Martin Spann & Gerard J. Tellis

Does the Internet Promote Better Consumer Decisions? The Case of Name-Your-Own-Price Auctions

The Internet has enabled consumers to make more informed decisions more conveniently with apparently more efficient price-clearing mechanisms than was available before its advent. One such mechanism is the name-your-own-price auction. The authors study the extent to which decisions made in such an auction are rational in relation to an economic model. The results from two independent markets show that a large number of consumers do not exhibit rational decision making.

The Internet has made it easier for sellers to inform consumers of their offers and for consumers to respond to those offers than has been possible in traditional retail channels (Bakos 1997; Brynjolfsson and Smith 2001; Geoffrion and Krishnan 2003). Several retail forms have evolved on the Internet, such as single-store offers, comparison sites with offers across multiple stores, and various types of auctions. One type of auction is the name-your-own-price mechanism (e.g., www.priceline.com), in which consumers bid for a product on sale at an unrevealed retailer's price. At Priceline, consumers are allowed to bid only once within seven days for a specific product (e.g., a flight); however, they can partially circumvent the time constraint (Fay 2004). Other name-your-own-price retailers have extended the model to allow multiple bidding for the same product.

Ideally, auctions enable a better market-clearing price between a buyer and a seller, assuming that both are rational. Sellers hope to extract the maximum buyer surplus by completing a transaction at the highest price that a buyer is willing to pay above their own marginal cost for that item. Buyers hope that they can obtain the lowest price a marketer is willing to take below their own reservation price. However, because buyers do not know the sellers' marginal cost, the only way a buyer can obtain such a good deal is to begin with a low price and raise it in increments up to his or her reservation price until the seller agrees to the price. Economic theory suggests the specific sequence of prices that a rational, price-minimizing consumer should adopt. However, to do so, buyers need time, thoughtfulness, and planning, all features that the Internet is supposed to provide. The specific issue we address in this article is whether consumers' actual bids fit the pattern suggested by economic theory in the case of name-your-own-price auctions. In general, we ascertain the extent to which shopping on the Internet facilitates consumers' rational, price-minimizing decisions.

The literature on name-your-own-price auctions is sparse. Some studies focus on the specific design of Priceline but do not provide empirical data (Chernev 2003; Ding et al. 2005; Fay 2004). A few studies analyze consumer characteristics on the basis of data on such auctions, but they do not examine whether consumer behavior is rational (Hann and Terwiesch 2003; Spann, Skiera, and Schäfers 2004). The current study analyzes the empirical behavior of consumers and compares it with the economic norm to ascertain the extent to which it is rational.

We conduct this analysis in three steps. First, we analyze whether observed bidding patterns follow the normative patterns. Second, we analyze what factors explain deviations from rational behavior. Third, we analyze the effect of these possible influencers of rational behavior on the value of consumers' bids. We apply our analysis to two large data sets of consumers' bids using a name-your-own-price auction: (1) a retailer selling flights from one country to various international and domestic destinations and (2) a low-cost airline selling its own flights within Europe.

We organized the remainder of this article as follows: In the next section, we describe the expected behavior of consumers at the name-your-own-price auction. Then, we describe the data and our analysis and present the results. Finally, we discuss the implications of our findings.

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Expected Behavior at Name-Your-Own-Price Auctions

Name-Your-Own-Price Auction

In a name-your-own-price auction, any consumer who bids above a seller's unrevealed threshold price receives the product at the price of his or her bid. In case of limited availability, consumers who are the first to bid above the threshold are served first. In contrast, a standard auction

ISSN: 0022-2429 (print), 1547-7185 (electronic)

determines the winning bidder as the one who places the highest bid (if bidding to buy) or the lowest bid (if bidding to sell) among rival bids.

Two broad types of name-your-own-price auctions are prevalent. In one type, firms more or less perfectly limit consumers to a single bid for a specific product. An example of such an auction is that of Priceline (Fay 2004). In the other type, firms allow consumers to bid again if their previous bid has been rejected. Several examples of the latter are available in Europe. In the latter type, if the seller accepts a buyer's bid, a purchase occurs because consumers' bids are binding (e.g., Priceline requires consumers to provide their credit card information before bidding). If a consumer's bid is unsuccessful, he or she can either withdraw or submit another bid (see Figure 1). Rejected bids provide some information about buyers and sellers. By bidding, consumers provide the lower limit of the range of their reservation price at that moment. In rejecting the bid, sellers indicate the lower limit of the range of their threshold price at that moment. According to economic theory, the threshold price should represent the sellers marginal cost for the product unless the seller hopes to attract consumers with higher prices.

Buyers' Optimal Behavior

How should buyers bid in a name-your-own-price auction such as that which we previously described? Economic theory provides a framework to answer this question, assuming that consumers are rational and want to minimize the prices they pay. Spann, Skiera, and Schäfers (2004) develop a model that arrives at the consumer's optimal strategy in terms of the optimal number of bids and the optimal prices of those bids. They apply the model to impute consumers' willingness to pay and bidding costs. We used their model to derive the optimal pattern of bid prices. Here, we describe the economic intuition of the model and derive the optimal pattern of bid prices. (Readers may go to the original article for details of the model development.)

In this model, consumers maximize their surplus, which is the difference between their reservation price and the price they pay. The latter is the amount of their bid if it is successful (i.e., above the firm's threshold price, which is unknown to consumers). Because this threshold price, and thus the success of a bid, is uncertain to consumers, they maximize their expected surplus (i.e., surplus × probability of success). Therefore, consumers need to form a belief about the probability distribution of the unknown threshold price. By submitting a bid, consumers accrue costs that reduce their surplus. The costs of a bid include the cost of thinking to determine the optimal amount of the bid, the transaction costs for the time and trouble of bidding, and the costs of waiting for the acceptance or rejection of a bid (Shugan 1980; Tellis 1986).

Consumers influence their surplus and the probability that a bid is successful by the size of their bid. On the one hand, the consumer can increase the probability that the bid is successful (i.e., above the seller's unrevealed threshold price) by increasing the amount of the bid. On the other hand, a higher bid leads to a lower consumer surplus in the case of a successful bid. Thus, the consumer must solve this trade-off between increasing consumer surplus and decreasing the probability of a successful bid. Consumers do not bid if they expect a negative surplus.

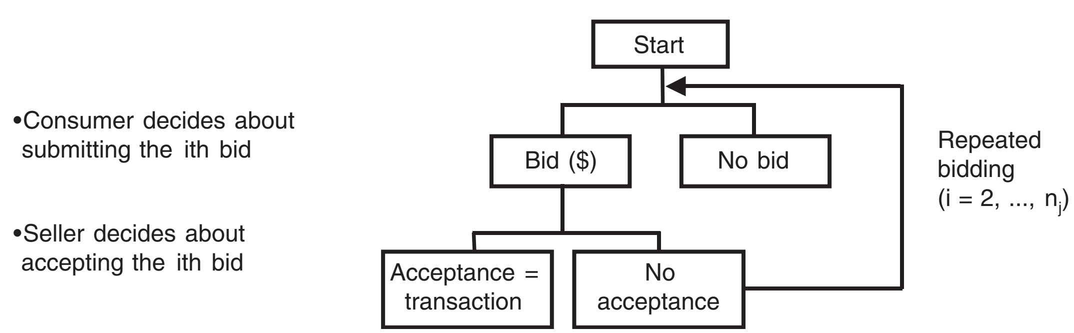
The consumer has the possibility of rebidding if a bid is not successful. In this case, consumers update their belief about the distribution of the threshold price because an unsuccessful bid signals a threshold price that is greater than the bid. Thus, the updated distribution for the threshold price is left-truncated at the value of the unsuccessful previous bid. The optimal bid price of a repeated bid is then determined on the basis of this updated belief (for the formal model, see Appendix A).

The optimal pattern of bid prices has three norms (for the proof, see Appendix B). First, consumers should begin with the lowest price that does not seem completely unreasonable given their reservation price and belief about the threshold price. The reason is that consumers do not know how many seats are left, under what duress the seller operates, and what the seller's marginal cost is. A reasonably low price can gather information about these factors.

Second, if their bids are rejected, buyers should increase them up to their reservation price, until the seller accepts the bid. The reason for increasing the bid is to offer a price that is more acceptable to sellers, as long as it is below the buyer's reservation price.

Third, if not under pressure of time, buyers should increase their bids in decreasing size of increments. The reasoning behind this third norm is the most difficult to

FIGURE 1
Multiple Bidding at a Name-Your-Own-Price Retailer



appreciate. The logic is as follows: Costs accruing with each bid reduce consumers' surplus. Given higher costs, the optimal strategy is to reduce the number of bids necessary to be successful. Consumers increase the probability of each bid being successful by bidding higher than their prior bid. However, at the same time, as they bid closer to their reservation price and the seller's unknown threshold price, they do not want to bid higher than is necessary to avoid giving up too much of their surplus to the seller. Therefore, they should increase their bid in smaller increments.

If we assume rational, price-minimizing buyers, the optimal bidding strategy is characterized with monotonically increasing bids, which have decreasing increments as long as consumers accrue bidding costs. We refer to such bidding sequences as being "strongly rational." If bidding costs are zero, consumers' bids monotonically increase at a constant rate. However, such costs are unlikely to be zero (e.g., Hann and Terwiesch 2003; Spann, Skiera, and Schäfers 2004). If consumers are under pressure or if they panic about not winning a bid, they may bid with increasing increments. We refer to this case as being "weakly rational."

Supply constraints, such as limited seats, can affect the probability of whether a consumer's bid is successful. Rational consumers would make estimates of these supply constraints as best they can before their first bid. They incorporate this risk of a supply constraint in their belief about the probability of winning the bid and the distribution of the unknown threshold price. They estimate the threshold price to be higher than when there are no constraints. Because rational consumers determine *ex ante* their optimal bidding behavior by simultaneously determining the optimal number of bids and optimal bid prices, the belief about supply constraints is already incorporated into their optimal bidding strategy. Next, we examine real markets to determine whether and to what extent observed buyer behavior conforms to the normative behavior we described previously (again, assuming rational, price-minimizing buyers).

Data

Study 1: Name-Your-Own-Price Retailer

Our first study examines the data of a name-your-own-price retailer based in Germany that sells airline tickets for various airlines and allows multiple bidding. Our data set consists of all bids at the name-your-own-price retailer for a period of 11 months between February 2000 and December 2000. We have 6539 bidding sequences and a total of 12,999 individual bids for flights from Germany to 86 different international and domestic destinations. A bidding sequence consists of the bids of a specific consumer for a specific destination. Table 1 shows the distribution of bidding sequences by bid length and the distribution of consumers by destinations for which they bid: 78% of all bidding sequences consist of only one or two bids, and 88% of all consumers bid for only one destination. Table 2 shows

TABLE 1
Description of Data from Name-Your-Own-Price Retailer

Distribution of Bidding Sequences by Bid Length		Distribution of Consumers by Destinations	
Bid Length	Number of Sequences	Destinations Bid[a]	Number of Consumers
1	3647	1	4965
2	1477	2	492
3	634	3	110
4	347	4	25
5	173	5	12
6	89	6	12
>6	172	7	4
All	6539	All	5620

[a]Destinations for which a consumer bids.

TABLE 2
Number of Destinations by Geographic Region (Name-Your-Own-Price Retailer)

Geographic Region	Destinations	Sequences	Proportion (%)[a]
Germany (domestic)	7	1160	18
Europe	32	3397	52
North America	21	1240	19
Rest of world	26	742	11
All	86	6539	100

[a]Proportion of sequences per geographic region according to all sequences.

the number of destinations by geographic region: Fewer than one fifth of all bidding sequences are for domestic flights, but a majority of sequences are for flights within Europe.

Study 2: Name-Your-Own-Price Low-Cost Airline

Our second data set consists of the application of the name-your-own-price auction during a promotional offering by a European low-cost airline. Low-cost airlines (e.g., Southwest, easyJet, JetBlue) differ from traditional airlines in several ways. First, they offer "no-frills" service at low prices. Second, they treat each flight as a separate product; that is, they do not apply any booking restrictions, such as a maximum stay restriction between the outward and the return flight. Third, they usually do not serve transcontinental destinations. Our data set consists of all bids for flights on this airline from a name-your-own-price auction during a promotional offering (from Friday, September 17, to Sunday, September 19, 2004). Consumers could bid for 14 different flight destinations in Europe on 30 different dates (between the end of September 2004 and the end of October 2004). We have 3598 bidding sequences and 12,280 individual bids for these destinations. Table 3 shows the distribution of bidding sequence by bid length and the distribution of consumers by destinations for which they bid: 53% of all bidding sequences consist of only one or two bids, and 80% of all consumers bid for only one destination.

Modeling Bidding Behavior

We analyze whether empirically observed patterns match the normative pattern of behavior (assuming rational, price-minimizing buyers). We do so through a hierarchical model that consists of two stages (e.g., Chandy et al. 2001). In the first stage, we estimate each consumer's pattern of bidding. In the second stage, we ascertain whether the patterns of bidding estimated in the first stage vary by characteristics of consumers and their bids.

First-Stage Analysis

Classification of bidding patterns. We consider only bidding sequences that are longer than two bids for a single itinerary. To capture various bidding patterns parsimoniously, we fit the following quadratic function to each sequence of bids:

$$(1) \quad B_{k,i} = \alpha_{1k} \times I_{k,i}^2 + \alpha_{2k} \times I_{k,i} + \alpha_{3k} + \varepsilon_{k,i} \qquad (I_{k,i} > 0),$$

where $B_{k,i}$ is the bid value; $I_{k,i}$ is the number of a bid in a kth bidding sequence; α_{1k}, α_{2k}, and α_{3k} are parameters that capture the shape of the quadratic function; and $\varepsilon_{k,i}$ are residuals, assumed to follow a normal distribution identically and independently. We estimate Equation 1 by minimizing the sum of squared residuals for each individual sequence to capture consumer heterogeneity.

On the basis of the estimated parameter values α_{1k} and α_{2k}, the first couple of bids, and the last bid number $I_{k,max}$ of each (kth) bidding sequence, we classified individual sequences into six different bidding patterns (see Figure 2). The constant term α_{3k} is irrelevant for classification. We begin by explaining the identification of the two simplest patterns (Pattern 2 and 6) and then move on to the more complex patterns.

Pattern 2 reflects linearly increasing bids. A sequence follows Pattern 2 if the quadratic term has a parameter of zero ($\alpha_{1k} = 0$) and the linear term has a parameter of positive value ($\alpha_{2k} > 0$).

Pattern 6 reflects constant or linearly decreasing bids. A sequence follows Pattern 6 if the quadratic term has a parameter of zero ($\alpha_{1k} = 0$) and the linear term has a parameter of negative value or zero ($\alpha_{2k} \leq 0$).

Pattern 1 reflects increasing bids at a decreasing rate; the last bid still is the highest in the sequence (i.e., only the upward portion of an inverted U shape). A sequence follows Pattern 1 if the parameter of the linear term is positive ($\alpha_{2k} > 0$), the parameter of the quadratic term is negative ($\alpha_{1k} < 0$), and the value of the last bid of the sequence is the highest ($B_{k,Imax} > B_{k,Imax-1}$). Appendix C shows that these conditions are met when

$$(2) \qquad 0 > \alpha_{1k} > \frac{-\alpha_{2k}}{2 \times I_{k,max} - 1}.$$

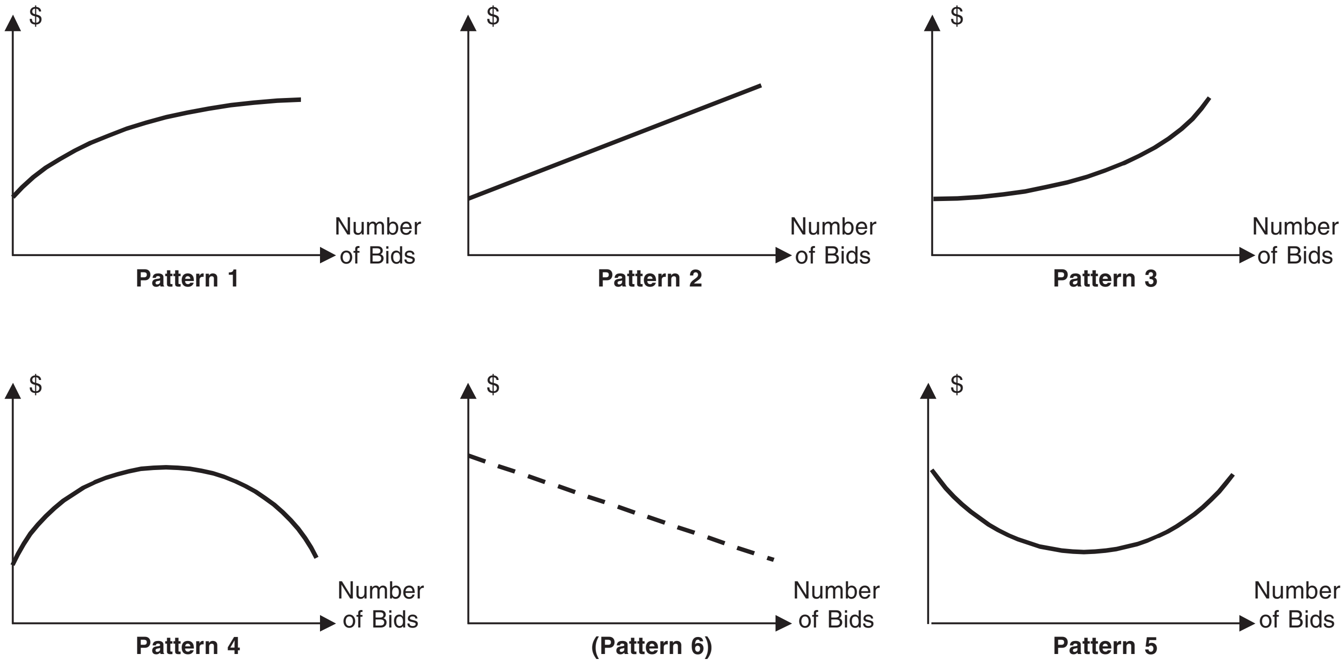
Pattern 4 reflects bids whose values follow a full inverted U shape. A sequence follows Pattern 4 if the

TABLE 3
Description of Data from Low-Cost Airline

Distribution of Bidding Sequences by Bid Length		Distribution of Consumers by Destinations	
Bid Length	**Number of Sequences**	**Destinations Bid[a]**	**Number of Consumers**
1	922	1	1937
2	981	2	377
3	600	3	110
4	322	4	22
5	227	5	—
6	156	6	1
>6	390	7	—
All	3598	All	2389

[a]Destinations for which a consumer bids.

FIGURE 2
Idealized Patterns of Quadratic Function



parameter of the quadratic term is negative ($\alpha_{1k} < 0$) and the value of the last bid is less than or equal to the value of the previous one ($B_{k,Imax} \leq B_{k,Imax-1}$); that is, the curve includes the right, decreasing part of the inverted U shape. The parameter of the linear term (α_{2k}) can be positive, zero, or negative. Appendix C shows that these conditions are met when

$$0 > \alpha_{1k} \leq \frac{-\alpha_{2k}}{2 \times I_{k,max} - 1}. \tag{3}$$

Pattern 3 reflects bids whose values follow an increasing curve at an increasing rate (i.e., exponential increase or only the increasing part of a U-shaped curve). A sequence follows Pattern 3 if the quadratic term has a parameter of positive value ($\alpha_{1k} > 0$) and the value of the second bid of the sequence is greater than the value of the very first one ($B_{k,2} > B_{k,1}$). The parameter of the linear term (α_{2k}) can be positive, zero, or negative. Appendix C shows that these conditions are met when

$$0 < \alpha_{1k} > \frac{-\alpha_{2k}}{3}. \tag{4}$$

Pattern 5 reflects bids whose values follow a U-shaped curve. A sequence follows Pattern 5 if the parameter of the linear term is negative ($\alpha_{2k} < 0$), the parameter of the quadratic term is positive ($\alpha_{1k} > 0$), and the value of the second bid of the sequence is less than or equal to the value of the first one ($B_{k,2} \leq B_{k,1}$); that is, the curve includes the left, decreasing part of a U-shaped curve. Appendix C shows that these conditions are met when

$$0 < \alpha_{1k} \leq \frac{-\alpha_{2k}}{3}. \tag{5}$$

Table 4 summarizes these criteria for classification of the patterns.

Pattern 1 is consistent with strongly rational behavior (i.e., a monotonically increasing pattern with decreasing increments, as expected by the normative predictions). Pattern 3 is weakly rational (i.e., a monotonically increasing pattern with increasing increments). Pattern 2 is rational if bidding costs are zero, a condition that is unlikely to be met in real markets. Patterns 4 and 5 are clearly irrational, showing both increasing and decreasing trends in the same sequence. Similarly, Pattern 6 is clearly irrational, showing linearly declining bids.

We do not have sufficient degrees of freedom to test the significance of each of the estimated parameters in Equation 1. However, we can test the validity of our classification in two ways: First, we test the extent to which people within a group vary from the mean of that group. We do this by testing the extent to which the group means for each of the estimated parameters are statistically different from zero, given the alternate hypothesis that they take on the values we specify in Table 4. In the cases that the mean itself should be zero, as we specify in Table 4, we expect not to reject the null hypothesis. Second, we test whether the means between groups are different from each other.

Results. Table 5, Panel A, displays the estimation results of fitting the quadratic function to individual bidding sequences at the name-your-own-price retailer. On average, our model explains 89% of the variance. The results of our two tests for these data are as follows: First, in Patterns 1, 3, 4, and 5, group means for the parameters of the quadratic term (α_{1k}) and the linear term (α_{2k}) are significantly different from zero and in the expected direction, which unambiguously classifies the pattern according to the criteria that Table 4 summarizes. For Pattern 2, the mean value of the parameter of the quadratic term (α_{1k}) is not different from zero, which is exactly the characteristic we expected. We did not observe Pattern 6 in our data. Second, to test differ-

TABLE 4
Criteria for Classifying Bidding Patterns

<table>
<tr><th colspan="2" rowspan="2"></th><th colspan="3">Range of Parameter of Quadratic Term</th></tr>
<tr><th>$\alpha_{1k} < 0$</th><th>$\alpha_{1k} = 0$</th><th>$\alpha_{1k} > 0$</th></tr>
<tr><td rowspan="3">Range of Parameter of Linear Term</td><td>$\alpha_{2k} > 0$</td><td>$0 > \alpha_{1k} > \frac{-\alpha_{2k}}{2 \times I_{k,max} - 1} \wedge \alpha_{2k} > 0$
1</td><td>$\alpha_{1k} = 0 \wedge \alpha_{2k} > 0$
2</td><td rowspan="2">$0 < \alpha_{1k} > \frac{-\alpha_{2k}}{3}$
3</td></tr>
<tr><td>$\alpha_{2k} = 0$</td><td rowspan="2">4
$0 > \alpha_{1k} \leq \frac{-\alpha_{2k}}{2 \times I_{k,max} - 1}$</td><td rowspan="2">$\alpha_{1k} = 0 \wedge \alpha_{2k} \leq 0$
6</td></tr>
<tr><td>$\alpha_{2k} < 0$</td><td>$0 < \alpha_{1k} \leq \frac{-\alpha_{2k}}{3} \wedge \alpha_{2k} < 0$
5</td></tr>
</table>

Notes: Numbers in circles show pattern numbers (see Figure 2). Shaded areas represent clearly irrational patterns (not monotonically increasing).

TABLE 5
Proportion of Bidding Patterns

Pattern	Observations	Proportion (%)	Mean Number of Bids	Mean R^2 (%)		Mean Parameter Estimates[b] α_{1k} SE (p Value)	Mean Parameter Estimates[b] α_{2k} SE (p Value)
A. Name-Your-Own-Price Retailer							
1	511	36	4.1	94		–22.88	161.02
						2.42 (.00)	12.37 (.00)
2[a]	75	5	3.8	98		.00	77.24
						.00 (1.00)	5.95 (.00)
3	325	23	4.5	94		20.35	–23.37
						1.46 (.00)	4.22 (.00)
4	317	23	4.8	81		–36.01	174.30
						3.25 (.00)	13.71 (.00)
5	187	13	5.4	78		44.21	–187.68
						5.93 (.00)	22.69 (.00)
All	1415	100	4.6	89	χ^2[c]	1054.72 (.00)	839.60 (.00)
B. Low-Cost Airline							
1	808	48	5.6	98		–1.34	12.30
						.08 (.00)	.43 (.00)
2[a]	206	12	4.0	99		.00	6.59
						.00 (1.00)	.38 (.00)
3	483	29	5.2	98		1.92	–1.10
						.26 (.00)	.77 (.15)
4	140	8	7.5	82		–4.12	22.50
						.64 (.00)	2.64 (.00)
5	58	3	8.1	77		4.35	–18.42
						1.03 (.00)	4.06 (.00)
All	1695	100	5.5	96	χ^2[c]	1333.22 (.00)	822.96 (.00)

[a]$\alpha_{1k} = 0$.
[b]First row: mean parameter for each group of similar patterns; second row: within-group standard errors; p value is in parentheses.
[c]Chi-square of Kruskal–Wallis test for parameter differences between groups of similar patterns; p value is in parentheses.

ences of the means between groups, we used a nonparametric test (a Kruskal–Wallis test) because standard deviations differ between the groups. The test yields significant differences of α_{1k} and α_{2k} between groups (for bivariate tests of differences of means between groups, see Appendix D). Only 36% of all bidding sequences fit Pattern 1 (i.e., strongly rational), 23% fit Pattern 3 (i.e., weakly rational), and 5% fit Pattern 2 (which would be rational if bidding costs were zero). However, Hann and Terwiesch (2003) and Spann, Skiera, and Schäfers (2004) find mean bidding costs (which they call "frictional costs") of approximately $6 and $3. Furthermore, 36% of all sequences are not monotonically increasing, which is clear evidence of irrationality. Thus, overall, at the name-your-own-price retailer, 64% of the bidding sequences range from weakly rational to clearly irrational.

Table 5, Panel B, depicts the estimation results of fitting a quadratic function to individual bidding sequences at the low-cost airline. On average, our model explains 96% of the variance. The results of our two tests for these data are as follows: First, group means for the parameters of the quadratic term (α_{1k}) and the linear term (α_{2k}) are significantly different from zero, except for the parameter α_{1k} of Pattern 2 and α_{2k} of Pattern 3. We already outlined that $\alpha_{1k} = 0$ is the characteristic of Pattern 2. In Appendix C, we outline that in case of Pattern 3, α_{2k} can take a positive value, zero, and, to a certain limit, a negative value. Thus, the insignificance of α_{2k} in this case does not reject Pattern 3. Second, the Kruskal–Wallis test yields significant differences of α_{1k} and α_{2k} between groups (for bivariate tests of differences of means between groups, see Appendix D): 48% of all bidding sequences fit Pattern 1 (strongly rational), 12% fit Pattern 2, and 29% fit Pattern 3. In addition, 11% of all sequences are not monotonically increasing. Therefore, at the low-cost airline, 52% of bidding sequences range from weakly to clearly irrational.

However, bidding at the low-cost airline shows less deviation from rational behavior than at the name-your-own-price retailer. The reason is that customers of the low-cost airline are more attuned to cost minimization and are more likely to follow the predictions of the economic model of rational bidding than are customer of the air ticket retailer.

Second-Stage Analysis

We begin by hypothesizing what factors could explain the occurrence of nonmonotonic patterns in the data. Then, we show the results of testing these hypotheses. Finally, we attempt to explain the values of the bids.

Explanation of nonmonotonic patterns. This subsection explains the factors that lead to monotonically increasing patterns. The dependent variable is the presence of a monotonically increasing bid pattern. The independent variables are the number of bids in a sequence, the number of destinations for which a consumer bids, the mean time between each consecutive bid of a bidding sequence (i.e., the mean interbid time), and the region of the destination (see Equation 6). For each independent variable, we develop a hypothesis for its effect on the dependent variable. We use a binary logit model for the analysis. Thus:

$$\text{(6)} \quad \mathrm{PR}(\mathrm{Mon}_k) = \frac{1}{1+\exp\left[-\begin{pmatrix}\beta_0 + \beta_1 \times \mathrm{NBid}_k + \beta_2 \times \mathrm{NDes}_{j,k} \\ + \beta_3 \times \mathrm{ITime}_k + \beta_4 \times \mathrm{Euro}_k \\ + \beta_5 \times \mathrm{NorAm}_k + \beta_6 \times \mathrm{RWor}_k\end{pmatrix}\right]} \quad (k \in K),$$

where

$\mathrm{PR}(\mathrm{Mon}_k)$ = the probability of a monotonically increasing pattern of the kth sequence,
NBid_k = the number of bids in the kth sequence,
$\mathrm{NDes}_{j,k}$ = the number of destinations for which the jth consumer in the kth sequence bid,
ITime_k = the mean time between consecutive bids in the kth sequence,
Euro_k = a dummy variable (1 if flight destination of the kth sequence is in Europe),
NorAm_k = a dummy variable (1 if flight destination of the kth sequence is in North America),
RWor_k = a dummy variable (1 if flight destination of the kth sequence is in the rest of the world, and
K = the index set of bidding sequences.

The rationale for the independent variables is the following: Consumers who bid for more destinations have more experience with the name-your-own-price auction than those who bid for less destinations. The reason is that each destination has its own configuration of dates, times, and competitors; consumers' assumptions about supply and threshold prices; and outcomes of consumers' bidding. A final acceptance indicates how low the seller's threshold price is, and a final rejection indicates how high it might be. Thus, consumers gain rich knowledge from experience with bidding for each destination (Remus, O'Connor, and Griggs 1996). Learning from experience can compensate for limited information and further rational behavior (Arthur 1991; Conlisk 1996). Thus, experienced consumers should be less prone to behavioral limitations and more likely to behave according to the normative model (i.e., rational):

> H_1: The number of destinations for which a consumer bids has a positive effect on the probability of a monotonically increasing pattern.

After we control for experience, the number of bids consumers place within a sequence may adversely affect the rationality of their bidding for several reasons. First, if consumers must take too much information into account, their mental capacity becomes limited, and their decisions can suffer (Jacoby, Speller, and Kohn 1974; Lurie 2004). As consumers make more bids, they are more likely to become confused with their prior bids. Thus, they are less likely to make rational bids. Second, bidding at a name-your-own-price auction requires consumers to develop some belief about the retailer's threshold price and update this belief when the bid is rejected, which can be difficult (Chernev 2003). Third, purely by chance, the more bids a consumer makes, the greater is the likelihood that the consumer will either make errors or become confused.

We suspect that, together, these three factors overwhelm the small increase in experience that may come from merely increasing the number of bids in each sequence. Similarly, these factors are likely to overwhelm the small decrease in learning costs that may occur with increasing lengths of bids in a sequence. Thus:

> H_2: The number of bids in a sequence has a negative effect on the probability of a monotonically increasing pattern.

In general, consumers' memory and recall of prices is low (Dickson and Sawyer 1990; Monroe and Lee 1999; Rajendran and Tellis 1994; Vanhuele and Drèze 2002). As interbid time increases, consumers are more likely to forget about their prior bids. Thus, we hypothesize that the time between consecutive bids adversely affects the rationality of consumer bidding behavior:

> H_3: The mean interbid time of bids in a sequence has a negative effect on the probability of a monotonically increasing pattern.

The flight time and cost of the ticket increase with the distance between the origin and the destination of a flight. Thus, the larger the distance, the greater a consumer can save by more careful planning and more rational bidding. The greater the saving, the more the consumer will be motivated to make a well-thought-out, rational decision (Tellis and Wernerfelt 1987). Thus, the longer the distance, the more a consumer will bid rationally to obtain a good deal. Because all bids were for flights originating in Germany, we operationalized distance through dummy variables for the region of the destination (Europe, North America, and the rest of the world); a flight within Germany was the baseline category:

> H_{4a}: An international destination has a positive effect on the probability of a monotonically increasing pattern.
>
> H_{4b}: The magnitude of the effect increases (becomes more positive) with the distance of the region.

Results. Table 6 shows the estimation results of the binary Logit model for the name-your-own-price retailer (second column) and the name-your-own-price offering at the low-cost airline (third column).

In both studies, contrary to H_1, the effect of the number of destinations on the probability of a monotonically increasing pattern is not significant (and is negative). Apparently, experience does not mitigate the behavioral limitations that lead to irrational bidding behavior (e.g., Prabhu and Tellis 2000). In both studies, consistent with H_2, the number of bids in a sequence has a highly significant, negative effect on the probability of a monotonically increasing pattern. In both studies, consistent with H_3, we find that mean interbid time of a sequence (i.e., the time between consecutive bids) has a negative influence on the probability of a monotonically increasing pattern. We measure interbid time at the name-your-own-price retailer because of the availability at the daily level, whereas we have data on the level of seconds for the low-cost airline. In Study 2, consistent with H_4, an increasing flight distance leads to a higher likelihood of a monotonically increasing pattern. Thus, the magnitude of the effect (positive value of the parameter of the dummy variable) increases with the distance (the rest of the world consists of destinations in South America, Africa, Asia, and Australia). We cannot test H_4 for the second data set of the name-your-own-price offering at the low-cost airline, because all flights were within Europe and had about the same distance (between one and two hours of flight time).

Both studies yield identical results for the factors that influence deviations from normative bidding behavior, indicating robust effects. However, the proportion of such deviations is much higher at the airline ticket retailer than at the low-cost airline (see Table 5). At the retailer, consumers bid for a flight that could be served by various airlines and had no knowledge of the actual airline, which was revealed only after a successful purchase (Priceline uses a similar policy). Thus, the task of generating the bid values is more difficult because of this greater uncertainty. At the airline, consumers could bid for a flight only at this specific low-cost airline; thus, they knew the product. Furthermore, the total duration of the offering at the low-cost airline was less than four days (i.e., there was less time to forget about previous bids).

Explanation of bid values. This section analyzes the maximum bid value of a bidding sequence. The indepen-

TABLE 6
Results of Binary Logit Model (Probability of Monotonically Increasing Patterns)

Parameters[b]	Retailer (Study 1)[a]	Low-Cost Airline (Study 2)[a]
Constant	1.17 (.00)	2.85 (.00)
Number of destinations	–.06 (.34)	–.16 (.11)
Number of bids	–.12 (.00)	–.09 (.00)
Mean interbid time[c]	–.03 (.00)	–.08 (.01)
DV_Europe[d]	.30 (.06)	
DV_North America[d]	.49 (.01)	
DV_rest of world[d]	.66 (.00)	
Likelihood ratio test: χ^2	123.72 (.00)	46.77 (.000)
Classification goodness (%)	69.4	88.4
Number of observations	1415	1695

[a]*p* value is in parentheses.
[b]Dependent variable: Prob(Y = 1) is the probability of monotonically increasing pattern.
[c]Mean time difference in days (hours) between consecutive bids of a sequence at retailer (low-cost airline).
[d]Baseline category: Germany.

dent variables are the same as in the analysis of nonmonotonic patterns. We use multiple regression to analyze the dependent variable:

$$\text{(7)}\quad \text{MaxBidV}_k = \beta_0 + \beta_1 \times \text{NBid}_k + \beta_2 \times \text{NDes}_{j,k} + \beta_3 \times \text{ITime}_k + \beta_4 \times \text{Euro}_k + \beta_5 \times \text{NorAm}_k + \beta_6 \times \text{RWor}_k + \mu_k \quad (k \in K),$$

where MaxBidV_k is the maximum bid value of the kth sequence and μ_k is the residual of the kth sequence.

Table 7 shows the estimation results of the regression analysis for the maximum bid value of a bidding sequence for the name-your-own-price retailer (second column) and for the name-your-own-price offering at the low-cost airline (third column). In both studies, the maximum bid value decreases with the number of destinations. Apparently, inexperienced consumers may overbid. Conversely, experienced consumers who bid for more than one destination are more likely to bid lower. Thus, experience does not lead to a higher likelihood of rational bidding behavior but reduces the consumer's maximum bid value.

In both studies, the maximum bid value of a sequence increases with the number of bids. Thus, even if consumers become confused with an increasing number of bids, they raise their average bid by the same amount and overbid. Interbid time has no significant effect on the maximum bid value in both studies. Apparently, the waiting time between consecutive bids influences the rationality of the bidding pattern but does not have an effect on the maximum bid value. The distance of a flight increases maximum bid value because consumers correctly anticipate that costs (especially fuel costs) increase with distance and that higher costs lead to a higher threshold price for a flight. Again, we cannot analyze this effect for the data for the low-cost airline because of similar distances of all destinations.

We found that the same factors explain maximum bid value in both studies. This indicates the stability of our results for name-your-own-price auctions because both studies differ with respect to currency, time of the study, duration of data gathering, and offering (multiple airlines versus one low-cost airline).

Discussion

The popularity of the Internet is supposed to have helped consumers make better decisions that are more consistent with rational economic theory than was possible before the Internet. We analyze bidding sequences for airline tickets at a name-your-own-price retailer and at a low-cost airline. We find that a majority of bidding sequences are not consistent with the predictions of an economic model of a rational, price-minimizing consumer. This finding indicates that the Internet does not eliminate or lower consumers' irrational decisions as many experts expected or hoped. Further analysis reveals that the deviations from rationality are mostly consistent with a priori expectations. In particular, consumers who place many bids with rather long interbid times are more likely to bid irrationally, which can be attributed to forgetting. Consumers are more likely to bid rationally for larger distances, which can be explained by higher involvement for or savings from such flights. Consumers who have more experience have lower bids on average, probably because of the knowledge they have gained. Our results have some important implications for managers, consumers, and researchers.

Implications for Managers

Price-discovery mechanisms, such as name-your-own-price auctions, are facilitated by the low transaction costs of trade on the Internet. Such mechanisms promise sellers two important benefits: First, prices based on the bidding process can be consumer specific and allow for better extraction of consumer surplus through this segmentation. Second, price discovery mechanisms can reduce efforts by third parties that post lowest market prices and thus thwart firms' price discrimination of consumers.

Our results indicate that despite the convenience of the Internet to consumers, most consumers still do not make strictly rational decisions. This finding suggests that firms

TABLE 7
Regression Results for Maximum Bid Value

Parameters	Retailer (Study 1)[a, d]	Low-Cost Airline (Study 2)[a, e]
Constant	265.93 (.000)	45.20 (.000)
Number of destinations	–8.80 (.098)	–3.73 (.000)
Number of bids	3.45 (.083)	1.57 (.000)
Mean interbid time[b]	–.08 (.808)	.55 (.172)
DV_Europe[c]	121.73 (.000)	
DV_North America[c]	632.38 (.000)	
DV_rest of world[c]	901.61 (.000)	
R^2	.694	.059
F-value	531.22 (.000)	35.32 (.000)
Number of observations	1415	1695

[a]*p* value is in parentheses.
[b]Mean time difference in days (hours) between consecutive bids of a sequence at retailer (low-cost airline).
[c]Baseline category: Germany.
[d]Bid value in Deutschmark (DM) (DM1 = approximately \$.5).
[e]Bid value in euro (€1 = approximately \$1.2).

can further segment consumers by their bidding patterns and exploit their irrationality for profit. For this purpose, firms would need to modify the design of such auctions or develop decision rules that alter acceptance of bids on the basis of the bidding pattern. For example, if enough seats are projected to be available, firms might accept bids early from those consumers who show declining bids, as long as the price is over the firms' threshold price. Alternatively, they could hold off accepting bids from consumers who seem to be in a panic mode and show increasing bids at an increasing rate. However, such a strategy might not be successful if anticipated by consumers who then try to conceal their true characteristics. In general, firms should not rely solely on models of behavior that assume strict rationality, because such models may not reflect reality and may recommend suboptimal pricing strategies.

Implications for Consumers

The Internet may allow for more informed shopping and more efficient price discovery mechanisms than before. In particular, name-your-own-price auctions promise consumers the option of obtaining a price that is below their reservation price but close to a seller's marginal cost. However, many consumers may not fully exploit these price discovery mechanisms to obtain as low a price as they hoped. This state of affairs may exist because these mechanisms are new, because consumers do not fully understand how they run, or because consumers are not experienced enough to exploit them fully. For example, we find that inexperienced consumers tend to overbid in name-your-own-price auctions, thus offering higher prices to sellers that use such mechanisms. Consumer advocate groups could issue warnings of the irrational bidding patterns that consumers are prone to make in such auctions. They could also develop advisories that educate consumers on how best to use such systems to retain as much consumer surplus as possible given supply constraints and their own urgency to travel.

Implications for Researchers

The assumption of rationality in economic models has been debated for decades. Behavioral economists, such as Simon (1955), Kahneman and Tversky (1979), and Thaler (1985), have not only questioned the validity of this assumption but also proposed alternate theories that do not depend on the assumption of strict rationality adopted in traditional economic models. Our results provide doubts about the assumption of strict rationality even in the context of the Internet, which is supposed to be a boon to consumers. As such, models that incorporate more realistic assumptions of consumer decision making are likely to have enhanced relevance and predictive accuracy.

Furthermore, such enhanced models may enable online auctioneers to improve revenue predictions or to extract consumer surplus more effectively through higher threshold prices, given predictions on the maximum bid values consumers submit. In addition, these models can allow the development of price discovery mechanisms that support consumer decision making and attain higher efficiency.

Although our results are robust across our two empirical studies of consumer bidding behavior, they are limited by geography and context. Replications across other markets and contexts would be useful to explore nonnormative behavior on the Internet further.

In addition to econometric analyses of behavioral data, this phenomenon lends itself to fruitful experimental research, in the laboratory and on the Internet. Laboratory experiments allow for the testing of specific theories as to why consumers behave in irrational ways. The Internet enables field experiments easily. Such field experiments can explore what ecological contexts promote or mitigate consumers' irrational behavior and how organizations can avoid or exploit such behavior.

Finally, our theoretical model does not take into account gaming strategies by firms that discover consumers' bidding patterns or consumers who expect firms to do so and thus hide their patterns. Such models make for interesting game theoretic solutions and might be worth pursuing.

Appendix A
Consumers' Optimal Bid Prices

The consumer optimizes the expected consumer surplus of the bid over the bid amount, solving Equation A1. A jth consumer's belief (i.e., expectation) about the seller's threshold price p is assumed to follow a uniform distribution on the interval $[\underline{p}_j, \overline{p}_j]$ with $\overline{p}_j \geq r_j$, where r_j is the consumer's reservation price (Ding et al. 2005; Hann and Terwiesch 2003; Spann, Skiera, and Schäfers 2004; Stigler 1961).

$$\text{(A1)} \quad \max_{b_{j,1},\,\ldots\,,b_{j,n_j}} ECS_{j,1} = (r_j - b_{j,1}) \times \text{Prob}(b_{j,1} \geq p) + ECS_{j,2} \times \text{Prob}(b_{j,1} < p) - c_{j,1}$$

$$= (r_j - b_{j,1}) \times \frac{b_{j,1} - \underline{p}_j}{\overline{p}_j - \underline{p}_j} + ECS_{j,2} \times \frac{\overline{p}_j - b_{j,1}}{\overline{p}_j - \underline{p}_j} - c_{j,1}$$

$$\text{subject to } ECS_{j,i} \geq 0,\ b_{j,i} \leq r_j \ \ \forall i \leq n_j.$$

The jth consumer's expected consumer surplus $ECS_{j,1}$ of the first bid $b_{j,1}$ has two components in this model (Equation A1). The first component represents the expected consumer surplus in case of a successful bid, which is weighted with the probability that the first bid is successful. Thus, the expected consumer surplus accounts for the bidding costs $c_{j,i}$, which accrue by submitting the ith bid. The second component illustrates the expected consumer surplus $ECS_{j,2}$ of a second bid, which is weighted with the probability that the first bid is unsuccessful. As such, $ECS_{j,2}$ consists of the expected consumer surplus of a second bid and further bids beyond the second, if the previous bids are not successful and if it is still beneficial for the bidder to make these additional bids. Thus, the consumer surplus of further bids beyond the ith bid is recursively included in the formula for the consumer surplus of the ith bid.

The consumer simultaneously determines the optimal number of bids and the optimal bid prices by solving this

TABLE A1
Bid Values of Optimal Bidding Strategies for One to Six Bids

	One Bid	Two Bids
First bid	$b_{j,1}^{*}=\frac{1}{2}\underline{p}_j+\frac{1}{2}r_j$	$b_{j,1}^{*}=\frac{2}{3}\underline{p}_j+\frac{1}{3}r_j+\frac{2}{3}c_{j,2}$
Second bid		$b_{j,2}^{*}=\frac{1}{3}\underline{p}_j+\frac{2}{3}r_j+\frac{1}{3}c_{j,2}$
	Three Bids	**Four Bids**
First bid	$b_{j,1}^{*}=\frac{3}{4}\underline{p}_j+\frac{1}{4}r_j+\frac{3}{4}c_{j,2}+\frac{2}{4}c_{j,3}$	$b_{j,1}^{*}=\frac{4}{5}\underline{p}_j+\frac{1}{5}r_j+\frac{4}{5}c_{j,2}+\frac{3}{5}c_{j,3}+\frac{2}{5}c_{j,4}$
Second bid	$b_{j,2}^{*}=\frac{2}{4}\underline{p}_j+\frac{2}{4}r_j+\frac{2}{4}c_{j,2}+\frac{4}{4}c_{j,3}$	$b_{j,2}^{*}=\frac{3}{5}\underline{p}_j+\frac{2}{5}r_j+\frac{3}{5}c_{j,2}+\frac{6}{5}c_{j,3}+\frac{4}{5}c_{j,4}$
Third bid	$b_{j,3}^{*}=\frac{1}{4}\underline{p}_j+\frac{3}{4}r_j+\frac{1}{4}c_{j,2}+\frac{2}{4}c_{j,3}$	$b_{j,3}^{*}=\frac{2}{5}\underline{p}_j+\frac{3}{5}r_j+\frac{2}{5}c_{j,2}+\frac{4}{5}c_{j,3}+\frac{6}{5}c_{j,4}$
Fourth bid		$b_{j,4}^{*}=\frac{1}{5}\underline{p}_j+\frac{4}{5}r_j+\frac{1}{5}c_{j,2}+\frac{2}{5}c_{j,3}+\frac{3}{5}c_{j,4}$
	Five Bids	**Six Bids**
First bid	$b_{j,1}^{*}=\frac{5}{6}\underline{p}_j+\frac{1}{6}r_j$ $+\frac{5}{6}c_{j,2}+\frac{4}{6}c_{j,3}+\frac{3}{6}c_{j,4}+\frac{2}{6}c_{j,5}$	$b_{j,1}^{*}=\frac{6}{7}\underline{p}_j+\frac{1}{7}r_j+\frac{6}{7}c_{j,2}+\frac{5}{7}c_{j,3}$ $+\frac{4}{7}c_{j,4}+\frac{3}{7}c_{j,5}+\frac{2}{7}c_{j,6}$
Second bid	$b_{j,2}^{*}=\frac{4}{6}\underline{p}_j+\frac{2}{6}r_j$ $+\frac{4}{6}c_{j,2}+\frac{8}{6}c_{j,3}+\frac{6}{6}c_{j,4}+\frac{4}{6}c_{j,5}$	$b_{j,2}^{*}=\frac{5}{7}\underline{p}_j+\frac{2}{7}r_j+\frac{5}{7}c_{j,2}+\frac{10}{7}c_{j,3}$ $+\frac{8}{7}c_{j,4}+\frac{6}{7}c_{j,5}+\frac{4}{7}c_{j,6}$
Third bid	$b_{j,3}^{*}=\frac{3}{6}\underline{p}_j+\frac{3}{6}r_j$ $+\frac{3}{6}c_{j,2}+\frac{6}{6}c_{j,3}+\frac{9}{6}c_{j,4}+\frac{6}{6}c_{j,5}$	$b_{j,3}^{*}=\frac{4}{7}\underline{p}_j+\frac{3}{7}r_j+\frac{4}{7}c_{j,2}+\frac{8}{7}c_{j,3}$ $+\frac{12}{7}c_{j,4}+\frac{9}{7}c_{j,5}+\frac{6}{7}c_{j,6}$
Fourth bid	$b_{j,4}^{*}=\frac{2}{6}\underline{p}_j+\frac{4}{6}r_j$ $+\frac{2}{6}c_{j,2}+\frac{4}{6}c_{j,3}+\frac{6}{6}c_{j,4}+\frac{8}{6}c_{j,5}$	$b_{j,4}^{*}=\frac{3}{7}\underline{p}_j+\frac{4}{7}r_j+\frac{3}{7}c_{j,2}+\frac{6}{7}c_{j,3}$ $+\frac{9}{7}c_{j,4}+\frac{12}{7}c_{j,5}+\frac{8}{7}c_{j,6}$
Fifth bid	$b_{j,5}^{*}=\frac{1}{6}\underline{p}_j+\frac{5}{6}r_j$ $+\frac{1}{6}c_{j,2}+\frac{2}{6}c_{j,3}+\frac{3}{6}c_{j,4}+\frac{4}{6}c_{j,5}$	$b_{j,5}^{*}=\frac{2}{7}\underline{p}_j+\frac{5}{7}r_j+\frac{2}{7}c_{j,2}+\frac{4}{7}c_{j,3}$ $+\frac{6}{7}c_{j,4}+\frac{8}{7}c_{j,5}+\frac{10}{7}c_{j,6}$
Sixth bid		$b_{j,6}^{*}=\frac{1}{7}\underline{p}_j+\frac{6}{7}r_j+\frac{1}{7}c_{j,2}+\frac{2}{7}c_{j,3}$ $+\frac{3}{7}c_{j,4}+\frac{4}{7}c_{j,5}+\frac{5}{7}c_{j,6}$

optimization problem. The optimal bidding strategy is to submit a further bid, if the previous one is declined, as long as the expected consumer surplus of this bid is not negative. Thus, the optimal number of bids n_j is determined. The optimal bidding strategy can be determined by the algorithm that Spann, Skiera, and Schäfers (2004) propose.

We can state the optimal bid values for different optimal numbers of bids n_j according to the following general formula (for bid values of optimal bidding strategies for one to six bids, see Table A1):

$$\text{(A2)} \quad b^*_{j,i|n_j} = \frac{n_j+1-i}{n_j+1} \times \underline{p}_j + \frac{i}{n_j+1} \times r_j + \sum_{\substack{l=2 \\ \text{for } i \geq 2}}^{i} \frac{(n_j+1-i) \times (l-1)}{n_j+1} \times c_{j,l} + \sum_{\substack{m=i+1 \\ \text{for } i < n_j}}^{n_j} \frac{(n_j+2-m) \times i}{n_j+1} \times c_{j,m}.$$

Because rational consumers determine *ex ante* their optimal bidding behavior, bidding costs influence their *ex ante* determination of bidding behavior and thus are not sunk.

Appendix B
Proof of Norms for Bidding Patterns

P_1: Any two consecutive bids $b^*_{j,i-1|n_j}$ and $b^*_{j,i|n_j}$ have positive increments $\Delta b^*_{j,i|n_j} = b^*_{j,i|n_j} - b^*_{j,i-1|n_j} > 0$.

Proof. Assuming constant bidding costs $c_j = c_{j,i}$ for each ith bid, we can state the general rule for the ith increment, which we derive from Equation A2:

$$\text{(B1)} \quad \Delta b^*_{j,i|n_j} = b^*_{j,i|n_j} - b^*_{j,i-1|n_j} = \frac{1}{n_j+1} \times (r_j - \underline{p}_j) + \frac{c_j}{n_j+1} \times \left[\frac{(n_j-1) \times n_j}{2} - 2 - (n_j+1) \times (i-2)\right]$$
$$= \frac{1}{n_j+1} \times (r_j - \underline{p}_j) + c_j \times \left[\frac{(n_j-1) \times n_j - 4}{2 \times (n_j+1)} - (i-2)\right].$$

Because Equation B1 decreases in the bid number i (for positive costs, which we develop a proof for subsequently), the increment value is lowest for the optimal bid number $i = n_j$. Thus, increments are positive for all $i \leq n_j$ if (inserting $i = n_j$ into Equation B1):

$$\text{(B2)} \quad \Delta b^*_{j,i=n|n_j} = \frac{1}{n_j+1} \times (r_j - \underline{p}_j) + \frac{c_j}{n_j+1} \times \left[\frac{(n_j-1) \times n_j}{2} - 2 - (n_j+1) \times (n_j-2)\right] > 0$$
$$= \frac{1}{n_j+1} \times \left[(r_j - \underline{p}_j) + c_j \times \frac{n_j - n_j^2}{2}\right]$$
$$> 0 \Leftrightarrow r_j - \underline{p}_j > c_j \times \frac{n_j^2 - n_j}{2}.$$

Thus, for bidding costs of zero, increments are positive for $r_j > \underline{p}_j$. The value of Equation B2 could become negative for high values of c_j and n_j. However, surplus-maximizing consumers would never place such a bid with a negative increment relative to the previous bid, because it would lead to a negative expected consumer surplus of this specific bid:

$$\text{(B3)} \quad ECS_{j,i} = (r_j - b_{j,i}) \times \frac{b_{j,i} - b_{j,i-1}}{\overline{p}_j - b_{j,i-1}} - c_j < 0$$
$$\text{for } b_{j,i} - b_{j,i-1} < 0 \text{ and } \overline{p}_j > b_{j,i-1}.$$

The second norm for the rational bidding pattern is given in P_1. If any two consecutive bids have positive increments, the first bid a consumer submits is the lowest, reflecting the first norm.

P_2: The increments between consecutive bids decrease by the amount of the bidding costs. Thus, the normative bidding pattern has decreasing increments for positive bidding costs.

$$\text{(B4)} \quad \Delta b^*_{j,i|n_j} - \Delta b^*_{j,i-1|n_j} = -c_j < 0 \text{ for } c_j > 0.$$

Proof. If we assume constant bidding costs $c_j = c_{j,i}$ for each ith bid,

$$\text{(B5)} \quad \Delta b^*_{j,i|n_j} - \Delta b^*_{j,i-1|n_j} = \left(b^*_{j,i|n_j} - b^*_{j,i-1|n_j}\right) - \left(b^*_{j,i-1|n_j} - b^*_{j,i-2|n_j}\right)$$
$$= \frac{1}{n_j+1} \times (r_j - \underline{p}_j) + c_j \times \left[\frac{(n_j-1) \times n_j - 4}{2 \times (n_j+1)} - (i-2)\right] - \left(\frac{1}{n_j+1} \times (r_j - \underline{p}_j) + c_j \times \left\{\frac{(n_j-1) \times n_j - 4}{2 \times (n_j+1)} - [(i-1)-2]\right\}\right)$$
$$= c_j[-(i-2) + (i-3)]$$
$$= c_j(-i+2+i-3) = c_j(-1) = -c_j.$$

or

$$\text{(B6)} \quad \frac{\partial \Delta b^*_{j,i|n_j}}{\partial i} = -c_j.$$

Thus, for positive and constant bidding costs, increments are decreasing on the basis of P_2, which is the third norm for the rational bidding pattern. For bidding costs of zero, increments are constant (and positive).

Appendix C
Proof for Criteria for Classification of Four Complex Bidding Patterns

Pattern 1

Pattern 1 reflects increasing bids at a decreasing rate; the last bid is still the highest in the sequence (i.e., only the upward portion of an inverted U shape). A sequence follows Pattern 1 if the parameter of the linear term is positive ($\alpha_{2k} > 0$), the parameter of the quadratic term is negative ($\alpha_{1k} < 0$), and the value of the last bid of the sequence is the highest ($B_{k,Imax} > B_{k,Imax-1}$). Inserting Equation 1 for bid values, this condition can be transformed as follows:

$$\text{(C1)}\quad \alpha_{1k} \times (I_{k,max})^2 + \alpha_{2k} \times I_{k,max} + \alpha_{3k} > \alpha_{1k} \times (I_{k,max} - 1)^2 + \alpha_{2k} \times (I_{k,max} - 1) + \alpha_{3k}$$

$$\Leftrightarrow \alpha_{1k} \times (I_{k,max})^2 + \alpha_{2k} \times I_{k,max} > \alpha_{1k} \times [(I_{k,max})^2 - 2 \times I_{k,max} + 1] + \alpha_{2k} \times (I_{k,max} - 1)$$

$$\Leftrightarrow 0 > \alpha_{1k} \times (-2 \times I_{k,max} + 1) - \alpha_{2k}$$

$$\Leftrightarrow 0 > \alpha_{1k} > \frac{-\alpha_{2k}}{2 \times I_{k,max} - 1}.$$

Pattern 4

Pattern 4 reflects the full inverted U shape. A sequence follows Pattern 4 if the parameter of the quadratic term is negative ($\alpha_{1k} < 0$) and the value of the last bid is less than or equal to the value of the previous one ($B_{k,Imax} \leq B_{k,Imax-1}$); that is, the right, decreasing part of the inverted U shape is included. The parameter of the linear term (α_{2k}) can be positive, zero, or negative. Inserting Equation 1 for bid values, this condition can be transformed analogously to Pattern 1:

$$\text{(C2)}\qquad 0 > \alpha_{1k} \leq \frac{-\alpha_{2k}}{2 \times I_{k,max} - 1}.$$

Pattern 3

Pattern 3 reflects an increasing curve at an increasing rate (i.e., exponential increase or only the increasing part of a U-shaped curve). A sequence follows Pattern 3 if the quadratic term has a parameter of positive value ($\alpha_{1k} > 0$) and the value of the second bid of the sequence is greater than the value of the first one ($B_{k,2} > B_{k,1}$). The parameter of the linear term (α_{2k}) can be positive, zero, or negative. Inserting Equation 1 for bid values, this condition can be transformed as follows:

$$\text{(C3)}\quad \alpha_{1k} \times 2^2 + \alpha_{2k} \times 2 + \alpha_{3k} > \alpha_{1k} \times 1^2 + \alpha_{2k} \times 1 + \alpha_{3k}$$

$$\Leftrightarrow \alpha_{1k} \times 4 + \alpha_{2k} \times 2 > \alpha_{1k} \times 1 + \alpha_{2k} \times 1$$

$$\Leftrightarrow \alpha_{1k} \times 3 + \alpha_{2k} \times 1 > 0$$

$$\Leftrightarrow 0 < \alpha_{1k} > \frac{-\alpha_{2k}}{3}.$$

Pattern 5

Pattern 5 reflects a U-shaped curve. A sequence follows Pattern 5 if the parameter of the linear term is negative ($\alpha_{2k} < 0$), the parameter of the quadratic term is positive ($\alpha_{1k} > 0$), and the value of the second bid of the sequence is less than or equal to the value of the first one ($B_{k,2} \leq B_{k,1}$), that is, the left, decreasing part of a U-shaped curve. Inserting Equation 1 for bid values, analogously to Pattern 3, the conditions for Pattern 5 reduce to the following:

$$\text{(C4)}\qquad 0 < \alpha_{1k} \leq \frac{-\alpha_{2k}}{3}.$$

Appendix D
Bivariate Tests of Differences of Means Between Groups

Table D1 displays the results for bivariate t-tests (accounting for different distributions within groups) of differences of means between groups for α_{1k} and α_{2k}. Thus, each cell in

TABLE D1
Bivariate Tests of Differences of Means Between Groups

	Parameter α_{1k}[a]				Parameter α_{2k}[a]			
Pattern	1	2	3	4	1	2	3	4
A. Name-Your-Own-Price Retailer								
2	–9.44 (.00)				6.10 (.00)			
3	–15.27 (.00)	–13.91 (.00)			14.11 (.00)	13.79 (.00)		
4	3.24 (.00)	11.10 (.00)	15.83 (.00)		–.71 (.47)	–6.49 (.00)	–13.78 (.00)	
5	–10.48 (.00)	–7.46 (.00)	–3.91 (.00)	–11.87 (.00)	13.49 (.00)	11.29 (.00)	7.12 (.00)	13.65 (.00)
B. Low-Cost Airline								
2	–17.81 (.00)				9.96 (.00)			
3	–12.12 (.00)	–7.44 (.00)			15.24 (.00)	8.95 (.00)		
4	4.29 (.00)	6.40 (.00)	8.71 (.00)		–3.81 (.00)	–5.97 (.00)	–8.59 (.00)	
5	–5.49 (.00)	–4.20 (.00)	–2.28 (.03)	–6.95 (.00)	–7.53 (.00)	6.14 (.00)	4.20 (.00)	8.46 (.00)

[a]Independent sample bivariate t-test (accounting for different distributions within groups) of differences of means between groups; *p* value is in parentheses.

Table D1 gives the t-value (and *p* value) for a bivariate test of differences of means between groups for parameter α_{1k} (left matrix) and parameter α_{2k} (right matrix) for both studies (Table D1, Panel A; Table D1, Panel B). Table D1 shows that all bivariate group means are significantly different from one another except for the means of parameter α_{2k} between Pattern 1 and Pattern 4 in Study 1 (name-your-own-price retailer).

REFERENCES

Arthur, Brian W. (1991), "Designing Economic Agents That Act Like Human Agents: A Behavioral Approach to Bounded Rationality," *American Economic Review*, 81 (2), 353–59.

Bakos, J. Yannis (1997), "Reducing Buyer Search Costs: Implications for Electronic Marketplaces," *Management Science*, 43 (12), 1676–92.

Brynjolfsson, Erik and Michael D. Smith (2001), "The Great Equalizer? Consumer Choice Behavior at Internet Shopbots," working paper, Massachusetts Institute of Technology.

Chandy, Rajesh, Gerard J. Tellis, Debbie MacInnis, and Pattana Thaivanich (2001), "What to Say When: Advertising Appeals in Evolving Markets," *Journal of Marketing Research*, 38 (November), 399–414.

Chernev, Alexander (2003), "Reverse Pricing and Online Price Elicitation Strategies in Consumer Choice," *Journal of Consumer Psychology*, 13 (1–2), 51–62.

Conlisk, John (1996), "Why Bounded Rationality?" *Journal of Economic Literature*, 34 (2), 669–700.

Dickson, Peter R. and Alan G. Sawyer (1990), "The Price Knowledge and Search of Supermarket Shoppers," *Journal of Marketing*, 54 (July), 42–53.

Ding, Min, Jehoshua Eliashberg, Joel Huber, and Ritesh Saini (2005), "Emotional Bidders: An Analytical and Experimental Examination of Consumers' Behavior in Priceline-Like Reverse Auctions," *Management Science*, 51 (3), 352–64.

Fay, Scott (2004), "Partial Repeat Bidding in the Name-Your-Own-Price Channel," *Marketing Science*, 23 (3), 407–418.

Geoffrion, Arthur M. and Ramayya Krishnan (2003), "E-Business and Management Science: Mutual Impacts (Part 1 of 2)," *Management Science*, 49 (10), 1275–86.

Hann, Il-Horn and Christian Terwiesch (2003), "Measuring the Frictional Costs of Online Transactions: The Case of a Name-Your-Own-Price Channel," *Management Science*, 49 (11), 1563–79.

Jacoby, Jacob, Donald E. Speller, and Carol A. Kohn (1974), "Brand Choice Behavior as a Function of Information Overload," *Journal of Marketing Research*, 11 (February), 63–69.

Kahneman, Daniel and Amos Tversky (1979), "Prospect Theory: An Analysis of Decision Under Risk," *Econometrica*, 47 (2), 263–91.

Lurie, Nicholas H. (2004), "Decision Making in Information-Rich Environments: The Role of Information Structure," *Journal of Consumer Research*, 30 (4), 473–86.

Monroe, Kent B. and Angela Y. Lee (1999), "Remembering Versus Knowing: Issues in Buyers' Processing of Price Information," *Journal of the Academy of Marketing Science*, 27 (2), 207–225.

Prabhu, Jaideep and Gerard J. Tellis (2000), "Do Consumers Ever Learn? Findings from an Experimental Market," *Journal of Behavioral Decision Making*, 13 (1), 19–34.

Rajendran, K.N. and Gerard J. Tellis (1994), "Is Reference Price Based on Context or Experience? An Analysis of Consumers' Brand Choices," *Journal of Marketing*, 58 (April), 10–22.

Remus, William, Marcus O'Connor, and Kenneth Griggs (1996), "Does Feedback Improve the Accuracy of Recurrent Judgmental Forecasts?" *Organizational Behavior and Human Decision Processes*, 66 (1), 22–30.

Shugan, Stephen (1980), "The Cost of Thinking," *Journal of Consumer Research*, 7 (2), 99–111.

Simon, Herbert A. (1955), "A Behavioral Model of Rational Choice," *The Quarterly Journal of Economics*, 69 (1), 99–118.

Spann, Martin, Bernd Skiera, and Björn Schäfers (2004), "Measuring Individual Frictional Costs and Willingness-to-Pay via Name-Your-Own-Price Mechanisms," *Journal of Interactive Marketing*, 18 (4), 22–36.

Stigler, George J. (1961), "The Economics of Information," *Journal of the Political Economy*, 69 (3), 213–25.

Tellis, Gerard J (1986), "Beyond the Many Faces of Price: An Integration of Pricing Strategies," *Journal of Marketing*, 50 (October), 146–60.

——— and Birger Wernerfelt (1987), "Competitive Price and Quality Under Asymmetric Information," *Marketing Science*, 6 (3), 240–53.

Thaler, Richard H. (1985), "Mental Accounting and Consumer Choice," *Marketing Science*, 4 (3), 199–214.

Vanhuele, Marc and Xavier Drèze (2002), "Measuring the Price Knowledge Shoppers Bring to the Store," *Journal of Marketing*, 66 (October), 72–85.