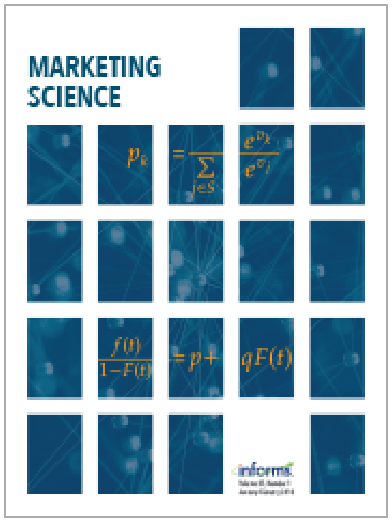

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Search and Choice in Online Consumer Auctions

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Price dispersion in simultaneous online auctions is a puzzle in light of the relatively low search costs required to find the lower price. Much of this price dispersion appears to be due to a lack of switching by bidders between auctions, which in turn could be due to inertia related to search costs. We identify some of the influencing factors through a controlled field experiment involving pairs of simultaneous auctions. Keeping the sellers and the goods sold identical between two auctions, we vary auction design features between and within pairs including shipping cost, open reserve, secret reserve price, and duration, and we provide bidders with incentives to search. We use a choice model that examines individual choice between pairs of simultaneous auctions. We find that within-pair price dispersion is substantial and that prices and auction choice by bidders are indeed related to search costs. We find strong inertia in auction choice and find that this effect significantly interacts with time left in the auction. Although individuals do not always choose a lower-priced auction, they are more likely to do so when search costs are low or search incentives are high.

Key words: experimental economics; auctions; field experiments; search
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1. Introduction

We report the results of a field experiment designed to measure the impact of consumer search on price dispersion in online auctions. Price dispersion in online auctions has been previously documented and could have both supply-side and demand-side causes. In our experiment the supply-side causes are ruled out because we use a pairwise design of two simultaneous auctions with the same seller and same auction characteristics. We find substantial price dispersion. Therefore, we study the relationship between demand-side frictions and search cost. An analysis of choice between concurrent identical auctions indicates that the price dispersion is largely due to inertia, indicating search cost as an explanation.

Consumers' apparent failure to equate prices is important to managers because it is indicative of market power in what might otherwise appear to be a competitive market. In a market with substantial friction, there is a potential premium to differentiation. We examine the possibility of differentiation in the form of small design attributes in the auction, rather than in the item itself.

To study price dispersion and its drivers, we focus on choice between auctions. Each bidder faces two simultaneous auctions by the same seller ending at the same time. A bid in one auction at time t can be perceived as a choice to bid in that auction over the other auction at time t. Auction theory (e.g., Peters and Severinov 2006) requires that the choice to bid in one auction over the other implies a higher expected utility by the bidder for that auction, given the previously highest bids in each auction and given that both auctions are evaluated. This allows us to use a standard choice model on each bid as a choice and a choice set restricted to the two auctions in a pair.

A major advantage of our choice modeling approach is that it does not necessitate knowing bidding strategies, characterizing equilibrium prices, or imposing restrictive assumptions. This is a major advantage in empirical auction research given the serious flaws with standard assumptions regarding bidding strategies (Zeithammer and Adams 2010, Haile and Tamer 2003).

One focus of the choice model is on search as an explanation for price dispersion. Search is unobserved and is gauged through attention to bidder inertia and its interaction with search incentives and time left in the auction (which affects the expected benefit to search). All design variables, including search incentives, also enter directly into expected bidder utility.

We vary search costs directly by providing direct search incentives to bidders in some of the auction pairs. In addition, we vary search costs indirectly by varying auction features that are unrelated to the good sold or its quality within pairs of identical product auctions. We examine the following features: (1) shipping costs, (2) open reserve price (the minimum starting bid), (3) duration, and (4) secret reserve. We study these questions with auction data drawn from a controlled field experiment on eBay that makes use of a simultaneous pairwise design.

2. Background

All auctions were conducted on eBay.com—the largest Internet platform for consumer auctions. Auctions on eBay use a feature called "proxy bidding," where the computer revises bids on behalf of the bidder up to the bidder's maximum bid. As subsequent maximum bids are submitted by other bidders, the bid rises by the minimum increment until the bidder's maximum bid is reached. When all bids have been submitted, the bidder with the highest maximum bid wins the item and pays the second-highest maximum bid plus the minimum bid increment. Note that computer-generated revisions are not the unit of analysis here because they are not active choices by bidders. Bidding takes place over a period of time, generally a few days, and bidders may manually revise their maximum bids upward at any time before the closing of the auction. (These manual revisions are considered active choices in the present work.)

Bidding strategy can be quite flexible. Bidders can state their highest willingness to pay early on and let the proxy bidding feature of eBay bid incrementally for them, or they can bid incrementally themselves. They can bid continually or intermittently, and they can view the bidding actively or rely on eBay e-mail reminders when they are outbid. Specifically, a bidder facing multiple simultaneous auctions may search across auctions for the best price or elect to limit attention to one auction or to rely on eBay reminders with a direct link to that one auction. Therefore any estimation of bidder valuations or strategies requires restrictive assumptions. For example, one may examine bidders' final bids to estimate valuations, or one may look at bid increments to deduce bidding strategies. Assumptions for empirical estimation might differ depending on the objective of the research (e.g., see Bradlow and Park 2007, Park and Bradlow 2005).

An advantage of the present design—looking at choice between a pair of simultaneous identical product auctions—is that we can attempt to be agnostic regarding the underlying strategic bidding process. We only make an inference on the difference between two auctions in a pair, which generally requires far fewer assumptions and restrictions. Accordingly, we extend the theoretical development to predictions based on the idea of evaluation and choice, rather than the derivation of bidding strategies.

The closest design in the literature is that of Anwar et al. (2006). They study groups of eBay auctions for CPUs with similar items and close ending times (but not starting times), starting price, and delivery method. They find that significant cross-bidding occurs but that not all bidders switch to lower-priced auctions and that significant price dispersion persists in concurrent auctions. There are several differences between our study and theirs. First, their data set involves less control as a result of variation in the sellers, the number of simultaneous auctions, the number of auctions by the same seller for the same or similar items, and the items themselves, resulting in significant variations in prices. Second, in contrast to Anwar et al. (2006), with our controlled design we can deliberately vary direct and indirect search costs by varying direct search incentives and features such as shipping cost, open reserve, secret reserve, and duration.

3. Model

It is important to begin by stressing that search is not the only explanation to price dispersion. Other explanations involve strategic variance by firms, unobserved consumer preferences, and unobserved or perceived product differences. Moreover, price dispersion can often be attributed to seller or time differences. By having two identical products with identical sellers and identical ending times, we can largely rule out these other explanations. *Search* is what we name the class of explanations that remains. These explanations most notably include inertia that effectively reduces search. It is important to stress that these do not collapse to a single explanation but are simply indicative of what drives search costs.

Our model includes static and dynamic variables that affect search costs. By *static* we mean variables that are known ex ante prior to the start of the auction. *Dynamic* variables are variables that change in the course of the auction. The static variables we manipulated include open reserve price, secret reserve, duration, and shipping costs. These are differences in characteristics that pertain to the auction process but not directly to the item.[1] The secret reserve price itself is unknown to bidders but its existence is known. This implies that the winner may not get the item and this should affect choice. All of these have been shown to impact final prices in auctions and are therefore candidates to influence price dispersion. Research showing the influence of these static variables includes shipping cost (positive

[1] Open and secret reserve may be indirect quality indicators or signals that positively influence prices in auctions (Li et al. 2009). However, because we run simultaneous pairs of identical product auctions (e.g., one auction with an open or secret reserve and the other without), if there are any quality signals, they should influence both auctions.

effect on ending price; e.g., Häubl and Popkowski Leszczyc 2003, Hossain and Morgan 2006), open reserve (positive effect on ending price; e.g., Ariely and Simonson 2003, Häubl and Popkowski Leszczyc 2003, Reiley 2006), secret reserve (negative effect on ending price; e.g., Elyakime et al. 1994, Katkar and Reiley 2006), and duration (positive effect on ending price; e.g., Haruvy and Popkowski Leszczyc 2010, Lucking-Reiley et al. 2007).

The dynamic variables we include are (1) inertia, which directly influences search; (2) bidding intensity, which influences price dispersion; and (3) price-related variables, which are discussed in the next section.

3.1. Bidder Choice Between Auctions

We propose a model of bidder behavior that involves an explicit comparison of simultaneous auctions followed by choice. The model requires only minimal assumptions about the structure of the bidding process: (1) bidders are expected utility maximizers, and (2) expected net value in an auction is a function of current observables, including the current prices in the two auctions as well as other variables relevant to expectations. From there, we still make some econometric assumptions and choose relevant variables, but we do not impose bidding strategies.[2]

It is reasonable to assume that a bidder facing a choice between two simultaneous auctions places his bid in the auction that gives him a higher expected surplus. Peters and Severinov (2006) have argued that in the case of identical products, bidders will alternate their bids between the auctions, keeping the prices in the auctions within a bidding increment of one another. The basic assumption behind that model is that a bidder treats each bid as if there is some positive probability for this to be his final and winning bid. As such, a bidder chooses the auction that would give him the highest net utility at the current high bid recorded for each auction.

A key assumption in a choice model is that all choices are evaluated at the time they are made. This is not a far-fetched assumption in the low-friction environment we study. The comparison task is easy because both auctions in a pair are adjacent to one another in a typical list of auctions that eBay produces,[3] and because the seller, prices, and shipping costs in each auction are shown on that list. A bidder can easily compare prices at any time by browsing, searching, or simply clicking on "View seller's other items."

The individual i is assumed to have a utility associated with bidding in each auction j in the set of simultaneous auctions that are available at time t_i. Time has an individual-specific subscript as the number of choices over time differs across bidders.

Because utility is not directly observed and only revealed through choice, the analysis can only identify the effect of variables that are different between the two auctions in a pair. Note that the choice model can determine how each observed variable affects the difference in expected utilities between the two auctions but does not allow one to compute the auction-specific expected utility in either auction.[4] Variables, like the time cost of placing a bid, that are expected to be the same across auctions will drop out. Thus, the relevant construct of concern is the difference between utilities:

$$\Delta U_{i,j,t_i} = \Delta Intercept_i + \alpha_i' \Delta F + \beta_i' \Delta RP_{i,t_i} + \gamma_i' \Delta Intensity_{i,t_i} + \delta_i' \Delta Inertia_{i,t_i} + \varepsilon_{i,j,t_i}. \quad (1)$$

The error term ε_{i,j,t_i} is assumed to be independent and identically distributed (iid) over individuals and time. Note that without some natural ordering of the two auctions in the pair, the bidder-specific intercept will drop out. To capture these bidder-specific effects, we order the auctions such that auction 1 is the one with the first bid in it (and thus ex ante preferred by the first bidder).

F is a vector of auction design features. It does not vary over bidders or time, but the coefficient on this operator varies across bidders because different bidders may have different preferences. The vector of auction features includes shipping charge, open reserve price, auction duration, and the presence or absence of a secret reserve price. These are included as potentially critical features because they have been deemed important and investigated in past literature (discussed at the beginning of this section). α_i denotes the parameter vector for the coefficients on auction features.

RP_{i,t_i} denotes a vector of price-related variables that are potentially useful for arriving at the expected price in the auction. These variables change over time and are different across bidders. They include the

[2] The approach of moving away from specifying restrictive bidding strategies was most eloquently advocated by Haile and Tamer (2003). They make two simple and reasonable assumptions: (1) a bidder never bids more than his own valuation, and (2) a bidder will not let another bidder win at a price lower than his own valuation. However, different from our approach, they do not use a choice model, and they focus on bidding behavior in a single auction.

[3] A bidder searching for an item on eBay will typically do so by browsing a product category and subcategories or by typing a specific key word in a search box. In both instances, eBay responds with a list of auctions that includes the experimental auctions listed after one another.

[4] This is because many terms drop out in the differencing of utilities, including a constant term for the product, the seller, and all attributes that do not vary between the two auctions in the pair.

price at each auction, an interaction of price with the product category, and an interaction of price with the number of competing auctions, done separately for each category. The specific product category and the number of competing auctions in each category are potential indicators of the expected price. Because these variables are the same in both auctions, they cannot be identified as main effects. We can only include their interaction with price. β_i denotes the individual-specific parameter vector for this set of variables.

$Intensity_{i,t_i}$ is the set of variables related to bidding pressure and process considerations. It includes bid-specific time-varying variables that were found useful in Park and Bradlow (2005). These variables control for the dynamics of the bidding process. They could be interpreted as proxies for aspects such as bidding aggressiveness, competitive arousal, or bidding frenzy. These variables are the (1) number of bids submitted before the kth bid (i.e., $k-1$), (2) bid rate operationalized as a lag number of bids divided by the total elapsed time, and (3) rate of bid increments operationalized as an incremental bid amount at the previous round divided by the elapsed time in the previous round. Park and Bradlow (2005) also had time left as a useful construct. In our design, time left is always the same between the two auctions and so it drops out. γ_i denotes the parameter vector relevant to intensity.

$Inertia_{i,t_i}$ includes the set of variables we consider to be directly related to inertia in placing a bid. This is where search cost considerations enter (see our discussion in §3.2). Note that whereas bidders may have differential inertia toward different options, we do not need to allow for differential variances for the options because we use a utility difference model. Hence, we only consider the difference in inertia between the two auctions. δ_i denotes the parameter vector relevant to inertia considerations. There are important alternative specifications for inertia, so we devote the next subsection to discussing these modeling considerations.

The parameter vector $[\alpha_i, \beta_i, \gamma_i, \delta_i]$ is iid over individuals but fixed over time for each individual.

Let $\theta_i = [\alpha_i, \beta_i, \gamma_i, \delta_i]$. Then $\theta_i \sim$ iid $f(\theta, V_\theta)$. The distribution function f for θ_i and the correlation between the different parameters are specified as the multivariate normal distribution.

The choice between simultaneous auctions in a pair follows a standard logit choice framework and the likelihood is simply the product of choice probabilities over all bids by all individuals, as specified below:

$$Likelihood(combinedchoices) = \prod_i \prod_t \frac{1}{1+e^{U_{i2t_i}-U_{i1t_i}}}. \tag{2}$$

To address the concern that misspecification of the distribution function for heterogeneity may lead to biased results (e.g., Dubé et al. 2010), we attempt four different distributions—normal, log normal, uniform, and triangular.[5] All coefficients were estimated as random coefficients with the exception of product category.[6] Because of the random coefficients, it is necessary to do numerical integration that involves draws. Hence, the maximum likelihood procedure is now a maximum simulated likelihood procedure.

We use a recent procedure called Halton sequences (Sándor and Train 2004, Bhat 2001) that has been proposed for the mixed logit model. This procedure takes "intelligent" draws rather than random ones. It thereby reduces the number of draws needed for estimation as well as the simulation error associated with a given number of draws. Bhat (2001) found that 100 Halton draws produced lower simulation error than 1,000 pseudorandom draws. Accordingly, we use Halton sequences with 100 draws. We verified the results with a larger number of draws, and the results are robust.

3.2. Inertia Specification

The inertia-related factors that we considered are loyalty, state dependence, incentive to search, and time left in the auction. *Inertia* refers to the tendency to choose an auction one has chosen in the past. One way we account for inertia is through the share of cumulative instances a bidder has placed bids in a given auction (e.g., Bucklin and Lattin 1991, Bucklin and Gupta 1992, and see a related measure in Dubé et al. 2010).[7] A second measure is through a dummy variable indicating whether a bidder placed his previous bid in the particular auction. This measure is sometimes interpreted as a direct indicator of switching cost (Dubé et al. 2010, 2008; Horsky et al. 2006). We refer to the first measure as *loyalty* and the second as *state dependence*.

Search costs might vary with the time left in the auction. Theoretically, the longer the time bidders can search, the lower the benefit to search relative to its cost. Moreover, search is more consequential as

[5] The triangular distribution is a flexible distribution, which is an approximation for the beta distribution (Johnson 1997).

[6] Because almost all individuals participated in auctions in only a single category, all category-specific coefficients cannot be estimated as random coefficients. We were able to estimate open reserve price, secret reserve, number of bids, and increment rate differences as random coefficients, but the variance covariance matrix could not be estimated with these variables, so they are assumed uncorrelated to the other random coefficients.

[7] In Bucklin and Lattin (1991) and Bucklin and Gupta (1992), the loyalty variable is preinitialized as it is meant to capture initial preferences. Here, there is no rationale for an initial preference over identical auctions, so we use it as a dynamic measure by letting it vary over bids.

the auction nears its end. Another factor related to search is the direct search incentive discussed earlier. The higher that incentive is, the higher the benefit to search relative to the cost of search. Each of these two variables cannot be identified because they are identical across the two auctions in a pair, but we can and do look at their interactions with the loyalty and state dependence variables as done in Dubé et al. (2010). Interactions are a direct test for the interpretations of inertia as search cost related and are structurally consistent.

Note that the interaction between loyalty and time left is also related to the endowment effect (e.g., Roth and Ockenfels 2002, Heyman et al. 2004). The endowment effect posits that the longer a person has been the winning bidder in an ongoing auction, the harder it would be to let go of the item. Thus, the interaction between loyalty (the number of previous bids[8] in an auction is equal to the number of times a person has been the winning bidder in that auction) and the time passed (inversely related to time left) could serve as a proxy for endowment. Thus, the endowment interpretation of this interaction predicts the opposite sign to the search explanation.

4. Experimental Design

The experimental design involves pairs of identical items sold simultaneously in eBay auctions. The seller is the same for the pair of items and is one of two seller identities we used for this study. Both identities had a large number of ratings, where these ratings are the number of feedback responses by unique buyers (seller ratings in the 500s and 600s, respectively); of these ratings, only one was negative for the first seller and zero negative for the second.

The two auctions in a pair always had the same end time and, except for one condition where we varied duration, the same start time. The picture and description of the items were the same in both auctions. Between conditions, we vary the key auction design features discussed in the previous section. To recap, these are (1) shipping costs, (2) open reserve price, (3) duration, (4) secret reserve, and (5) direct incentive to search. The first four features have been previously investigated in the literature but never in a pairwise design, which provides a stronger test of the effect of these features. The last feature is unique to the present investigation. Each auction pair manipulates only one of the five variables under investigation. Table 1 indicates how many pairs of auctions were run for each manipulation in each product and what the manipulation levels were.

[8] Note that a bidder could place a bid and not become the highest bidder.

In total, we ran 580 auctions over a period of two months from April 12 to June 13, 2007. Some auction pairs were not usable because in some of the auctions, in the open reserve price condition, the reserve price was not met. In total, we obtained 281 pairs of usable auctions for analysis.

Including the benchmark, there were six different conditions that varied over nine different products (see rows 1–6 in Table 1). The first row is the benchmark condition, which consisted of running two ex ante identical simultaneous auctions. The numbers displayed are the shipping cost for each of the auctions in the pair with the number of auction pairs in parentheses. Shipping charges for these auctions were based on actual shipping costs and are equal to the amount of the small shipping difference condition. Furthermore, no secret or open reserve price was present, nor any search incentives, and the duration was identical: one day, three days, or five days for both auctions in each pair.

The levels of the other conditions are shown in rows 2–6 of Table 1. For each product and each variable under manipulation, there are three different levels: none, low, or high. Only for secret reserve are there two levels: present or not. With the exception of duration, the determination of what values constitute low and high for each variable is product specific. For each of the conditions, we vary one variable within the auction pair. All other variables are kept constant across auctions, and values are identical to those for the benchmark condition.

The three levels for shipping costs are free shipping, a low shipping cost, and a high shipping cost (see row 2, Table 1). These three levels of shipping costs result in two different shipping conditions between pairs of auctions: a small difference (low versus no shipping costs) and a large difference (high versus no shipping costs).

The small and large open reserve price condition worked in a similar way, where one auction sold with either a small or a large open reserve price, and the other auction sold without an open reserve. The magnitude of the open reserve price was based on the expected selling prices. To ensure that most items would sell, we set the high open reserve price at about 75% of the average selling price of past auctions for the identical item. The low open reserve price was set at half of that.

In the duration conditions, we ran one-day auctions paired with either a three-day or a five-day auction, such that both auctions had the same end time. For the secret reserve price condition, one auction in the pair always had a secret reserve present and the other did not. The secret reserve was set to 25% above retail price such that it was present for the duration of the auction.

Table 1 Summary of Experimental Conditions Across Different Products

	Prod1[a]	Prod2	Prod3	Prod4	Prod5	Prod6	Prod7	Prod8	Prod9
Condition									
Benchmark—identical auctions[b] number shown is the shipping cost	4.99 (4)	3.25 (4)	3.99 (4)	5.99 (3)	3.25 (5)	4.99 (2)	3.25 (3)	6.99 (2)	3.25 (4)
Small/large shipping cost difference	0 vs. 4.99/ 0 vs. 9.99 (8)	0 vs. 3.25/ 0 vs. 8.00 (5)	0 vs. 3.99/ 0 vs. 8.00 (8)	0 vs. 5.99/ 0 vs. 11.99 (7)	0 vs. 3.25/ 0 vs. 6.00 (8)	0 vs. 4.99/ 0 vs. 9.99 (3)	0 vs. 3.25/ 0 vs. 6.00 (8)	0 vs. 6.99/ 0 vs. 12.99 (10)	0 vs. 3.25/ 0 vs. 6.00 (7)
Small/large open reserve difference	0 vs. 5/ 0 vs. 10 (2)	0 vs. 15/ 0 vs. 30 (4)	0 vs. 12.5/ 0 vs. 25 (4)	0 vs. 10/ 0 vs. 17.5 (2)	0 vs. 5/ 0 vs. 10 (3)	0 vs. 5/ 0 vs. 10 (1)	0 vs. 3.5/ 0 vs. 7 (7)	0 vs. 7.5/ 0 vs. 15 (2)	0 vs. 5/ 0 vs. 10 (4)
Small/large duration difference	1 vs. 3/ 1 vs. 5 (2)	1 vs. 3/ 1 vs. 5 (5)	1 vs. 3/ 1 vs. 5 (4)	1 vs. 3/ 1 vs. 5 (2)	1 vs. 3/ 1 vs. 5 (4)	1 vs. 3/ 1 vs. 5 (2)	1 vs. 3/ 1 vs. 5 (7)	1 vs. 3/ 1 vs. 5 (2)	1 vs. 3/ 1 vs. 5 (4)
Secret reserve	Yes vs. No (10)	Yes vs. No (6)	Yes vs. No (7)	Yes vs. No (5)	Yes vs. No (7)	Yes vs. No (6)	Yes vs. No (5)	Yes vs. No (9)	Yes vs. No (6)
Small/large shipping cost used as search incentive	4.99/9.99 (4)	3.25/6.00 (9)	3.99/8.00 (8)	4.00 / 8.00 (9)	3.25 / 6.00 (9)	N/A [c]	3.25 / 6.00 (9)	6.99/ 12.99 (6)	3.25 / 6.00 (10)
Additional information[d]									
Retail price ($)	30.00	47.25	32.09	22.98	19.99	19.69	17.99	30.87	17.97
Average final price + shipping	$24.9 (0.71)	$38.7 (0.49)	$33.0 (0.56)	$23.7 (0.37)	$16.8 (0.42)	$14.0 (0.43)	$11.6 (0.26)	$24.7 (0.60)	$18.0 (0.42)
Average number of bidders	5.8 (0.2)	6.2 (0.3)	6.2 (0.2)	6.9 (0.4)	5.7 (0.2)	4.3 (0.3)	4.5 (0.2)	4.8 (0.2)	5.9 (0.3)
Average number of manual bids[e]	13.2 (0.8)	10.4 (0.5)	14.2 (0.9)	14.0 (0.9)	10.2 (0.5)	8.5 (0.8)	8.1 (0.6)	10.0 (0.7)	10.0 (0.7)
Average number of competing auctions	1.66 (0.04)	1.47 (0.04)	3.71 (0.12)	2.01 (0.06)	3.47 (0.18)	1.07 (0.02)	5.45 (0.21)	1.47 (0.04)	7.01 (0.35)
Average number of auction pairs	30	33	35	28	36	14	39	31	35

Note. Number of repetitions is in parentheses.

[a]Prod1 = Fisher-Price aquarium gym; Prod2 = *Harry Potter* audiobook; Prod3 = *Harry Potter* boxed set; Prod4 = Pampers diapers; Prod5 = Dr. Brown baby bottles; Prod6 = Happy Hippo gym; Prod7 = *Harry Potter* book 6; Prod8 = Fisher-Price baby rocker; Prod9 = *The Secret* audiobook.

[b]For the base case shipping charges are equal to the "low" shipping costs, the duration is three days, and there is no open reserve, no search incentive, and no secrete reserve price.

[c]This product was not used for the search condition because of a lack of availability.

[d]Numbers in parentheses are standard errors.

[e]Manual bids are instances where the bidder manually entered a number in the bidding text box.

We also provided direct incentives to search in some instances. To do that, we ran two identical auctions where we offered bidders an incentive to search by promising to waive shipping costs if the final price in the auction ended up lower than any identical auction ending within 30 minutes of the current auction. The bidder in the more expensive auction in the pair had to pay the shipping charges indicated in the auction. Shipping charges were either low or high, providing either a low or high search incentive. To avoid bidder confusion, all auctions with search incentives were run separately from the auctions in the other conditions.

We provide summary statistics concerning the number of bidders, the number of manual bids, and the number of competing auctions. The average number of bidders in each of our auctions is small, but these numbers are fairly representative of eBay auctions in their respective categories, as well as for more expensive items like automobiles (6.4 bidders; 13.8 bids based on a random sample). The limited number of bidders may present limitations in analysis, but we think it is an acceptable trade-off for obtaining field data. Manual bids, or instances where a human actively enters a bid in the bid box, are available in the history of the auction, and only these instances are counted as active bidder choices.

The number of competing auctions is a time-varying variable, computed by counting the number of other auctions ending on the day of each observed bid.

An important design consideration pertains to the impact of competition by outside auctions (e.g., Chan et al. 2007, Jank and Shmueli 2007). In the data

Table 2 Summary Statistics by Search Incentive Condition

Search incentive	No. of auction pairs	Dollar price diff. within pairs	Percentage price diff. within pairs	No. of visitors	No. of bidders	No. of bids	No. of switchers	Average price
No incentive	216	\$3.07 (0.21)	13.82 (0.84)	95.61 (2.83)	5.60 (0.10)	11.04 (0.28)	1.02 (0.05)	\$19.22 (0.47)
Low incentive	42	\$2.13 (0.28)	9.87 (1.15)	121.27 (10.00)	6.11 (0.24)	11.29 (0.61)	1.15 (0.15)	\$18.58 (0.97)
High incentive	23	\$2.04 (0.56)	8.71 (2.31)	123.85 (12.58)	5.30 (0.25)	9.85 (0.66)	1.22 (0.21)	\$15.38 (1.28)

t-Tests for	Dollar price diff.	Percentage price diff.	No. of visitors	No. of bidders	No. of bids	No. of switchers
Low vs. no incentive	$t[256] = 1.90$, $p = 0.058$	$t[256] = 1.99$, $p = 0.047$	$t[222] = 3.22$, $p = 0.001$	$t[514] = 1.97$, $p = 0.049$	$t[514] = 0.36$, $p = 0.723$	$t[514] = 0.98$, $p = 0.326$
Low vs. high incentive	$t[63] = 0.16$, $p = 0.874$	$t[63] = 0.51$, $p = 0.615$	$t[51] = 0.16$, $p = 0.874$	$t[128] = 21.7$, $p = 0.032$	$t[128] = 1.49$, $p = 0.138$	$t[128] = 0.25$, $p = 0.802$
No vs. high incentive	$t[237] = 1.53$, $p = 0.127$	$t[237] = 1.90$, $p = 0.059$	$t[209] = 2.93$, $p = 0.004$	$t[476] = 0.90$, $p = 0.370$	$t[476] = 1.32$, $p = 0.186$	$t[476] = 1.13$, $p = 0.259$

Note. Standard errors are in parentheses.

collection phase, we collected data on related auctions running simultaneously, and we include the number of such auctions as an explanatory variable in all our regressions. Online Appendix A lists the key words used to determine whether an auction is a competing auction in a given category (an electronic companion to this paper is available as part of the online version that can be found at http://mktsci.pubs.informs.org/). These competing auctions included different formats for the identical product (e.g., both hardcover and softcover books), as well as new and used items.

The experimental design carefully controls for the outside competition and other external factors in three ways: (1) it uses a pairwise design—whatever else is happening should affect both auctions in the pair; (2) it uses a design over several months—this should result in averaging out competition over a longer period; and (3) it uses some categories with lots of outside competition and some with nearly none.

5. Results

5.1. Final Prices

We first look at final prices and determine the extent of price dispersion. Online Appendix B in the electronic companion shows a plot of relative prices over time for each product category, suggesting no price trends over time. The first, and most telling, summary statistic pertains to the existence of price dispersion in pairs of auctions for identical goods with identical sellers and identical closing times. The average price difference (here, price is the full price paid by the bidder, including shipping cost) over the 281 auction pairs we ran is \$2.87. This is significant ($t = 16.36$, $\text{df} = 280$, $p < 0.001$). In percentage terms, this is 15.25% of the average price observed (average price of \$18.82). Limiting our attention to auction pairs that had identical auction design features (shipping costs, open reserve price, secret reserve price, and duration), we get a price difference of \$2.69 ($t = 9.88$, $\text{df} = 101$, $p < 0.001$). Hence, we conclude that price dispersion is highly significant for both nearly identical and completely identical auctions in a pair.

Our next set of results, summarized in Table 2, pertains to the effect of having a search incentive on variables related to price dispersion. In the present design, the search incentive is directly tied to the shipping cost because this incentive constitutes a refund on one's shipping cost. Therefore, manipulating the shipping cost changes the incentive to search, and this is the effect we seek to quantify.[9] A reasonable conjecture is that price dispersion is inversely related to the magnitude of the search incentive. Whereas the low search incentive condition is identical in shipping cost (in all but the diapers category) to the no search baseline condition in terms of shipping cost, the high search incentive condition involves a higher shipping cost, and this is expected to have an adverse effect on demand. This will be disentangled in a regression. For now, the conjecture is that moving from the no search incentive to a low search incentive will result in increased switching within the auction pairs, resulting in an increase in the number of bidders and the

[9] Note that the mere mention of an incentive to search may cause a demand effect where participants are alerted to the purpose of the experiment. However, all search incentive treatments had the same wording, differing only on the shipping cost (the incentive amount). Moreover, the participants here are eBay bidders who are presumably not there to participate in an experiment, but rather to maximize personal payoff. Therefore, demand effects are somewhat less of a concern.

number of bids per auction while reducing price differences in both absolute and relative terms. The averages and standard errors are reported in the top panel of Table 2. The t-tests between search conditions are reported in the bottom panel of the table.

We observe a decrease in price dispersion when providing bidders with a low search incentive relative to no search incentive. This difference is significant at the 3% level (based on a one-sided t-test) for dollar difference and at 2.5% for relative (percentage) difference. Hence, we conclude that search incentives reduce price dispersion. This is likely due to more active search, manifested in both the number of visitors to the auctions (number of nonunique people viewing but not necessarily bidding) and the number of active bidders. It does not directly translate to (significantly) more manual bids.

We find significantly fewer bidders per auction in auctions with high search incentives. This is likely a result of the fact that high search incentive implies a high shipping fee. However, as expected, when we look at the number of switchers, we see that the highest number of switchers (albeit not significant) is in the high search incentive auctions.

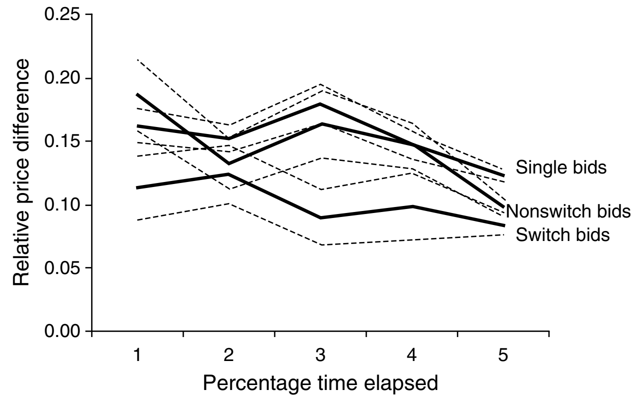
We ran a simple linear regression with price difference as the dependent variable. In this model, the only coefficients that are significant are the intercept ($\alpha = 3.211$, S.E. $= 0.761$) and the search incentive (search dummy $\times$ shipping, $\beta = -0.203$, S.E. $= 0.088$). In other words, the attribute differences do not significantly affect final price differences in simultaneous pairs, with the exception of search incentives.[10] This is in line with the choice regressions findings we report later in the paper.

5.2. Bidder Choice Between Auctions

The average number of bids per bidder in a pair of auctions, over all auction pairs, was 2.33. There were 2,129 unique bidders in the data set (2,952 nonunique bidders if we look at each auction pair separately). Only 408 (19.2%) bidders out of 2,129 unique bidders ever switched between auctions in a pair. This number is not significantly different over search conditions. Many bidders placed a single bid in an auction. Out of 2,129 bidders over pairs of items, 939 bidders submitted only a single bid on one item in a pair, and 1,190 bidders submitted more than one bid on an item in a pair. These 1,190 bidders are the bidders that will enter our choice analysis later on (because

[10] We also ran a regression where the final price in each auction, rather than the price difference in each auction pair, is the dependent variable. In this model, the coefficients on shipping, open reserve price, and duration came out significant. This suggests that although auction design features influence ending prices, this influence does not extend to price differences in concurrent auctions.

Figure 1 **Price Dispersion Between Identical Auctions Over the Course of an Auction**



Note. Dotted lines indicate the 90% confidence interval.

of the interest here in repeated choice). If two identical auctions have few traders that only bid once, they will typically not produce the same final prices. However, our analyses show that bids by single-bid bidders do not result in greater price dispersion than comparable bids by bidders who enter multiple bids (see Figure 1).

Of all switches from one auction to a different auction, 78.8% of bids were to the lowest-priced option and 21.2% of switches were to a higher-priced option. One possible explanation for these seemingly suboptimal choices, suggestive of a lack of search, is that bidders may wait till the end of the auction when "it really counts." Hence, price dispersion may be time dependent. To investigate this, Figure 1 shows the relative price dispersion between identical product auctions over the course of an auction. Price dispersion is measured at each bid instance. We separate out price dispersion at instances of switch bids, where the bidder's previous bid was in a different auction, and nonswitch bids and see how both of these measures vary over time. In addition, we plotted the bids for those bidders who only placed a single bid. The dotted lines are the 90% confidence intervals, which indicate that relative price differences are statistically significantly ($p = 0.10$) higher for nonswitch bids. In addition, price differences are not statistically significant for the nonswitch bids and the single bids.

Figure 1 indicates that early on in the bidding, price dispersion is mild. This suggests that bidders pay attention to prices when entering an auction (though 26.8% of the bidders did not enter the lowest-price auction when given the choice) and is likely indicative of some initial search. However, price dispersion increases slightly over time for both switch and nonswitch bids. Finally, both types of bids reveal some reduced dispersion in the final stages of the auction, but significant price dispersion remains toward the end of the auction, when bids are the most meaningful.

Table 3 Results of Random Coefficients Mixed Logit Regressions with State Dependence

	State dependence		Loyalty		Encompassing	
	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.
Search incentive × Price	−0.157**	0.079	−0.221***	0.059	−0.229***	0.082
Duration in days	−0.061	0.061	−0.073	0.060	−0.033	0.067
Price	−0.171***	0.053	−0.237***	0.057	−0.219***	0.058
Shipping	0.122*	0.065	0.146**	0.069	0.189***	0.071
Open reserve	−0.015	0.034	−0.002	0.035	0.009	0.034
Secret reserve	0.068	0.083	0.172**	0.083	0.163*	0.091
State dependence	3.124***	0.127			1.900***	0.193
State dependence × Search incentive	−0.092	0.161			0.077	0.211
State dependence × Time left	−0.034***	0.008			−0.019*	0.010
Loyalty			1.981***	0.090	1.057***	0.126
Loyalty × Search incentive			−0.176	0.128	−0.087	0.169
Loyalty × Time left			−0.030***	0.006	−0.020***	0.008
Bid rate	0.016	0.012	0.039***	0.012	0.026**	0.014
No. of bids	−0.087	0.080	−0.116**	0.056	−0.122	0.079
Increment rate	0.014	0.152	0.154	0.096	0.095	0.148
Constant	−1.386***	0.068	−0.086**	0.044	−0.931***	0.094
Log likelihood function	−1,627.05		−1,662.93		−1,588.67	
AIC	0.911		0.930		0.908	
BIC	1.021		1.040		1.073	
Adjusted BIC	0.931		0.970		0.965	
McFadden pseudo R^2	0.056		0.063		0.063	
Adjusted R^2	0.039		0.046		0.038	
No. of individuals/observations	1,190/3,718		1,190/3,718		1,190/3,718	
No. of coefficients incl. intercept and covariance coefficients	66		66		99	
No. of significant coeff.	25		34		50	

Note. Product-specific and product-competition-specific interactions with price were included in the regression, but estimates are not reported here to preserve space (see Online Appendix F in the electronic companion for complete results).
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

To further examine the causes of price dispersion, we resort to a regression on bidder choice between auctions, as specified by Equation (2).

The variables we consider (exact rationale and discussion are in §3) are (1) variables falling under features in Equation (1), including shipping cost, open reserve, duration, and secret reserve price; (2) price-related variables in Equation (1), which include price, interactions between price and product dummies, and interaction between price and the number of outside auctions; (3) variables pertaining to the bidding intensity, which control for differences in price levels for auctions, including *number of bids, bid rate, and increment rate*; (4) variables pertaining to inertia, including the interaction of search incentive with price, and the interaction of search-related variables with measures of inertia; these include *state dependence*, *state dependence × search incentive, state dependence × time left, loyalty, loyalty × search incentive*, and *loyalty × time left.*

We estimated a number of different models, starting with a homogeneous specification (see Online Appendix C in the electronic companion). Next we estimated a model that accounts for differences between individuals with randomly distributed coefficients (see Table 3) where the individual random coefficients are correlated with one another through a variance–covariance matrix. Because the different sets of models give the same major qualitative results and all fit statistics indicated a significantly better fit for the random coefficient model with correlation and a normal distribution for the heterogeneity (including the Akaike information criterion (AIC) and Bayesian information criterion (BIC), which adjust for the number of parameters estimated), we only report the results of this model in the paper. Of the four heterogeneity distributions, the multivariate normal distribution obtained the best fit, and as results are qualitatively the same, we only report those results.[11]

[11] It is important to note that although full specification of heterogeneity is important for the correct interpretation of state dependence and loyalty coefficients and their interactions, it does not in itself alter the major qualitative patterns observed from a simple regression that does not account for heterogeneity in error terms and correlations between individual coefficients. A replication of Table 3 without any panel data methods is available in Online Appendix C (in the electronic companion) and shows the same qualitative results, albeit a much worse likelihood and somewhat different coefficient estimates. However, the interpretation of the simple model is subject to the usual criticism of state dependence in the literature.

The coefficients on time left in minutes were rescaled by 10,000.

Because of concern about the correlation between state dependence and loyalty, we report regressions using each separately as well as the encompassing model with both measures (see Table 3).

The results of the model fit statistics do not provide a consistent best-fitting model. Therefore, it is difficult to pick between the different models. As expected, log likelihood is highest for the encompassing model, which also has the highest number of parameters. However, on both BIC and adjusted BIC (BIC with only the number of significant parameters entering the computation), the state dependence only model has the lowest BIC. In the encompassing model, we find that both state dependence and loyalty are highly significant and not accounting for both results in an underestimation of the effect of search incentives. Furthermore, state dependence and loyalty are moderated by time left in the auction, an element related to search, as discussed below. Using only the main variables that came out significant in Table 3, we see that the ranking of the models on fit measures is preserved (see Online Appendix D in the electronic companion).

Because results are consistent between the models, it appears that the correlation of the two inertia measures, estimated at 0.390, should not be a major concern. (The correlation matrix for the coefficients also indicates a low correlation between the two coefficients. See Online Appendix E in the electronic companion.)

Shipping cost is significant in all three models, although only marginally in the state dependence model. Secret reserve is significant in the loyalty model and marginally significant in the encompassing model. The significance of shipping in the encompassing model holds with the robustness check such as taking out the insignificant variables.

Because shipping is already included in the price, results imply that bidders do not fully account for shipping costs. For example, in the encompassing model, it implies that each additional dollar in shipping increases price by 81% (consistent with the results of Häubl and Popkowski Leszczyc 2003). The positive effect of secret reserve price indicates that bidders tend to continue to bid in auctions with a secret reserve price. This is consistent with the interpretation that a secret reserve price acts as an additional bidder in an auction, thereby raising prices.

Furthermore, price has a significant effect when a search incentive is present. This means that bidders who are given a search incentive are more price sensitive and are more likely to switch to a lower-price auction. This supports the result we obtained through final price comparisons—namely, that price dispersion reduces with search incentives.

The *intensity* variables do not come up significant in the state dependence model regression but the bid rate comes out significant and positive in both the loyalty model regression and the encompassing model regression. This positive effect of bid rate on choice could be indicative of some frenzy or competitive arousal. In the loyalty model regression, the number of bids has a negative and significant effect consistent with the rational expectation that more bids would translate to higher future prices. Increment rate is never significant. We also reestimated the model in Table 3 without the bidding intensity measures, but this did not significantly impact the model results.

Loyalty is positive and highly significant, suggesting that consumers are less likely to switch auctions the more bids they have made in a particular auction relative to the other auction. *State dependence* has a positive significant effect as well. That is, recent experience matters, and bidders are more likely to continue to choose the option they selected last.

We also see that more time left decreases the impact of loyalty. As one gets closer to the end of the auction, loyalty plays a greater role, consistent with the endowment effect described earlier. State dependence also plays a greater role toward the end of the auction, but this role is only marginally significant in the encompassing model.

To preserve space, we did not report in Table 3 the interactions between product category and price and the number of competing auctions and price. The complete results are provided in Online Appendix F in the electronic companion. The interaction effects between product-specific dummies and price produces a significant positive effect for the *Harry Potter* audiobook and *Harry Potter* boxed set in the encompassing model. The number of competing auctions only has a significant negative interaction with price for the *Harry Potter* audiobook. Increased competition resulted in greater price sensitivity for the *Harry Potter* audiobook. There is, however, no strong underlying theoretical reason to expect the sign to be positive or negative. More competition may mean more opportunities for finding bargains (justifying increased price sensitivity) but may also mean less pricing power for the competitors (justifying less price sensitivity).

In summary, we conclude that bidders predominately switch between auctions because of price. Furthermore, we find a strong impact of both loyalty and state dependence, indicating that bidders are more likely to continue bidding in the same auction. Moreover, time remaining moderates these effects—they get stronger over time.

6. Conclusions

We examine data from pairs of eBay auctions running simultaneously. We showed that in the case of seemingly identical items sold by the same seller and listed next to one another on the same platform, consumer search and mobility between auctions appear limited. Bidders rarely switched between auctions and often did not choose the lowest available price, even though such activities seemingly involve relatively little effort. Although bidders searched and optimized more when first entering an auction, even then, close to 30% of entrants selected the higher-priced auction.

Failure to search was costly to bidders. Bidders who switched between auctions were clearly better off than winning bidders who are nonswitchers. These bidders saved on average \$1.22 ($p = 0.01$). On average, across all conditions bidders in the higher-priced auction paid a price premium of 15.25%, which is highly significant ($p < 0.01$). In addition, by providing a sufficient search incentive to bidders, we were able to reduce this price premium by 33.8%. This provides strong evidence of price disparities in the final prices and suggests that bidders who evaluate both auctions in a pair can take advantage of these inefficiencies.

This is surprising given the widely held belief that electronic auctions should make it easier for consumers to search for price and product offerings (Smith et al. 2000), resulting in increased price competition (Bakos 1997) and decreased price dispersion (Smith et al. 2000). In contrast to the claim by prominent researchers that the Internet is a new frictionless medium, our results add to a growing body of empirical evidence that suggests that this is not the case. Instead, price dispersion is substantial, and the relative lack of switching between auctions appears to be largely responsible for this. Sellers can and should take advantage of this market inefficiency but should be aware of the bidder rationale for the absence of search.

We found that bidder reluctance to search was largely driven by the cost of search, as evidenced by the impact of our direct search incentives on final prices. Additional evidence is obtained from our measure of inertia, which we interpret here as a direct indicator of switching cost (also see Dubé et al. 2010, 2008; Horsky et al. 2006). Results indicated the importance of inertia as captured by both loyalty (the share of bids in a particular auction) and state dependence (last choice). Although the two measures are somewhat correlated, they significantly improve on one another and each interacts with search elements in a slightly different way. With either loyalty or state dependence as the measure of inertia, time left was found to moderate inertia. This suggests that as bidders are exposed to an auction they are less likely to switch, and this effect becomes larger as one gets closer to the end of the auction, consistent with an endowment effect, although this may also be consistent with bargain hunting behavior.[12]

We also found that prices could be affected by varying auction attributes, including shipping costs and secret reserve price relative to parallel auctions. Hence, the difference in these auction characteristics could impede search, leading to greater price dispersion within identical pairs. This means that sellers have plenty of room to maneuver in reducing price competition, either with competitors or between their own simultaneous offerings. The importance of differentiating one's offering from the competition cannot be overstated. This can be done either by enhancing desired features or by removing them. Although the latter approach may reduce consumer utility for one's offering, it will also reduce competition, which may far outweigh the utility reduction. It is also important to consider which auction design features attract more bidders, given that relatively few bidders switch once they enter an auction. Studying these different tradeoffs is an important direction for future research.

The implications of the present research extend to online environments in general. In any online environment, retailers face choices regarding multiple offerings as well as multiple channels for their products. First, a retailer must decide whether to list its merchandise on an auction platform exclusively, in parallel to other platforms, or even whether to put it up for auction at all. Second, the retailer must decide how many items to list concurrently and under what formats. Friction makes it more profitable and less cannibalistic to list on multiple platforms and/or to have multiple offerings in parallel. Friction also makes auction pricing decisions such as open reserve price (minimum starting bid), secret reserve price, and buy-it-now price more relevant because the manager has pricing power. Studying optimum listing strategies and auction design features in competitive auctions markets is an important area of future research.

A potential limitation regarding the direct search incentive is that we gave a direct dollar incentive to bidders who win an auction at the lowest price. Psychologically, this may frame the task in a way that might encourage lower bids even without search. Although behaviorally this might happen, it would not be rational on the bidder's part to do so because one's bid cannot affect the price he pays if he wins the auction. This is because of the second-price nature of the bidding, where a bidder pays the highest price entered by another bidder. There are two ways in which the incentive might result in lower bids other than the explanation we suggested: one is related to framing and the other is collusive. Neither one is

[12] For example, if someone places a low early bid and later returns to the same auction.

rational. However, we caution against overinterpreting the exact effect of our search incentives.[13]

Another limitation is the need to control for simultaneous auctions outside of experimental manipulation. Whereas the number of competing auctions by other sellers was included as an explanatory variable and found insignificant for all but one of the products, the extent to which outside competition is influential might also depend on whether demand and supply (number of competing auctions) are exogenous. We leave these questions as areas of future research.

Last, the paired-auction design may not be representative of settings with a larger number of alternatives. On the one hand, this design makes the comparison of the available auctions easier relative to settings with more alternative auctions. In that sense, it might make switching to the lower-priced auction more salient. On the other hand, this design concentrates demand in these two auctions, thereby possibly overinflating stickiness. Thus, the design is likely to affect bidder stickiness, although it is difficult to say in which direction. Future research should consider varying the number of competing auctions.

We think the present research can be extended in two important directions. First, search is an important area of investigation in marketing, and electronic auctions provide a unique platform in which to investigate the determinants of search. Electronic auctions involve the most minimal effort required for search that we could identify, and the bidders in such auctions are highly motivated to identify price savings, so failures to search in such an extreme environment need to be resolved before attempting to approach more complex environments. This field is ripe for the investigation of mechanisms to promote search and competition.

Second, in the area of auction research itself, choice modeling is a promising avenue for empirical research that can overcome many of the complicated and potentially restrictive assumptions discussed earlier. Particularly if one wants to map consumer preferences to consumer behavior, choice between auctions does not require any account for bidding strategies. We would like to pursue this direction in other investigations of consumer preferences in auctions. For example, in Haruvy and Popkowski Leszczyc (2009), charitable motives are identified in this manner. There are also other factors that might influence search costs. These include listing under different category names, bundling (e.g., Popkowski Leszczyc and Häubl 2010), and manipulating the number of simultaneous (overlapping) auctions (e.g., Zeithammer 2006).

[13] To examine the possibility of framing effects, we ran additional auctions where we provided a 25% discount to the high price bidder (whereas here, the incentive is to the low price bidder). In 80 pairs of auctions, we observed a significant reduction in price dispersion when a search incentive was provided (from 18.37% without a search incentive to 9.56% with a search incentive). This offers some indication that the search incentive in the current treatments does not merely serve as an incentive to bid low but rather as an incentive to search.

7. Electronic Companion

An electronic companion to this paper is available as part of the online version that can be found at http://mktsci.pubs.informs.org/.

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