent variable reflects the number of minutes between the bid and the auction close. Negative (positive) coefficient values indicate where increases in the variable correspond with delayed (early) bid submission. Regressions (7.1) and (7.2) explain bid timing in terms of auction characteristics, while (7.3) and (7.4) introduce bidders' experience as an explanatory variable. While eBay posts the reputation of all participants, only winning bidders' reputation ratings are available for Yahoo auctions.

Table 7: Bid Timing Regression Results for Yahoo! and eBay

Dependent variable: Minutes between bid and auction close

	(7.1) all bids		(7.2) last bids only		(7.3) last bids only	(7.4) winners only
	all auctions	Yahoo!	all auctions	Yahoo!	eBay	all auctions
item effects	yes	yes	yes	yes	yes	yes
site effect	-406.683		-438.083			-1217.650
	(308.63)		(415.36)			(744.46)
ending rule effect	-342.213	-223.327	47.223	118.351		663.065
	(345.36)	(344.95)	(469.30)	(476.84)		(730.53)
reserve effect	**-2311.512**	**-1828.738**	**-2063.783**	**-1888.365**	**-2151.031**	**-685.001**
	(238.33)	(485.74)	(283.45)	(551.71)	(325.85)	(302.24)
"Intermediate" experience					**1417.973**	465.300
					(600.22)	(759.94)
"Advanced" experience					-380.027	90.465
					(481.50)	(674.62)
"Expert" experience					-299.737	-146.272
					(484.94)	(377.95)
constant	**4576.589**	**5592.761**	**3671.758**	**4397.104**	**2322.800**	747.307
	(424.49)	(547.05)	(524.37)	(720.68)	(625.60)	(402.29)
# of observations	749	375	432	192	239	82
R^2	0.11	0.11	0.10	0.19	0.19	0.14

Notes: Robust standard errors in parentheses. Values in bold are statistically significant at a 5 percent level. "Item effects" indicates whether item dummy variables were included in the regression."Site effect" equals 1 if auction site was eBay. "Ending rule effect" equals 1 if auction end was fixed. "Reserve effect" equals 1 if reserve value is non-zero. Experience effects represent quartiles of the reputation rating of bidders, where the "Novice" experience dummy variable was omitted to avoid collinearity. "Intermediate" experience equals 1 if reputation is [46, 127]. "Advanced" experience equals 1 if reputation in [128,262]. "Expert" experience equals 1 if reputation greater than 262.

Reputation values range from 1 to 4368 on eBay ($mean$ = 242.5, $stdev$ = 458.6), and 1 to 1418 for Yahoo bidders ($mean$ = 232.1, $stdev$ = 420.1). Because preliminary analysis suggested the strong influence of reputation outliers, I include reputation quartiles, '*novice*', '*intermediate*', '*advanced*' and '*expert*', to control for differences in online auction experience. Table 8 reports results of timing regressions by experience level. Note again that Yahoo bidders' reputations are excluded from results in Table 8 since reputation values are not available. R^2-values are considerably lower for timing regressions compared to the revenue regressions, suggesting that the linear model may not capture all causes of variation in bid timing.

Table 8: eBay Bid Timing Regression Results

Dependent variable: Minutes between bid and auction close

	(8.1) Novice bidders		(8.2) Intermediate bidders		(8.3) Advanced bidders		(8.4) Expert bidders	
	all bids	last bids only	all bids	last bids only	all bids	last bids only	all bids	last bids only
item effects	yes	yes	yes	yes	yes	yes	yes	yes
reserve effect	**-2987.918**	**-2286.057**	**-4100.543**	**-4150.040**	**-2236.710**	-432.386	**-2528.590**	**-2811.404**
	(595.92)	(757.40)	(859.72)	(846.75)	(499.74)	(550.83)	(522.73)	(586.43)
reputation	-12.705	-8.802	16.525	14.395	3.611	-2.500	0.198	0.073
	(27.36)	(36.06)	(25.87)	(26.86)	(8.28)	(5.68)	(0.39)	(0.43)
constant	**1987.539**	1945.711	3605.936	3297.446	**3620.937**	2755.516	807.110	1890.237
	(936.39)	(1189.16)	(2529.37)	(2740.08)	(1809.79)	(2275.24)	(674.92)	(1221.81)
# of obs.	73	46	77	68	149	66	74	59
R^2	0.43	0.27	0.22	0.22	0.14	0.05	0.38	0.37

Notes: Robust standard errors in parentheses. Values in bold are statistically significant at a 5 percent level. "Item effects" indicates whether item dummy variables were included in the regression. "Reserve effect" equals 1 if reserve value is non-zero. "Novice" users have reputation in [0,46]. "Intermediate" users have reputation in [46,127]. "Advanced" users have reputation in [128,262]. "Expert" users have reputation greater than 262

The following subsections use the statistical evidence in Tables 4 to 8 to evaluate the three major predictions, and discuss the findings. The consistently-statistically significant site effect is addressed in part H1, while subsection H2 discusses the positive reserve effect on revenues, bids and timing. The next subsection examines the evidence that ending rule affects neither bidder behavior nor auction revenue, and section 4 concludes with a summary of the statistical findings.

H1: Site effect

As discussed in section 2.2, a site dummy variable ('*site*') is included in all pooled regressions to account for any effects of the number of bidders-price spread interaction. Ellison, Fudenberg and Möbius (2004) suggest that the two sites coexistence relies on prices being approximately equal between the sites and, controlling for auction characteristics, I expect no difference to exist between Yahoo and eBay revenues. Instead, results indicate significant and pervasive differences between bid values and revenues on the sites.

Site dummy coefficient values in Table 4 suggest that, when controlling for other item and auction differences, eBay revenues are approximately \$15 above those on Yahoo. Regressions in Table 5 and 6 strengthen the claim that eBay differs significantly from Yahoo, with consistently-statistically significant and positive site effect coefficients. Comparing regressions with and without reserve effects and with item fixed effects, linear wholesale coin values and bookvalues, these results appear robust to model specification.[20]

The magnitude of the difference is remarkable, averaging one-quarter of the wholesale price of the coins. Since the bidder count and price spread components of the site variable cannot be directly disentangled, further analysis is required to identify whether the revenue disparity can be attributed to differences in the number of bidders, differences in valuations of eBay and Yahoo bidders, or both. While the independent private values model with uniformly-distributed valuations suggests that more bidders results in higher revenues, and eBay has inarguably larger user pools, the presence of more sale items could offset this effect. In fact, these offsetting effects motivate the stress on buyer-seller ratios in the work of Ellison, Fudenberg and Möbius (2004).

As mentioned in section 2.2, the number of bidders is endogenous to the auction mechanism. Ideally, I could extract information on bidder counts directly from a well-specified regression, without the collinearity issues caused by the inclusion of the site variable. Instead, however, an *ad hoc* two-stage regression approach aims to separate the confounding bidder count and valuation effects. The hedonic first-stage regresses the number of bidders on item, site, reserve and ending rule effects to generate predicted bidder counts, $\hat{n}$,

$$\hat{n} = \alpha_0 + \alpha_1 item + \alpha_2 site + \alpha_3 reserve + \alpha_4 close \tag{3}$$

The second-stage regresses revenues on the predicted number of bidders and a site variable, where

$$revenue = \gamma_0 + \gamma_1 \hat{n} + \gamma_2 site + \varepsilon \tag{4}$$

Results of the first- and second-stage regressions are reported in Table 9. Failure to reject of the null hypothesis of γ_2=0 implies that variation in the number of bidders may explain the wide revenue

[20] Regressions on ln(revenue) were also conducted. Because coefficients' signs and significance are qualitatively consistent with the linear form, results have not been included.

variation between sites. That is, the number of bidders alone may be driving the price disparity.

Table 9: Two-stage site effect regressions

	First-stage		Second-stage
Dep. Variable:	number of bidders	**Dep. Variable:**	Revenue
item effects	yes	item effects	no
site effect	**2.344**	predicted # of bidders	**7.394**
	(0.53)		(0.98)
ending rule effect	-0.083	site effect	-0.150
	(0.59)		(5.80)
reserve effect	**-3.039**	constant	**17.537**
	(0.46)		(5.57)
constant	**4.918**		
	(0.73)		
# of obs.	88		88
R^2	0.49		0.28

Notes: Robust standard errors in parentheses. Values in bold are statistically significant at a 5 percent level. "Item effects" indicates whether item dummy variables were included in the regression."Site effect" equals 1 if auction site was eBay. "Ending rule effect" equals 1 if auction end was fixed. "Reserve effect" equals 1 if reserve value is non-zero.

Although these results relate revenue differences to bidder counts, this statistical approach does not address *why* eBay buyers and Yahoo sellers are not pursuing opportunities to increase their profits on the alternate site. It seems reasonable to argue that search and switching costs would need to be large to deter users from re-listing or re-bidding on a rival site, or that payment default rates would need to be substantial to explain site premium. Section 5 discusses possible rationale at length to understand this continued arbitrage opportunity.

Bid timing regressions in Table 7 show no difference in bid submission timing between sites, suggesting that Yahoo and eBay bidders employ similar time-related strategies. Further discussion of the bid timing results relate to the reserve hypothesis, H2, and the ending rule hypothesis, H3.

H2: Reserve effect

Both Yahoo and eBay allow sellers to choose the opening bid value for a given auction. The reserve effect on revenue and bid timing is captured by the dummy variable '*reserve*'. Coefficients are expected to be equal to zero in all revenue-related regressions where more than one actual bid is received. In addition, coefficient values are expected to be positive for regressions on all- and last-bids, since high reserve values screen out low-bidding participants. Reserve coefficient expectations are ambiguous for bid timing regressions.

When revenue data is pooled across sites in regressions (4.2)-(4.4), reserve coefficients are consistently positive. This suggests that selecting the positive reserve value increased overall auction revenues by approximately $5, contrary to expectation. However, as predicted, reserve effects for

Yahoo alone are not significantly different from zero. Results for eBay are inconsistent, and the statistical effect of the positive reserve appears sensitive to model specification. Overall, the effect of reserve on revenue is ambiguous. In contrast, the reserve effects on all- and last-bids in Tables 5 and 6 are as expected; positive reserve values appear to screen out low-bidding participants and raise average bid values by approximately $21.

Regressions on the bid timing variable in Tables 7 and 8 indicate that positive reserves result in delayed bid submission.[21] For example, the reserve coefficient in regression (7.1) suggests that positive reserves delay all bidding by more than 38 hours, while results from regression (7.4) indicate that positive reserves delay winning bids by an average of 11 hours. Two possible effects may be at play; the positive reserve value may screen out low-bidding participants who would tend to submit bids early in the auction, or the non-trivial opening bid may cause bidders to wait to submit bids later in the auction. The first effect appears most plausible in light of the previous regression results on all- and last-bid values in Tables 5 and 6.

H3: Ending rule effect

Yahoo allows sellers to select a hard-close or an automatic extension ending rule, while eBay uses only the hard-close rule. Although there were no expectations relating to revenue differences and ending rule, work by Ockenfels and Roth (2001) suggests that the automatic extension rule eliminates the benefits of last-minute bidding. That is, in the regressions on bid timing, I expected the coefficient on the ending rule dummy variable ('*close*') to be significant and negative. A negative coefficient value would suggest that bidders in the hard-close auctions delay their bids.

In fact, in the majority of regressions presented in Tables 4 to 7, the ending rule coefficient fails to achieve statistical significance. Although not significant, coefficient values in the revenue regression in Table 4 are consistently positive and small in magnitude. Results suggest that even if ending rule does affect revenue, the impact of selecting a hard-close over the automatic extension ending rule is less than a $1 increase.

More surprisingly, examining bid timing, ending rule again appears to have little effect. Ending rule coefficients in regressions (7.1) on all bids takes the expected sign, but are not significant, while

[21] Note that a negative coefficient value in the regressions on time indicates fewer minutes between bid submission and the auction close. That is, a negative coefficient suggests that bidders delayed their bids.

coefficient values in last and winning bids regressions (7.2) and (7.3) are positive and not significant. These ambiguous results suggest that ending rule choice was immaterial in the Yahoo auctions.

No Yahoo auctions were extended under the going-going-gone rule, a subgame perfect result according to Ockenfels and Roth (2001), yet bidders' behavior appears unaffected by the auction feature. One might speculate that the relatively discrete position of the ending rule indicator on the Yahoo selling page might contribute to the feature's insignificance. Yet, were bidders who typically submit last-minute bids unaware of the changed end rule, one might reasonably expect to see at least a small number of auctions extended "accidentally".

4.3 More Results and Summary

Although the identification of substantial revenue disparity between eBay and Yahoo represents the most remarkable result of the field experiment analysis, the rich dataset permits discussion of other interesting results as well.

Discussed in section 1.1, Ockenfels and Roth (2001) and Wilcox (2000) suggest a relationship between bidder experience and late-bidding behavior. Taking reputation as a proxy for bidder experience in Table 7, the coefficient on the dummy variable for intermediate bidders is positive and statistically-significant in regression (7.3). This result suggests that intermediate bidders tend to bid earlier than novice bidders. Segmented by reputation quartiles, the results presented in Table 8 show that all reputation coefficients fail to achieve statistical significance. However, intercept values indicate that novice and expert bidders tend to bid closer to the auction deadline on average; bidders who are new to online auctions may be reluctant to bid early-on, while expert users may bid later to protect their information about true coin value and to avoid triggering incremental bidding. Experience breeds confidence, but not necessarily wisdom; on average, intermediate bidders submit the earliest bids, followed by slightly more advanced users. This pattern suggests an "unlearning-relearning" phenomenon. A novice bidder may adopt the late-bidding strategy by accident, and then develop a boldness to bid early as he gains experience. After much exposure to the mechanism and strategies of others, the bidder "relearns" the benefits of late-bidding behavior.

5 Discussion

While results in section 3.3 indicate repeated opportunities for arbitrage and attribute the phenomenon to high bidder counts on eBay, statistical results alone do little to answer *why* the disparity persists. Free from other motives or costs, one would expect rational buyers to switch to Yahoo and rational sellers to use eBay until gains from switching approach zero. The following discussion examines several possible explanations: limited information about alternative platforms, high registration switching costs, high value on established reputation and low trust in rival site's reliability.

The real world is not one of perfect information; is it possible that these eBay buyers and Yahoo sellers are simply not aware that the other service exists? Searches on several popular online search engines provides some evidence to suggest that both Yahoo and eBay are easy to find on the Internet; keywords 'auction', 'internet auction' and 'online auction' put Yahoo and eBay in the top five results for Google and Yahoo search services.[22] If the field experiment participants were all novice Internet users, then we could speculate that search engines directed them to either eBay or Yahoo, and that they were unaware of other options. Yet, with average Yahoo and eBay reputation values of 232.1 and 242.5, respectively, the majority of participants are quite experienced.[23] Therefore, the argument that many eBay users are ignorant in terms of service selection is unconvincing.

Even if aware of the alternatives, high switching costs may prevent users from moving their business between eBay and Yahoo. Registration cost alone is low; on both sites users complete identification information and select a username and password. Yahoo simplifies its sign-up process by allowing uesrs with Yahoo e-mail addresses to bypass the personal information page.

While registration is not costly in terms of time or effort, some users may feel invested in terms of reputation rating on a site. In general, buyer reputation matters little, since a seller can hold an item until payment is received. However, many of our bidders are also sellers in the collectible coin market.[24] From a bidder's perspective, high seller reputation values may signal quality and reliability. Reputation points can be gained through feedback from both selling and purchasing activities and are not allocated based on the value of the transaction. That is, users may boost their rating through many low-value transactions; 10 one-dollar purchases are indistinguishable from 10

[22] Searches were conducted on November 20, 2004.

[23] Of the 31 winning bidders on eBay, 24 had multiple coin-related transactions in their buying and selling histories.

[24] eBay users' buying, selling and feedback histories were examined for evidence of participation on both sides of the coin market; ten of 31 winning bidders were also actively selling collectible coins.

thousand-dollar transactions.[25] Casually, it seems plausible that users value positive feedback scores; rebuilding reputation stocks after switching services could be costly.

When one considers the magnitude of the price disparity, however, this argument becomes much weaker. If the disparity were mere cents, then this reputation argument might be convincing, but with 20 to 60 percent premiums, reputation would need to be extremely valuable to deter switching. Consider a user with a reputation of 100 on eBay. Since Yahoo lists many items valued at or below \$1 (often with the option to buy without bidding), the user could rebuild his reputation for approximately \$100.[26] With the average eBay-Yahoo price disparity, if he purchases seven Yahoo coins, the user's savings have more than offset switching costs.[27] Clearly, this assumes user preferences over reputation but not site itself.

Neither eBay nor Yahoo endorse the reliability of their sellers, yet, is it possible that eBay bidders simply do not trust Yahoo members? Perhaps Yahoo sellers have a reputation for failing to deliver products, or selling damaged or counterfeit goods. Are eBay bidders paying a premium to avoid default? A back-of-the-envelope calculation suggests that default rates would need to exceed 18 percent to deter switching.[28] That is, for a bidder to be indifferent between the sites, he would need to believe that one of five transactions would result in total loss. Even if this is a reasonable estimate of Yahoo sellers' trustworthiness, it is not an equilibrium explanation. No credible signal exists for reliable sellers, as both good and bad sellers are motivated to switch to eBay.

Although these proposed rationales fail to completely explain the existence of persistent revenue disparity, they raise interesting economic questions about the value of reputation, the importance of switching costs and online trust.

Regardless of underlying reasons, the eBay-Yahoo revenue disparity is substantial and economically interesting. We may be witnessing an unexploited economic opportunity or a market in transition.

[25] Although negative ratings are rarer and more informative, the auction services promote positive ratings by simply subtracting negative from positive feedback (Resnick and Zeckhauser, 2002).

[26] This assumes that sellers generally provide feedback to the buyer.

[27] Insufficient purchases to recoup switching costs does not appear to be relevant for many participants. Winning bidders' user histories, listing all transactions in the previous 30 days, were examined on March 12, 2005. Only 4 of the 31 winners had not recently participated in a coin-related auction. In fact, these active collectors had purchased between 2 and 76 coins during that month-long period alone.

[28] A buyer with valuation V is indifferent between the sites where $(1\text{-}\lambda)V\text{-}P_y = V\text{-}P_e$,implying a Yahoo default rate, λ, of $\lambda = \frac{P_e - P_y}{V}$. Estimate V as the PCGS book values, and P_e and P_y as the average revenue by coin by site (Table 2). The implied default rate is 18 percent, the average λ across the coins.

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