

How much is a Dollar Worth? Tipping versus Equilibrium Coexistence on Competing Online Auction Sites*

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Abstract

The equilibrium model of Ellison, Fudenberg, and Möbius (2004) predicts that, if two competing auction sites are coexisting, then seller revenues and buyer-seller ratios on each site should be approximately equal. We examine these hypotheses using field experiments selling identical items on the eBay and Yahoo auction sites. We find evidence that is inconsistent with the equilibrium hypotheses, and suggest that the eBay-Yahoo market is in the process of tipping. Robust statistical tests indicate that revenues on eBay are consistently 20 to 70 percent higher than those on Yahoo. In addition, eBay auctions attract approximately two additional buyers per seller than equivalent Yahoo auctions. We also vary the Yahoo ending rule from a hard close to soft close but find no statistically or economically significant changes in revenue or numbers of bidders. Moreover, the magnitude of the revenue and buyer-seller ratio disparities remain inconsistent with the notion of equilibrium coexistence even after accounting for various differentiators between the sites.

Keywords: Tipping, equilibrium coexistence, field experiments, auctions

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1 Introduction

With over 83 million active users listing more than one billion items per year, eBay dominates the online auction industry (eBay, 2008). In 2001, it had a 64.3% market share in the US (Nielsen/NetRatings, 2001). At the time, eBay dwarfed Yahoo, its most notable rival; however, even with a mere 3% market share, Yahoo Auctions had hundreds of thousands of listings and members.¹ Both sites brought 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.”

Competition in global online auction markets has often been “winner-take-all.” In 2001, Yahoo overwhelmed eBay in Japan while, in 2002, eBay’s dominance forced the closure of Yahoo Auctions in Europe. The two rivals seemed to fight to a draw in the US market. That situation changed in June 2007 when Yahoo Auctions shuttered its North American operations, a move that coincided with a management shake-up that saw the return of Jerry Yang as Yahoo CEO.

While the pattern of competition between eBay and Yahoo suggests that tipping to a single platform is inevitable, Ellison, Fudenberg and Möbius (2004) offer a model where both platforms can coexist in equilibrium.² They suggest that “the law of one price” should hold across competing sites; that is, eBay and Yahoo buyers should pay approximately the same amount for identical items. Furthermore, coexisting sites should have similar ratios of buyers to sellers. When a market is in the process of tipping, there is no reason to expect either similar prices or buyer-seller ratios across platforms.

To study tipping and coexistence, we conduct a series of field experiments with collectible coins, comparing prices and buyer-seller ratios across platforms. Field experiments offer several advantages over data from uncontrolled transactions. First, field experiments eliminate the problem of unobserved product and seller heterogeneity. Second, by using experiments, we control for difference in product mix across the sites. Finally, experiments let us isolate the effects of selling procedure without the usual endogeneity problems.

We find little evidence of equilibrium coexistence in the US market. The law of one price did not hold; eBay buyers paid 20 to 70% more than Yahoo buyers for identical items. Moreover, buyer-seller

¹ubid.com and egghead.com had 15 and 4 percent of online auction market share in 2001, respectively. Both sites differ from eBay and Yahoo: ubid provides business-to-buyer auction services only, while egghead auctioned computers and computing accessories before being acquired by Amazon.com in December, 2001.

²See also Ellison and Fudenberg (2002) for a more general treatment.

ratios were far from equal; an eBay auction attracted, on average, 50% more buyers per seller than an identical Yahoo auction. We supplement our experimental results with field data that confirm not only the presence of the price and buyer-seller ratio disparity, but also its persistence over time. Switching costs, vertical differentiation, trust, and liquidity cannot account for the magnitude of the disparity. However, a model where platform choice is driven by imitation dynamics can rationalize our results.

Our empirical work examines one specific category of products, yet the tipping phenomenon has widespread relevance. First, Yahoo's persistent presence in the US market may have provided a check on eBay's market power; Yahoo's exit has obvious antitrust implications. Our findings also have important policy implications for China, India and other developing markets where competition among online auction platforms is still in flux. Indeed, in these areas, Yahoo and eBay are rapidly acquiring smaller auction platforms. We believe our results suggest that competition authorities in these countries must scrutinize these transactions if they wish prevent a single player from exerting considerable market power.

Online auctions are not unique in their tipping potential. Our work has implications for other "two-sided markets" (see Rochet and Tirole, 2003). For instance, the online dating industry shares many of the features of online auctions. Will dating end as "winner-takes-all," or can sites like Yahoo Personals and Match.com continue to coexist?

We also use the field experiment data to test the effect of ending rules and reserve prices on auction revenues. By allowing the seller to choose either a fixed or variable ending time, Yahoo offers an ideal venue for reexamining the observations about ending rule effects first made by Roth and Ockenfels (2002). They observed that hard-close auctions on eBay led to considerably more late bidding than did soft-close auctions on Amazon. The theory model in Ockenfels and Roth (2006) rationalizes this difference and implies further that expected revenues should be higher in soft-close auctions. Of course, it is difficult to test this hypothesis using field data owing to the many differences between the two auction platforms. Using controlled laboratory experiments, Ariely, Ockenfels and Roth (2005) observe higher revenues and earlier bidding in soft-close auctions. To our knowledge, we are the first to study the effects of ending rules using field experiments. Somewhat surprisingly, at least compared to our prior beliefs, we find that the choice of ending rule on the Yahoo site has no effect on bid timing, number of bidders or auction revenues.

The remainder of this section highlights some additional related work, both theoretical and em-

pirical. Section 2 derives the testable predictions of the Ellison *et al.* model. Section 3 outlines the experiments. Section 4 describes key results of the statistical analysis. Section 5 explores several alternative hypotheses. A model of imitation dynamics capable of rationalizing the data appears in Section 6. Our conclusions appear in Section 7.

1.1 Related Literature

The question of when markets will tip dates back to the seminal paper of Schelling (1972). More recent theoretical studies examining competing markets include, among others, Baye and Morgan (2001), Caillaud and Jullien (2003), Ellison and Fudenberg (2002 and 2003), Gehrig (1998), McAfee (1993), Peters and Severinov (1997), Rochet and Tirole (2003), Schwartz and Ungo (2003), and van Raalte and Webers (1998). While there is a burgeoning literature on field experiments using auctions (cf. Hossain and Morgan, 2006; Jin and Kato, forthcoming; Katkar and Lucking-Reiley, 2000; List and Lucking-Reiley, 2000 and 2002; Lucking-Reiley, 1999 and 2000; as well as Reiley, 2005 and 2006), to the best of our knowledge, we are the first to examine the question of tipping versus equilibrium coexistence of competing auction sites using field experiments.

2 Theory

In this section, we show that the model of Ellison *et al.* (hereafter EFM) offers two testable implications. In that model, two competing effects determine buyer and seller location: The “scale effect” leads to concentration since more buyers and sellers on a single site lead to higher surplus for all participants. The countervailing “market impact effect” favors site multiplicity since competition on the same side of the market decreases the surplus of a given participant—both buyers and sellers prefer to locate where they compete with fewer other agents of the same type. EFM offer conditions under which these offsetting effects permit the equilibrium coexistence of auctions with very unequal market shares.

Consider the following version of the model: Two auction sites compete in a market with B buyers and S sellers. Each seller wishes to sell one unit of a homogeneous product. Each buyer has unit demand for the good and a willingness to pay of v , where v is drawn from a uniform distribution on the unit interval. The objects are allocated by uniform price auctions on two competing online auction sites $a \in \{e, y\}$, where e and y are mnemonics for eBay and Yahoo. Buyers and sellers simultaneously

choose the site a on which they will trade. All agents are assumed to “single-home”—they restrict their activities to only one site. Let (s_a, b_a) denote the number of sellers and buyers choosing to participate on site a . After participants have chosen their preferred platform, buyers learn their valuations and the auctions are conducted.

Given an allocation of buyers and sellers, the payoff to a seller is the price received. When b_a buyers and s_a sellers participate on site a and $b_a > s_a + 1$ (i.e. there is no excess supply), then the expected price is simply the expected value of the $s_a + 1$ st highest of b_a draws from a uniform distribution:

$$u_s(s_a, b_a) = \bar{p}(s_a, b_a) = \frac{b_a - s_a}{b_a + 1} \quad (1)$$

A buyer’s payoff is equal to her expected surplus—the difference between her willingness to pay and the expected price paid, times the probability of receiving an item. Conditional on receiving an item, a buyer’s expected willingness to pay is $E[v|v > v^{s_a+1:b_a}]$, where $v^{s_a+1:b_a}$ is the realized price:

$$\begin{aligned} w(s_a, b_a) &= E[v|v > v^{s_a+1:b_a}] \\ &= \int_0^1 \left(\int_x^1 v \frac{1}{1-x} dv \right) f^{s_a+1:b_a}(x) dx \\ &= \int_0^1 \left(\frac{1+x}{2} \right) f^{s_a+1:b_a}(x) dx \end{aligned}$$

Since $f^{s_a+1:b_a}(x)$ is a Beta density with parameters $b_a - s_a$ and $s_a + 1$, it follows that

$$w(s_a, b_a) = \frac{1}{2} \left(\frac{2b_a - s_a + 1}{b_a + 1} \right)$$

The buyer’s probability of receiving an object is equal to the seller-buyer ratio on the site since buyers are *ex ante* identical. Thus, the probability that a buyer receives an object is simply s_a/b_a and her expected payoff is

$$\begin{aligned} u_b(s_a, b_a) &= (w(s_a, b_a) - \bar{p}(s_a, b_a)) \Pr(v > v^{s_a+1:b_a}) \\ &= (w(s_a, b_a) - \bar{p}(s_a, b_a)) \frac{s_a}{b_a} \\ &= \frac{1}{2} \frac{s_a(s_a + 1)}{b_a(b_a + 1)} \end{aligned} \quad (2)$$

An equilibrium consists of an allocation of buyers and sellers such that neither type has an incentive

to switch platforms. In their Proposition 1, EFM show that the following inequalities hold in any quasi-equilibrium:³

$$\begin{aligned} u_s(s_y, b_y) - u_s(s_y + 1, b_y) &\geq u_s(s_y, b_y) - u_s(s_e, b_e) \\ u_s(s_e, b_e) - u_s(s_e + 1, b_e) &\geq u_s(s_e, s_e) - u_s(s_y, b_y) \end{aligned}$$

Using equation (1), we have

$$\begin{aligned} \bar{p}(s_y, b_y) - \bar{p}(s_y + 1, b_y) &\geq \bar{p}(s_y, b_y) - \bar{p}(s_e, b_e) \\ \bar{p}(s_e, b_e) - \bar{p}(s_e + 1, b_e) &\geq \bar{p}(s_e, b_e) - \bar{p}(s_y, b_y) \end{aligned}$$

The left-hand side of these inequalities is the change in price when one additional seller participates on a given site. Empirically, the addition of a single seller in a relatively thick market is likely to have little effect on price. Formally, the price difference is no more than the price change associated with one additional seller on either site. This implies:

Hypothesis 1 (Price Equalization) If eBay and Yahoo are coexisting in equilibrium, then the average prices on the two sites for the same item should be approximately equal.

In their Proposition 1, EFM derive the following quasi-equilibrium conditions for buyers:

$$\begin{aligned} u_b(s_y, b_y) - u_b(s_y, b_y + 1) &\geq u_b(s_y, b_y) - u_b(s_e, b_e) \\ u_b(s_e, b_e) - u_b(s_e, b_e + 1) &\geq u_b(s_e, b_e) - u_b(s_y, b_y) \end{aligned}$$

Using equation (2), we have

$$\begin{aligned} \frac{1}{2} \frac{s_y + 1}{b_y + 1} \frac{s_y}{b_y} - \frac{1}{2} \frac{s_y + 1}{b_y + 1} \frac{s_y}{b_y + 2} &\geq \frac{1}{2} \frac{s_y + 1}{b_y + 1} \frac{s_y}{b_y} - \frac{1}{2} \frac{s_e + 1}{b_e + 1} \frac{s_e}{b_e} \\ \frac{1}{2} \frac{s_e + 1}{b_e + 1} \frac{s_e}{b_e} - \frac{1}{2} \frac{s_e + 1}{b_e + 1} \frac{s_e}{b_e + 2} &\geq \frac{1}{2} \frac{s_e + 1}{b_e + 1} \frac{s_e}{b_e} - \frac{1}{2} \frac{s_y + 1}{b_y + 1} \frac{s_y}{b_y} \end{aligned}$$

When markets are large, as is the case on eBay and Yahoo, the seller-buyer ratio on site a , γ_a ,

³A “quasi-equilibrium” is simply an incentive compatible allocation that ignores integer constraints. In large markets, such as those on eBay and Yahoo, this is of little consequence.

satisfies $\gamma_a \equiv \frac{s_a}{b_a} \approx \frac{s_a+k}{b_a+l}$ for all finite k and l and the above inequalities reduce to

$$\begin{aligned} 0 &\geq (\gamma_y)^2 - (\gamma_e)^2 \\ 0 &\geq (\gamma_e)^2 - (\gamma_y)^2 \end{aligned}$$

It then follows that:

Hypothesis 2 (Buyer-Seller Ratio Equalization) If eBay and Yahoo are coexisting in equilibrium, then the average number of buyers per seller on each site should be approximately equal.

3 Experiments

We test directly the price equalization and buyer-seller ratio hypotheses using eBay and Yahoo Auctions. At the time of our experiments, Yahoo was one-tenth the size of eBay, and its coin market was thick and active; searches for “Morgan Dollars (1878-1921)” on eBay and Yahoo, performed November 5, 2004, revealed 12,559 and 1,209 items for sale, respectively.⁴

Online auctions provide platforms on which individuals and firms can trade a wide variety of items. Listings can be searched by keywords, broad categories and price-ranges. Visitors may search without logging in, while bidders and sellers must register a username and password. Sellers may post product descriptions, digital images and other information on the product page. Sellers pay fees for their listings.⁵ Neither site charges bidders for participation. Both sites use a proxy bidding system: Buyers submit their maximum bid and, as price increases, bids are submitted automatically on their behalf up to their indicated maximum. The current price is set at the second-highest bidder’s

⁴Ebay lists many items not available 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. The quality of many collectibles is not established systematically 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.

⁵Throughout the experiments, Yahoo fees were two-part; listing fees were based on the starting price of the sale item, ranging from \$0.05 for low-value items to \$0.75 for prices over \$50, and the final value fee was 2 percent of the final value up to \$25 and 1 percent of the remaining closing price. Reserve fees were \$0.40 or \$0.75 depending on chosen value.

eBay fees were higher than Yahoo’s fees. eBay listing fees ranged from \$0.30 to \$4.80, and the final value fee was 5.75 percent of the initial \$25 and 2.75 percent of the remaining value up to \$1,000. Reserve fees were \$1 or \$2 depending on the chosen reserve. eBay also charged for displaying more than one photo (\$0.15 each), highlights, borders and other display options.

To compare site fees, consider the sale of a \$100 coin with three photos, no reserve and a \$50 starting price. Yahoo fees would amount to \$2, while eBay would collect \$6.08 from the sale.

maximum bid plus some small increment, and is updated as new high bids are received.⁶ All eBay auctions have a fixed ending time while Yahoo auctions allow sellers to choose between two ending rules: a hard-close rule that specifies an exact ending time and a soft-close rule where the auction is extended by five minutes if a bid is placed close to the auction end. A small ending rule indicator appears on the Yahoo item description screen (see Figure 1 for the Yahoo screenshot).⁷

Experiments on eBay and Yahoo, conducted between August, 2003 and November, 2004, address the hypotheses in Section 2. Eight types of Morgan and Peace Dollar series coins, described in Table 1, were purchased from a dealer in 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 date, denomination, grade, and an identification number. Table 1 lists the prices that we paid the dealer, as well as the “book value” as posted by the Professional Coin Grading Service (PCGS) on August 1, 2004. Book value is an estimate of a coin’s retail price, compiled from trade paper advertisements, dealer fixed price lists, significant auctions, and activity at major coin shows. Note that the book values of our coins are higher than our purchase prices.

We chose coins that are popular, yet not particularly rare. Furthermore, the market is thick enough to limit our effect on market prices and to conceal the experimental nature of our auctions.⁸ All coins were sold with nearly identical descriptions, varying only by coin age and rating, with three digital photographs.⁹ All auctions were seven days in length. We varied the reserve price through the opening bid amount rather than using the secret reserve option. We offered free shipping and handling in all auctions.

We divided the coins into “batches” of eight different Morgan and Peace silver dollars identified in Table 1. In total, we conducted eighty-eight auctions (11 batches). All the coins in a batch were auctioned using the same site, ending rule, and reserve. Our treatments consist of varying the identity of the site, the ending rule, and the reserve price. The paired design, depicted in Figure 2, allows for comparison between sites holding reserve price and ending rule constant, and within sites varying

⁶On both sites, increments depend on current price, ranging from less than \$1 for items valued below \$100 to \$100 for items valued over \$5000.

⁷For the hard-close ending rule, the text states: “This auction does not get automatically extended.” For the soft-close rule, the text states: “Auction may get automatically extended.”

⁸This mitigates any behavior changes that could arise as a consequence of bidders’ awareness of the experimental aspect of the auctions.

⁹The 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 paydirect, paypal, cash and money order only.”

reserve price and ending rule. The complete experimental design is summarized below:

Baseline. We test the predictions of Hypotheses 1 and 2 in the simplest possible fashion. We auctioned two batches of coins on Yahoo and three batches on eBay specifying a zero reserve and a hard close.¹⁰

High Reserve. We conducted auctions with positive reserve values to examine Hypotheses 1 and 2 in the presence of a significant reserve price. Starting prices in positive-reserve auctions were equal to 70% of the purchase price of the coins from the dealer. Two batches of coins were auctioned on each site under this treatment.¹¹

Ending Rule. Ockenfels and Roth (2006) suggest that an auction’s ending rule may affect revenue. Yahoo offers sellers the choice of a hard or soft close, while eBay offers only a hard close. To investigate ending rule effects, we auctioned four batches of coins on Yahoo with a zero reserve—two batches used the hard-close rule and two used the soft-close rule. We also sold two batches on Yahoo with a 70% reserve price—one with the hard close and one with the soft close.

Yahoo and eBay maintain reputation ratings for 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 by one point. 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 auctioned on each site. Our reputation values were reasonably high: 87 and 245 for Yahoo and eBay, respectively.

The auctions were posted on Tuesday, Wednesday or Thursday evenings. We scheduled these auctions in advance, so that all auctions in a batch were 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 auction completion, the product and bidding history pages were saved electronically. All items were shipped promptly to the winners and payments were received in full. While field data suffers from unobserved heterogeneities, our field experiments hold constant product quality, product description, shipping fees, auction length, and seller identity.

¹⁰The no-reserve treatment used a reserve of \$1, a trivial price relative to the coins’ actual values.

¹¹For the Yahoo auctions, one batch was auctioned with a hard close and one with a soft close. Ending rule has no effect on auction revenues. Thus, we pool these two batches for the high reserve tests.

4 Results

Table 2 presents descriptive statistics for the experiments, pooled by site. Five Yahoo auctions finished without a sale and were dropped from the data.¹² The average revenues and numbers of bidders were higher on eBay compared to Yahoo under all treatments. Consistent with auction theory, the presence of a reserve price raises revenues and reduces the average number of bidders. Bidders typically placed 1 or 2 bids in a given auction, with slightly more multiple bidding on eBay. Winning bidders were quite experienced with average feedback scores of approximately 263 on eBay and 232 on Yahoo. Winning bidders were not “snipers” submitting bids only seconds before the auction close; the last bid by the winning bidder was entered an average of 296 minutes (almost five hours) before the close on eBay and 1050 minutes (17.5 hours) before the close on Yahoo. On average, we received 9.38 and 7.88 bids per auction on eBay and Yahoo, respectively.

Hypotheses 1 and 2 suggest that both revenues and numbers of bidders per auction should be approximately equal across the two sites. As shown in Table 3, average Yahoo revenues are lower than average eBay revenues for each coin type—eBay buyers paid between 20 and 70% more than Yahoo buyers for identical items. Table 3 also suggests that the average number of unique bidders per auction is lower on Yahoo than on eBay for each coin type—there were 35 to 120% more bidders per auction on eBay compared to Yahoo.¹³

The summary statistics in Table 3 suggest the presence of arbitrage opportunities. For example, a user could buy a 1902 Morgan Dollar (Coin 4) on Yahoo for an average price of \$83 and sell it on eBay for \$110. After eBay and postage fees (totally \$6 and \$2, respectively), the arbitrageur would earn a profit of \$19 on a single coin.¹⁴

Table 3 is merely suggestive of significant differences across the sites; we test Hypotheses 1 and 2 formally using econometric techniques. Let $revenue_{air}$ denote the revenue obtained from an auction

¹²Failure 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.

¹³We construct the bidder count variable by observing the number of unique bidder identification names participating in an auction. To the extent that the same physical bidder places multiple bids under different user IDs, we would be overcounting the number of bidders. However, given the high average “experience level” of our bidders (with feedback ratings of 232.1 on Yahoo and 242.5 on eBay), this does not seem to be a serious issue.

¹⁴Finance theory has suggested that potential arbitrageurs may be reluctant to exploit some opportunities due to the large fixed costs and capital outlays (Shleifer and Vishny, 1997). Moreover, if there is uncertainty about the distribution of returns from arbitrage, price disparities may persist while potential arbitrageurs determine whether expected payoffs cover fixed costs (Mitchell, Pulvino and Stafford, 2002). Here, however, capital requirements are low and the price disparity is consistent across coins and over time.

held at site a for coin i under treatment r . Hypothesis 1 suggests the following econometric specification:

$$revenue_{air} = \beta_0 + \beta_1 site_{air} + \gamma X_{ir} + \varepsilon_{air}, \quad (3)$$

where $site_{air}$ is a dummy variable which equals 1 for eBay auctions and zero for Yahoo, and X_{ir} is a matrix of controls that include coin fixed effects as well as the following variables, depending on the specification:^{15,16}

Reserve - We use a dummy variable, equal to one under the high reserve treatment, to reflect the possibility that reserve price affects revenue (see, for instance, Myerson (1981)).

Ending Rule - We use an ending rule dummy variable, equal to one for a hard close, to reflect the possibility that ending rule affects revenue (see Ockenfels and Roth (2006)).

Finally, ε_{air} represents an error term. We report robust standard errors to control for heteroskedasticity.¹⁷ Hypothesis 1 states that revenues should be approximately equal across the sites; thus, we expect that the site coefficient should be zero ($\beta_1 = 0$) under specification (3).

Let $bidders_{air}$ be defined as the number of bidders participating in a particular auction. Hypothesis 2 suggests the following econometric specification:

$$bidders_{air} = \beta_0 + \beta_1 site_{air} + \gamma X_{ir} + \varepsilon_{air}, \quad (4)$$

where the right-hand side variables are defined identically to equation (3). Hypothesis 2 predicts that the site coefficient is zero ($\beta_1 = 0$) in this specification.

Equations (3) and (4) assume that any site-specific effect is constant for all coins. Given the variation in coin prices, one might worry that such a specification is overly restrictive. Accordingly, we also examine equations (3) and (4) where the dependent variable is $\ln(revenue_{air})$ and $\ln(bidders_{air})$, respectively. For these cases, the site coefficient, β_1 , represents the percentage change in revenue or number of bidders per auction. Once again, our hypotheses suggest that $\beta_1 = 0$ in both specifications.

¹⁵We also ran specifications replacing item dummies with both the PCGS book value and dealer price to control for variation in retail demand and the cost of acquisition, respectively. Regression coefficients of interest were virtually identical to those reported in the tables.

¹⁶We also ran a coin-specific random effect specification. Our results are substantially unaffected by the inclusion of random effects.

¹⁷White's general test for heteroskedasticity was conducted. The null hypothesis of constant variance is rejected in all cases.

Baseline

Table 4 displays the results of the regression specifications under the baseline treatment. Model 1 presents the coefficients from equation (3) while Model 2 presents the log specification. Models 3 and 4 are the analogues for equation (4).

The results show that eBay auctions yield significantly higher revenues than the equivalent auctions on Yahoo—we reject the hypothesis that $\beta_1 = 0$ at the 1% significance level. The economic magnitude of the coefficient estimates is substantial; according to Model 2, seller revenues are 26.8% higher on eBay. Similarly, examining the number of bidders, we reject the hypothesis that $\beta_1 = 0$ at the 5% significance level. Again, the economic magnitude of the coefficients is considerable—an eBay auction attracts more than two additional bidders compared to an equivalent Yahoo auction.

High Reserve

We next investigate whether the zero reserve price in the baseline treatment is responsible for the revenue differences between the sites—perhaps this seller “mistake” has a greater effect on Yahoo than on eBay. We pool the hard-close auctions across the sites and include a dummy variable for auctions with positive reserve prices. Table 5 displays the results. Inclusion of positive reserve auctions has little impact on the magnitude and significance of the site effects; our estimates are similar to those in Table 4. We reject the hypothesis that $\beta_1 = 0$ at the 1% significance level—eBay auctions generate 29.3% higher revenues and attract 2.124 more bidders than their Yahoo equivalents.

Reserve prices also appear to affect auction outcomes. In Models 1 and 2, we reject the hypothesis that the positive reserve coefficient is zero at the 5% significance level. Setting a positive reserve price increases revenues by approximately 7%. The effect of a positive reserve price on the number of bidders is consistent with theoretical predictions and statistically significant at conventional levels. High reserve auctions attract nearly 2.9 fewer bidders than low reserve auctions.

Ending Rule

Theoretical work by Ockenfels and Roth (2006) implies that revenues in soft-close auctions may be higher than under a hard-close rule.¹⁸ Since Yahoo provides a soft close option, the revenue differences may be due to our use of the hard-close rule on Yahoo. Table 6 displays results from specifications analogous to equations (3) and (4) for Yahoo auctions only. The ending rule coefficient is not statistically significantly different from zero in any model. Moreover, the magnitude of the

¹⁸Specifically, the revenue ranking result follows from Ockenfels and Roth’s theorems characterizing equilibrium behavior in hard-close auctions (2006, page 303) and bidding behavior in soft-close auctions (page 309).

coefficients is small—Model 2 of Table 6 indicates that revenue increases by 0.5% when a seller selects the soft close over the hard-close rule. In short, there is little evidence that revenues on Yahoo are affected by the ending rule.

We also examined the impact of ending rule on bid timing in Yahoo auctions using the following specification:

$$bidtime_{ir} = \beta_0 + \beta_1 endingrule_{ir} + \gamma X_{ir} + \varepsilon_{ir} \quad (5)$$

where $bidtime_{ir}$ is the minutes between the time a bid was placed and the auction end and $endingrule$ is the hard-close dummy variable. The matrix X_{ir} includes coin fixed effects and a dummy for the reserve treatment. Again, we use robust estimation to account for heteroskedasticity. Roth and Ockenfels (2002) report that late bidding occurs more frequently in hard-close auctions, a finding that would be consistent with a negative coefficient on $endingrule$ ($\beta_1 < 0$). In Table 7, we report the results of estimating equation (5) using two measures of timing. Model 1 includes the timing of last bids only, omitting earlier bids posted by the same bidder in a given auction. The sign of β_1 in Model 1 is consistent with Roth and Ockenfels’ prediction—bidders bid an average of 223 minutes later with a hard close. However, we cannot reject the null hypothesis that $\beta_1 = 0$ at conventional significance levels. Model 2 includes the timing of all bids. Here, β_1 reverses sign—bidders bid an average of 118 minutes *earlier* in hard close auctions—but the coefficient is not statistically significant at conventional levels. Overall, results appear rather different from the findings contained in Roth and Ockenfels (2002), Ariely, Ockenfels, and Roth (2005), and Ockenfels and Roth (2006).

Interestingly, the presence of a high reserve price does have a significant effect on bid timing. Using both bid timing measures, the reserve dummy variable coefficient is negative and significant at the 1% level. A positive reserve price delays bids by approximately 30 hours.

Pooled Results

The results of “pooled” regressions, using all of the data from the field experiments, are displayed in Table 8. Again, we reject the hypotheses that site has no effect on revenue or number of bidders at the 1% significance level for all models. The results indicate that eBay auctions generate 29.6% higher revenues and attract 58.3% more bidders than Yahoo auctions.

5 Alternative Hypotheses

Our results are inconsistent with equilibrium coexistence in the EFM model. However, there are a number of factors absent from that model that might explain our findings. Specifically, we examine five alternatives:

1. Platform Differentiation. The theory model assumes that sites do not differ in inherent quality. Yet, eBay’s platform might offer superior service, and this might lead to the observed revenue differences.
2. Switching Costs. There are no switching costs in the theory model. Perhaps the presence of such frictions might account for our results.
3. Trustworthiness. In the theory model, seller reputation is inconsequential to buyers. A large existing literature suggests that reputation does matter. Perhaps sellers on eBay simply have superior reputations relative to Yahoo sellers, and this accounts for the site differences.
4. Liquidity. The theory model does not consider the possibility that a desired item is not available for sale at a given platform. Perhaps the price differences between the two sites reflect an eBay “liquidity premium.”¹⁹
5. Anomalous Data. Our study focuses on 88 auctions at a particular point in time. Perhaps with either a larger number of auctions or a different time period, the observed revenue differences would disappear.

5.1 Platform Differentiation

Our hypotheses were derived in model with homogeneous platforms—given the same number of buyers and sellers on the sites, users derive equal payoffs on eBay and Yahoo. In reality, one of the sites may be more attractive than the other. Could differences in price and buyer-seller ratios stem from vertically differentiation? To consider this possibility, suppose that payoffs from Yahoo are unchanged from the original model, but eBay payoffs now reflect its superior service. Specifically, buyer payoffs on eBay are

$$u_b(s_e, b_e) = \frac{1}{2} \frac{s_e(s_e + 1)}{b_e(b_e + 1)} + q^B$$

¹⁹We are grateful for an anonymous referee for suggesting this alternative.

while seller payoffs on eBay are

$$u_s(s_e, b_e) = \frac{b_e - s_e}{b_e + 1} + q^S$$

where $q^B, q^S > 0$ represents eBay’s vertical differentiation advantage.

To study large markets, we fix the seller-buyer ratio in the market at $\gamma < 1$ and examine properties of equilibria as buyers and sellers increase proportionately. We first show that tipping is inevitable when markets are large.

Proposition 1 *In large markets with vertical differentiation, equilibrium coexistence is impossible.*

To gain some intuition for Proposition 1, suppose that both sites are active in a large market. Here, both the scale and market impact effects are negligible; however, eBay’s vertical differentiation advantage is non-negligible. Thus, Yahoo buyers and sellers will want to switch sites, destroying the possibility of coexistence. We next show that, even when interior equilibria exist, their properties are inconsistent with our empirical findings.

Proposition 2 *In any quasi-equilibrium in which the sites coexist and eBay enjoys a vertical differentiation advantage and more than 50% market share: (1) More buyers are attracted to a given Yahoo auction than an eBay auction; and (2) Prices are higher on Yahoo than on eBay.*

When eBay enjoys greater than 50% market share, it benefits both from scale and differentiation advantages. From the perspective of sellers, coexistence is only possible if Yahoo enjoys some compensating price advantage. This can only arise when Yahoo’s buyer-seller ratio is greater than eBay’s. Of course, this exactly contradicts the data—eBay sellers enjoy higher prices and more favorable buyer-seller ratios than do Yahoo sellers. Proofs for propositions 1 and 2 are contained in the Appendix.

5.2 Switching Costs

Our results suggest that, free from other motives or constraints, rational buyers should switch to Yahoo and rational sellers switch to eBay until the gains from moving approach zero. Indeed, Hypotheses 1 and 2 assume zero switching costs. In practice, however, the cost of registration, (re)building reputation and general “hassle” are non-trivial. Could significant switching costs be driving the observed disparities?

If significant numbers of eBay buyers and Yahoo sellers were unaware of the other service, their effective switching costs would be infinite and could rationalize our findings. This explanation seems unlikely. We conducted searches for “auction,” “internet auction,” and “online auction” on Yahoo and Google on November 20, 2004. Both engines put Yahoo Auctions and eBay in the top five results for these search terms. Moreover, while one might argue that the lesser-known status of Yahoo’s auction service makes it invisible to eBay buyers, it seems implausible that Yahoo sellers are unaware of eBay.

The cost of registration itself is low: Registration is free and takes approximately one minute to complete. For these costs alone to account for the \$15 price disparity shown in Table 7, the opportunity cost of time even for a buyer wishing to purchase only one coin would have to exceed \$900 per hour. This seems unreasonable.

Resnick and Zeckhauser (2002), among others, show that reputation (feedback rating) is valuable to sellers. To reduce the possibility of fraudulent payments, sellers may also prefer to sell to bidders with positive feedback ratings. For an established Yahoo user, rebuilding her reputation on eBay is a switching cost. In practice, however, the reputation rebuilding costs cannot account for the 20 to 60% price disparity between sites. A seller with 100 feedback points on Yahoo could rebuild his reputation on eBay for as little as \$100 simply by purchasing 100 items for \$1 each.²⁰ Such a seller would fully recoup the cost of this investment after only *seven* coin sales.

5.3 Trustworthiness of the Sites

Neither eBay nor Yahoo endorses their sellers’ reliability. If Yahoo sellers have a reputation for failing to deliver products, or selling damaged or counterfeit goods, then perhaps potential buyers simply view Yahoo as a less trustworthy platform. eBay bidders might be willing to pay a premium to avoid this. While several online reviews characterized Yahoo sellers as fraudulent, blaming Yahoo’s perceived inaction on abuse claims (see e.g. Ciao, 2005), searches for eBay complaints yield similar results.²¹

To examine whether trust differences between the sites can explain our results, consider the following worst-case scenario. Suppose that a Yahoo buyer does not receive the item and loses her entire bid with probability λ while an eBay buyer always receives the product. Using our data, we calculate

²⁰Reputation building of this sort is not a mere theoretical possibility. Brown and Morgan (2006) identify markets on eBay whose sole purpose is the “manufacture” of reputation for users. By trading seemingly-valueless items for pennies, users routinely enhance (or rebuild) their eBay reputations at small cost.

²¹Google searches for “eBay rip off” (omitting the term “Yahoo”) and “Yahoo auction rip off” (omitting the term “eBay”) revealed 725,000 and 234,000 results, respectively (July 26, 2005).

the implied default rate λ needed to deter switching. An individual is indifferent between eBay and Yahoo purchases when:

$$(1 - \lambda)U_g + \lambda U_b = U_e \tag{6}$$

where U_g is the utility associated with a successful Yahoo transaction, U_b is the utility from a Yahoo transaction that results in total loss, and U_e is the utility from a (always) successful eBay transaction.²² Solving (6) yields

$$\lambda = \frac{U_e - U_g}{U_b - U_g}$$

Suppose, as in Cox *et al.*(1988), that consumer utility exhibits constant relative risk aversion, then

$$U(w) = \frac{1}{1 - \rho} w^{1-\rho}$$

where $\rho \in [0, 1)$ is the coefficient of relative risk aversion and w is total wealth. With this specification, we have

$$\begin{aligned} U_g &= \frac{1}{1 - \rho} (W + V - P_y)^{1-\rho} \\ U_b &= \frac{1}{1 - \rho} (W - P_e)^{1-\rho} \\ U_e &= \frac{1}{1 - \rho} (W + V - P_y)^{1-\rho} \end{aligned}$$

where W is wealth, V is the value of the item and P_a is the price on auction site a .

To calibrate the model, we fix W at \$55,000, the median household wealth level in the US in 2000 (US Census Bureau, 2005). This (likely) underestimates the wealth of coin collectors and hence biases the results in favor of conservative implied default rates. We estimate V as the PCGS book value for the coins, and P_e and P_y as the average revenue by coin by site (Table 2). We then vary the risk aversion parameter and compute the default rate solving equation (6). For reasonable parameter values of ρ , the implied default rates range from 12% ($\rho = 0.9$, coin 1) to 19% ($\rho = 0.1$, coin 8). To be indifferent, a buyer must believe that at least one of eight transactions on Yahoo would result in total loss. This seems implausibly high.²³

²²Suppose that vertical differentiation between the sites leads to the sorting of bidders by risk preferences. Interpreting the indifference expression for the *marginal* bidder implies that the risk preferences of the marginal bidder must be identical across the two platforms.

²³Of course, this is not an equilibrium explanation. Since no credible signal exists for reliable sellers, both good and bad sellers will switch to eBay.

5.4 Liquidity

While items in general product categories, such as coins, are always available on both platforms, specific items, such as a 1902 Morgan Dollar MS-65, may not be. Since the “inventory” of products depends on the size of a platform, it seems intuitive that “stockouts” are more likely on Yahoo than on eBay. Perhaps the observed price differences are attributable to an eBay liquidity advantage—consumers pay higher prices on eBay to avoid the cost of unsuccessful searches.

To investigate this possibility, suppose that it costs c per platform for a consumer to search for her desired product. The product is always available on eBay, but available only with probability $\lambda < 1$ on Yahoo. Let V denote the value of the item to the consumer, and suppose that the expected surplus from acquiring the item is sufficient to induce a consumer to continue to search until it is found. A consumer has two possible search strategies: (1) Go directly to eBay; or (2) First visit Yahoo in search of a “bargain” and proceed to eBay if the Yahoo search fails. In competitive markets, prices on the two platforms will adjust until consumers are indifferent between the competing search strategies. Thus, in equilibrium,

$$V - P_e - c = \lambda(V - P_y - c) + (1 - \lambda)(V - P_e - 2c) \quad (7)$$

Rearranging equation (7) yields the following expression for the probability of a stockout on Yahoo.

$$1 - \lambda = \frac{P_e - P_y}{P_e - P_y + c} \quad (8)$$

While we observe the price premium in our data, we do not observe the cost of search or the stockout probability. Hong and Shum (2006) structurally estimate the value of the search cost parameter for online textbook markets. We use their estimates to calibrate c and infer the stockout probability implied by equation (8). Using Table 2 of Hong and Shum, each coin is matched with a cost estimate (Δ_1 in their notation) for a textbook with the most similar price. We use the average price difference between eBay and Yahoo to obtain $P_e - P_y$ for each coin. Table 9 presents the results. The implied stockout rates are extremely high, ranging from 76% to over 90%. While liquidity may account for some of the price differences between the two platforms, the eBay premium seems to be too great to be explained solely by liquidity.

5.5 Anomalous Data

Are the observed disparities artifacts of the experimental design? Do they persist beyond the time of the experiment? To examine these possibilities, we gathered data from over 25,000 Morgan and Peace series coin auctions on eBay and Yahoo in April, May, June and August of 2006. To compare the experimental and field data, we identified items with descriptions and grades similar to the coins used in our experiments. For example, for 1898 Morgan dollar coins, we selected only those coins graded MS-64. As we found during our experiments, the market for Morgan and Peace series coins on eBay was substantially larger than Yahoo.

Table 10 presents summary statistics for the field data, including 1652 auctions in total—371 coins on Yahoo and 1281 coins on eBay. Pooling the eight coin types, the mean price on eBay is \$60, while the average price on Yahoo is only \$54. EBay auctions also continue to attract more bidders—on average eBay auctions attract 7 bids, while Yahoo auctions attract only 5. Table 11 presents the results from regressions similar to equations (3) and (4) for this dataset. Coefficients are all statistically significant and confirm the persistence of the revenue and bid count disparities. Controlling for other auction features, eBay yields a \$11 or 15% revenue premium relative to Yahoo. Examining the number of bids per auction, we conclude that eBay auctions attracted approximately 2 more bidders per seller than comparable Yahoo auctions—equivalent to approximately 70% more bids per seller on eBay relative to Yahoo.²⁴

In short, the field data suggests that the observed revenue and bid count differences were not an artifact of our particular experimental design or the time at which the experiments were conducted.

6 Imitation

In the previous section, we found that each friction by itself was incapable of explaining the data. However, this does not rule out the possibility that some *combination* of frictions might account for our observations. Rather than pursue this route, we offer a parsimonious model with only one friction—imitation dynamics—that is capable of rationalizing our findings. Specifically, if imitation

²⁴In our field experiments, the number of bidders per seller was the variable of interest. Since unique bidder counts per auction are not available for our field data, we use the number of bids per auction to proxy for the buyer-seller ratio. To alleviate concerns about potential bias, consider the following: in our field experiments, the average number of bids per bidder on eBay and Yahoo are 1.56 and 1.98, respectively (see Table 1). Were bids-per-bidder statistics equal, total *bid* count would be simply a transformation of total *bidder* count. Because Yahoo bidders tend to submit fewer bids, our total bid counts actually underestimate the difference in buyer-seller ratios on eBay and Yahoo.

drives platform choice, then persistent price disparities are possible. To see this, we study behavior in the EFM model when platform choice is characterized by a simple deterministic replicator dynamic. As Gintis (2000) suggests, this dynamic might arise when a fraction of buyers or sellers learn the payoff of another randomly chosen agent of the same type and probabilistically imitate the more successful strategy.

In this framework, there are two “types” of buyers and sellers—those that go to eBay and those that go to Yahoo. The “state” of the system at any point in time is summarized by the pair (s, b) , the number of sellers and buyers who are eBay types. The remaining $S - s$ sellers and $B - b$ buyers are Yahoo types. Suppose that S and B are large enough that we can neglect integer constraints. Types evolve in proportion to the payoffs from their strategy relative to the average payoffs in the population. For seller types, this amounts to

$$\begin{aligned}\dot{s} &= s \left(\pi_e - \left(\frac{s}{S} \pi_e + \frac{S-s}{S} \pi_y \right) \right) \\ &= s \left(\frac{S-s}{S} \right) (\pi_e - \pi_y)\end{aligned}$$

While for buyer types, we have

$$\dot{b} = b \left(\frac{B-b}{B} \right) (u_e - u_y)$$

where π_a and u_a for $a \in \{e, y\}$ are the expected payoffs to sellers and buyers, respectively, in state (s, b) . Using the payoff expressions given in equations (1) and (2), the system becomes

$$\dot{s} = s \left(\frac{S-s}{S} \right) \left(\frac{b-s}{b+1} - \frac{B-b-(S-s)}{B-b+1} \right) \quad (9)$$

$$\dot{b} = \frac{1}{2} b \left(\frac{B-b}{B} \right) \left(\frac{s(s+1)}{b(b+1)} - \frac{(S-s)(S-s+1)}{(B-b)(B-b+1)} \right) \quad (10)$$

A fixed point of this system is a state (s^*, b^*) where $\dot{s} = \dot{b} = 0$. Equations (9) and (10) reveal states $(0, 0)$ and (S, B) as fixed points. In other words, once the market has tipped, it remains tipped. Perhaps of greater interest are fixed points where the two sites coexist. While there are typically a continuum of interior equilibria in the EFM model, imitation dynamics always produces a *unique* interior fixed point given by $(S/2, B/2)$. Formally,

Proposition 3 *Under imitation dynamics, equilibrium coexistence only occurs when both platforms enjoy equal market shares.*

What accounts for the differences between the EFM model and imitation dynamics? In the EFM model, market impact effects sustain equilibrium coexistence. Small price differences between platforms do not induce sellers and buyers to switch because increased competition would wipe out any possible gains. Under imitation dynamics, agents may be thought of as boundedly rational. They simply gravitate toward whichever platform offers higher payoffs not accounting for the competitive impact of their decision. In other words, the disciplining force of the market impact effect vanishes when agents merely imitate more successful strategies.

Next, we study the stability properties of the fixed points. The Hartman-Grobman theorem (see Nayfeh, 1995, pp. 62-63) states that the stability properties in the neighborhood of a fixed point may be understood by considering the Eigenvalues of a linearization of the system evaluated at the fixed point. Performing this analysis, we find that

Proposition 4 *The interior fixed point, $(s_1 = \frac{S}{2}, b_1 = \frac{B}{2})$, is a saddle point while the tipped fixed points, $(s = 0, b = 0)$ and $(s = S, b = B)$, are attractors.*

Proposition 4 shows that, for almost all initial states, the system will eventually tip. Figure 3 presents a phase diagram of the system for the region where eBay starts out with the majority of buyers and sellers. The dashed line in the figure, labeled $\dot{s} = 0$, represents the locus of states where prices on the platforms are equal. The dotted line, labeled $\gamma_e = \gamma_y$ represents the locus of states where the buyer-seller ratios are equal. Owing to scale effects, as the number of sellers on eBay increases, the buyer-seller ratio must become increasingly uneven for prices to be equal—hence the divergence between the $\dot{s} = 0$ and $\gamma_e = \gamma_y$ lines up to the tipping point. The line labeled $\dot{b} = 0$ represents the locus of states where buyers enjoy the same surplus on both sites. Again owing to scale effects, this line lies (almost) everywhere below the line where buyer-seller ratios are equal. The black arrows in the figure indicate the signs of \dot{s} and \dot{b} in each state.

Consider the initial state labeled s_0 in the figure. At this point, both price and buyer-seller ratio are higher on eBay than on Yahoo. Sellers are attracted to higher prices and gravitate toward the eBay platform. Buyers, however, head toward the better bargains available on Yahoo. This process continues until buyers are indifferent between the two platforms. At that point, sellers continue to

switch to eBay and, owing to scale effects, the flow of buyers reverses—buyers now start deserting Yahoo in favor of eBay. Thereafter, eBay’s market share grows monotonically until there is complete tipping.²⁵ This model is capable of rationalizing the qualitative results we observe in the data. For initial conditions like s_0 , the system dynamics have the property that eBay’s price is always higher than Yahoo’s. Furthermore, for a portion of this path, the buyer-seller ratio favors eBay as well.

Finally, we turn to the speed of tipping. While the model itself says nothing about the length of a path in real time, we use data from the field experiments to simulate the dynamic process. Formally, the discrete approximation

$$\begin{aligned} s(t + \Delta t) &= s(t) \left(1 + \left(\frac{S - s(t)}{S} \right) (\pi_e(t) - \pi_y(t)) \Delta t \right) \\ b(t + \Delta t) &= b(t) \left(1 + \left(\frac{B - b(t)}{B} \right) (u_e(t) - u_y(t)) \Delta t \right) \end{aligned}$$

converges to equations (9) and (10) as $\Delta t \rightarrow 0$. In our simulations, we let $\Delta t = 1$ and interpret this as one day. In terms of imitation and learning, this implies that each day all of the buyers and sellers learn another agent’s payoffs and switch platforms in proportion to the difference in these payoffs. Based on the experimental and field data from November 2004, we estimate that the Morgan and Peace silver dollar market consists of about 14,000 sellers and 81,500 buyers. Of these amounts, about 89% of sellers and 93% of buyers were on eBay. We used these values as our initial condition and then simulated dynamic process.

The dynamic process produces tipping to the eBay platform, but is quite slow. If we say that the market has tipped once eBay commands 99% market share of both buyers and sellers, then the simulation indicates that it takes about 245 years to tip. Lowering the “tipping point” to a 95% market share reduces this time to 96 years. If treat Δt as representing one hour, instead of one day, the simulation suggests that tipping takes about four years. The process is so slow because, as Yahoo agents become increasingly rare, fewer agents choose to switch each period. Of course, we do not mean for these simulations to be taken too literally—the model is quite abstract and no doubt inaccurate in many respects. Still, if imitation dynamics are a reasonable approximation of platform choice, then eBay and Yahoo might well coexist for a considerable period of time despite persistent price disparity.

²⁵ Once the system reaches a state (s, b) such that $\dot{s} \geq 0$ and $\dot{b} \geq 0$ with at least one strict inequality, then all future states of the system are such that $\dot{s} \geq 0$ and $\dot{b} \geq 0$.

7 Conclusion

The relationship between eBay and Yahoo evolved since the time of our field experiments. On May 25, 2006, Yahoo and eBay announced a US advertising alliance (eBay, 2006) in an apparent bid to dampen Google's internet dominance. eBay and Yahoo Auctions also planned to collaborate in search-based advertising. In July of 2007, Yahoo announced that it was closing its auction site. The market had tipped.

During their coexistence, we identified significant differences in revenues and number of bidder per seller for identical items on eBay and Yahoo. Switching costs, vertical differentiation, trustworthiness, liquidity, and anomalous data could not reconcile our results with a theory of equilibrium coexistence. Yet, a simple replicator dynamic, where agents imitate successful strategies, plausibly rationalizes our results and the eventual shuttering of Yahoo Auctions in the US.

It may be too early to detect anti-competitive effects of Yahoo's exit from the US auction market. However, about six months after Yahoo's exit from the US auction market, eBay did announce significant changes to its fee structure. While it reduced most listing fees, it raised final value fees collected for successful auctions, in some cases by as much as 67%. The changes provoked a boycott of eBay by many sellers and, indeed, a third-party website noted a 17% decline in eBay's listings during the boycott period.²⁶ The combined evidence of platform competition in online auctions in Europe, Japan, Taiwan, and the US suggests a strong tendency for these markets to tip and, consequently, the need for careful scrutiny by competition authorities. This is particularly true for emerging markets like China and India, where competition among the major players in the online auction space is still in flux.

²⁶Medved.net tracks and publishes eBay listing counts over time. eBay does not publicly release its listing statistics.

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Appendix: Proofs of Propositions

Proposition 1 *In large markets with vertical differentiation, equilibrium coexistence is impossible.*

Proof. Fix the ratio of sellers to buyers at $\gamma < 1$ and consider equilibria as the number of buyers becomes infinite. It will be convenient to denote the number of buyers as N (rather than B as we did previously). For a fixed N number of buyers, an equilibrium is described by the number of sellers and buyers on eBay, $(s_e(N), b_e(N))$.

Suppose that, contrary to the proposition, there exists a sequence of equilibria $(s_e(N), b_e(N))$ such that both markets are active in the limit. Formally, this amounts to the condition that, for some sequence of equilibria, $\{s_e(N)\}_{N=1}^{\infty}, \{b_e(N)\}_{N=1}^{\infty}, \{N\gamma - s_e(N)\}_{N=1}^{\infty}, \{N - b_e(N)\}_{N=1}^{\infty}$ are all divergent.

Define the limit buyer-seller ratios in each market as

$$\rho_y = \lim_{N \rightarrow \infty} \frac{\frac{N}{\gamma} - s_e(N)}{N - b_e(N)} \quad \text{and} \quad \rho_e = \lim_{N \rightarrow \infty} \frac{s_e(N)}{b_e(N)}$$

Equilibrium requires that the following system of inequalities hold for all N :

$$\begin{aligned} \frac{b_e(N) - s_e(N)}{b_e(N) + 1} + q^S &\geq \frac{N - b_e(N) - (\gamma N - s_e(N) + 1)}{N - b_e(N) + 1} \\ \frac{N - b_e(N) - (\gamma N - s_e(N))}{N - b_e(N) + 1} &\geq \frac{b_e(N) - s_e(N) - 1}{b_e(N) + 1} + q^S \\ \frac{s_e(N)(s_e(N) + 1)}{2b_e(N)(b_e(N) + 1)} + q^B &\geq \frac{(\gamma N - s_e(N))(\gamma N - s_e(N) + 1)}{2(N - b_e(N) + 1)(N - b_e(N) + 2)} \\ \frac{(\gamma N - s_e(N))(\gamma N - s_e(N) + 1)}{2(N - b_e(N))(N - b_e(N) + 1)} &\geq \frac{s_e(N)(s_e(N) + 1)}{2(b_e(N) + 1)(b_e(N) + 2)} + q^B \end{aligned}$$

Taking limits, we obtain

$$\begin{aligned} 1 - \rho_e + q^S &\geq 1 - \rho_y \\ 1 - \rho_y &\geq 1 - \rho_e + q^S \\ \rho_e^2 + q^B &\geq \rho_y^2 \\ \rho_y^2 &\geq \rho_e^2 + q^B \end{aligned}$$

The first two inequalities imply that

$$\rho_y = \rho_e - q^S$$

while the second two inequalities imply that

$$\rho_y = \sqrt{\rho_e^2 + q^B}$$

Thus, for any such sequence, it must be the case that

$$\begin{aligned}\rho_e &= \frac{1}{2} \left(q^S - \frac{q^B}{q^S} \right) \\ \rho_y &= -\frac{1}{2} \left(q^S + \frac{q^B}{q^S} \right)\end{aligned}$$

Notice that this implies that $\rho_y < 0$, which is a contradiction.

It remains to show that it is not the case that only one of $\{s_y(N)\}_{N=1}^\infty$, $\{b_y(N)\}_{N=1}^\infty$, $\{N\gamma - s_y(N)\}_{N=1}^\infty$, $\{N - b_y(N)\}_{N=1}^\infty$ is convergent while the rest diverge. To confirm this, suppose that $\{s_a(N)\}_{N=1}^\infty$ was convergent for one of the sites. In that case, buyers using that site earn zero payoffs in the limit when they could earn positive payoffs from switching to the other site. This is a contradiction. Similarly, if $\{b_a(N)\}_{N=1}^\infty$ is convergent for one of the sites, then sellers on that site earn zero payoffs in the limit and have a profitable deviation as well. QED

Proposition 2 *In any quasi-equilibrium in which the sites coexist and eBay enjoys a vertical differentiation advantage and more than 50% market share: (1) More buyers are attracted to a given Yahoo auction than an eBay auction; and (2) Prices are higher on Yahoo than on eBay.*

Proof. Suppose that there is an interior equilibrium (s_e, b_e) where eBay enjoys more than 50% market share. Incentive compatibility for Yahoo sellers requires:

$$s_e \geq b_e - \frac{b_e + 1}{B + 2} (B - S - q^S (B - b_e + 1))$$

Let $\mu \geq \frac{1}{2}$ denote eBay's market share of buyers. To prove part (1) of the proposition, we show that the market share of sellers on eBay must strictly exceed μ . We rewrite the incentive constraint for Yahoo sellers as

$$\begin{aligned}s_e &\geq \mu B - \frac{\mu B + 1}{B + 2} (B - S) + \frac{\mu B + 1}{B + 2} q^S (B - \mu B + 1) \\ &> \mu B - \frac{\mu B + 1}{B + 2} (B - S) \\ &= \frac{S - B + B\mu(S + 2)}{B + 2}\end{aligned}$$

where the strict inequality follows from the fact that $q^S > 0$. We claim that $\frac{S - B + B\mu(S + 2)}{B + 2} \geq \mu S$ whenever $\mu \geq \frac{1}{2}$. Notice that

$$\frac{S - B + B\mu(S + 2)}{B + 2} - \mu S = \frac{(2\mu - 1)(B - S)}{B + 2} \geq 0$$

Thus, we have shown that the seller-buyer ratio on eBay $\gamma_e > \gamma$. From the adding up condition on buyer-seller ratios, it then follows that $\gamma_e > \gamma > \gamma_y$.

To establish part (2) of the proposition, recall that the expected price spread between the sites is

$$\bar{p}_y - \bar{p}_e = \frac{(1 - \mu)B - (S - s_e)}{(1 - \mu)B + 1} - \frac{\mu B - s_e}{\mu B + 1}$$

which takes on the same sign as $B - S + (B + 2) s_e - B\mu(S + 2)$. Since $s_e > \frac{S-B+B\mu(S+2)}{B+2}$, it follows that

$$B - S + (B + 2) s_e - B\mu(S + 2) > 0$$

The Yahoo price always exceeds the eBay price when eBay enjoys more than 50% market share. QED

Proposition 3. *Under imitation dynamics, equilibrium coexistence only occurs when both platforms enjoy equal market shares.*

Proof. From equations (9) and (10), it follows that if $s = \frac{S}{2}$ and $b = \frac{B}{2}$, then $\dot{s} = \dot{b} = 0$. To prove uniqueness, suppose that some interior state (s, b) is a fixed point. Then (s, b) has the property that

$$\begin{aligned} u_e &\equiv \frac{b - s}{b + 1} = \frac{B - b - (S - s)}{B - b + 1} \equiv u_y \\ \pi_e &\equiv \frac{s(s + 1)}{b(b + 1)} = \frac{(S - s)((S - s) + 1)}{(B - b)((B - b) + 1)} \equiv \pi_y \end{aligned}$$

Solving for s in the first equation yields

$$s = \frac{S - B + 2b + Sb}{B + 2}$$

Substituting this into the second equation, we have

$$\frac{\frac{S-B+2b+Sb}{B+2} \left(\frac{S+2b+Sb+2}{B+2} \right)}{b(b+1)} = \frac{\left(S - \frac{S-B+2b+Sb}{B+2} \right) \left(S - \frac{S-2B+2b+Sb-2}{B+2} \right)}{(B-b)((B-b)+1)}$$

which, after some rearrangement, becomes

$$\frac{(S - B + 2b + Sb)(S + 2b + Sb + 2)}{b(b + 1)} = \frac{(SB + S + B - 2b - Sb)(SB + S + 2B - 2b - Sb + 2)}{(B - b)((B - b) + 1)} \quad (11)$$

We claim that the left-hand side of equation (11) is strictly increasing in b while the right-hand side is decreasing in b . Differentiating the left-hand side of equation (11) with respect to b , we obtain

$$\frac{\partial LHS}{\partial b} = \frac{1}{b^2} (B - S)(S + 2) > 0$$

since $B > S$.

Differentiating the right-hand side of equation (11) with respect to b , we obtain

$$\frac{\partial RHS}{\partial b} = -(B - S) \frac{S + 2}{(B - b)^2} < 0$$

Thus, equation (11) has a unique solution. QED

Proposition 4: *The interior fixed point, $(s_1 = \frac{S}{2}, b_1 = \frac{B}{2})$, is a saddle point while the tipped fixed points, $(s = 0, b = 0)$ and $(s = S, b = B)$, are attractors.*

Linearizing the system and evaluating at $(0, 0)$ or (S, B) yields Eigenvalues of $\left(-\frac{B-S}{B+1}, -\frac{1}{2} \frac{S(S+1)}{B(B+1)} \right)$. Since these are real and negative, $(0, 0)$ and (S, B) are both hyperbolic fixed points that are attractors. Linearizing the system and evaluating at $(S/2, B/2)$ yields Eigenvalues that are both real but with opposite signs. The product of these Eigenvalues is $-\frac{(B-S)S(S+2)}{B(B+2)^3}$. Thus $(S/2, B/2)$ is a hyperbolic fixed point that is a saddle point. QED

Figure 1 – Yahoo Screenshot

The screenshot shows a Yahoo! Auctions item page for a "1878-S MORGAN DOLLAR NGC SLAB MS-64 MS64 FREE S/H". The page is divided into several sections:

- Seller Info:** Seller is "coinconnect (87)", a member since September 27, 2001. Payment types accepted include Yahoo! PayDirect from HSBC and cashiers checks. Shipping info indicates the buyer pays shipping and the seller ships on payment.
- Auction Info:** Current bid is \$61.32. The auction is closed. The winner is [redacted] (1418). Available quantity is 1. Location is Berkeley, CA. Auction opened on Aug 13 13:47 PDT and closes on Aug 20 19:47 PDT. Starting price is \$51.10. ID #: 77867501.
- You are the Seller:** Total Pageviews: 25, Total Emails Sent: 0, Total Times added to a Watchlist: 2. A note states: "Your auction has winner(s). Follow the instructions above, and be sure to click the link above and rate the buyer after the transaction is complete."
- Navigation:** Includes links for "Seller's Current Auctions", "Seller's Closed Auctions", "Comments About Seller", and "Ask Seller a Question". A "Not Online" status is shown.
- Bottom Navigation:** "Item Information", "Bid History", and "Question & Answer".

Figure 2: Experimental Design

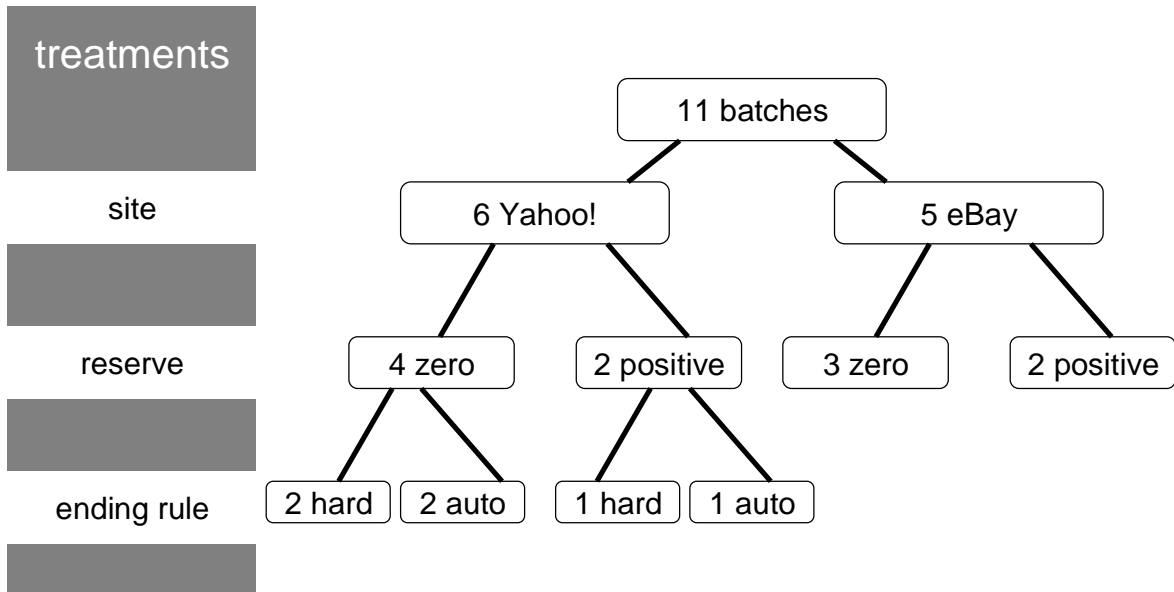


Figure 3: Phase Diagram for Replicator Dynamic

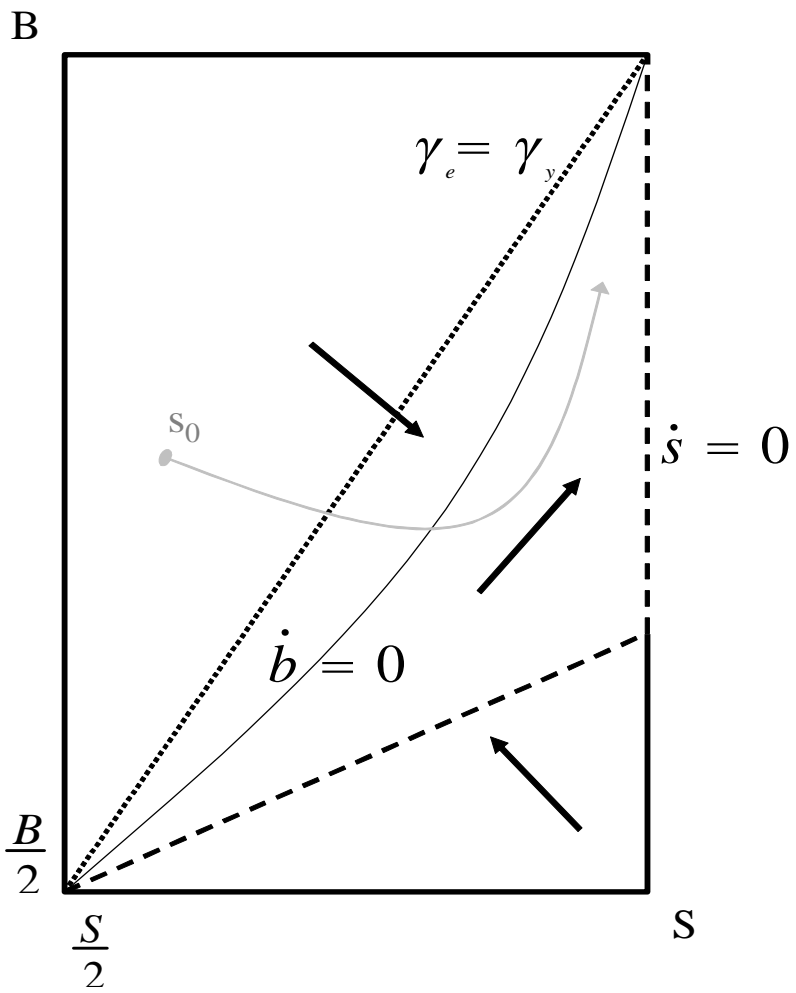


Table 1: Auctioned Coins

Item #	Item Description	PCGS	
		Book Value	Dealer 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 August 1, 2004. Dealer price was our cost from a coin dealer in Southern CA.

Table 2: Field Experiment Summary Statistics

		Mean Values	
		eBay	Yahoo
Revenue (\$)	Hard-close, No reserve	59.88 (30.94)	46.71 (25.39)
	Hard-close, Positive reserve	66.41 (35.27)	50.14 (29.37)
	Soft close, No reserve	-	49.37 (23.58)
	Soft-close, Positive reserve	-	47.33 (29.40)
# of Bidders	Hard-close, No reserve	7.25 (2.23)	5.13 (3.10)
	Hard-close, Positive reserve	4.38 (1.67)	2.17 (1.17)
	Soft close, No reserve	-	5.36 (2.68)
	Soft-close, Positive reserve	-	2.43 (1.27)
Bids/Auction		9.38 (4.74)	7.88 (6.61)
Bids/Bidder		1.56 (1.44)	1.98 (1.62)
Winning Bidder Reputation		262.67 (692.47)	232.12 (420.19)
Minutes from Close (All Bids)		2938.73 (3345.79)	3854.58 (3404.11)
Minutes from Close (Winning Bid)		296.05 (874.05)	1048.36 (2351.53)
# of Observations	Auctions	40	43
	Bids	374	368

Notes: Values in parentheses are standard deviations.

Table 3: Descriptive Statistics by Coin Type

		Item							
		1	2	3	4	5	6	7	8
Revenue (\$)	<i>Yahoo</i>	58.66 (5.14)	25.06 (2.93)	77.81 (4.31)	83.33 (6.22)	37.36 (4.76)	16.75 (0.96)	19.66 (4.27)	54.37 (6.23)
	<i>eBay</i>	71.54 (3.98)	32.80 (2.16)	97.13 (15.02)	110.52 (15.98)	44.73 (4.28)	23.91 (3.03)	33.33 (4.85)	85.96 (11.12)
Yahoo-eBay Price Spread (%)		21.95	30.88	24.83	32.63	19.73	42.72	69.52	58.11
# of Bidders / Auction	<i>Yahoo</i>	4.17 (2.64)	2.83 (1.47)	5.17 (3.06)	5.50 (2.59)	4.83 (3.37)	2.33 (2.16)	2.67 (2.42)	4.50 (4.28)
	<i>eBay</i>	5.60 (2.97)	4.60 (2.70)	7.20 (1.92)	7.60 (2.41)	6.40 (3.36)	5.20 (1.48)	4.60 (1.82)	7.60 (1.52)
Yahoo-eBay Bidder Count Spread (%)		34.29	62.54	39.26	38.18	32.51	123.18	72.28	68.89

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. Yahoo-eBay bidder count spread is the difference in the number of bidders on eBay and Yahoo as a percentage of the average price on Yahoo.

Table 4: Regression Results under the Baseline Treatment

	1	2	3	4
Dependent Variable	Revenue	ln(Revenue)	# of Bidders	ln(# of Bidders)
β_1 : Site Dummy	13.173 ** (2.420)	0.268 ** (0.036)	2.125 ** (0.818)	0.498 * (0.192)
γ : Constant	55.952 ** (2.757)	3.988 ** (0.048)	5.125 ** (0.675)	1.518 ** (0.129)
Item Dummies	Yes	Yes	Yes	Yes
# of Observations	40	40	40	40
R ²	0.94	0.97	0.45	0.42

Notes: Robust standard errors are in parentheses. * and ** denote significance at the 5% and 1% levels, respectively. "Site Dummy" equals 1 if auction site was eBay.

Table 5: Regression Results under Baseline and High-Reserve Treatments

	1	2	3	4
Dependent Variable	Revenue	ln(Revenue)	# of Bidders	ln(# of Bidders)
β_1 : Site Dummy	14.945 ** (1.977)	0.295 ** (0.028)	2.118 ** (0.562)	0.570 ** (0.140)
γ : Reserve Dummy	4.756 * (2.042)	0.071 ** (0.026)	-2.868 ** (0.446)	-0.578 ** (0.108)
Constant	54.332 ** (2.169)	3.961 ** (0.034)	4.627 ** (0.570)	1.307 ** (0.141)
Item Dummies	Yes	Yes	Yes	Yes
# of Observations	62	62	62	62
R ²	0.94	0.97	0.56	0.54

Notes: Robust standard errors are in parentheses. * and ** denote significance at the 5% and 1% levels, respectively. "Site dummy" equals 1 if auction site was eBay. "Reserve dummy" equals 1 if reserve is positive.

Table 6: Regression Results under Ending Rule Treatment on Yahoo

Dependent Variable	1	2	3	4
	Revenue	ln(Revenue)	# of Bidders	ln(# of Bidders)
γ : Ending Rule Dummy	0.117 (1.495)	0.005 (0.044)	-0.168 (0.741)	-0.115 (0.171)
Reserve Dummy	1.365 (1.546)	0.030 (0.042)	-2.714 ** (0.571)	-0.749 ** (0.142)
Constant	58.143 ** (2.417)	4.056 ** (0.051)	5.155 ** (1.109)	1.587 ** (0.205)
Item Dummies	Yes	Yes	Yes	Yes
# of Observations	43	43	43	43
R ²	0.97	0.96	0.41	0.5

Notes: Robust standard errors are in parentheses. * and ** denote significance at the 5% and 1% levels, respectively. "Reserve Dummy" equals 1 if reserve is positive. "Ending Rule Dummy" equals 1 if hard-close ending rule.

Table 7: Bid Timing Regression Results for Yahoo

Dependent Variable	Minutes from close	
	1	2
	All Bids	Last Bids
β_1 : Ending Rule Dummy	-223.327 (344.95)	118.351 (476.84)
Reserve Dummy	-1828.738 ** (485.74)	-1888.365 ** (551.71)
Constant	5592.761 ** (547.05)	4397.104 ** (720.68)
Item Dummies	Yes	Yes
# of Observations	375	192
R ²	0.11	0.19

Notes: Robust standard errors are in parentheses. * and ** denote significance at the 5% and 1% levels, respectively. "Reserve Dummy" equals 1 if reserve is positive. "Ending Rule Dummy" equals 1 if hard-close ending rule.

Table 8: Regression Results under Baseline, Reserve and Ending Rule Treatments

	1	2	3	4
Dependent Variable	Revenue	ln(Revenue)	# of Bidders	ln(# of Bidders)
β_1 : Site Dummy	15.053 ** (1.855)	0.297 ** (0.028)	2.120 ** (0.566)	0.581 ** (0.139)
Reserve Dummy	4.666 ** (1.766)	0.072 ** (0.028)	-2.793 ** (0.379)	-0.618 ** (0.096)
Ending Rule Dummy	0.508 (2.012)	0.008 (0.046)	-0.167 (0.701)	-0.106 (0.166)
Constant	55.602 ** (2.333)	3.993 ** (0.049)	4.992 ** (0.788)	1.452 ** (0.158)
Item Dummies	Yes	Yes	Yes	Yes
# of Observations	83	83	83	83
R ²	0.94	0.95	0.53	0.53

Notes: Robust standard errors are in parentheses. * and ** denote significance at the 5% and 1% levels, respectively. "Site Dummy" equals 1 if auction site was eBay. "Reserve Dummy" equals 1 if reserve is positive. "Ending Rule Dummy" equals 1 if hard-close ending rule.

Table 9: Implied Stockout Rate by Coin

Coin	Price Difference (Pe-Py)	search cost (Hong & Shum, 2006)	Implied Stockout Rate
1	\$12.88	\$2.40	84%
2	\$7.74	\$1.30	86%
3	\$19.32	\$2.90	87%
4	\$27.19	\$2.90	90%
5	\$7.37	\$2.30	76%
6	\$7.16	\$1.30	85%
7	\$13.67	\$1.30	91%
8	\$31.59	\$2.90	92%

Notes: Search costs were gathered from Hong and Shum (2006). Coins were matched with products of similar value. For example, a coin with an average eBay price of \$97 was matched with the search cost associated with a \$100 item in their study.

Table 10: Field Data Summary Statistics

	Mean Values	
	eBay	Yahoo
Revenue (\$)	59.900 (40.455)	54.179 (32.012)
# of Bids	7.064 (4.726)	4.509 (5.850)
# of Obs.	1281	371

Table 11: Regression Results with Field Data

Dependent Variable	1	2	3	4
	Revenue	ln(Revenue)	# of Bids	ln(# of Bids)
β_1 : Site Dummy	11.605 *** (1.869)	0.148 *** (0.028)	2.002 *** (0.300)	0.691 *** (0.053)
Reserve (Opening price)	0.456 *** (0.027)	0.006 *** (0.000)	-0.083 *** (0.004)	-0.018 *** (0.001)
Constant	46.366 *** (2.164)	3.797 *** (0.035)	7.890 *** (0.352)	1.513 *** (0.060)
Item Dummies	Yes	Yes	Yes	Yes
# of Observations	1652	1652	1652	1652
R ²	0.31	0.31	0.35	0.51

Notes: Robust standard errors are in parentheses. * and ** denote significance at the 5% and 1% levels, respectively. "Site Dummy" equals 1 if auction site was eBay.