Implications of Expected Changes in the Seller’s Price in Name-Your-Own-Price Auctions

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The seller’s threshold price in name-your-own-price auctions varies over time. However, consumers must bid without knowing when these variations occur because the threshold price is unobservable to them. This paper uses an analytical model and laboratory auctions to explore how the frequency of changes in the threshold price impacts consumer bidding behavior in name-your-own-price auctions. In particular, we consider how the frequency of these expected changes affects the optimal pattern of bid sequences (e.g., strictly increasing over time or following a nonmonotonic pattern). We find that when the probability of a price change is moderate, consumers may have an incentive to use nonmonotonic bidding patterns. Rather than steadily increasing their bids over time, consumers will, at some point in the bid sequence, decrease their bid. However, when the expected probability of a price change is very low or very high, consumers do not have an incentive to use nonmonotonic bidding patterns. Interestingly, impatient bidders are more likely to decrease their bids at some point in the bid sequence than patient bidders. Finally, we find that more frequent price changes may increase customer satisfaction.

Key words: name-your-own-price channel; bidding; rational decision making; buyer impatience; Priceline

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1. Introduction
The Internet allows companies to interact with customers in ways that may have been prohibitively costly using traditional channels. In particular, the Internet has facilitated the emergence of name-your-own-price (NYOP) auctions. In such auctions, as popularized by Priceline, buyers bid for a product or service. If a bid exceeds the seller’s concealed threshold price, the buyer receives the product at the price of her bid. This selling mechanism has been used predominantly in the market for travel services, although Priceline and other companies, such as Cybra-Direct, Imandi, and NexTag, have sold nontravel goods through the NYOP mechanism (Dolan and Moon 2000, Doyle 2000). Practitioners and academics have become interested in this selling mechanism and are seeking to better understand how consumers behave in NYOP markets and how companies can use an NYOP format to become more profitable (e.g., Power 2000; Chernev 2003, 2006; Ding et al. 2005; Leocha 2005; Segan 2005).

Buyers in NYOP auctions face a trade-off. If a buyer bids too high, the bid will exceed the seller’s unrevealed threshold price and the buyer will have overpaid for the product. If a buyer bids too low, the bid will be rejected and she either will not receive the product or will incur the cost of additional bids. Several normative models have been proposed regarding the optimal bid sequence (Hann and Terwiesch 2003, Fay 2004, Spann et al. 2004, Terwiesch et al. 2005). In this paper, we consider the impact of an important and ubiquitous factor on consumer bidding that has not been considered in previous models—the NYOP seller’s threshold price can change over time. We find evidence that expectations about how frequently the price threshold changes (i.e., temporal variability, hereafter called “variability”) can significantly impact bidding behavior.

This is the first paper to explore how different expectations about price changes will impact bidding patterns. For instance, when would it be optimal for consumers to bet on the chance that a company will lower the price of a product and thus place a lower bid than a previously placed bid (i.e., “drop bid”)? We use a combination of analytical and empirical approaches to understand bidders’ behavior in NYOP auctions (for a similar approach, see Amaldoss and Jain 2008). We begin by introducing a theoretical model capable of predicting bid levels based on different expectations of price changes. Based on
the intuition developed from this model, we form several hypotheses regarding how consumers’ bidding behavior might vary with different expectations about price changes. We predict that drop bidding is unlikely to occur if the expected probability of change is either very low or very high. However, drop bidding is a component of a consumer’s optimal bidding strategy if the consumer is sufficiently impatient and the expected probability of change is at a moderate level. This is an especially important result because the extant research has suggested that rational consumers would always increase their bids over time and that any drop bids must be the result of consumer irrationality or forgetfulness (Spann and Tellis 2006). We are the first to show when and why drop bidding can be an optimal strategy for fully rational consumers. We supplement our analytical results with a laboratory market experiment. The lab experiment confirms our hypotheses, especially that the frequency of drop bidding does indeed have an inverse-U-shaped relationship with the expected probability of change. In addition, we find that differing expectations about price changes impact consumer satisfaction.

In §2, we offer a preliminary empirical study to explore the temporal variability of threshold prices in real markets. Then we review the relevant literature. In §3, we introduce an analytical model to explore the optimal bidding behavior by consumers who expect variability in the threshold price. Based on the intuition developed from this analysis, we identify a series of testable hypotheses about the pattern of bid sequences (e.g., strictly increasing over time or following a nonmonotonic pattern). In §4, we use a laboratory market to test these hypotheses. Results are highly consistent with our theory. In §5, we offer concluding remarks, including important managerial implications.

2. Preliminaries

2.1. Evidence of Price Changes

In this section, we offer a brief study of price changes in actual NYOP auctions in the travel industry to establish that threshold price changes indeed occur rather frequently. We seek to explore the magnitude of such volatility, especially over short time horizons. For example, it may be obvious that the price for a flight purchased two months in advance very likely differs from the price for that same flight only a week in advance. However, we focus on much shorter time horizons (e.g., from one day to the next) because bid sequences are likely to occur over a relatively short period of time.

Our empirical examination focuses on the NYOP seller Priceline. To explore how expectations are formed for consumers of Priceline, we consider the pricing behavior of Priceline’s chief competitor, Hotwire. Hotwire and Priceline both sell “opaque” travel services, i.e., services for which details of the itinerary (e.g., flight times and airline) are not revealed to the consumer until the purchase has been completed. But whereas Priceline’s price thresholds are not observable, Hotwire’s prices are. Another noteworthy feature is that Hotwire explicitly informs the consumer whether an opaque flight is available or not for a given travel request—information that is not directly provided by Priceline.

We collected data about price patterns at Hotwire. First, we identified the 50 largest airports in the United States and created a set of 100 roundtrip itineraries, where each itinerary was built by taking a randomly selected departure airport and a randomly selected arrival airport (hereafter referred to as a “city-pair”). Then for each city-pair, on August 22, 2007, we recorded whether an opaque flight was available on Hotwire for an itinerary that would depart August 30, 2007, and return September 2, 2007 (coded “zero” for not available and “one” for available). We also recorded the lowest offered price. We repeated this process the next four days (i.e., August 23, 24, 25, and 26), finding the price for the same city-pair for an August 30–September 2 itinerary. From this information, we can observe how prices vary over time.

In Table 1, we report statistics about the temporal variability of prices and opaque flight availability, both on a day-to-day basis (e.g., did the price decrease, increase, or remain constant over the five days).

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**Table 1 Volatility Measures**

<table>
<thead>
<tr>
<th></th>
<th>Number</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price the next day</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lower</td>
<td>159</td>
<td>39.75</td>
</tr>
<tr>
<td>Higher</td>
<td>131</td>
<td>32.75</td>
</tr>
<tr>
<td>Same</td>
<td>110</td>
<td>27.50</td>
</tr>
<tr>
<td>Availability of opaque flight the next day</td>
<td></td>
<td></td>
</tr>
<tr>
<td>From not available to available</td>
<td>64</td>
<td>16</td>
</tr>
<tr>
<td>From available to not available</td>
<td>24</td>
<td>6</td>
</tr>
<tr>
<td>Not available either day</td>
<td>175</td>
<td>43.75</td>
</tr>
<tr>
<td>Available both days</td>
<td>137</td>
<td>34.25</td>
</tr>
<tr>
<td>Price sequence for a city-pair</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Contains at least one instance of a decrease in price</td>
<td>87</td>
<td>87</td>
</tr>
<tr>
<td>Contains at least one instance of an increase in price</td>
<td>96</td>
<td>96</td>
</tr>
<tr>
<td>The price is constant for all five days</td>
<td>2</td>
<td>2</td>
</tr>
<tr>
<td>Availability sequence for a city-pair</td>
<td></td>
<td></td>
</tr>
<tr>
<td>An opaque flight is available at least once, but less than all five days</td>
<td>63</td>
<td>63</td>
</tr>
<tr>
<td>An opaque flight is available all five days</td>
<td>13</td>
<td>13</td>
</tr>
<tr>
<td>An opaque flight is not available any of the five days</td>
<td>24</td>
<td>24</td>
</tr>
</tbody>
</table>

*Note.* The average coefficient of variation across the 100 itineraries equals 11.72%.
go down the next day) and at the week level (e.g., was there any day during the week when the price decreased from the previous day). From Table 1, it is clear that there is large variation in prices and availability for a given itinerary. In particular, we find that from one day to the next, the price changes 72.5% of the time (290 out of 400). The price change involves a reduction in price 55% of the time (159 out of 290). The magnitudes of these price changes are non-trivial, at an average of $60.22 each. Furthermore, there is wide variability in the availability of an opaque flight. From one day to the next, 22% of the time (88 out of 400), the availability status changes either from not offering an opaque flight to offering an opaque flight (73% of changes) or from offering an opaque flight to not offering an opaque flight (27% of changes).

Finally, variability is not confined to a few very volatile city-pairs: 98% of the city-pairs experience at least one price change and 63% experience at least one change in availability status over the five consecutive days. Furthermore, 87% experience one or more reductions in price over these five days. We find that the largest price reduction exceeds $10 for 84% of all city-pairs, $25 for 65% of all city-pairs, and $50 for 45% of all city-pairs. These observations provide strong evidence that there are frequent and sizable price changes even over relatively short time periods.

Although the current price threshold for any particular product offering at Priceline is not observable to consumers or to the researcher, there is anecdotal evidence that Priceline users expect that Priceline’s threshold prices change over time and that this expectation influences their bidding strategies. The influence can be observed in the detailed bidding strategy discussions on the Internet forum BiddingForTravel.com. For example, a very experienced user (with more than 10,000 posts), suggests that a bidder for a Beverly Hills hotel “keep repeating [your bidding strategy] until you win… rates change daily up to 6 times in 1 day.”

On another occasion, the same poster proposes a bid sequence for bidding on a Beverly Hills hotel and then advises, “keep repeating till u win.” Another very experienced user (with more than 10,000 posts), suggests that a bidder for a Tampa hotel “keep repeating the same [strategy of bidding up to $60] once a week through March.” Notice that any time a user intentionally bids lower than the level of a bid previously rejected, she must be anticipating that the threshold price might have fallen since the previous bid was placed. Examples of such intentional drop bids are found throughout BiddingForTravel.com.

In fact, it seems likely that changing threshold prices would be a feature of any NYOP auction that sells multiple units of the same product over a prolonged period of time. Web forums such as BiddingForTravel.com facilitate word-of-mouth communication. If an NYOP seller repeatedly sold the same product at the same price, consumers would eventually learn the threshold price, never bid above it, and thus eliminate the information rents for the seller. Furthermore, when prices vary over time, Web forums should help users form more accurate estimates about the price threshold distribution and the frequency at which price changes occur.

2.2. Literature Review

There is a vast literature on Internet auctions. Much research has explored the effects of alternative auction formats, with an emphasis on understanding how a seller might improve its revenues by appropriately structuring its selling mechanism, for example, by using reserve prices, shilling, or particular ending rules (Sinha and Greenleaf 2000, Ariely et al. 2005, Krishna and Unver 2008, Feng 2008). Inherently, such analysis depends on understanding how consumers actually behave in online auctions (e.g., see the empirical examinations conducted by Park and Bradlow 2005 and Bapna et al. 2004). Emerging research suggests that many consumers act in a sophisticated manner. For instance, Zeithammer (2006) finds that eBay bidders act very rationally by taking into account upcoming auctions when deciding upon bids for a current auction. The anticipation of future opportunities to bid results in lower bids and thus lower profit for the seller (Zeithammer 2007).

Even in posted-price settings, uncertainty about future prices can have an important effect upon buyer behavior. For example, Krishna (1992) considers how the timing and order sizes are affected by uncertainty about when deals will be offered. Krishna (1994) finds that when there is greater uncertainty, consumers’ optimal response is to buy in larger quantities. Sellers need to account for such responses to determine what pricing strategies to implement. For instance, Anderson and Wilson (2003) find that the use of standard yield management approaches by airlines can result in significantly reduced revenues when buyers are using an informed and strategic approach to purchasing. In the durable good market of video games, Nair (2007) finds that strategic, forward-looking customers significantly “reduce the profitability of price-skimming.” In this paper, we add to this literature...
by exploring how expected variability in the threshold price of an NYOP seller can impact the way a consumer bids. Furthermore, we explore whether consumers do indeed bid in a rational and strategic manner. This is a particularly important concern because the optimal bidding strategy in the complex NYOP environment (in which even current prices are not observable) is not easy to calculate analytically. Thus, it is unclear whether consumers are likely to adopt bidding strategies that closely approximate the optimal one.

3. Theory

3.1. General Model

A consumer has a willingness-to-pay of $WTP$. There are $N$ periods, and a consumer can bid once per period. The net value from having a bid of $b_i$ accepted is $d(WTP - b_i)$, where $d < 1$ indicates the consumer’s preference for winning the bid earlier rather than later. Let $p_t$ be the seller’s threshold price at time $t$ (where $p_t$ is not observed by the consumer).

After each bid, if that bid is rejected, the consumer decides whether to submit another bid or exit the auction. A bid sequence, $b$, is a series of $N$ bids: $b = (b_0, b_1, \ldots, b_{N-1})$. Notice that a consumer will place bid $b_k$ only if all previous bids ($i < k$) were rejected. The expected utility of a bid sequence, $EV(b)$, is the expected value of this stream of bids:

$$EV(b) = \text{prob}(b_0 \geq p_0)(WTP - b_0) + d\text{prob}(b_0 < p_0; b_1 \geq p_1)(WTP - b_1) + d^2\text{prob}(b_0 < p_0; b_1 < p_1; b_2 \geq p_2)(WTP - b_2) + \cdots + d^{N-1}\text{prob}(b_0 < p_0; b_1 < p_1; \ldots; b_{N-1} \geq p_{N-1}; b_{N-1} \geq p_{N-1})(WTP - b_{N-1}).$$

3.2. Expected Temporal Variability in the Seller’s Threshold Price

To evaluate the expected value of bid sequence $b$, consumers rely on their expectations regarding the probability that each bid is accepted. Previous models (e.g., Hann and Terwiesch 2003, Spann et al. 2004) assume that consumers expect the seller’s threshold price to be distributed uniformly over the interval $[P, \bar{P}]$, where $\bar{P} \geq WTP$, and that the threshold price is the same for all time periods. In such a scenario, the probability that a bid of $b_i$ is accepted is

$$\text{prob}(b_0 < p_0; b_1 < p_1; \ldots; b_{i-1} < p_{i-1}; b_i \geq p_i) = \frac{b_i - \max\{b_0, b_1, \ldots, b_{i-1}\}}{\bar{P} - \max\{b_0, b_1, \ldots, b_{i-1}\}}.$$ 

(2)

In contrast to previous researchers, we allow for the possibility that the seller’s threshold price is not constant over time. In particular, let $\varphi$ be the consumer’s expected probability that the threshold price at $t$ will differ from the threshold price at time $t - 1$, where $\varphi \in [0, 1]$. Thus, the consumer believes the threshold price remains constant from one period to the next with a probability $(1 - \varphi)$. Whenever a price change occurs, we assume the consumer expects the new threshold price is drawn from the uniform interval $[P, \bar{P}]$.

3.3. Finding the Optimal Bid Sequence

The consumer’s objective is to choose a bid sequence, $b$, to maximize her expected utility (as given by (1)). The consumer must balance bidding too low and not receiving the item with bidding too high and overpaying. Furthermore, in an NYOP auction that allows multiple bids, there is a dynamic element to this decision. The consumer must account for the fact that if a bid is rejected, she will still have an opportunity to win the item at a later time. But, because consumers are impatient ($d < 1$), a later win is less valuable than an earlier win. The complexity of the decision is further complicated by the fact that the threshold may change over time.

Taking into account such complications significantly increases the complexity of the analysis. For example, when a consumer is willing to place up to $N$ bids, then there are $2^{N-1}$ possible bidding patterns because after each rejected bid the consumer has the option to increase or (weakly) decrease her bid. For illustration purposes, we focus on a four-period model. Figure 1 illustrates the eight possible bid sequence patterns. For example, pattern (a) represents an “Increasing” bid sequence in which each bid is strictly larger than the preceding one. Each of the other patterns contains at least one instance where a bid is lower than the preceding bid. We refer to an instance in which the consumer lowers her bid as a drop bid. In pattern (b), the second, third, and fourth bids are all drop bids because each bid is lower than the previous one. In pattern (c), bids increase over the first three bids, but then the last bid of the sequence is a drop bid.

To identify the optimal bidding strategy, we first find the bid levels that maximize the consumer’s
Figure 1 Illustration of Bidding Patterns When $N = 4$

(a) “Increasing”: $b_0 < b_1 < b_2 < b_3$
(b) “Decreasing”: $b_0 > b_1 > b_2 > b_3$
(c) “Last drop”: $b_0 < b_1 < b_2 > b_3$
(d) “Last up”: $b_0 > b_1 > b_2 < b_3$
(e) “See-saw up”: $b_0 < b_1 > b_2 < b_3$
(f) “See-saw down”: $b_0 > b_1 < b_2 > b_3$
(g) “Left hill”: $b_0 < b_1 > b_2 > b_3$
(h) “Left dip”: $b_0 > b_1 < b_2 > b_3$

expected payoff if she were to use each of the eight bidding patterns identified in Figure 1. For example, a consumer wishing to adopt an “Increasing” bidding pattern would face the following maximization problem:

$$\max_{b_0, b_1, b_2, b_3} \left[ \frac{b_0 - P}{P - P} (WTP - b_0) + d \left( 1 - \frac{b_0 - P}{P - P} \right) \cdot \left( (WTP - b_1) \left( 1 - \varphi \right) \frac{b_1 - b_0}{P - b_0} + \varphi \frac{b_1 - P}{P - P} \right) \right]$$

$$+ d^2 \left( 1 - \frac{b_0 - P}{P - P} \right) \cdot \left( (WTP - b_2) \left( 1 - \varphi \right) \frac{b_2 - b_1}{P - b_0} + \varphi \frac{b_2 - P}{P - P} \right)$$

$$+ d^3 \left( 1 - \frac{b_0 - P}{P - P} \right) \cdot \left( (WTP - b_3) \left( 1 - \varphi \right) \frac{b_3 - b_2}{P - b_2} + \varphi \frac{b_3 - P}{P - P} \right)$$

s.t. $b_0 < b_1 < b_2 < b_3$. \hspace{1cm} (3)

Notice that rejected bids provide information to the consumer. In particular, if a bid of $b_i$ was rejected at time $t$, then the consumer knows that the threshold price at time $t$ must have exceeded $b_i$. Thus, the consumer believes that with probability $(1 - \varphi)$ the threshold price at $t + 1$ is distributed according to a distribution that is truncated from below at $b_i$.

Let $CS_a$ be the expected consumer surplus under the optimally chosen bid levels when a consumer follows bidding pattern (a). Similarly, one can construct the relevant maximization problem for each of the other seven bid patterns. In the appendix, we report the maximization problem for each of these other patterns. Let $CS_i$ be the expected consumer surplus under the optimally chosen bid levels when a consumer follows bidding pattern (i), where $i = a, \ldots, h$. The consumer chooses the bid pattern that yields the highest expected surplus.

3.4. Effect of Expected Variability in Threshold Price on Optimal Bidding Pattern

Previous research (Spann et al. 2004, Spann and Tellis 2006) has found that the optimal bidding pattern is monotonically increasing (i.e., pattern (a)) when there is no expected variability in the threshold price ($\varphi = 0$). Allowing for $\varphi \geq 0$, Figure 2 illustrates the optimal bidding pattern using the parameters $WTP = 0.8$, $P = 0$, and $\bar{P} = 1$. Interestingly, pattern (a), “Increasing,” is only optimal for a subset of the parameters. In particular, continuously increasing one’s bid is optimal if the expected price variability is either very low or very high or if consumers are sufficiently patient ($d$ is close to 1). On the other hand, the optimal bidding pattern involves a drop bid (as the third or as the fourth bid) if bidders are impatient and the expected probability of change is moderate.
We now discuss the intuition behind these results. First, consider the case in which the seller’s threshold price is not expected to change over time (\( \phi = 0 \)). Here we can prove analytically that the optimal bidding strategy is to increase one’s bid over time (see the appendix). A consumer has no incentive to place a drop bid because such bids are always rejected. Furthermore, as long as the probability of change is sufficiently small, a drop bid will almost always be rejected; it is not worthwhile to place a bid that is very unlikely to be successful and therefore will almost surely prolong the time it takes to win the product. This suggests the following hypothesis:

**Hypothesis 1 (H1).** Drop bids will not be observed when the expected variability in the seller’s threshold price is very low (i.e., \( \phi \) is close to 0).

Second, consider the other extreme, in which a consumer believes the seller’s threshold price is constantly changing (\( \phi = 1 \)). Here also we can demonstrate analytically that the optimal bidding strategy does not include drop bids. Notice that when the expected variability in the threshold price is very high, a rejected bid provides very little additional information because the threshold price that was in place last period is not likely to be still in effect. If a consumer were infinitely patient, she would continually place bids equal to \( P \) until one is eventually accepted. But once we add the realism that consumers are impatient and thus unwilling to place an infinite number of bids, consumers have an incentive to steadily increase their bids over time. Each period is almost exactly like the previous one except for one major exception—there is one less bidding opportunity left. This “nearing of the end” induces consumers to ratchet up their bids. Thus, we have the following hypothesis:

**Hypothesis 2 (H2).** Drop bids will not be observed when the expected variability in the seller’s threshold price is very high (i.e., \( \phi \) is close to 1).

Third, consider the case in which the expected variability in the threshold price is more modest (\( 0 < \phi < 1 \)). Here we have not been able to obtain closed-form solutions for the optimal bids for each of the bidding strategies identified in Figure 1. Instead, using a search algorithm over the range of possible bid values, we numerically calculated the maximum surplus obtainable under each bidding strategy and illustrate these results in Figure 2. Intrinsically, the consumer faces a difficult decision after each rejected bid. If she raises her bid, then the bid is more likely to be accepted, but the value of winning decreases (because the difference between her WTP and her bid is relatively small). If she reduces her bid, then the bid is less likely to be accepted, but the value of winning increases. As the size of the previous bid increases, the value of winning a “raise bid” decreases and thus a drop bid may eventually become optimal. Notice that as the consumer continues to increase her bid, a higher and higher bid is necessary for a bid to be a raise bid. Thus, the consumer is bidding closer and closer to her WTP. Eventually, the expected benefit from winning a raise bid may be so small that the consumer prefers to submit a drop bid instead. Thus, a crucial question is as follows: Under what circumstances will bids reach a high enough level that a drop bid becomes optimal? A key factor is the degree of consumer impatience. If a consumer is sufficiently patient (i.e., \( d \) is large), bids increase slowly from one round to the next and the threshold to induce drop bids is never reached. However, less patient consumers raise their bids more sizably from one round to the next in an effort to get the product sooner. For such consumers, the optimal bid sequence involves a drop bid. The above intuition suggests the following three hypotheses:

**Hypothesis 3 (H3).** Drop bidding may be observed when the expected variability in the seller’s threshold price is moderate.

**Hypothesis 4 (H4).** For moderate expected variability, drop bidding is more likely when consumers are less patient.

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5 This conclusion is based on the assumption that a consumer has only a finite number of bidding opportunities. Such a limit on bids could be due to consumers’ willingness to devote only a limited amount of time to bidding or restrictions imposed by the seller, such as when there are only a limited number of “free re-bids” that a consumer can utilize to circumvent Priceline’s single-bid restriction (see BiddingForTravel.com and the related discussion in Fay 2004).
Hypothesis 5 (H5). For moderate expected variability, the higher the level of the previous bid, the more likely is drop bidding.

H4 is especially counterintuitive. Because impatient consumers are motivated to get the auctioned item sooner, one might have conjectured that impatient consumers would be less likely to drop bid than patient consumers. However, the relationship between bid levels and impatience is more nuanced. Although it is true that impatient consumers may bid higher initially, if these early bids are rejected, impatient consumers have increased their bids nearer to their WTP. Thus, we find that impatient consumers are more likely to reach the point where it becomes optimal to lower their next bid in the hope that the price threshold has changed.

4. Laboratory Auction
We now turn to an empirical investigation of whether actual bidding behavior corresponds to the predictions of our model. Given the sophisticated mathematical nature of our predictions, it is unclear whether bidders will be so analytical when developing a bidding strategy. We also investigate an additional consequence of variability in the threshold prices: namely, consumer satisfaction. To test our predictions, we conducted auctions in the laboratory that mimic an NYOP website. To guarantee a realistic procedure, we created a bidding environment that is close to the one experienced online and paid participants based on their success in obtaining good prices, similar to a real-life purchasing situation.

4.1. Design, Stimuli, and Procedure
One hundred and three students participated in laboratory auctions in exchange for course credit and cash payoffs based on their performance. In this computer-based experiment, participants were told that they would participate in online auctions for products with real monetary payoffs.

We manipulated bidders’ expectations about how often the seller’s threshold price changes. Participants were explicitly told before the auctions the probability that the price of a product would change from one round to the next. Five probabilities of a price change from one round to another, manipulated between subjects, were used: 0 (hereafter called Change0 condition), 0.25 (Change1/4), 0.5 (Change1/2), 0.75 (Change3/4), and 1 (Change1). The probability of price change factor (called “change factor” hereafter), represented by \( \varphi \) in the normative model, is the probability that the threshold price for round \( t \) will be different from the threshold price in round \( t - 1 \). Participants placed up to five bids in nine different NYOP product auctions. Participants were simply informed about the probability of change and the WTP for each product (an average product value that was told to participants prior to each auction). The threshold prices were, of course, concealed from participants, and they were not informed of the distribution from which these prices were drawn.

The threshold price was randomly selected from a uniform distribution of values ranging from “WTP − $100” to “WTP + $50” of each category (e.g., for weekend car rental, the WTP was $210, and we randomly selected prices in the $110–$260 range). In the Change0 condition, the threshold price was the same in all bidding rounds (i.e., \( \varphi = 0 \)). To select prices for the other conditions, we randomly selected the initial price within the stated distribution; the extent to which a new price was randomly drawn from this distribution depended on the change condition in which the auction was being held. For example, in the Change1/4 (Change3/4) condition, we rolled a four-sided die and selected a new price each time the result was (not) four. Participants in each condition were informed of this procedure so they could appropriately form expectations of price changes.

We randomly selected the order in which the auctions for each of nine products occurred. When participants placed bids that were smaller than the threshold price, they were told the bid was rejected and were sent to the next bidding round—unless they were already in the fifth round, in which case they did not get the product being auctioned. The number of points participants made in each auction was calculated by subtracting the winning bid value from the WTP for a given product. At the end of each auction, participants were told their point total for that particular auction and their cumulative point total for all auctions up to that point. Participants then advanced to the next auction. After having participated in nine auctions, participants answered questions about how satisfied they were with those product auctions (1—not satisfied at all to 9—very satisfied) and about how impatient they are (1—very patient to 9—very impatient). Participants finally learned how much money they had made (calculated by paying one dollar for every 50 points earned over all nine auctions), received payment, and left.

4.2. Results
We recorded each participant’s bid sequence for the nine auctions. Our data set includes each bid value; the number of bids placed; whether the bid was a drop bid, a raise bid, or a bid that remained the same; and the WTP for that product. The analysis is conducted at the bid level, so that each bid is considered as one data point. The bid-level data have 2,663 observations. However, bid sequences that consist of a single bid, such as those in which a participant’s first bid was accepted, cannot shed light on
the factors that determine the likelihood of a drop bid. Thus, we eliminated the single-bid sequences, leaving us with 1,773 observations. Each participant placed bids for nine different products. The products, their mean bid values, and standard deviations were weekend hotel ($M = 260.93; SD = 82.56$), weekend car rental ($M = 258.92; SD = 96.68$), airplane ticket ($M = 274.31; SD = 90.52$), theme park tickets ($M = 288.34; SD = 95.63$), cruise ($M = 269.31; SD = 85.48$), television ($M = 291.18; SD = 99.40$), digital camera ($M = 284.73; SD = 94.68$), MP3 player ($M = 283.61; SD = 88.86$), and desktop computer ($M = 290.19; SD = 93.27$).

An analysis of the proportion of drop bids supports H1–H3. As can be seen in the proportions of the entire sample in Table 2, there were very few drop bids for the low (Change0 = 0.8%) and high (Change1 = 2.8%) probabilities of change. However, drop bids were present to a much higher extent at a moderate probability of change (Change1/4 = 8.7%, Change1/2 = 17.8%, Change3/4 = 10.9%). Chi-square tests revealed that the proportion of drop bids as the probabilities of change moved from one level to the other was significantly different from the previous level in all instances (all $p < 0.05$). To test H4, we conducted a median split of the variable measuring bidders’ level of impatience, dividing the sample between patient and impatient bidders. We also collapsed the drop bidding data for the Change1/4, Change1/2, and Change3/4 conditions to see how impatient versus patient bidders behave at moderate levels of change probability. The results support H4. Patient bidders were less likely to place drop bids (8.7%) than impatient bidders (15.0%; $\chi^2 = 11.1$, $p < 0.01$).

In addition to the analysis of proportions, we conducted repeated measures logistic regressions to test all hypotheses. To operationalize this analysis, bids that remained the same from one round to another were coded as drop bids (i.e., a bid that remains the same, like a drop bid, can only be accepted if the price has gone down). Regression I in Table 3 uses all of the data, and Change1/2 is the omitted change condition. In accordance with H1–H3, drop bids significantly decline as the probability of change either decreases or increases from Change1/2. Furthermore, drop bids are affected by impatience and one’s closeness to his or her WTP ($\text{WTP} - \text{PreviousBidval}$). However, H4 and H5 suggest that these factors are particularly relevant when the probability of change is moderate. To test this conjecture, we run two additional regressions. In regression II, we use the data from the Change0 and Change1 conditions (i.e., low and high probability of change conditions; Change1 is the hidden variable). Drop bidding in these conditions is not influenced by the difference between one’s closeness to one’s WTP or impatience. Interestingly, there are fewer drop bids in the Change0 than in the Change1 condition, which may signify that it is more difficult for participants to recognize the optimality of an increasing bidding pattern in the Change1 condition than in the Change0 condition. In other words, it is rather obvious that drop bidding is not optimal if the threshold price never changes, but less obvious when the threshold price changes in every bidding round. This conclusion, of course, has to be interpreted with caution given that the difference is quite small between the Change0 and Change1 conditions. In regression III, we use only the data from the Change1/4, Change1/2, and Change3/4 conditions (i.e., moderate probability of change conditions; Change1/2 is the hidden variable) to test H4 and H5. This model shows fewer drop bids in the Change1/4 ($B = -1.69$, $\text{Wald} = 17.04$, $p < 0.01$) and Change3/4 conditions ($B = -1.01$, $\text{Wald} = 4.02$, $p < 0.05$) than in the Change1/2 condition. Most importantly, in contrast to regression II and in support of H4 and H5, respectively, we find that drop bidding at these moderate probability of change levels is more common for more impatient participants ($B = 1.29$, $\text{Wald} = 13.42$, $p < 0.01$) and as one’s bid value gets closer to one’s WTP ($B = -0.96$, $\text{Wald} = 4.94$, $p < 0.01$).

Finally, we looked at the impact of change probability on consumer satisfaction. There was an effect of

### Table 2

<table>
<thead>
<tr>
<th>Condition</th>
<th>Entire sample</th>
<th>Patient</th>
<th>Impatient</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Drop Raise Same</td>
<td>Drop Raise Same</td>
<td>Drop Raise Same</td>
</tr>
<tr>
<td>Change0</td>
<td>0.8 98.6 0.6</td>
<td>0 100 0</td>
<td>1.2 98.0 0.8</td>
</tr>
<tr>
<td>Change1/4</td>
<td>8.7 89.7 1.6</td>
<td>2.4 95.3 2.4</td>
<td>10.9 87.7 1.4</td>
</tr>
<tr>
<td>Change1/2</td>
<td>17.8 77.6 4.6</td>
<td>10.1 86.0 3.9</td>
<td>25.5 69.2 5.3</td>
</tr>
<tr>
<td>Change3/4</td>
<td>10.9 87.1 2.0</td>
<td>11.9 87.5 0.6</td>
<td>9.9 86.6 3.5</td>
</tr>
<tr>
<td>Change1</td>
<td>2.8 96.3 0.9</td>
<td>3.0 96.3 0.6</td>
<td>2.0 96.0 2.0</td>
</tr>
</tbody>
</table>

### Table 3

<table>
<thead>
<tr>
<th>Independent variable</th>
<th>Regression coefficients</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>I</td>
</tr>
<tr>
<td>Change0</td>
<td>$-3.78^{**}$</td>
</tr>
<tr>
<td>Change1/4</td>
<td>$-1.62^{**}$</td>
</tr>
<tr>
<td>Change3/4</td>
<td>$-0.94^{**}$</td>
</tr>
<tr>
<td>Change1</td>
<td>$-1.92^{**}$</td>
</tr>
<tr>
<td>Impatience</td>
<td>$0.82^{**}$</td>
</tr>
<tr>
<td>WTP - PreviousBidval</td>
<td>$-0.01^{**}$</td>
</tr>
<tr>
<td>Intercept</td>
<td>7.49^{**}</td>
</tr>
</tbody>
</table>

Notes. The models estimate the probability of a drop bid. Change0, Change1/4, Change3/4, and Change1 are indicator variables for each change condition, respectively. In regressions I and III, the omitted condition is Change1/2 condition. In regression II, the omitted condition is Change1. PreviousBidval is the (normalized) bid value of the previous bidding round. *Not statistically significant.

*Statistically significant at the 0.05 level; **statistically significant at the 0.01 level.
probability of change on satisfaction \(F(4, 902) = 16.65, p < 0.01\). Satisfaction was the same in the Change0 \((M = 5.52)\) and Change1/4 conditions \((M = 5.35, p > 0.10)\), but increased from these conditions to the Change1/2 \((M = 5.77)\), Change3/4 \((M = 6.12)\), and Change1 conditions \((M = 6.38, \text{all } ps < 0.05)\).

4.3. Discussion

The laboratory auctions provide support for our predictions. Bidders become more likely to drop bid when there is a probability that the seller’s threshold price may change. However, as the probability of a price change becomes considerably higher, the probability of drop bids decreases. This nonmonotonic drop bidding behavior may be attributed to the fact that when the seller’s price is constantly redrawn, each bidding round provides a new starting point to the auction sequence, and given that the number of bidding opportunities is limited, raising one’s bid is a reasonable strategy. This pattern of drop bidding is interesting and shows how strategic and sophisticated bidders can be. When the seller’s price remains constant, there is no incentive to drop bid, and drop bidding is almost nonexistent. When there is a moderate probability that the seller’s price will change, drop bidding becomes an important strategy to maximize expected surplus.

Furthermore, we found that, when the probability of change was moderate, as the difference between the bid value and the WTP got smaller, the likelihood of a drop bid increased. If the previous bid was large, and the bidder believes that the price is likely to change, placing a higher bid is not optimal because winning a bid will generate only a relatively small surplus. Instead, a drop bid is the optimal strategy. Thus, our normative model and experimental evidence make it hard to argue that we should observe only monotonic bidding patterns in every NYOP auction, as previous models have proposed. In addition, consistent with our theory but somewhat counter-intuitively, we found that at a moderate probability of change, drop bids are used to a greater extent by impatient consumers. Prior to the current investigation, one might have conjectured that impatient consumers would rapidly increase their bids in an effort to get the auctioned item sooner. However, as argued previously, the relationship between bid levels and impatience is more nuanced. Impatient consumers, who bid higher initially, are more likely to reach a sufficiently high bid level that triggers a drop bid in the hopes that the price threshold has changed.

It is particularly interesting that impatience and the level of one’s previous bids do not affect drop bidding when the probability of change is zero or very high. In these cases, the model predicts that no drop bids will be observed. In actuality, we observe a few instances of drop bidding in our laboratory auctions (approximately 1.5%). However, this drop bidding is essentially random. This is consistent with Spann and Tellis (2006), who attribute nonmonotonic bidding to forgetfulness or some other deviation from fully rational behavior. However, taken as a whole with the rest of our findings, it seems that such “errors” only account for a small proportion of drop bids. For the majority of cases, drop bidding is better explained as being a component of a bidding strategy utilized by rational and strategic consumers.

Finally, the impact of the probability of change on consumer satisfaction is an interesting finding. Although it is difficult to determine the reasons for this result from the current data, we speculate that it is due to the perception that an increase in the probability of change makes the bidding process appear more favorable to the consumer because it gives consumers a chance to get better prices. Particularly, a consumer who is willing to wait and bid strategically becomes more likely to get a good price for a certain product, which makes perceptions about the seller more positive.

5. Concluding Remarks

In this paper, we argue that bidders’ expectations of changes in the seller’s threshold price can have a significant impact on the incentive to drop bid in online NYOP product auctions. Through laboratory auctions, we find evidence that is highly consistent with the predictions of our normative model. One interesting implication of our research is that the nonmonotonic bidding patterns in NYOP auctions that have been observed by Spann and Tellis (2006) might very well be attributed to sophisticated, rational decision making rather than to some form of error. This helps rehabilitate the notion that the Internet should facilitate more rational, not less rational, decision making.

5.1. Managerial Implications

We find that expectations of changes in a seller’s threshold price lead to more drop bids and an unwillingness of consumers to increase their bid levels continuously. Therefore, a firm may benefit from lowering consumers’ expectations that the price may change in order to discourage drop bids. NYOP firms may take several steps to achieve this goal. For instance, an NYOP firm may benefit from decreasing the frequency it makes changes to the threshold price. Whenever a price drop occurs, it is potentially observable because a bidder may have a lower bid accepted whereas a preceding, higher bid was rejected. Such experiences are likely to be reported through word-of-mouth, especially in online discussion forums (Kanna and Kopalle 2001). By decreasing
the frequency of such price changes, a firm can limit the number of reports that document threshold price reductions. Also, an NYOP firm may benefit from trying to influence expectations directly, without any actual change in its policy for setting threshold prices. For example, an NYOP firm may attempt to stem the flow of word-of-mouth. This may be achieved by reducing or eliminating support for online discussion sites or even taking actions to make it more difficult for these sites to operate (e.g., by pursuing litigation to strictly enforce copyrights).

The preceding paragraph suggests that an NYOP seller may benefit from making few, if any, changes to its threshold price. However, this recommendation should be tempered for two reasons. First, introducing threshold price variability may have a positive impact on information rents. Both the popular press and academics assert that a major benefit of the NYOP format is its ability to provide firms with information rents (e.g., Elkind 1999, Dolan 2001, Kanna and Kopalle 2001, Hann and Terwiesch 2003). In essence, because consumers do not know the threshold price, they may pay more than the asking price. This difference is information rent. If an NYOP firm were to fix its threshold price for a given product over a prolonged period of time, we might expect that word-of-mouth would enable many consumers to learn this threshold price and thus erode the information rent obtained by the firm. Perhaps a firm would benefit from ensuring that all price changes are price increases. However, it is not clear whether this is a credible policy, especially in the face of changing competitive and supply chain factors.

Second, our results regarding satisfaction indicate that an NYOP seller may attract and retain more customers if it introduces variability in its threshold price. The positive correlation between satisfaction and the probability of change poses an interesting challenge to NYOP firms. The seller must balance the objective of maximizing its immediate profits, which may occur by adopting and publicizing a policy of rarely, if ever, changing its threshold price, with the objective of enhancing its long-term profitability, where fluctuations in the price threshold may enable the seller to acquire new customers and stimulate a higher rate of return visits. Research has shown that similar trade-offs between short-term and long-term profits are important to many other markets. As one example, Kopalle and Lehmann (2006) posit that to find the optimal quality level to advertise, firms should take into account how expectations of quality may affect initial sales of a market entrant as well as its long-run success and identify factors that affect which objective should be emphasized. The same logic applies here, and marketing research could be instrumental in determining the optimal frequency at which NYOP retailers should change their threshold prices.

5.2. Future Research

To the best of our knowledge, this is the first study to consider how the perceived probability of change in the threshold price impacts bidding in NYOP auctions. Our arguments for the existence and impact of this perception provide a number of different directions for future research. First, there is a need to formally study the impact of change from an NYOP seller’s perspective. Ultimately, one must recognize that sellers can behave strategically when setting the probability of change. The discussion in §5.1 suggests that there are many nuances to consider in order to optimally balance the trade-offs between changing and not changing the threshold price.

Second, a seller can adjust how the price threshold distribution varies over time, thus affecting the magnitude of price changes. This paper has focused on the impact of the frequency of price changes on bidding behavior. However, our results also suggest that the magnitude of these changes has an important impact on the incentive to drop bid. Suppose that the consumer’s bid of \( b_i \) was rejected in the last period. This implies that the expected mean of the price threshold for the last period is \( (\bar{P} + b_i)/2 \). On the other hand, if a change in the threshold price occurs, the new expected mean of the price threshold is \( (\bar{P} + \bar{P})/2 \). Thus, the expected magnitude of a price change is \( (\bar{P} + b_i)/2 - (\bar{P} + \bar{P})/2 = (b_i - \bar{P})/2 \). According to H5 and the evidence from our laboratory auctions, drop bidding is more likely as \( b_i \) rises. An increase in \( b_i \) also increases the expected magnitude of a price threshold change. Thus, holding the frequency of price changes constant, drop bidding is more likely as the expected magnitude of a price change increases. In this case, it is beneficial to drop bid not because a price change is more likely to occur but because a price change, if it were to occur, would likely be more sizable. It would be interesting for future research to explore in greater depth how consumers form expectations about the probable magnitude of price threshold changes and how a seller can optimally adjust the price threshold distribution over time to manage these expectations and to maximize profit.

Third, it would be interesting to consider how the probability of change impacts absolute bid levels, which obviously affects the profitability of NYOP auctions. We conjecture that bids, on average, will be lower as the probability of change increases. However, in the laboratory auctions we conducted, the probability of change did not have a statistically significant effect on bid levels. Given that bidders were not informed of the distribution from which prices were drawn, we suspect that this is the result of the high variability in bidders’ expectations about what exactly the reservation price would be. We conducted an additional market experiment in which bidders were explicitly told the distribution from which
the seller’s reservation price was drawn (the probability of change was 0, 0.5, or 1). In this environment, we found that the maximum bid for a given bid sequence was higher in the Change0 condition \((M = 72.76)\) than in the Change1/2 \((M = 61.39)\) and Change1 conditions \((M = 60.64)\). This is a more powerful test than our original study because it allows us to filter out unobserved heterogeneity in expectations about the price distribution. Although these findings are interesting, it is important for future research to further analyze (both theoretically and empirically) the impact of price changes on bid levels, for example, by allowing for a more extensive range of change values and a more realistic environment that better reflects the type of information consumers are likely to have about the threshold price distribution.

Fourth, the normative model should be verified using real-world data. Although this may be hard to execute due to the difficulty in simultaneously measuring consumers’ willingness-to-pay, expectations about the frequency at which the threshold price may change, and expectations about the distribution from which threshold prices are drawn, it may be very worthwhile. For instance, assuming that consumers believe the threshold price is constant throughout a given bid sequence, previous research estimates WTP, frictional costs, and expected threshold prices using observations of bid sequences (Hann and Terwiesch 2003, Spann et al. 2004). However, this estimation may be based on a flawed or at least incomplete normative model. Consumers do place drop bids, and according to our results this may be a function of consumer expectations that the threshold price may change. Our alternative model may facilitate a closer fit with the data and thus more accurate estimates of WTP and frictional costs, which ultimately may help an NYOP firm choose its prices and other policies (e.g., whether to allow re-bidding) more wisely.

Finally, it is important to understand how consumers form expectations about the probability of change in the threshold price. For instance, in an additional study, we found that passage of time itself may impact the perception that the threshold price has changed. In this additional study, we told participants, after some bidding rounds, to assume that 12 hours had passed after the previous bidding round. We found that the likelihood of a drop bid increases as there is a perception that more time has passed between two bidding rounds as long as there is any probability that the price may change. When participants were told that the threshold price could change, the number of drop bids was lower after a 1-hour delay \((18.34\%)\) than after a 12-hour delay \((48.31\%); \chi^2 = 40.54, p < 0.01\). It would be interesting to study how information acquired by the consumer between bids affects the frequency of drop bids, e.g., “If I check Expedia and see that prices for a ticket went down, I may lower my bid on Priceline because I may think Priceline’s threshold price has also gone down.” Differences across product categories are also likely to play an important role. For instance, in markets where new versions of products are frequently released or the cost of inputs changes frequently (such as electronics and fashion goods), customers may naturally expect threshold prices to change more frequently than in markets that are more consistent over time.

**Acknowledgments**

The authors thank Jagmohan S. Raju, Steve Shugan, Jinhong Xie, the associate editor, and the anonymous reviewers for their helpful input.

**Appendix**

The expected consumer’s surplus for each of the bidding patterns identified in Figure 1 is as follows:

\[
\max_{b_0, b_1, b_2, b_3} C_S \quad \text{s.t. } b_0 < b_1 < b_2 < b_3,
\]

\[
\max C_{S_0} = \max_{b_0, b_1, b_2, b_3} \frac{b_0 - P}{P - \frac{\omega}{1}} (WTP - b_0) + d \left(1 - \frac{b_0 - P}{P - \frac{\omega}{1}}\right)
\]

\[
\left(\frac{WTP - b_1}{P - b_1} \right) \left(1 - \frac{b_1 - b_0}{P - b_0} + \frac{b_1 - P}{P - b_0}\right)
\]

\[
+ d^2 \left(1 - \frac{b_1 - b_0}{P - b_0}\right) \left(1 - \frac{b_0 - P}{P - \frac{\omega}{1}}\right)
\]

\[
\left(1 - \frac{b_1 - b_0}{P - b_0} + \frac{b_1 - P}{P - b_0}\right)
\]

\[
\left[\left(WTP - b_2\right)\left(1 - \frac{b_2 - b_1}{P - b_1} + \frac{b_2 - P}{P - b_1}\right)\right]
\]

\[
+ d^3 \left(1 - \frac{b_1 - b_0}{P - b_0}\right) \left(1 - \frac{b_0 - P}{P - \frac{\omega}{1}}\right)
\]

\[
\left(1 - \frac{b_1 - b_0}{P - b_0} + \frac{b_1 - P}{P - b_0}\right)
\]

\[
\left(1 + \left(1 - \frac{b_2 - b_1}{P - b_1} + \frac{b_2 - P}{P - b_1}\right)\right)
\]

\[
\left(1 - \frac{b_2 - b_1}{P - b_1} + \frac{b_2 - P}{P - b_1}\right)
\]

\[
\left[\left(WTP - b_3\right)\left(1 - \frac{b_3 - b_2}{P - b_2} + \frac{b_3 - P}{P - b_2}\right)\right]
\]
\[
\begin{align*}
\text{max} & \quad \max_{b_0, b_1, b_2, b_3} \frac{b_0 - P}{P - P} (WTP - b_0) + d \left( 1 - \frac{b_0 - P}{P - P} \right) \\
& \quad \quad \cdot \left( \frac{b_1 - b_0}{P - P} \right) \left( 1 + \frac{b_1 - P}{P - P} \right) \\
& \quad \quad \cdot \left[ (WTP - b_3) \frac{b_3 - P}{P - P} \right] \\
\text{s.t.} & \quad b_0 > b_1 > b_2 > b_3, \quad (5) \\
\text{max} CS_c & \quad = \max_{b_0, b_1, b_2, b_3} \frac{b_0 - P}{P - P} (WTP - b_0) + d \left( 1 - \frac{b_0 - P}{P - P} \right) \\
& \quad \quad \cdot \left( \frac{b_1 - b_0}{P - P} \right) \left( 1 + \frac{b_1 - P}{P - P} \right) \\
& \quad \quad \cdot \left( 1 - \frac{b_0 - P}{P - P} \right) \left( 1 - \frac{b_0 - P}{P - P} \right) \left( 1 + \frac{b_0 - P}{P - P} \right) \\
& \quad \quad \cdot \left[ (WTP - b_2) \left( 1 - \frac{b_2 - b_1}{P - b_1} + \frac{b_2 - P}{P - P} \right) \right] \\
& \quad \quad \cdot \left( 1 - \frac{b_1 - b_0}{P - b_1} + \frac{b_1 - P}{P - P} \right) \\
& \quad \quad \cdot \left( 1 + (1 - \frac{b_1 - b_0}{P - b_1} + \frac{b_1 - P}{P - P}) \right) \\
& \quad \quad \cdot \left[ (WTP - b_3) \frac{b_3 - P}{P - P} \right] \\
\text{s.t.} & \quad b_0 < b_1 < b_2 < b_3, \quad (6) \\
\text{max} CS_f & \quad = \max_{b_0, b_1, b_2, b_3} \frac{b_0 - P}{P - P} (WTP - b_0) + d \left( 1 - \frac{b_0 - P}{P - P} \right) \\
& \quad \quad \cdot \left( \frac{b_1 - b_0}{P - P} \right) \left( 1 + \frac{b_1 - P}{P - P} \right) \\
& \quad \quad \cdot \left( 1 - \frac{b_0 - P}{P - P} \right) \left( 1 - \frac{b_0 - P}{P - P} \right) \left( 1 + \frac{b_0 - P}{P - P} \right) \\
& \quad \quad \cdot \left[ (WTP - b_2) \left( 1 - \frac{b_2 - b_1}{P - b_1} + \frac{b_2 - P}{P - P} \right) \right] \\
& \quad \quad \cdot \left( 1 - \frac{b_1 - b_0}{P - b_1} + \frac{b_1 - P}{P - P} \right) \\
& \quad \quad \cdot \left( 1 + (1 - \frac{b_1 - b_0}{P - b_1} + \frac{b_1 - P}{P - P}) \right) \\
& \quad \quad \cdot \left[ (WTP - b_3) \frac{b_3 - P}{P - P} \right] \\
\text{s.t.} & \quad b_0 < b_1 < b_2 < b_3, \quad (9) \\
\text{max} CS_d & \quad = \max_{b_0, b_1, b_2, b_3} \frac{b_0 - P}{P - P} (WTP - b_0) + d \left( 1 - \frac{b_0 - P}{P - P} \right) \\
& \quad \quad \cdot \left( \frac{b_1 - b_0}{P - P} \right) \left( 1 + \frac{b_1 - P}{P - P} \right) \\
& \quad \quad \cdot \left[ (WTP - b_3) \frac{b_3 - P}{P - P} \right] \\
& \quad \quad \cdot \left[ (WTP - b_3) \left( 1 - \frac{b_3 - b_2}{P - b_2} + \frac{b_3 - P}{P - P} \right) \right] \\
\text{s.t.} & \quad b_0 > b_1 > b_2 < b_3, \quad (7) \\
\text{max} CS_g & \quad = \max_{b_0, b_1, b_2, b_3} \frac{b_0 - P}{P - P} (WTP - b_0) + d \left( 1 - \frac{b_0 - P}{P - P} \right) \\
& \quad \quad \cdot \left( \frac{b_1 - b_0}{P - P} \right) \left( 1 + \frac{b_1 - P}{P - P} \right) \\
& \quad \quad \cdot \left[ (WTP - b_3) \left( 1 - \frac{b_3 - b_2}{P - b_2} + \frac{b_3 - P}{P - P} \right) \right] \\
\text{s.t.} & \quad b_0 > b_1 > b_2 < b_3, \quad (8) 
\end{align*}
\]
\[ +d^3 \left( \frac{b_0 - P}{P - P} \right) \left( \frac{b_1 - P}{P - P} \right) \left( \frac{b_2 - P}{P - P} \right) \left( \frac{b_3 - P}{P - P} \right) \] 

s.t. \( b_0 < b_1 < b_2 < b_3 \). \hspace{1cm} (10)

\[
\text{max } CS_h = \max_{b_0, b_1, b_2, b_3} \frac{b_0 - P}{P - P} (WTP - b_0) + \frac{b_1 - P}{P - P} (WTP - b_1) + \frac{b_2 - P}{P - P} (WTP - b_2) + \frac{b_3 - P}{P - P} (WTP - b_3) + d \left( 1 - \frac{b_0 - P}{P - P} \right) 
\]

\[
\text{s.t. } b_0 < b_1 < b_2 < b_3. \hspace{1cm} (11)
\]

Using these expressions, we find \( b_0^* < b_1^* < b_2^* < b_3^* \) when \( WTP < 2 \).

Now turn to \( \varphi = 0 \). Here, every drop bid will be rejected. Thus, the optimal bid pattern is increasing. Formally, substituting \( \varphi = 0 \) into Equations (4)-(11):

\[
CS_a = CS_b = CS_c = CS_d = CS_f = CS_{a'} = CS_{b'} = CS_{c'} = CS_{d'} = CS_{h'}
\]

\[
\text{max } CS_a = \max_{b_0, b_1, b_2, b_3} \frac{b_0 - P}{P - P} (WTP - b_0) + \frac{b_1 - P}{P - P} (WTP - b_1) + \frac{b_2 - P}{P - P} (WTP - b_2) + \frac{b_3 - P}{P - P} (WTP - b_3) + d \left( 1 - \frac{b_0 - P}{P - P} \right) 
\]

\[
\text{s.t. } b_0 < b_1 < b_2 < b_3. \hspace{1cm} (12)
\]

Thus, the question that remains is “What are the relationships between the bids that maximize this surplus?” In particular, normalizing the price distribution (i.e., \( P = 0 \) and \( P = 1 \)), deriving the FOCs and solving for the optimal bids, we find the following:

\[
b_0^* = \frac{1}{32768} < \text{WTP}[16384 + d \text{ WTP}(-4096 - d(16 + d^2 \text{WTP}^2)]
\]

\[
\cdot (16 + \text{WTP}(d \text{ WTP} - 8)(16 + d + \text{WTP}(d \text{ WTP} - 8)))]
\]

\[
b_1^* = \frac{WTP[64 - d(16 + \text{WTP}(d \text{ WTP} - 8))]}{128}
\]

\[
b_2^* = \frac{WTP(4 - d \text{ WTP})}{8}
\]

\[
b_3^* = \frac{WTP}{2}.
\]

(13)

\[
\text{Using these expressions, we find } b_0^* < b_1^* < b_2^* < b_3^* \text{ when } WTP < 2.
\]
that is optimal. Figure 2 summarizes the data from these
pattern (using Equations (4)-(11)) to find the bid sequence
each of the eight patterns identified in Figure 1. Then we
First we numerically solve for the optimal bid levels for
opportunities to bid. Allotherpatterns.Includeatleastone
(wasted) drop bid and thus afford the consumer only three
opportunities to bid. All other patterns are larger than the
surplus from the other patterns. Pattern (a) allows the consumer to have four
opportunities to bid. All other patterns include at least one (wasted) drop bid and thus afford the consumer only three
opportunities to bid. More opportunities to bid must be (weakly) better than having fewer opportunities to bid.

For intermediate $\phi$ (i.e., $0 < \phi < 1$), analytical closed-form solutions are not available. Instead, Mathematica is used
to solve numerically for each particular set of parameters. First we numerically solve for the optimal bid levels for
each of the eight patterns identified in Figure 1. Then we
compare the resulting expected surplus from each bidding
pattern (using Equations (4)-(11)) to find the bid sequence
that is optimal. Figure 2 summarizes the data from these
calculations.

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