# On the value of added surcharge

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***Abstract.***

A hidden surcharge is an added cost, such as shipping and handling. Retailers frequently use hidden surcharges to make it harder to compare prices. Our primary objective is to map the relationship between added surcharge and revenue, as well as its boundaries. We examine hidden surcharges in auctions for identical items but different surcharges, examining bidders' willingness to pay in auctions with different added surcharges. We find that bidders do not accurately process price plus surcharge when the added surcharge difference is small but they become more attentive when the charge difference is higher. This leads to an inverted U-shape relationship between added surcharge level and price premium – the expected surplus to the seller for the auction with the higher surcharge. Further, the optimal surcharge changes inversely with bidder experience and the expected number of bidders. As bidders gain more experience, they tend to avoid bidding at higher surcharge auctions.

*Keywords: Partitioned pricing; Surcharges; Internet auctions; Field study*

## 1. Introduction.

Retailers commonly partition product prices into the base price and a surcharge (e.g., shipping and handling [S&H], processing fees, taxes). The practice of added surcharges is widespread. Nearly half of the biggest 50 online retailers obtain high profit margins by charging S&H fees in excess of their cost (Orr 2001; Lewis, Singh and Fay 2006) and approximately 40 percent of online shopping cart abandonment occurs because of S&H charges (Suman 2002). Other examples of added surcharges include the automatic addition of gratuity for large parties at some restaurants, additional charges for services by airlines (e.g., some airlines charge extra for bringing a suitcase) and the addition of a separate 'port charge' to the base price of a cruise (Morwitz et al. 1998). Given the prevalence of added surcharge and the economic impact of lost sales (abandoned shopping carts), it important to study how consumers are influenced by different level of added surcharges (Kukar-Kinney and Close 2010).

According to the literature, dividing the price has a favorable impact on consumer evaluations relative to a single combined price (Morwitz et al. 1998) and this may translate into increased revenues. Some of that effect is due to imperfect processing of information, as firms may be "shrouding" the price of particular product attributes (Gabaix and Laibson 2006). In general, the literature seems to suggest that added surcharge tends to make a product's total price less transparent and more difficult to process (Greenleaf et al., 2016) and may distort consumers' perceptions of total cost (e.g., Morwitz et al., 1998; Lee and Han 2002; Kim 2006).

Surcharges are common and consequential in online purchase decisions (Koukova et al. 2012) and online auctions in particular. Morwitz et al. (1998), for example, referring to the practice by some auctions that charge a buyer's premium in addition to the winning bid, examined whether subjects process the total price equally in two sealed bid auctions for a jar of pennies—one with a 15% added surcharge and one without. They found that the added surcharge increased demand in the auction after controlling for the subjects' value perceptions. The literature has further documented that when consumers bid they do not fully incorporate shipping costs into their bids (Brown et al. 2010; Clark and Ward, 2008; Hossain and Morgan, 2006). This in turn makes a shipping surcharge a revenue-enhancing approach. Häubl and Popkowski Leszczyc (2003) report an auction field experiment that shows that shipping cost has an increasing effect on auction ending price (that includes shipping cost). Häubl and Popkowski Leszczyc (2003) also examine added auction surcharges in the laboratory and conclude that consumers tend to underestimate the effect of the added surcharges.

Our primary objective is to map the relationship between added surcharge and revenue —specifically price premium defined as the difference in total price (sales price plus added surcharges) in a matched pair of auctions. We conjecture that moderate surcharges translate to higher price premiums than either lower or higher surcharges.[1]

In addition, we want to identify and quantify the boundary conditions of the relationship between price premiums and surcharges. Towards that goal, we focus on the trade-off between the surcharge amount and search, and variables that influence this relationship. The literature documents several factors that affect response to the added surcharge. These include consumer's attention to surcharge-related attributes (Bertini and Wathiew 2008), the amount of product information available and expectations about product composition (Bertini, Ofek and Ariely, 2009), the posted price's position relative to the consumer's reference price (Wathieu and Bertini

[1]Burman and Biswas (2007), in search for a boundary condition, showed in a series of experiments that there are limits. While moderate, added charges can increase willingness to purchase and perception of value, excessive added charges decrease them. They attribute this pattern to perceived reasonableness of the surcharge by consumers.

2007), perceived fairness (Sheng et al. 2007), and the number of surcharges (Xia and Monroe, 2004).

We focus on several variables that influence the relationship between price premiums and surcharges, including the surcharge amount, the number of bidders, and bidder experience. We expect a non-linear (inverted u-shaped) relationship between price premium and surcharges, as low surcharges will have lower impact on the price premium whereas medium to high surcharges are expected to result in greater search, reducing the premium compared to medium surcharges.

The number of bidders increases competition. This increased competition in turn drives price in both auctions in matched pair of auctions closer to the retail price and is therefore expected to reduce the price difference between the auctions. Finally, bidder experience is expected to reduce the price premium as bidders learn to avoid auctions with higher surcharges.

Our research focuses on online auction settings. Online auctions are particularly well suited to studying the effect of added surcharges because they commonly incorporate added surcharges (such as shipping or insurance) and because the auction mechanism elicits willingness to pay. More generally, auctions relate to a large number of pricing mechanisms known as participative pricing mechanisms (Kim et al., 2009), including exchanges, bargaining, contests, name-your-own-price and pay-what-you-want mechanisms, which allow us to measure consumers' willingness to pay for different levels of surcharges. Specifically, we can determine differences in willingness to pay for identical product auctions with different surcharges. Hence, using an experimental design we can determine the price premiums for different levels of surcharges.

We employ a field study with a pairwise design of simultaneous auctions selling identical products by the same seller, but with different added surcharges. This allows us to assess the price premium; i.e., the difference in total amount paid (including both ending price and surcharge) bidders are willing to pay for identical items with different surcharges. To find out about the magnitude of the added surcharges bidders need to search by clicking on specific auctions. One of the auctions (within the identical pairs) has a greater added surcharge. We study bidders' behavior by examining the bid history and clickstream data. All bidders on the auction website are registered bidders and we can track their behavior on the website and in the auctions. Hence, we can identify the impact of added surcharges on consumers' search and bidding behavior.

Critical in that respect is the fact that a bidder can determine relevant surcharges via search. We therefore delve deeper into the search process of consumers. We are able to do so with detailed auction data from a large North American auction site. Data consists of clickstream data providing information concerning consumer search, and bid history with information about bidding behavior and auction outcome. Our contribution to the extant literature lies in our two-stage decision process, which posits that consumers first decide on which auction to visit and then decide on whether to place a bid in that auction. Our unique access to clickstream data permits us to identify the model without the need for restrictive assumptions.

We map the relationship between added surcharge and revenue—specifically the price premium, and find an inverted U-shape relationship between added surcharges and price premium. The explanation is that a higher added surcharge means a higher price premium but lower probability of bidding in a given auction. In other words, when the added surcharge is large bidders are less likely to place premium bids because they become increasingly more measured in bidding decisions. However, the price premium's magnitude conditional on placing a premium bid naturally increases.

Among the premium bids, the first visit to the auction pair (as captured by the significant effect for the dummy indicator new visitor) is most critical. Therefore, by implication, inexperienced bidders and bidders constrained to few bids are more important in mapping higher surcharge to higher revenues. Likewise, auctions with fewer expected bidders are more likely to translate higher surcharge to higher revenues. But the optimal surcharge changes inversely with bidder experience and the expected number of bidders. As bidders gain experience, they learn to shun higher surcharge auctions. We find that the expected amount of price premium per bid is maximized when the added surcharge is around a quarter of the retail price.

## 2. The data

The data came from a local auction website in a mid-sized metropolitan area in North America having a population of over one million. The website has been in operation since 2002, and had about 10,000 registered bidders at the time of this study. The website had been promoted through advertisements in the local media, locally distributed flyers, and posters at different locations throughout the city. Bidders for the experimental study in this paper were recruited through e-mails sent to registered bidders, as well as through flyers and posters.

Auctions were in pairs of ex-ante identical listings, except that one auction in each auction pair had a greater surcharge. The bidders could find pairs of identical products with current price information but they would have needed to click on a specific auction to bid or to know the surcharge.

Once an auction was clicked, the added surcharge would be displayed in the product description – in bold letters – just above the location where bidders place their bid. The added surcharges was systematically manipulated, with the surcharge ranging from zero to $39.99 and the surcharge difference within a pair ranging from $0.25 to $38.99.

Data included clickstream information which tracked the bidders' behavior on the website. The products sold included household items, sports items, electronic devices, DVD & games, and more. We used for analysis a total of 552 auctions (276 identical pairs) which had bidders in both auctions in a pair. Auction items' retail prices ranged from $5 to $249.99. The descriptive statistics of the data are provided in Table 1, including ending price net of surcharge, number of bidders and bids, number of bids per bidder, jump bid amount, time elapsed between competing bids, time elapsed between a bidder's own bids[2], price differences between auctions, and percentage of cross-visits and cross-bids. Additional details about the types of products and average selling prices and surcharges are provided in Appendix A.

All auctions were ascending bid auctions with a fixed ending time. Auctions had a duration of approximately one day starting between 10 and 11 pm. The total study duration was 10 days.

Clickstream data collected each bidder's page visits and the time of their visits. Bidders first go to a summary page (e.g. the entrance page of the auction platform listing all the auctions), and from there they can either directly, or through search for a specific type of auctions, click on any listed auction. These clicks are of crucial importance here because a click is the only way by which a bidder can access the surcharge. We define a click on a given auction's page as a visit to that auction. The clickstream data also provides information on whether a person places a bid in either auction. A bidder can only place a bid after visiting a page. Hence, we model the two decisions—visits and bids-- as sequential.

Table 1 provides a summary of the visit and bidding behavior across auctions with the lower and the higher surcharge. The average selling prices without surcharges were as expected higher

[2] Note that average time elapsed between competing bids is higher than the average time elapsed between a bidder's own bids. This is because bidders submit multiple bids in highly competitive situations, resulting in more rapid bidding.

in auctions with the lower surcharge. However, after including the surcharge the selling price in the auction with the higher surcharge, is on average $2.80 higher. Higher surcharges, as expected, have a negative impact on bidder entry; 3.5 bidders bid on average in auctions with a higher surcharge compared to 3.9 bidders in auctions with lower surcharges. The number of bids per bidder in a pair (5.2) indicates a fair amount of cross bidding since 37.0 percent of bidders placed a bid in both auctions within a pair. 41.4% of bidders visited both auctions, indicating that more than half of the bidders did not observe both surcharges.

Note from Table 1 that the difference in time between competing bids, 3.0 hours, is higher than the difference in time for a bidder's own bids of 1.7 hours. This is because when a bidder finds the need to submit multiple bids, the bidder is typically in a highly competitive situation. When competition is high, time is shorter between bids.

Table 1. Visiting and bidding statistics for auctions with lower and higher surcharges.

| Auction Characteristics | Lower surcharge auction (N=276) | Higher surcharge auction (N=276) |
|---|---|---|
| Ending price (net of surcharge) | $16.9 (18.7)[a] | $13.41 (15.7) |
| Surcharge | $1.3 (1.4) | $5.9 (6.3) |
| Number of bidders per auction | 3.9 (1.6) | 3.5 (1.6) |
| Number of bids per auction | 7.3 (4.3) | 6.1 (3.8) |
| Number of bids per bidder in a pair | 5.2 (2.2) | |
| Jump bid amount ($) | $1.4 (2.7) | $1.4 (3.1) |
| Time elapsed between competing bids (hours) | 3.0 (4.9) | 3.48 (5.2) |
| Time elapsed between a bidder's own bids (hours) | 1.7 (3.8) | 1.50 (3.3) |
| Price differences (after surcharge) w/n pairs (high surcharge - low surcharge auction) | $2.8 ($8.2) | |
| % of bidders who visit both auctions in a pair | 41.4% | |
| % of bidders bidding in both auctions in a pair | 37.0% | |

[a] Standard deviations in parentheses.

## 3. **Uncovering the relationships between visit, bid, and premium**

We define a "premium bid" as a bid placed in the higher surcharge auction that exceeds the total price in the other auction. We investigate how the higher surcharge auction obtains a premium from bidders.

To investigate how consumers respond to the manipulated pricing format we use clickstream data and bidding information. Potential bidders on the auction website first see a listing of running auctions with the current price (high bid without the surcharge). The two identical items within a pair are always listed adjacently. The bidder chooses which auctions to visit, at which point they can see detailed information about the current status of the auction, such as number of bids, current high bid, and added surcharge, and they can decide whether to place a bid. Figure 1 shows a summary of the sequential decision process. We have a total of 6,183 visits to all auctions and 44.95% choose to visit the higher surcharge auction in a pair. Among 2,787 visits in higher surcharge auction, 59.78% of visits resulted in a bid being placed, and 76.17% of those bids results in a premium bid. That is, bids in higher surcharge auctions are very likely to result in a premium.

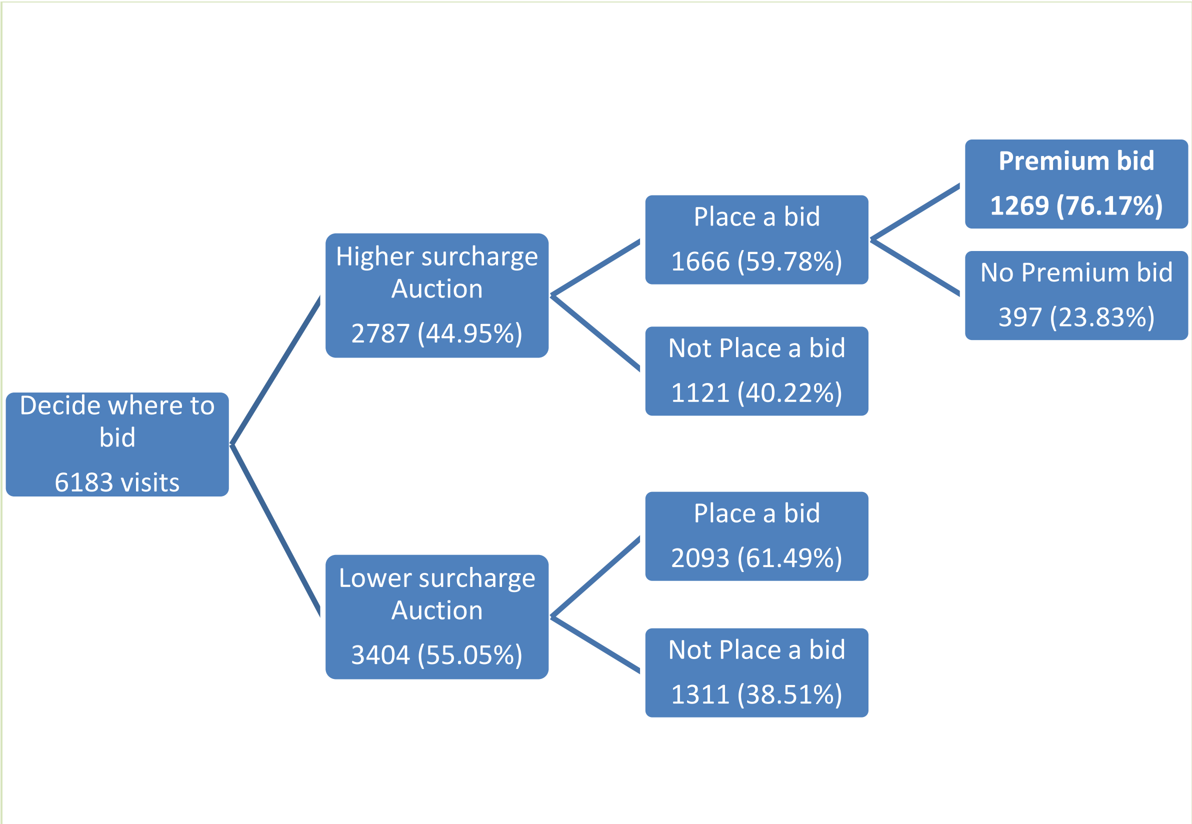


Figure 1. Visiting and bidding in low and high surcharge auctions[3]

We plot the relationship between the surcharge difference and the resulting premium. In Figure 2, it can be seen that bidders are less likely to place premium bids when the difference in surcharges is substantial. However, with greater surcharge differences, conditional on a bid being placed, the average price premium tends to get larger (second plot in Figure 2). These preliminary results show that bidders are largely cautious in placing bids when the surcharge difference is large. But conditional on placing a bid (including by bidders who did not visit both auctions and are therefore uninformed), the surcharge nevertheless results in a price premium. In other words, in considering raising its surcharge, a firm must consider the implied trade-off between the probability of a bid and the price premium of that bid. In some respect, this tradeoff

[3] A "premium bid" is defined as a bid placed in the higher surcharge auction that exceeds the total price in the other auction.

is reminiscent of a simple pricing problem—in that higher price results in higher margin but also in lower quantity demanded. But here, in contrast to pure posted pricing, the posted price is just a component of the overall price. Strictly speaking, bidders could entirely offset the surcharge by incorporating it in part or in whole into their bids.

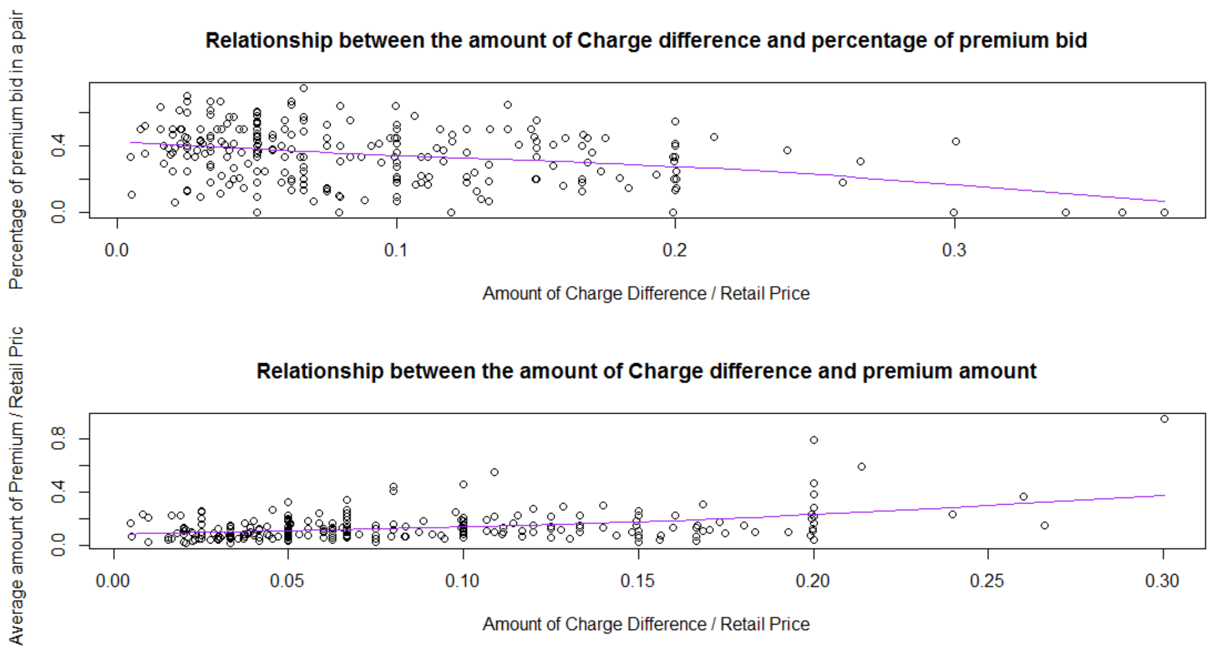


Figure 2. Relationship between added surcharge difference and seller's premium

## 4. Model Development

We develop a model of bidder behavior to investigate the determinants of auction visits and bid sequences. As shown in Figure 1, we find that 76.17% of bids in the higher surcharge auction are premium bids. Placing a premium bid in the higher surcharge auction may potentially result in a price premium to the seller for the higher surcharge auction.

We examine how consumers respond to the different surcharge amounts in terms of propensities to visit an auction and bid in it. We are further interested in identifying how consumers' search behavior and experiences with the auction format and auction characteristics affect the visit and bid decisions.

The model employs a two-part sequential analysis—where each part in the sequence involves a binary choice between two alternatives. The first binary choice is a choice of which auction to visit. The second binary choice—sequentially following the previous choice-- is a choice of whether or not to place a bid. For the two sequential binary choice models, we employ the Probit model by taking into account selection bias (discussed below). In addition, when a seller determines the amount of surcharge in an online auction, the presumed objective for the seller is to maximize the expected price premium. The goal of this model is to map the determinants that affect the optimal amount of added surcharge.

### 4.1. Visits and Bids

We are interested in identifying the determinants of a bidder's decision to visit an auction, as well the decision on whether or not to place a bid in an auction. We model these as two sequential choices by the bidder—first the decision to visit and then the decision to bid. The first decision is denoted as:

$$\text{visit}_{\text{ijk}} = \begin{cases} 0 & \text{if bidder i visits lower surcharge auction in auction pair j at time k} \\ 1 & \text{if bidder i visits higher surcharge auction in auction pair j at time k} \end{cases} \tag{1}$$

Next bidder $i$ chooses to place a bid or not at the visited auction, and we denote that decision as a binary choice $bid_{ijk}$.This is expressed as:

$$bid_{ijk} = \begin{cases} 1 & if\ bidder\, i\ places\ a\ bid\ at\ the\ visited\ auction \\ 0 & if\ bidder\, i\ does\ not\ place\ a\ bid\ at\ the\ visited\ auction \end{cases} \tag{2}$$

Since a bid can only be observed in an auction if the auction has been visited, this presents a sample selection bias in the bid choice estimation. We employ Heckman's (1976) correction to solve this sample selection problem. Heckman's correction requires the use of the probit specification for the binary choice model. Let $x_{ijk}^{1}$ denote a vector of independent variables for the visit decision and let $x_{ijk}^{2}$ denote a vector of independent variables for the bid decision. We further distinguish in the bid decision between the lower and higher surcharge auctions in a pair with an added superscript *h* for the higher surcharge auction ($x_{ijk}^{2h}$ ; $bid_{ijk}^{h}$) and superscript *l* for the lower surcharge auction ($x_{ijk}^{2l}$; $bid_{ijk}^{l}$). The model then consists of a system of three simultaneous latent variable equations[4]. The * superscript denote the latent utility associated with each discrete variable, such that each discrete variable y equals 1 when the corresponding latent variable y* is greater than 0, and y equals 0 otherwise. The latent variable can now be expressed as continuous linear functions of the explanatory variables.

$$\begin{bmatrix} visit_{ijk}^{*} \\ bid_{ijk}^{h*} \\ bid_{ijk}^{l*} \end{bmatrix} = \begin{bmatrix} \beta^{1'} x_{ijk}^{1} + \epsilon_{ijk}^{1} \\ \beta^{2'} x_{ijk}^{2h} + \epsilon_{ijk}^{2} \\ \beta^{3'} x_{ijk}^{2l} + \epsilon_{ijk}^{3} \end{bmatrix} \qquad (3)$$

The matrix of error terms is

$$\begin{bmatrix} \epsilon_{ijk}^{1} \\ \epsilon_{ijk}^{2h} \\ \epsilon_{ijk}^{2l} \end{bmatrix} = N\left( \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho_{12} & \rho_{13} \\ \rho_{12} & 1 & \rho_{23} \\ \rho_{13} & \rho_{23} & 1 \end{bmatrix} \right)$$

Through Heckman's solution we have

$$E\left[bid_{ijk}^{h*} \middle| x_{ijk}^{2h}, x_{ijk}^{1}, visit_{ijk} = 1\right] = x_{ijk}^{2h'} \beta^{2} + E\left[\epsilon_{ijk}^{2} \middle| \epsilon_{ijk}^{1} > -x_{ijk}^{1'} \beta^{1}\right]$$

$$E\left[bid_{ijk}^{l*} \middle| x_{ijk}^{2l}, x_{ijk}^{1}, visit_{ijk} = 0\right] = x_{ijk}^{2l'} \beta^{3} + E\left[\epsilon_{ijk}^{3} \middle| \epsilon_{ijk}^{1} < -x_{ijk}^{1'} \beta^{1}\right] \qquad (4)$$

and hence

[4] This model is similar to a nested logit (also known as sequential logit) where the bid decision is conditional on the visit decision. The difference is that in the present estimation, we are relaxing the independence assumption between the sequential logits as well as within the logits on the same level. When the $\rho$'s are at zero, our model reduces to a simple nested logit.

$$bid^*_{ijk} = \begin{cases} x^{2h}_{ijk}{}'\beta^2 + \rho_{12}\lambda\left(x^1_{ijk}{}'\beta^1\right) + \eta^2_{ijk} & \text{if } visit^*_{ijk} > 0 \text{ (In a higher surcharge auction)} \\ x^{2l}_{ijk}{}'\beta^3 - \rho_{13}\lambda\left(-x^1_{ijk}{}'\beta^1\right) + \eta^3_{ijk} & \text{if } visit^*_{ijk} < 0 \text{ (In a lower surcharge auction)} \end{cases} \quad (5)$$

where E[$\eta^2_{ijk}$] = E[$\eta^3_{ijk}$]=0 and $\lambda(\cdot) = \varphi(\cdot)/\Phi(\cdot)$ is the inverse Mill's ratio which can be calculated using the probit estimate.

The explanatory variable vector for the visit decision include (1) bidder specific characteristics across all auctions which include overall past usage rate and propensity to switch between auctions, (2) bidder characteristics within an auction pair include variables related to a bidder's propensity to visit auctions with higher surcharges (overall and during their last visit), and indicators whether bidders were exposed to information about surcharges. (3) Auction specific characteristics include the amount time elapsed and retail price, which both may influence bidding behavior in higher and lower surcharge auctions. Finally, (4) relevant price information, concerning base prices and surcharges differences (the interaction between Surcharge difference x Know both surcharges).

Besides many of the variable discussed above the bid decision includes several other variables. The average jump bid amount, which is an indicator of bidder aggressiveness, while the number of bidders in the auctions is an indicator of the amount of competition in an auction. Both may differ between auctions with auctions with lower versus higher surcharges. *TotalPrice* is an indicator for whether the current auction has the higher total price (i.e., current bid price + surcharge), which will provide an indication to what extent bidders process surcharges when placing a bid. Finally the Inverse Mill's Ratio is included to adjust for selection bias. This measure estimates the correlation between the visit decision and bidding decision.

Table 2. Overview of variables included in visit and or bid equations

| Visit or Bid Equation | *Variable Name* | Variable Description |
|---|---|---|
| ***(1) Bidder characteristics across all auctions in the study*** | | |
| Both $\beta_1^1, \beta_1^2$ | $TotBidderVisits_{ik}$ | Total number of past visits by bidder *i* to all auctions in the study by time *k* |
| Both | $BidderSwitchingPct_{ik}$ | Percent of visits by bidder *i* that are switches between auctions within an identical pair by time *k* |
| ***(2) Bidder characteristics within a pair of identical auctions*** | | |
| | ***Past propensity towards higher surcharge*** | |
| Visit | $ShareVisitsHigher\text{-}Surcharge_{ijk}$ | Share of visits to the higher surcharge auction, by bidder *i* in (auction) pair *j* by time *k* |
| Visit | $LagHigherSurcharge_{ijk}$ | Bidder *i* selected the higher surcharge auction for pair *j* by time *k-1*. |
| | ***Information exposure*** | |
| Both | $KnowBothCharges_{ijk}$ | An indicator whether bidder $i$ has seen both surcharges or not, for pair *j* by time *k*. |
| Both | $NewVisitor_{ijk}$ | An indicator whether bidder $i$ is a first time visitor to pair *j* by time *k* |
| Bid | $AverageJumpAmount_{ijk}$ | Average jump bid amount for bidder *i* in the currently visited auction in pair *j* by time $k$. |
| Bid | $NewVisitor_{ijk}$ x $ElapsedTime_{ijk}$ | Interaction between new visitor and elapsed time |
| ***(3) Auction characteristics*** | | |
| Both | $ElapsedTime_{ijk}$ | Amount of time elapsed in seconds for bidder *i* in pair *j* by time *k* |
| Both | $RetailPrice_j$ | Retail price of auction item in pair *j* |
| Bid | $NumBidders\ CurrAUC_{ijk}$ | Number of bidders in the currently visited auction by bidder *i* in pair *j* by time *k* |
| ***(4) Price information*** | | |
| Both | $BasePriceDiff_{ijk}$ | Higher surcharge auction's base price minus lower surcharged auction's base price for bidder *i* in pair *j* by time *k* |
| Bid | $SurchargeDiff_j$ | Higher surcharge – lower surcharge in pair *j* |
| Both | $SurchargeDiff_j$ x $KnowBothCharges_{ijk}$ | Interaction between Surcharge difference and Know both surcharges |
| Bid | $HigherTotalPrice_{jk}$ | Indicator whether the current auction in pair *j* has the higher total price (current high bid + surcharge) by time *k* |
| ***Interdependence between decisions*** | | |
| Bid | $IMR_{ijk}$ | Inverse Mill's Ratio |

Table 2 provides the classification of the different variables included in both visit and bid equations. In addition, both equations include individual and Category dummies, incorporated as fixed effects (dummy variables) for bidder and product category.

This results in the following two regression specifications:

Visit decision:

$x_{ijk}^{1}{}' = \beta_1^1 TotBidderVisits_{ik} + \beta_2^1 BidderSwitchingPct_{ik} + \beta_3^1 KnowBothCharges_{ijk} + \beta_4^1 ShareVisitsHigherSurcharge_{ijk} + \beta_5^1 LagHigherSurcharge_{ijk} + \beta_6^1 NewVisitor_{ijk} + \beta_7^1 ElapsedTime_{ijk} + \beta_8^1 RetailPrice_j + \beta_9^1 BasePriceDiff_{ijk} + \beta_{10}^1 SurchargeDiff_j$ x $KnowBothCHarges_{ijk}$ *+Individual bidder + Product category dummies*

Bid decision:

$x_{ijk}^{2}{}' = \beta_1^2\ TotBidderVisits_{ik} + \beta_2^2\ BidderSwitchingPct_{ik} + \beta_3^2 KnowBothCharges_{ijk} + \beta_4^2 NewVisitor_{ijk} + \beta_5^2 AverageJumpAmount_{ijk} + \beta_6^2\ ElapsedTime_{ijk} + \beta_7^2 NumBiddersCurrAUC_{ijk} + \beta_8^2 NewVisitor_{ijk}$ x $ElapsedTime_{ijk} + \beta_9^2 RetailPrice_j + \beta_{10}^2 BasePriceDiff_{ijk} + \beta_{11}^2 SurchargeDiff_j + \beta_{12}^2 SurchargeDiff_j$ x $KnowBothCharges_{ijk} + \beta_{13}^2 HigherTotalPrice_{jk} + \beta_{14}^2 IMR_{ijk}$ *+Individual bidder and Product category dummies*

## 5. Results

### 5.1 Model Free Findings

When characterizing online auctions, it is important to characterize propensities as well as magnitudes of bidding (Feng et al. 2016). Accordingly, our investigation focuses on both aspects. We first check for the existence of bidders who exhibit high inertia in auction visit and bid choice in either auction, finding that approximately 40% of bidders visit only a single auction in a pair and that approximately 34% of people bid at only a single auction in a pair (see Table 3). This result is consistent with previous studies (e.g., Sun 2005; Haruvy and Popkowski Leszczyc 2009, 2010) that argue for the existence of search cost for online auction bidders.

To uncover the determinants of the price premium for a higher surcharge auction, we analyze

Table 3. Bidders' Migrating Behavior

| Visits (n = 1225, the total number of individuals who visited at least three times to either of the auctions in a pair) | |
|---|---|
| Percent visiting only lower surcharge auction in a pair | 24.73% |
| Percent visiting only higher surcharge auction in a pair | 14.20% |
| Percent visiting both auctions in a pair | 61.06% |
| **Bids (n = 902, number of individuals who placed at least three bids in a pair)** | |
| Percent bidding only on the lower surcharge auction in a pair | 11.75% |
| Percent bidding only on higher surcharge auction in a pair | 22.06% |
| Percent bidding on both auctions in a pair | 66.19% |

premium bids and find that approximately 60% of premium bids are placed by bidders unaware of both added surcharges. We refer to such bids as "uninformed premium bids." The high incidence of uninformed premium bids means that the majority of premium bids are placed by uninformed bidders who only visited the higher surcharge auction in a pair. Interestingly, 67.16% of uninformed premium bids are placed on a bidder's first visit. That is, if a bidder chooses the higher surcharge auction in a pair, and then places a bid, then such a bid is highly likely to deliver a price premium to the seller for the higher surcharge auction (see Table 4). Since most uninformed premium bids are placed during first time visits, this raises a question about the timing of such bids across auctions. Figure 3 shows the relationship between auction elapsed time and the uninformed premium bids. We can see that as an auction approaches closing time, uninformed premium bids are less likely to be placed. This means that bidders become more careful in their bidding at the end of auction period.

Table 4. Determinants of price premium to seller for higher surcharge

| Premium bids (n = 1269) | Number of uninformed premium bids: 749 (59.02%) | Number of informed premium bids: 520 (40.98%) |
|---|---|---|
| Number of each on First visit | 503 (67.16%) | 0 |
| Number who only visited higher surcharge auction (excluding first visit) | 246 (32.84%) | 0 |
| Only bid in higher surcharge auction | 749 (100%) | 9 (1.73%) |
| Average bidder's percent of switching in a pair | 0% | 42.78% |
| Average bidder's percent of switching | 22.89% | 35.78% |
| Number of winning bids | 137 (18.29%) | 77 (14.81%) |
| Average premium amount | $8.13 | $4.93 |

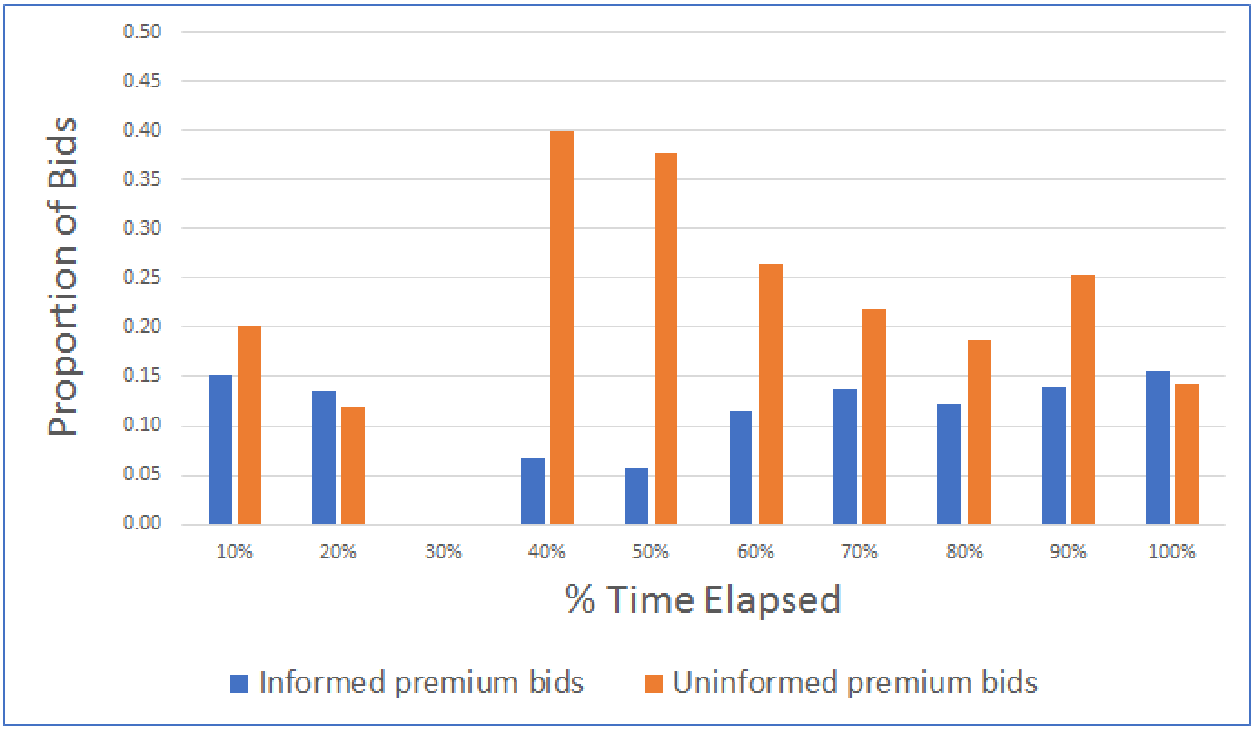


Figure 3. Percentage of premium bids by decile of time

## 5.2 Visit Decision and Bid Decision

For our second study objective, we model bidders' sequential decisions—auction visit followed by a bid choice. Through model estimation, we find how auction visit and the bid decision are impacted by the surcharge magnitude as well as knowledge about price, bidder characteristics (search behavior and experience) and auction characteristics (retail price and elapsed time).

5.2.1 Results for the visit decision

Table 5 provides the estimation results for the visit decision. As described in section 4, the dependent variable is whether a bidder visits the higher surcharge auction ($visit_{ijk}$ = 1) or visits the lower surcharge auction ($visit_{ijk}$ = 0). The result shows that informed bidders who know both added surcharges are more likely to visit the higher surcharge auction ($\beta_3^1 = 0.120$, p =.017), but they are less likely to visit the higher surcharge auction when the surcharge difference is larger ($\beta_8^1$= -0.026, p=.266). Though the switching history is not significant in the visit decision ($\beta_2^1 =$ -0.003, p=.951), experience (based on total number of past visits) is ($\beta_1^1 =$ -0.139, p=<.001). As bidders gain experience, they are less likely to visit the higher surcharge auction.

As shown in the model-free analysis, bidders are highly likely to place a premium bid on their first visit. So the auction choice decision on the first visit is also of critical importance for the higher surcharge auction. Model estimates show that when a bidder first arrives, she is more likely (after controlling for base price differences) to visit the higher surcharge auction ($\beta_6^1 =$ 0.333, p=<.001), which often coincides with being the auction with the lower current bid level.

Table 5. Determinants of visit to the higher surcharge auction in a pair.

| | Estimate | p-value |
|---|---|---|
| (Intercept) | 0.775 | 0.429 |
| ***Bidder characteristics across all auctions*** | | |
| Total number of past visits ($\beta_1^1$) | -0.139** | <0.001 |
| Percent of past switches ($\beta_2^1$) | -0.003 | 0.951 |
| ***Bidder characteristics in an auction pair*** | | |
| Know both surcharges in a pair ($\beta_3^1$) | 0.120** | 0.017 |
| Share of visits to the higher surcharge auction ($\beta_4^1$) | 0.301** | < 0.001 |
| Chose higher surcharge auction last period ($\beta_5^1$) | -0.104* | 0.081 |
| New visitor ($\beta_6^1$) | 0.333** | < 0.001 |
| ***Auction/item characteristics*** | | |
| Elapsed Time ($\beta_7^1$) | -0.003 | 0.891 |
| Retail Price ($\beta_8^1$) | -0.054** | 0.017 |
| ***Price information*** | | |
| Base Price difference ($\beta_9^1$) | -0.162** | < 0.001 |
| Surcharge difference x Know both surcharges ($\beta_{10}^1$) | -0.026 | 0.266 |
| Number of observations | 6183 | |
| Log Likelihood | -3917.4 | |
| AIC | 8,138.8 | |

The higher share of visits to a higher surcharge auction that a bidder has, the more likely is the bidder to visit the higher surcharge auction in a pair ($\beta_4^1 = 0.301$, p=<.001). This shows a degree of inertia in visit choices. Lastly, the base price coefficient shows that bidders are less likely to visit the higher surcharge auction when the higher surcharge auction's base price is relatively higher ($\beta_7^1$= -0.162, p=<.001).

### 5.2.2 Results for the bid decision

Table 6 provides the result of bidding decisions at the visited auction. In this model, investigating the determinants of bidding at the higher surcharge auction is very important to the auction sellers. The number of past visits has a negative effect on placing bids in higher surcharge auctions ($\beta_1^2$ =-0.219**, p<0.001) but the opposite positive effect ($\beta_1^2$ =0.363**, p< 0.001) for lower surcharge auctions. This suggests that as bidders gain more experience, they tend to avoid bidding at higher surcharge auctions. This holds a critical managerial implication to sellers' strategy of adding surcharges, while building long-term relationships with customers.

Bidders who switch more frequently, indicative of search, are less likely to place a bid in either type of auction ($\beta_2^2$ = -0.441**, p<0.001 for higher surcharge auctions, and $\beta_2^2$ = -0.557**, p<0.001 for lower surcharge auctions). The negative impact of information on the incidence of bids is also indicated by the coefficient for bidders who know both charges in a pair ($\beta_3^2$ = -0.421**, p<0.001 for higher surcharge auctions, and $\beta_3^2$ = -1.075**, p<0.001 for lower surcharge auctions).

The effect of bidders' characteristics in an auction pair, are consistent across both types of auctions. A new visitor is more likely to place a bid ($\beta_4^2$ = 1.431**, p<0.001 in higher surcharge auctions, and $\beta_4^2$=1.575**, p<.0001 in lower surcharge auctions), but is less likely to place a bid towards the end of an auction ($\beta_8^2$ = -0.388**, p< 0.001 in higher surcharge auctions, and $\beta_8^2$ = -0.402**, p<0.001 in lower surcharge auctions).

Bidders whose average jump bid amount is high are more likely to place a bid at either auction ($\beta_5^2$=0.474**, p<0.001 in higher surcharge auctions, and $\beta_5^2$=0.591**, p<0.001 in lower surcharge auctions).

For the impact of auction/item characteristics on bidding decision, we find that when item's retail price is high, bidders are less likely to place a bid at the higher surcharge auction ($\beta_9^2$=-0.144**, p=0.006) but more likely in the low surcharge auctions ($\beta_9^2$=0.212**, p<0.001 ).

Likewise, when the number of bidders is high, fewer bidders place a bid at the higher surcharge auction ($\beta_7^2$=-0.093**, p=0.033), but there is no significant difference in the low surcharge auctions ($\beta_7^2$=-0.058, p=0.175).

For the impact of price information, base price difference affect the bid negatively in the high surcharge auction but positively in the lower surcharge auction ($\beta_{10}^2$ = -0.445**, p<0.001; $\beta_{10}^2$ = 0.378**, p<0.001). Base price difference can be thought of as an incentive to search. When prices are vastly different in otherwise seemingly identical auctions, one is incentivized to search, thus reducing the bid in the high surcharge auction and increasing it in the low surcharge auction.

Total price has a negative effect on the bid decisions, suggesting that bidders do tend to process surcharges (calculate the total price) when making a bid decisions. In addition, this effect is stronger for higher surcharge auctions ($\beta_{13}^2$= -0.270, p=0.002) than for lower surcharge auctions ($\beta_{13}^2$= -0.178**, p<0.001).

The Inverse Mill's ratio in both auctions is significantly positive. This means that visit decision and bidding decision are positively correlated ($\beta_{14}^2$=2.980**, p<0.001 for higher surcharge auctions, and $\beta_{14}^2$=3.177**, p<0.001 for lower surcharge auctions).

### 5.3 The relationship between profitability and added surcharges

We report the coefficients of the bid choice model in Table 6. The dependent variable is the decision to bid or not in each of the two auctions in a pair. The explanatory variables are as specified in Table 2.

Based on the result of the bid choice model, we find that the number of bidders plays a significant role in the bidding decision for the high surcharge auction. We therefore divide

Table 6. The bid choice model: Determinants of placing a bid in either auction.

| | Dependent variables: | | | |
|---|---|---|---|---|
| | Bid at higher surcharge auction ($bid^{\mathrm{h}}$) | | Bid at lower surcharge auction ($bid^{l}$) | |
| | estimate | p-value | estimate | p-value |
| *Intercept* | -0.892 | 0.401 | -0.707 | 0.062 |
| ***Bidder characteristics across all auctions*** | | | | |
| Total number of past visits ($\beta_1^2$) | -0.219** | <0.001 | 0.363** | <0.001 |
| Percent of past switches ($\beta_2^2$) | -0.441** | <0.001 | -0.557** | <0.001 |
| ***Bidder characteristics in an auction pair*** | | | | |
| Know both charges in a pair ($\beta_3^2$) | -0.421** | <0.001 | -1.075** | <0.001 |
| New visitor ($\beta_4^2$) | 1.431** | <0.001 | 1.575** | <0.001 |
| Average jump bid amount ($\beta_5^2$) | 0.474** | <0.001 | 0.591** | <0.001 |
| New visitor x Elapsed Time ($\beta_8^2$) | -0.388** | <0.001 | -0.402** | <0.001 |
| ***Auction/item characteristics*** | | | | |
| Elapsed Time ($\beta_6^2$) | 0.453** | <0.001 | 0.458** | <0.001 |
| Number of bidders ($\beta_7^2$) | -0.093** | 0.033 | -0.058 | 0.175 |
| Retail Price ($\beta_9^2$) | -0.144** | 0.006 | 0.212** | <0.001 |
| ***Price information*** | | | | |
| Base Price difference ($\beta_{10}^2$) | -0.445** | <0.001 | 0.378** | <0.001 |
| Surcharge difference ($\beta_{11}^2$) | 0.140 | 0.119 | 0.041 | 0.327 |
| Surcharge difference x Know both surcharges ($\beta_{12}^2$) | -0.194** | 0.012 | -0.006 | 0.870 |
| Higher Total price ($\beta_{13}^2$) | -0.270** | 0.002 | -0.178** | 0.028 |
| ***Invers Mills Ratio*** ($\beta_{14}^2$) | 2.980** | <0.001 | 3.177** | <0.001 |
| Observations | | 2702 | | 3290 |
| Log Likelihood | | -1143.2 | | -1369.2 |
| AIC | | 2570.4 | | 3038.5 |

auction pairs into two groups – auction pairs with a high number of bidders and auction pairs with a low number of bidders. We use fitted values from Poisson regression for the number of bidders in pair, and divide two groups by median value of number of bidders in pairs (4.99).

Figure 4 shows that when an auction pair is characterized by fewer bidders, the relative expected premium (expected amount of premium divided by retail price) per bid-- conditional on placing a bid-- increases as the surcharge difference increases. When auctions have more bidders, the relative expected premium decreases. Hence, the premium of high surcharges is significantly greater in auctions with few bidders, and it appears that competition eliminates the price premium. Managers in auctions may want to use higher surcharges for items that are less in demand (attract fewer bidders). In a way surcharges may act like a reserve price, in that, the item will not sell below the price plus the added surcharge.

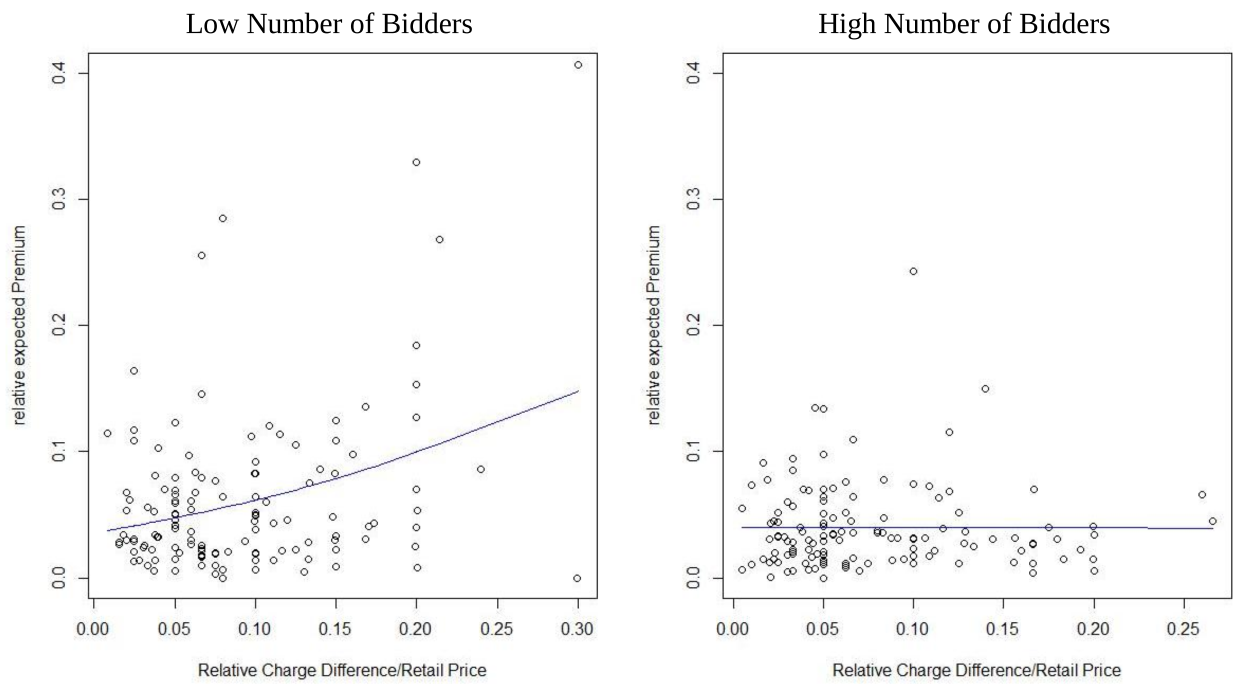


Figure 4. Relationship between the expected premium and surcharge difference by number of bidders in a pair

## 6. **Conclusions**

In pairs of identical auctions, we found a significant price premium in the intermediate bids, and this premium is sustained in final prices, for high surcharge auctions. An important goal of the present investigation is to uncover the relationship between this surcharge premium and inadequate search as well as to see whether bidders who are more informed mitigate such a premium. (They do. Table 4 suggests that uninformed bidders exhibit nearly twice the premium exhibited by informed bidders). A surcharge has two opposing impacts on revenues. On the one hand, a high surcharge increases search which has a depressing effect on revenue. Specifically, we find was that when the surcharge difference is small to moderate, bidders are less likely to expend the effort to visit both auctions and become informed. As a result, bidders' bids are less likely to incorporate the surcharge when the surcharge difference is small to moderate. When the surcharge difference is high, however, bidders find it prudent to expend the effort needed, and as a result, their bid choices are more careful and less likely to leave a high price premium to the seller. Heterogeneity plays some role in this pattern. Confirming what has been shown in previous studies (e.g., Haruvy and Popkowski Leszczyc 2009, 2010), we identified individual bidders who were more limited than others in search and mobility. Such bidders are more likely to visit a higher surcharge auction and more likely place a bid at the visited auction. However, results do indicate that bidders tend to process surcharges (as indicated by the negative effect of total price on the decision to bid).

On the other hand, uninformed bidders who bid in higher surcharge auctions may ignore the higher surcharge, and this results in a higher surcharge having a positive effect on revenues. Due to these opposing influences, we find that under certain conditions the surcharge magnitude has an increasing effect on the price premium in the auction when the surcharge is small to moderate, but a decreasing effect on the price premium as the surcharge increases relative to the retail price. On average, a surcharge difference of around 25% of the retail value results in the highest price premium.

Another key factor in this patter is the first visit decision in a pair of auctions. Because many bidders only visit one auction in a pair, this first choice is critical from the seller's perspective. When bidders have not visited both auctions, they are uninformed. Therefore, they are more likely to place a premium bid than bidders who are informed.  Second, the sellers should bear in mind that as bidders gain greater experience with the pricing format they tend to avoid bidding at the higher surcharge auction due to learning how to navigate the price landscape-- distinct from being merely informed about prices. These arguments mean that the partitioned pricing format is perhaps a less attractive long-term strategy if the sellers want to build long-term relationship and loyalty with customers.

Though we kept the model as simple as possible to be able to isolate bidders' key behavioral patterns, there are several limitations in our study. First, due to bidders' reluctance to bid in extremely high surcharge differences settings, we have a sparsity of observations at the high end of the range of added surcharge differences. Hence, identification is more limited in the higher end of the range.

Second, though we show key behavioral aspects with the pairwise auction format, in online auctions like eBay.com, there are many simultaneous and temporally overlapping auctions selling identical items, nearly identical items and close substitutes. In more than two auctions with identical items, an auction bidder may consider the distribution of the price dispersion during auctions rather than merely comparing all auctions' prices. Therefore, investigating bidders visit and bid decisions in more complex settings with click-stream data would require additional assumptions and possibly additional implications.

**Appendix A:**

Table A. Summary statistics of products by product category

| Product Category | Level of Surcharges | # of Auctions | Mean Retail Price | Mean Surcharge | Mean Ending Price |
|---|---|---|---|---|---|
| Bath | Lower Surcharges | 11 | 68 | 1.41 (0.86) | 9.57 (7.25) |
| | Higher Surcharges | 11 | (42.22)[a] | 5.27 (2.75) | 5.33 (3.12) |
| Collectibles | Lower | 24 | 31.31 | 0.98 (0.96) | 7.96 (6.37) |
| | Higher | 24 | (23.88) | 3.60 (2.65) | 5.67 (5.87) |
| Computers | Lower | 37 | 48.71 | 1.39 (1.34) | 18.32 (19.06) |
| | Higher | 37 | (48.37) | 6.11 (6.65) | 14.56 (19.00) |
| DVD & Games | Lower | 23 | 34.75 | 0.83 (0.90) | 6.44 (5.12) |
| | Higher | 23 | (10.94) | 4. 35 (4.07) | 4.26 (4.25) |
| Electronics | Lower | 64 | 83.63 | 1.67 (1.70) | 27.38 (27.25) |
| | Higher | 64 | (49.26) | 9.25 (8.95) | 20.68 (20.97) |
| Fine Dining | Lower | 2 | 150.00 | 3.75 (1.77) | 81.5 (1.41) |
| | Higher | 2 | (0.00) | 10.00 (0.00) | 69.00 (4.95) |
| Handicrafts | Lower | 7 | 22.13 | 0.14 (0.24) | 3.04 (1.60) |
| | Higher | 7 | (2.57) | 1.79 (0.57) | 2.58 (2.06) |
| Household | Lower | 54 | 31.03 | 0.88 (0.97) | 10.73 (5.9) |
| | Higher | 54 | (13.05) | 4.38 (5.21) | 9.33 (6.67) |
| Jewelry | Lower | 35 | 69.03 | 1.57 (1.51) | 19.57 (10.92) |
| | Higher | 35 | (46.5) | 6.16 (3.92) | 17.05 (11.9) |
| Sports | Lower | 19 | 54.49 | 1.58 (1.34) | 18.22 (14.46) |
| | Higher | 19 | (32.16) | 4.74 (4.76) | 15.16 (11.98) |

[a] Standard deviations in parentheses.

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