What does it take to make consumers search?

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Abstract.

We examine the extent of search in auction markets with relatively low search costs. In a field auction experiment, we examine individual choice between pairs of simultaneous auctions, where the sellers and the goods sold are identical between two auctions. We demonstrate that in this relatively low friction environment, price dispersion is substantial. Search costs are varied either directly or indirectly. Direct search costs are varied by providing incentives to search. Indirect search costs are varied by making simultaneous auctions less comparable through design features, such as shipping costs or reserve price. We show that by varying auction design features sellers can obtain higher revenues. We find that while many individuals do not choose a lower priced auction when given the opportunity, they do so when search costs are low or search incentives are high. We propose a two-stage model of evaluation and choice. In that model, bidders first decide whether to incur the effort of evaluating the two alternatives, followed by a choice between auctions. The two-stage model fits the data better than the benchmark choice model, leading to important implications for auction sellers regarding competitive strategies.
1. INTRODUCTION

Though price dispersion is typically attributed to search costs (Stigler, 1961; Varian, 1980; Bakos, 1997, 1998), there is ample empirical evidence that price dispersion and high prices persist on the Internet despite potentially reduced search costs (Baily, 1998; Brynjolfsson and Smith, 2000; Pan, Ratchford and Shankar 2004; Smith, Bailey and Brynjolfsson, 2000). The evidence further suggests that price dispersion online may be higher than it is offline (Clay et al., 2003; Degeratu, Rangaswamy and Wu, 2000; Lee, 1998; Lynch and Ariely, 2000; Shankar, Rangaswamy and Pusateri, 1998). This is particularly evident in online auctions (Ahlee and Malmendier, 2005; Ariely and Simonson, 2003).

In this work, we examine price dispersion in a low friction environment and investigate whether a search cost explanation can account for the high price dispersion we observe. The environment we focus on has pairs of auctions for identical products, listed next to one another, sold by the same seller, and run simultaneously, with identical starting and ending times, and the price prominently shown.

The first part of this work establishes the existence of price dispersion in this environment. Given the existence of price dispersion, we next focus on search as an explanation for price dispersion. Search is a latent variable, which we operationalize through observing how bidders select between simultaneous auctions for identical products (hereafter referred to as auction pairs). We look at auction choice as a two-stage process consisting of the decision to actively compare the two auctions in a pair, followed by the choice between the two auctions once a comparison takes place—based on present prices and expectations regarding final prices.

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1 Vakrat and Seidmann (1999) propose that bidders in Internet auctions have three types of relevant costs-- monitoring costs, delay costs, and search costs, which are the costs of searching the website looking for an item, as well as looking for alternative items (either similar items or items sold by competing sellers). In addition, these costs may be a function of the duration of the auction. In our studies we keep the monitoring cost and the delay cost constant (except when varying duration), while varying search costs either directly by providing incentives to search or indirectly by (influencing components in search costs).
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 design features, within pairs of identical product auctions, that are not related to the good sold or its quality. We examine the following features that could increase search costs indirectly: (1) shipping costs, (2) open reserve price, (3) duration and (4) secret reserve. We study these and other questions with auction data drawn from a controlled field experiment on eBay that makes use of a simultaneous pair-wise design.

2. BACKGROUND

In this work we deal with auction data—specifically eBay data. As the largest auction website, eBay boasts 86 million active users worldwide (as of 2008), in over thirty countries.

Auctions on eBay use a feature called “proxy bidding,” where the computer submits bids on behalf of the bidder up to the bidder’s maximum bid. Under proxy bidding, bidders enter prices in a text box labeled “Your maximum bid.” As subsequent maximum bids are submitted by other bidders, the bid rises by the minimum increment until reaching one’s maximum bid. Hence, a bidder could enter his willingness to pay for the item as the maximum bid and let the proxy bidding take place\(^2\).

When all bids have been submitted, the bidder with the highest maximum bid wins the item and pays the second highest maximum bid, plus a bid increment. Bidding takes place over a period of time, generally a few days, and bidders can revise their maximum bids upwards anytime before the closing of the auction. 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 bid actively or rely on eBay email reminders when they are outbid. Specifically, a bidder facing multiple simultaneous

\(^2\) Many bidders however opt instead to bid some increment above the currently displayed high price and revise their bids as they are outbid. In addition, some bidders may submit last minute bids in the hope that the competition will not have time to respond, a practice known as *sniping*. 
auctions may 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 auctions-- is that we can, at least in part, claim to be agnostic regarding the underlying strategic bidding process. Our focus is largely limited to pair-wise comparisons of simultaneous auctions with the same ending times and identical goods. Hence, we only make inferences of the differences between two auctions in a pair, which generally requires far fewer assumptions and restrictions. Accordingly, to the extent we can, we limit 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, McMillan and Zheng (2006). They study groups of eBay auctions for CPU’s with similar items and near ending times (but not starting time), 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 occurs in concurrent auctions. There are several differences between our study and theirs. First, their data set involves less control due to 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. THEORY

The theory is divided into two distinct parts. The first part deals with final prices and price dispersion. We make the claim that search costs play a role in final prices and price dispersion. This implies that both direct search incentives and varying auction features within pairs of identical product auctions would make evaluation more costly and would result in increased price dispersion. We review the extant literature related to each of the features we vary.

The second part of the theory proposes a model of bidder behavior that involves an explicit comparison of simultaneous auctions, followed by choice, conditional on comparison. The model requires only minimal assumptions about the structure of the bidding process, but it is intended to shed light on the drivers of search cost as distinguished from the factors involved in choice. The individual bidding analysis also allows us to characterize heterogeneous behavior by bidders.

3.1. Final Prices

The simplest prediction regarding the presence of search costs is that there will be substantial price dispersion in final auction prices. This dispersion may or may not apply to intermediate bids (which we deal with shortly), depending on the nature of expectation formation and bidding strategy. A second prediction is that if we can reduce the search cost, we can reduce the price dispersion. Lastly, we predict that auction design variables influence search costs, impacting the final price and the resulting price dispersion. These variables, including open reserve price, secret reserve, duration, and shipping costs, are differences in characteristics that pertain to the auction process but not directly to the item. All of these have been shown to impact final prices in auctions and are therefore candidates to influence price dispersion.

*Open reserve price.* Open reserve price is a minimum starting bid that is publically displayed and known by bidders. Open reserve price has been shown to be critical to price determination in
auctions (Bajari and Hortacsu, 2003; Engelbrecht-Wiggans, 1987; Levin and Smith, 1996; Riley and Samuelson, 1981; Reiley, 2006). In addition, a number of papers have suggested that open reserve prices may have a significant reference price effect on final price (Ariely and Simonson, 2003; Häubl and Popkowski Leszczyc, 2003; Kamins, Dreze and Folkes, 2004; Suter and Hardesty, 2005; Shunda, 2007). It is therefore expected that a higher open reserve price will result in a higher final price.

*Secret reserve.* Whereas open reserve price, in theory, affects auction process by eliminating potential entrants early on, it need not affect choice between simultaneous auctions once it is exceeded. In contrast, secret reserve looms throughout the auction as a threat that the bidder may not get the item even if he wins. Hence, the bidder needs to form a prior of what that secret reserve might be. Katkar and Reiley (2006) find a significant negative effect of a secret reserve on ending price.³ Therefore, the presence of a secret reserve price is expected to decrease price.

*Auction duration.* The longer the auction, the longer a bidder needs to monitor it. This may reduce the incentive to search – except for at the beginning or end of the auction. In addition, longer auctions may also attract more bidders leading to higher prices (e.g. Lucking-Reiley et al. 2007). Therefore, longer duration is expected to lead to higher price.

*Shipping.* Shipping costs in auctions has been shown critical to price (where price incorporates shipping costs) and dispersion in previous studies (Häubl and Popkowksi Leszczyc, 2003; Morwitz, Greenleaf, and Johnson, 1998; Hossain and Morgan, 2006). Perhaps bidders are unable to fully incorporate the cost of shipping into their bids, either due to reduced attention to or awareness of such costs or to errors when making the arithmetic operation of incorporating the costs to the bids. Hence, greater shipping fee should also lead to higher price paid (including shipping fee).

While final price is an important outcome to sellers, it is not necessarily the best indicator of bidder valuations, preferences, or choice. However, the final price is a valid outcome in itself. That is,

³Related findings are also discussed in Elyakime, Laffont, Loisel and Vuong (1994), Katkar, and Reiley (2006), Lucking-Reiley et al. (2007) and Reiley (2006).
a seller may care more about final price than about bidder valuation. Hence, both measures (price and choice) are valid as dependent variables but can be used to answer different questions. In our opinion, final price paid is a variable more useful to making revenue predictions whereas choice is useful to mapping preferences.

3.2. Bidder choice between Auctions

It is reasonable to assume that a bidder facing a choice between two simultaneous auctions will place a bid in the auction that gives him a higher surplus. Peters and Severinov (2006) have argued that in the case of identical products, bidders will alternate their bids between the two auctions, keeping the prices in the two auctions within a bidding increment of one another.

A key assumption in a choice model is that all choices are evaluated and compared. This is not a far-fetched assumption in the low friction environment we study, since comparing the two auctions in a pair appears to be a trivial task. 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,⁴ 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, search, or by simply clicking on “View seller's other items.”

Even though comparing two auctions is easy, a bidder is not required to compare the two auctions with every bid. After the initial bid, when placing subsequent bids in an auction, a bidder may opt to use a direct link to an auction shown on their eBay account and in all email correspondence. The main premise of the current work is that a bidder will indeed fail to compare the auctions at all times.

Prior to making a choice between the two alternatives, the bidder needs to decide whether to incur the effort of evaluating the two alternatives. This decision will depend on the potential gain to such evaluation. This potential gain is modeled here as a function of a constant, time left and the search

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⁴ A bidder searching for an item on eBay will typically do so by browsing a product category and sub-categories or by typing a specific keyword in a search box. In both instances eBay responds with a list of auctions that includes the experimental auctions listed after one another.
incentive. Time left is important because it directly affects the incentive to search as well as attention to competing auctions.

\[ Pr(\text{evaluation}_t) = \frac{1}{1 + \exp(-\text{Intercept} - \alpha_1 \text{Time Left}_t - \alpha_2 \text{Search Incentive})} \]  

(1)

The choice between simultaneous auctions only happens following an instance of evaluation. Hence, we refer to this choice as conditional and denote it by \( Pr_{\text{cond}}(\text{choice}_t = 1|\text{evaluation}_t) \). Other than the conditional aspect, it is a standard logit choice framework.

\[ Pr_{\text{cond}}(\text{choice}_t = 1|\text{evaluation}_t) = \frac{e^{U_t}}{e^{U_t} + e^{V_t}} \]  

(2)

Finally, the unconditional specification has to take into account both evaluation and choice.

\[ Pr_{\text{uncond}}(\text{choice}_t = 1) = Pr_{\text{cond}}(\text{choice}_t = 1|\text{evaluation}_t)Pr(\text{evaluation}_t) + (1 - Pr(\text{evaluation}_t))\chi(\text{choice}_{t-1} = 1) \]  

(3)

where \( \chi(\text{choice}_{t-1} = 1) \) is a characteristic function that takes on the value of 1 if auction 1 was chosen last and 0 otherwise.

Note that this choice model cannot identify the valuation of a particular consumer for either of the two simultaneous alternatives, but it can identify, with enough observations and the correct distributional assumptions, the valuation difference between the alternatives. In other words, it captures attention to price as well as the other features we varied, such as shipping costs, secret reserve, etc.

Note that with consumer heterogeneity, we do not need to assume common values for the distinguishing feature, unlike the final price difference framework. Moreover, bids need not be incremental or optimal for the choice model. Indeed, bid amounts are not considered at all. The only assumption is that consumers, with ‘mistakes’ permitted, tend to choose the alternative that, given the
most recent price bid, would give them a higher surplus. It is not an assumption-free framework and it has limitations we will discuss, but it is far more flexible than other empirical investigations that do not have the advantage of the pairwise structure in our data.

3.3. Bidder strategic Considerations

It is plausible that a bidder will strategically bid in the higher priced auction, thinking that this auction will end up being the lowest price auction. This could be based on observing the process, or even considering one’s own action’s effect on the continuation of the auction. While such thinking is plausible, it is not generally incorporated into theory (e.g., Peters and Severinov, 2006; Szentes, 2007). This is because when bids are costless, one should never bid in the less preferred auction. Our data suggests that the vast majority of bidders do not place many bids and that some of them do not bid on the lowest price auction, even initially. We control for possible strategic considerations by putting time left in the auction. Process measures are notoriously endogenous (for example, we could look at the entire history of prices as an expectation formation driver), so this tradeoff is delicate. We leave this by saying that we tried various configurations and the results are not qualitatively different.

4. EXPERIMENTAL DESIGN

The experimental design involves pairs of identical items sold simultaneously in eBay auctions (see background section for overview of 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 500’s and 600’s, respectively); of these ratings, only one was negative for the first seller and zero negative for the second.
The two auctions in pair always had the same ending time and, except for one condition where we varied duration, the same starting time. The picture and description of the items was the same in both auctions. Between conditions, we vary the key auction design features discussed above.

In total we ran 580 auctions over a period of two months from April 12 to June 13, 2007. Table 1 provides a summary of the experimental design differences. Some auction pairs were not usable since 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. The cells in each row contain the difference, in terms of the variable represented by the row, between two auctions in a pair. In total there were six different conditions, which varied over nine different products. The control condition consisted of running two ex-ante identical simultaneous auctions. The shipping charge for these auctions was equal to the amount of the small shipping difference condition, no secret or open reserve was present, nor any search incentives, and the duration was 1 day, 3 days, or 5 days for both auctions in each pair.

For each product and each variable under manipulation, there are three different levels: None, Low or High. With the exception of duration, the determination of what values constitutes low and high for each variable is product-specific. For example, shipping charges for the different products are based on actual shipping costs. In the case of the Harry Potter book, the Secret audio CD and the baby bottles the low shipping costs were $3.25 and the high shipping costs were $6.00. For the Fisher Price baby rocker low and high shipping costs are $5.99 and $11.99. For the small (large) shipping difference condition in the case of Fisher Price baby rocker one item is sold with shipping charge of $5.99 ($11.99) and the other has zero shipping charge.

The small and large starting price condition worked in a similar way where one item sold with either a small or a large starting price and the other auction without a starting price. The magnitude of the starting price was based on the expected selling prices. 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
ending time. For the secret reserve price condition, one auction in the pair had a secret reserve present and the other did not. The secret reserve was set to 25% above the retail price. The secret reserve auctions were spread out over the three months of the experiment and across two different sellers, to minimize any possible reputation effects.

As discussed in the introduction, 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.

5. RESULTS

5.1. Final Prices

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, includes shipping cost) over 281 auction pairs we ran is $2.87. This is significant ($t=16.36$, d.f. 280, $p < 0.001$). In percentage terms, this is 15.25% of the average price observed (average price is $18.82$). 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 $2.69$ ($t=9.88$, df=101, $p < 0.001$). Hence we conclude that price
dispersion is highly significant for both nearly identical and completely identical auctions. The
influence of the auction design features on price dispersion will be discussed shortly.

Result 1. Price dispersion between identical simultaneous auctions in a pair is substantial.

Our next result pertains to the effect of increasing search incentives on price dispersion. If there
is a direct relationship, then we can conclude that price dispersion is inversely related to search costs.
While lack of search is the most likely culprit for the price dispersion we found in result 1, having
eliminated pretty much any other cause by design, result 1 by itself is not a proof that the lack of search
is caused by high search costs. The conjecture was that increasing search incentives by providing free
shipping for bidders who win the lowest price auction would result in more search and lower price
dispersion. Manipulating the shipping cost changes the incentive to search and this is the effect we
seek to quantify.\(^5\)

We summarize the findings in the table below.

\[ \begin{array}{|c|c|}
\hline
\text{Insert Table 2 about here} \\
\hline
\end{array} \]

These results indicate that we observe a significant decrease in price dispersion when providing
bidders with a search incentive. This gives us the second result in the investigation of final prices.

Result 2. Price dispersion declines between no search incentives and some search incentives.

\(^5\) 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.
A regression with price difference as the dependent variable and both a search indicator variable and the monetary search incentives as explanatory variables indicates that the search incentive dummy is not significant, and rather the monetary incentive amounts are significant. This is an important result in that it indicates that the search conditions did not affect bidder behavior by merely focusing attention on the price differences between auctions, but rather by incentivizing search.

A fixed effects regression with ending price as the dependent variable and all important auction attributes is reported in Table 3.

We see from Table 3 that the auction features of shipping fees, open reserve, and duration affect final prices, including shipping, whereas theoretically they should not. For example, each additional dollar in shipping fees increases the final price paid (after adding in shipping) by 13 cents. Each additional dollar in the open reserve price also increases final price by about 13 cents. Finally, each additional day of duration translates to a 53 cents increase in price. Surprisingly, secret reserve does not significantly adversely affect price, although the sign is consistent with past findings. As discussed earlier, each additional dollar of search incentives reduces price by 26 cents. Since we varied these auction features within pairs of identical product auctions they directly influence the extent of price dispersion.

Result 3. The auction features of shipping fees, open reserve, and duration affect final prices in the predicted directions.
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, with 2952 bidders. Only 457 (15.5%) bidders out of 2952 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 2952 bidders over pairs of items, 1460 submitted only a single bid on an item in a pair and 1492 submitted more than one bid on an item in a pair.

Of all switches from one auction to a different auction, 78.8% of bids were to the lowest price. That means that 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 price dispersion between identical product auctions over the course of an auction. It indicates that bidders pay attention to prices when entering an auction (still, 26.8% of the bidders did not enter the lowest price auction when given the choice). This is indicative of some search. However, after the initial choice, price dispersion increases over time for both switch and non-switch bids. Switch bids reveal some increased optimization in the final stages of the auction, as price dispersion reduces by 5.9% in the final stages of the auction, however, since only a small percentage of bids are switch bids, overall price dispersion actually increases by 10.7%.

To examine the effect of auction features on bidder choice we resort to a regression on bidder choice between auctions, as specified by equations 1-3. We account for differences between products with product dummies. We account for differences between individuals with random normally distributed coefficients. The equations specified a two-stage process wherein the bidder first decides whether to evaluate the two auctions in a pair, and then, conditional on evaluating, decides which is better. The likelihood was specified as the product of choice probabilities6 specified in equation 3. The

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6 This product was computed at different points on the integral implied by random coefficients.
results are reported in Table 4. The coefficient on Time Left in minutes was rescaled by 10000 to make it fit the table.

The first column of Table 4 indicates the model stage or the decisions faced by the consumer, and the second column pertains to the parameter included in each of the model stages. Each choice model variable is the difference between the corresponding variables for auction 1 and auction 2.

Starting with the evaluation stage, we see that direct search incentives increase the probability of evaluation. This supports Result 2 we obtained through final price comparisons. We also see that the more time left increases the probability of evaluation. We could offer a theory that would support this direction (for example, once a customer searched initially, the returns to search with each additional bid decline). But we could also offer a theory to the contrary (the closer one gets to the end, the more consequential the bid is). Instead, we will leave it as an interesting result. We also note that this result is remarkably robust to specifications and data sets and deserves to be studied carefully. Finally, we should note that the intercept is negative and relatively high. It implies that as the auction nears its end and without search incentives, the probability of evaluation of both auctions in a pair is roughly 0.28. This is consistent with the summary statistics reported above on individual bidders’ failure to select the lowest price auction and reluctance to switch.

We next turn to bidder choice between auctions, conditional on evaluation. Unlike the final price analysis, here none of the auction attributes show up as significant. Only price comes out strongly statistically significant. Hence, when it comes to choice between auctions in a pair, bidders pay close
attention to price differences rather than differences in auction attributes. Note that while price is also significant in the standalone choice model (reported in Table 4 as well), it is nearly six times larger in magnitude when accounting for the possibility of failure to evaluate. This implies a potentially grave misspecification in the commonly used choice model.

6. DISCUSSION

Taken together, our data show remarkably little search and optimization taking place in a setting where such activities involve relatively little effort. While bidders do search and optimize more when first entering an auction, even then close to 30% of first time entrants select the higher priced auction. This observation suggests the need for a two-stage model of choice between auctions, where in the first stage bidders decide whether to evaluate both auctions in a pair, and in the second stage they make a choice. The two-stage decision model resulted in a large likelihood improvement over the traditional choice model. The coefficient on time left in the search component is positive. This suggests that bidders are more likely to evaluate the two auctions earlier in the process.

Moreover, the price coefficient in the two-stage model relative to the price coefficient from the choice model alone shows that bidders are more price sensitive than it would seem from choice alone. Hence, without accounting for search considerations, an observer might erroneously conclude that bidders are simply not very price sensitive. That would be a costly error in term of auction design.

One potential explanation for the failure to search and optimize in intermediate (non-final) bids is that bidders might expect such activities to be less consequential when there is plenty of time remaining to the close of the auction. However, the evidence does not support this conjecture. The coefficient on Time Left in the choice regression suggests the opposite—bidders are more likely to evaluate both auctions when there is more time remaining. Likewise, the switching and optimization rates mostly remain stable for the duration of an auction with a small decrease towards the end of the
auction. That is, we do not find significant increased switching or optimization towards the end of the auctions.

A related question is to what extent winning bidders who were observed to switch auctions-- who presumably evaluate more-- are better off than winning bidders who are non-switchers. We find that winning bidders who are switchers 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 that the price disparities persist to the final prices and that bidders who evaluate both auctions in a pair can take advantage of these inefficiencies.

7. CONCLUSIONS

We showed that even in the extreme case of seemingly identical items sold by the same seller and listed following one another on the same platform, consumer search and mobility between auctions appeared limited. Bidders rarely switched between auctions and often enough did not choose the lowest available price. This is surprising given the widely held belief that electronic auctions should make it easier for consumers to determine price and product offerings from a wider base of potential sellers (Smith, Bailey and Brynjolfsson, 2000) resulting in increased price competition (Bakos, 1997; 1998) and decreased price dispersion (Smith, Bailey and Brynjolfsson, 2000). In contrast to the claim by prominent researchers that the Internet is a new frictionless medium, the results add to a growing body of empirical evidence that suggests that this is not the case. Indeed, as the cost of physical search
(as in walking or driving between stores) has declined, it appears that so has the willingness to search by an increasingly Internet-savvy generation of online shoppers\(^7\).

We further found that the reluctance to search is largely driven by the cost of search, as evidenced by the impact of our direct search incentives on final prices. While sufficiently high direct incentives to search proved effective in increasing search, we also found that prices could be impacted by varying any number of auction (not product-related) characteristics, such as shipping, open reserve price, and auction duration, relative to parallel auctions. Hence, these auction characteristics appear to impede search, leading to greater price dispersion within identical pairs. This means that sellers have plenty of room to manoeuvre 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. While 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 trade-offs is an important direction for future research.

We next sought to examine individual bidder choice between auctions to gain insight regarding search and optimization behavior. Typically in empirical works analyzing intermediate bids, some inference is made about bidder valuations. This is problematic in the best of cases due to insufficient independent observations per individual and due to the questionable relevance of auction attributes to product valuations. But the real criticism of such approaches is that optimal bidding strategies are unknown and restrictive assumptions put in place to enable identification are generally assailable. In contrast to the standard approaches, we examined behavior in a two-stage choice modeling framework. By looking at choice, we overcome a critical modeling barrier. Choice is driven by the current price of

\(^7\) As educators will readily admit, students are highly demanding regarding the ease of finding lecture material online and reluctant to search for it, although their cost of search is drastically lower than previous generations’ cost of search for similar classes.
each auction, which is not contingent on one’s intended bid. While the model we use is the natural approach to investigating auction choice and mobility, as far as we know this is the first attempt to do so.

There are several limitations to the current research and we list some here. To overcome them, we tried different specifications to verify that the general qualitative conclusions remain unchanged. One limitation is endogeneity. The experimental treatments could be said to impact all aspects of the outcome including price and the number of bidders at any given point in time. We used such outcome variables as explanatory variables and we find that they add a great deal to the fit of the model, but do not introduce major changes to the qualitative insights. Since this debate in the literature is not conclusive (Shugan, 2004) we opted for the regressions with the best fit.

Another limitation is the relative lack of control for simultaneous auctions outside of the experimental manipulation. One reason for the absence of analysis such as ours in the literature is that it is notoriously difficult to account for outside substitutes. In the case of a new Harry Potter hard cover book, for example, is a soft cover version of the same book also considered by the buyer? A used version? An audio version? These issues are outside the scope of the paper but could bias the results. While the Harry Potter categories are hard to characterize for that reason, we have a sufficient number of categories with nearly no substitutes on eBay. For example, in the aquarium gym category, there were 1.7 outside auctions ending on the same day as ours on average. In Pampers Swaddlers newborn diapers, this number is 2. These are categories where parents have strong brand and size preferences and so substitution is not likely. The fact the directional outcomes are the same in our various categories implies that our findings are robust to unobserved substitution.

We think the present research can be extended in two important directions. First, we think 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, we think choice modeling is a promising avenue for empirical research that can overcome many of the complicated and potentially restrictive assumptions discussed earlier. If one wants to map consumer preferences to consumer behavior, choice between auctions does not require any account for bidding strategies and 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 were identified in this manner. There are also other factors that might influence search costs. These include listing under different category names, bundling, and manipulating the number of simultaneous (overlapping) auctions (e.g., Zeithammer 2006).
REFERENCES


Table 1  Summary of Experimental Conditions across Different Products

<table>
<thead>
<tr>
<th>Condition</th>
<th>Prod1</th>
<th>Prod2</th>
<th>Prod3</th>
<th>Prod4</th>
<th>Prod5</th>
<th>Prod6</th>
<th>Prod7</th>
<th>Prod8</th>
<th>Prod9</th>
</tr>
</thead>
<tbody>
<tr>
<td>large shipping diff</td>
<td>9.99</td>
<td>9.99</td>
<td>12.99</td>
<td>6.00</td>
<td>11.99</td>
<td>6.00</td>
<td>8.00</td>
<td>8.00</td>
<td>6.00</td>
</tr>
<tr>
<td>small start price diff</td>
<td>5</td>
<td>5</td>
<td>7.5</td>
<td>5</td>
<td>10</td>
<td>3.5</td>
<td>15</td>
<td>12.50</td>
<td>5</td>
</tr>
<tr>
<td>Large start price diff</td>
<td>10</td>
<td>10</td>
<td>15</td>
<td>10</td>
<td>17.5</td>
<td>7</td>
<td>30</td>
<td>25.00</td>
<td>10</td>
</tr>
<tr>
<td>Small duration diff</td>
<td>1 vs 3</td>
<td>1 vs 3</td>
<td>1 vs 3</td>
<td>1 vs 3</td>
<td>1 vs 3</td>
<td>1 vs 3</td>
<td>1 vs 3</td>
<td>1 vs 3</td>
<td>1 vs 3</td>
</tr>
<tr>
<td>Large duration diff</td>
<td>1 vs 5</td>
<td>1 vs 5</td>
<td>1 vs 5</td>
<td>1 vs 5</td>
<td>1 vs 5</td>
<td>1 vs 5</td>
<td>1 vs 5</td>
<td>1 vs 5</td>
<td>1 vs 5</td>
</tr>
<tr>
<td>Secret-reserve</td>
<td>Yes/no</td>
<td>Yes/no</td>
<td>Yes/no</td>
<td>Yes/no</td>
<td>Yes/no</td>
<td>Yes/no</td>
<td>Yes/no</td>
<td>Yes/no</td>
<td>Yes/no</td>
</tr>
<tr>
<td>Large search diff</td>
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<td>N/A</td>
<td>12.99</td>
<td>6.00</td>
<td>8.00</td>
<td>6.00</td>
<td>6.00</td>
<td>8.00</td>
<td>6.00</td>
</tr>
<tr>
<td>Retail Price</td>
<td>$30.00</td>
<td>$19.69</td>
<td>$30.87</td>
<td>$19.99</td>
<td>$22.98</td>
<td>$17.99</td>
<td>$47.25</td>
<td>$32.09</td>
<td>$17.97</td>
</tr>
<tr>
<td>Number of auction pairs</td>
<td>30</td>
<td>14</td>
<td>31</td>
<td>36</td>
<td>28</td>
<td>39</td>
<td>33</td>
<td>35</td>
<td>35</td>
</tr>
</tbody>
</table>


*bThis product was not used for the search condition due to lack of availability.

Table 2  Price Dispersion by Search Incentive Condition

<table>
<thead>
<tr>
<th>Search Incentives</th>
<th>Number of pairs of auctions</th>
<th>Price Difference within pairs</th>
<th>Std. Errors Price Differences</th>
<th>Number of Bids</th>
<th>Average Price</th>
<th>P-valuesa</th>
</tr>
</thead>
<tbody>
<tr>
<td>No incentive</td>
<td>216</td>
<td>$3.10</td>
<td>0.64</td>
<td>11.2</td>
<td>19.24</td>
<td>0.003</td>
</tr>
<tr>
<td>Low incentive</td>
<td>42</td>
<td>$2.13</td>
<td>0.76</td>
<td>11.3</td>
<td>18.58</td>
<td>0.007</td>
</tr>
<tr>
<td>High incentive</td>
<td>23</td>
<td>$2.04</td>
<td>0.61</td>
<td>9.9</td>
<td>15.38</td>
<td>0.087</td>
</tr>
</tbody>
</table>

*aP-values are reported as comparisons of no incentive to some incentive, no incentive to low incentive, and no incentive to high incentive.
Table 3  Results Regression Analyses of Auction Final Price on Auction Features.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Coefficient (std. error)</th>
<th>T-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>13.564 (1.05)</td>
<td>12.880</td>
</tr>
<tr>
<td>Search incentive</td>
<td>-0.255 (.072)</td>
<td>-3.540</td>
</tr>
<tr>
<td>Shipping</td>
<td>0.128 (.075)</td>
<td>1.700</td>
</tr>
<tr>
<td>Open Reserve</td>
<td>0.125 (.056)</td>
<td>2.220</td>
</tr>
<tr>
<td>Duration</td>
<td>0.534 (.222)</td>
<td>2.410</td>
</tr>
<tr>
<td>Secret Reserve</td>
<td>-0.320 (.521)</td>
<td>0.610</td>
</tr>
<tr>
<td>Number of bidders</td>
<td>0.401 (.087)</td>
<td>4.590</td>
</tr>
<tr>
<td>Fisher Price gym</td>
<td>6.798 (.679)</td>
<td>10.000</td>
</tr>
<tr>
<td>Harry Potter audio book</td>
<td>20.509 (.649)</td>
<td>31.620</td>
</tr>
<tr>
<td>Harry Potter boxed set</td>
<td>14.791 (.645)</td>
<td>22.940</td>
</tr>
<tr>
<td>Pampers diapers</td>
<td>5.259 (.705)</td>
<td>7.460</td>
</tr>
<tr>
<td>Dr Brown baby bottles</td>
<td>-1.140 (.633)</td>
<td>-1.800</td>
</tr>
<tr>
<td>Happy Hippo gym</td>
<td>-3.744 (.863)</td>
<td>-4.340</td>
</tr>
<tr>
<td>Harry Potter book 6</td>
<td>-5.947 (.633)</td>
<td>-9.390</td>
</tr>
<tr>
<td>Fisher Price baby rocker</td>
<td>6.830 (.704)</td>
<td>9.700</td>
</tr>
</tbody>
</table>
Table 4: Results of Two-stage Versus One Stage Choice Model

<table>
<thead>
<tr>
<th>Decision</th>
<th>Parameter</th>
<th>Two-stage decision</th>
<th>Choice model only</th>
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</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Coefficient (std. error)</td>
<td>T-value</td>
</tr>
<tr>
<td>Evaluation</td>
<td>Intercept</td>
<td>-1.288 (.143)</td>
<td>9.009</td>
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<tr>
<td></td>
<td>Search Incentive</td>
<td>0.396 (.197)</td>
<td>2.005</td>
</tr>
<tr>
<td></td>
<td>Time Left</td>
<td>0.049 (.010)</td>
<td>4.746</td>
</tr>
<tr>
<td>Optimal Choice</td>
<td>Price</td>
<td>-1.419 (.291)</td>
<td>4.867</td>
</tr>
<tr>
<td></td>
<td>Shipping</td>
<td>0.046 (.038)</td>
<td>1.224</td>
</tr>
<tr>
<td></td>
<td>Open Reserve</td>
<td>-0.087 (.069)</td>
<td>1.257</td>
</tr>
<tr>
<td></td>
<td>Secret Reserve</td>
<td>-0.039 (.216)</td>
<td>0.181</td>
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<td></td>
<td>Fisher Price gym</td>
<td>0.050 (.026)</td>
<td>18.986</td>
</tr>
<tr>
<td></td>
<td>Harry Potter audio book</td>
<td>0.050 (.026)</td>
<td>18.986</td>
</tr>
<tr>
<td></td>
<td>Harry Potter boxed set</td>
<td>0.050 (.026)</td>
<td>18.986</td>
</tr>
<tr>
<td></td>
<td>Pampers diapers</td>
<td>0.258 (.376)</td>
<td>0.686</td>
</tr>
<tr>
<td></td>
<td>Dr Brown baby bottles</td>
<td>1.006 (.430)</td>
<td>2.339</td>
</tr>
<tr>
<td></td>
<td>Happy Hippo gym</td>
<td>-1.851 (.343)</td>
<td>5.394</td>
</tr>
<tr>
<td></td>
<td>Harry Potter book 6</td>
<td>0.100 (.026)</td>
<td>3.797</td>
</tr>
<tr>
<td></td>
<td>Fisher Price baby rocker</td>
<td>-1.005 (.152)</td>
<td>6.631</td>
</tr>
<tr>
<td>Log Likelihood</td>
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<td>-1418.8</td>
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</tbody>
</table>
Figure 1 Price Dispersion Between Identical Auctions Over the Course of an Auction

$ Difference between identical auctions

% of time elapsed in an auction

switch bids
non-switch bids