

# Emotional Bidders—An Analytical and Experimental Examination of Consumers' Behavior in a Priceline-Like Reverse Auction

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E-commerce has proved to be fertile ground for new business models, which may be patented (for up to 20 years) and have potentially far-reaching impact on the e-commerce landscape. One such electronic market is the reverse-auction model popularized by Priceline.com. There is still uncertainty surrounding the survival of such new electronic markets currently available on the Internet. Understanding user behavior is necessary for better assessment of these sites' survival. This paper adds to economic analysis a formal representation of the emotions evoked by the auction process, specifically, the excitement of winning if a bid is accepted, and the frustration of losing if it is not. We generate and empirically test a number of insights related to (1) the impact of expected excitement at winning, and frustration at losing, on bids across consumers and biddings scenarios; and (2) the dynamic nature of the bidding behavior—that is, how winning and losing in previous bids influence their future bidding behavior.

*Key words:* online auction design; electronic markets; pricing; behavioral decision models; experimental economics

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## 1. Introduction

In the late 1990s there was a great deal of excitement over Priceline.com's business model (for more details, see Rust and Eisenmann 2000). Unlike most of the hyped e-businesses at the time, however, Priceline survived the Internet downturn and has actually prospered. Rather than requiring consumers to find the supplier with the lowest offering, Priceline takes a bid from a consumer and then searches to find suppliers who match that bid. It is termed a reverse auction because, instead of consumers bidding for a supplier's business, a consumer sets a price and the suppliers act as if they are bidding for the consumer's business, rather than the consumer bidding against other consumers for a supplier's offering. For example, in the purchase of an airline ticket, the consumer submits a bid to Priceline. Upon receiving the bid, Priceline searches its price database, which contains the lowest acceptable prices by various airlines partners at that time. If the bid price is higher than the lowest fare available to Priceline, it will accept the bid

and retain the spread (bid – lowest fare) as its profit. Otherwise, Priceline will reject the bid. Priceline gives consumers a good idea about what prices are likely to be accepted, showing typical "retail" prices and indicating that savings such as 40% can be expected. However, the important conceptual point is that individual consumers do not know the lowest ("unpublished") fares that Priceline commands, and the airlines do not know the actual bid (also unpublished) submitted by an individual consumer. As a result, Priceline functions as a market maker instead of a pure facilitator of reverse auction.

In this paper, we focus on bidders' behavior in a site similar to the one Priceline offers. It is similar to a reverse auction in that multiple suppliers compete for the buyer's business. However, in our case, and in the Priceline business model, the buyer's bidding behavior does not have an impact on other bidders and their corresponding outcomes, taking away the benefit of acting strategically. Instead, the setting we study can be considered as a "game against nature,"

where the buyer sets a bid towards a random distribution<sup>1</sup> that generates the best supplier's asking price. Because such a setting abstracts from strategic behavior on either party's part, it is the ideal setting in which to examine the role emotions play in determining the actual bid submitted.

We examine both analytical and empirical behavior in a context that mimics Priceline's process generally, but differs by making precise two processes that are only approximated by Priceline. First, we assume that the bidder can correctly assess the likelihood of winning the bid. This knowledge of win probabilities is facilitated by Priceline as it gives normal prices, and the 40% expected discount, whereas we will provide an exact distribution. Second, we assume that the gain from a transaction is also precisely known in the form of the market price minus the bid. In Priceline, the benefit is the difference between the bid and the available market price (also called the transaction value Monroe 2002), but this available market price may not be known with certainty. In our behavioral simulation, where the expected profit can be determined, we can incorporate the impact of bidding-related emotions on the bids people make. Our analytical model shows that the excitement at winning or the frustration at losing results in bids that deviate systematically from the simple (classic) profit-maximizing strategy. We then test the model's prediction in various experimental settings.

The model developed here builds on two major literature streams. The first literature stream is economic theory. Utility (or profit, in the case of risk neutrality) maximization serves as the foundation of this paper, where the maximization is done by the consumer, based on his/her utility function (von Neumann and Morgenstern 1944). We propose that expected excitement and frustration are appropriate arguments that need to be incorporated into the bidder's multi-attribute utility function. The second literature stream that inspires our work is the research that investigates how psychological constructs influence behavior in economic settings. In particular, we review research addressing how emotions influence decision making, research that informs the appropriate functional form under which emotions enter the utility function. This research on how emotions influence decision making in general, and under uncertainty in particular, has progressed in two largely disparate directions (Loewenstein 2000). One direction deals with how

the *current emotional* state influences decision making. Numerous psychological experiments demonstrate that behavior is affected by current emotional states (Elster 1998, Lerner and Keltner 2001, Slovic et al. 2002). In terms of economic decisions, positive affect has been shown to influence risky decisions. Generally, people in positive affective states were found to assume less risk in realistic situations (Isen 1993). The other stream of research, which has direct bearing on our current study, focuses on how *anticipated emotions* influence decisions. These are emotions such as regret and disappointment, which are expected to be experienced in the future. For example, Mellers et al. (1999, p. 332) argue that "excitement about winning a lottery, pleasure about getting a promotion, guilt about telling a lie, and frustration at not achieving a goal" may all be emotions that are anticipated in advance, and are incorporated into the choice process. These anticipated emotions considered by descriptive regret theory (Loomes et al. 1989), which have also been acknowledged normatively (Bell 1985), resulted in adjustments to expected utility that deviate from standard expected utility theory (Connolly and Zeelenberg 2002, Simonson 1992, Mellers et al. 1999). Anticipated regret is similar to our construct of anticipated frustration. The analogous positive construct, anticipated excitement (elation), has seen less attention (e.g., Inman et al. 1997), but is one that we expect will be just as important.

Our general model is that the consumer examines the utility of a bid, including its possible frustration and excitement. We generate an index of the propensity to bid for each consumer that is a positive function of anticipated excitement in winning and a negative function of frustration from losing. If the value of that bid is within the feasible range, then the individual is predicted to place a bid in our Priceline-like site. Integrating and building upon the research streams noted above, we generate a number of theoretical propositions relating this index to (1) the potential for submitting a nonextreme bid, (2) the specific magnitude of the bid submitted, (3) the relationship between the bids submitted and the bidder's propensity to bid under both favorable and unfavorable bidding environments, and (4) the extent to which consumers overbid/underbid relative to a benchmark classic economic model. We observe empirical support for most, but not all, of the theoretical propositions derived from the analytical model.

This research contributes to both the extant academic literature as well as to the business practice of the Internet. To our knowledge, including the excitement of winning and frustration of losing in bidding situations has not been thoroughly explored either from analytical or empirical perspectives. Cox et al. (1982), for example, suggest that there is a utility of

<sup>1</sup> This is a reasonable assumption, as such electronic reverse-auction sites allow suppliers to compete simultaneously and independently in thousands or more auctions, possibly against a set of different suppliers in each of these auctions. As a result, a supplier simply picks its lowest acceptable price at any given time, based on a group of internal parameters. Such a price, in general, is a random variable.

“suspense” that causes people to wait longer and thus bid lower in Dutch auctions. This theoretical result has not been experimentally confirmed, however (Kagel 1995). To our knowledge, the only paper that explicitly uses emotional constructs in any auction setting is Bosman and Riedl (2003). This paper studies the effect of current emotional states on future bidding behavior. The authors induce artificial economic shocks that are designed to alter the moods of the bidders in a first-price sealed-bid auction setting. They find that subjects in bad moods place significantly higher bids than subjects in good moods. However, the underlying explanation for this behavior may have less to do with *emotions* and more to do with *wealth effects*. Because a negative economic shock reduces the bidder's wealth, this could alter bidding strategy in a way similar to that being reported in literature (Thaler and Johnson 1990, Neilson 1998). In this research, we test whether such findings are also applicable in a context in which wealth effects are minimal. We limit wealth effects by telling subjects that only one of their bids could be played for real money. Thus, wealth effects from previous wins/losses should not, strictly speaking, influence a bidder's decisions in our experiments. By controlling for any potential wealth effects, our research therefore studies the isolated role that evoked emotions play in influencing the bids submitted in future rounds.

The paper is organized as follows. Section 2 develops and describes the general model formulation, while §3 discusses theoretical insights and develops propositions under the bidder's uniform distribution assumption with respect to the product's cost—an assumption commonly employed in auctions and bilateral bargaining situations. Section 4 then presents an empirical test of the model's predictions derived in §3, as well as the corresponding findings. Section 5 closes with a summary and suggested avenues for future research.

## 2. Model Development and General Insights

We model the market for a given product (e.g., an airline ticket) over time at the individual consumer (bidder) level, where each consumer is interested in exactly one unit of the product during each of the successive time periods. In addition to studying the dynamic behavior of a particular bidder, we are also interested in capturing bidders' heterogeneity by allowing them to be different from one another in terms of their expressed excitement at winning or frustration at losing. Further, a bidder has the option of purchasing the product through regular channels at a known market price (best price from nonauction channels) or he/she could come to a reverse-auction

site to bid for the same product. Each consumer has a reservation price (maximum prices he is willing to pay for the product) that may vary across bidders and over time. Finally, while unaware of the actual product cost, the consumer is assumed to have a probability distribution over the cost to the suppliers participating in the reverse-auction site.

In such a setting, the bidder faces the following trade-off: Submitting a higher bid brings a greater probability of winning, but a lower profit if accepted; alternatively, the bidder may submit a lower bid with greater profit potential, but lower probability of gaining that profit. As discussed earlier, the implications of such trade-off-based decisions have been known to cause emotional reactions—at the time when the decision is being made, as well as when the consequences of one's decision are revealed (Elster 1998, Loewenstein 2000). In our reverse-auction setting, a win is likely to evoke a positive emotional state, and a loss, a negative one. We build on previous literature about emotions in decision making under uncertainty, which have primarily focused on “elation” and “disappointment” as anticipated emotions when individuals choose amidst monetary lotteries (Mellers et al. 1999, Loomes and Sugden 1986, Inman et al. 1997). Richins (1997) undertook six studies and thoroughly assessed the domain of consumption-related emotions. The author identified 16 relevant clusters of emotion. A careful examination shows that two of these, “excitement” and “frustration,” are most likely to be evoked during a reverse auction-type transaction. Excitement, closely allied with the emotion of elation, will be induced when a bid is accepted, while frustration, closely allied with the emotion of disappointment, arises when a bid is rejected.

The concept of disappointment has received quite a bit of attention by mathematical modelers. Gul (1991), for example, identifies three streams in the literature that he labels as (1) emphasizing the need for accommodating descriptive issues within the expected utility framework (e.g., Bell 1985), (2) rejecting the normative appeal of the independence axiom (e.g., Machina 1982), and (3) modifying the independence axiom (e.g., Deckel 1986). Our conceptualization in this paper is primarily in line with (1). Similarly to Inman et al. (1997), we also rely on a multiattribute utility framework (Keeney and Raiffa 1976). Specifically, we allow the consequences of win/lose to be comprised of two additive components: monetary and emotional. The overall utility of the bid is then idiosyncratic to the bidder and thereby provides an opportunity to identify differences in bidding behavior across individuals.

We begin with the following constructs:

$C_i$ : The lower bound of the site's cost, as expected by a bidder.

$C_u$ : The upper bound of the site's cost, as expected by a bidder.

$C_t$ : Cutoff price (minimum acceptable bid) in period  $t$  (bid number).

$P_{o,t}$ : The price offered by a bidder in period  $t$ .

$P_{m,t}$ : The market price for the product, or perceived price for the product. This is the lowest price a consumer could pay to buy the product from nonauction channels in period  $t$ . At the same time, it is the highest price the consumer is willing to bid on the reverse-auction site.

$t$ : The number of periods or bid number (equivalent) after a consumer starts to use the reverse-auction site ( $t \geq 1$ ).

$P_{r,t}$ : The nonauction reservation price of a bidder in period  $t$ .

$U_t(P_{o,t})$ : The utility a bidder derived from participating in the reverse auction at period  $t$ .

$u_{1,t}(P_{o,t})$ : The utility derived from the money saved from a winning bid in period  $t$ .

$u_{2,t}(P_{o,t})$ : The total emotional utility in period  $t$ .

$u_{2,t,\text{accept}}(P_{o,t})$ : The excitement induced by acceptance of a bid in period  $t$ .

$u_{2,t,\text{reject}}(P_{o,t})$ : The frustration induced by rejection (losing) of a bid in period  $t$ .

$\alpha_t$ : Excitement coefficient at period  $t$ , represents how sensitive a bidder is to winning. It is affected by prior bidding outcomes.

$\beta_t$ : Frustration coefficient at period  $t$ , represents how sensitive a bidder is to losing. It is affected by prior bidding outcomes.

$\theta$ : Monetary coefficient represents how much bidder values money.

$\varphi(C_t)$ : The probability density function of the true cost of the product to the site.

The decision rule for the reverse-auction site (market maker) is straightforward. In the absence of subsidy, the site will only accept a bid if it is the same or above its cost (lowest price offered to the site by suppliers of goods) and reject it otherwise. That is:

$$\text{If } P_{o,t} - C_t \begin{cases} \geq 0, & \text{then accept bid} \\ < 0, & \text{then reject bid.} \end{cases} \quad (1)$$

The individual bidder utility function is given by

$$U_t(P_{o,t}) = u_{1,t}(P_{o,t}) + u_{2,t}(P_{o,t}), \quad (2)$$

where the monetary (economic) utility  $u_{1,t}(P_{o,t})$  is

$$u_{1,t}(P_{o,t}) = \begin{cases} \theta(P_{m,t} - P_{o,t}) & \text{if bid is accepted} \\ 0 & \text{if bid is rejected,} \end{cases} \quad (3)$$

and the emotional utility  $u_{2,t}(P_{o,t})$  is

$$u_{2,t}(P_{o,t}) = \begin{cases} u_{2,t,\text{accept}}(P_{o,t}) & \text{if bid is accepted} \\ u_{2,t,\text{reject}}(P_{o,t}) & \text{if bid is rejected.} \end{cases} \quad (4)$$

The expected utility associated with bidding  $P_{o,t}$  can be represented as

$$\begin{aligned} E[U_t(P_{o,t})] &= E[u_{1,t}(P_{o,t})] + E[u_{2,t}(P_{o,t})] \\ &= \int_{C_t}^{P_{o,t}} u_{1,t}(P_{o,t}) \varphi(C_t) dC_t \\ &\quad + \int_{C_t}^{P_{o,t}} u_{2,t,\text{accept}}(P_{o,t}) \varphi(C_t) dC_t \\ &\quad - \int_{P_{o,t}}^{C_u} u_{2,t,\text{reject}}(P_{o,t}) \varphi(C_t) dC_t. \end{aligned} \quad (5)$$

We further develop the functional forms of the emotional constructs employed here in a manner akin to approaches employed in consumer behavior. Weber's Law of Psychophysics, for instance, relates proportional changes in a stimulus to a psychological response (see Winer 1988),

$$\frac{\Delta S}{S} = K, \quad (6)$$

where  $S$  is the stimulus and  $K$  is the response. This suggests that, in general, the magnitude of emotional constructs such as those of interest here (excitement or frustration) should be captured by adjusting the incremental gain or loss relative to a reference point. The literature on emotions also supports this notion. Goeree et al. (2002) find that the extent of overbidding in auctions is roughly proportional to the value of the auction. It has been widely accepted that "the intensity of emotion depends on the relationship between an event and some frame of reference against which the event is evaluated" (Frijda 1988, p. 353). In our individual bidding behavior model we chose the bidder's nonauction reservation price to define this frame of reference.

As far as the incremental benefits/costs of winning/losing bids are concerned, an observation with regard to reverse auctions inspired our operationalization of the utility components. The actual amount of a bid affects the magnitude of the emotional utility induced. A consumer tends to be more excited if she/he wins with a relatively low bid. For example, a consumer will be more excited about a \$100 winning bid than a \$300 winning bid for a round-trip airline ticket between Boston and Philadelphia, assuming the ticket sells for \$400 through a regular travel agency. By contrast, following a loss a consumer tends to be more frustrated if he/she loses with a relatively high bid, to a large extent because those are bids associated with a higher probability of winning.

Consistent with this reasoning we propose

$$u_{2,t,\text{accept}}(P_{o,t}) = \alpha_t \frac{P_{m,t} - P_{o,t}}{P_{r,t}}, \quad (7)$$

and

$$u_{2,t,\text{reject}}(P_{o,t}) = \beta_t \frac{P_{o,t}}{P_{r,t}}. \quad (8)$$

In terms of time line or bid number, we model a situation where  $t = 0$  represents the calendar time before the first bid is submitted and the bidder is characterized by parameters  $\alpha_0$  and  $\beta_0$ . That is, these parameter values are used by the bidder in his/her evaluation of the expected utility associated with the first bid. The expected utility associated with the following bids is based on updated parameter values:  $\alpha_t$  and  $\beta_t$ .

A potential bidder is also subject to two consistency checks before making a bid in the reverse-auction site. First, the price to be submitted by him/her must be strictly smaller than the best alternative market price, but strictly higher than the minimum cost to the site. Second, she/he must have a positive expected utility for this submitted bid. Thus, the bidder's problem at any given time is to find a bidding price that will maximize the sum of monetary and emotional utility, subject to the two constraints stated above.

Mathematically, the bidder (consumer) seeks to

$$\max_{P_{o,t}} E[U_t(P_{o,t})], \quad (9)$$

subject to (for  $t \geq 1$ )

$$C_l < P_{o,t} < P_{m,t} \leq C_u \quad (10)$$

$$E[U_t(P_{o,t})] \geq 0. \quad (11)$$

It is reasonable to assume, and we allow for this possibility, that the excitement and frustration coefficients ( $\alpha_t, \beta_t$ ) will vary over bids (time periods). That is, we view them as nonstationary coefficients. This variability is consistent with studies of bidders' behavior. Not unlike sensitization (increased pleasure) observed from, for example, successive use of marijuana or high-quality wine (Groves and Thompson 1973), people engaged in reverse auction exhibit similar behavioral patterns. The next bidding behavior is essentially driven through the dynamic changes in  $\alpha_t$  and  $\beta_t$ , based on past bidding outcomes. While it is reasonable to assume that a bidder, initially at least, will get more excited after each win, and more frustrated after each loss, there may exist either monotonic counterforces due to fading effect (e.g., the excitement of a win becomes smaller as time passes) or an inverted-U type of adaptation effect (e.g., bidder gets more excited after the first few wins, but less excited after winning too many bids). In both cases, we expect to see  $\alpha_t$  and  $\beta_t$  decrease at some point in time. While we do not have prior hypotheses with respect to the directionality of the changes, in §4 we provide some preliminary empirical evidence as to how  $\alpha_t$  and  $\beta_t$  change from one round to the next as a function of the bidding outcome.

Having set up the model in generality, its key analytical insights are summarized below.

Define the individual's propensity to bid (bidder's characteristic) as

$$X_t = \frac{\alpha_t + \theta P_{r,t}}{\beta_t}, \quad \text{where } \beta_t > 0. \quad (12)$$

Notice that this propensity to bid appropriately increases with excitement at winning and the value of that winning, while it decreases with frustration at losing.

**PROPOSITION 1. THRESHOLD REQUIREMENT FOR BIDDING: A NECESSARY CONDITION.** *For certain types of probability distribution functions that the bidder has with respect to the product's cost, a necessary condition for the bidder to submit a bid is that his/her propensity to bid exceeds a threshold level.*

**PROOF.** See Appendix 1 (online at <http://mansci.pubs.informs.org/ecompanion.html>).

Mathematically, Proposition 1 establishes a condition for the concavity of the objective function described in Equation (9). In general, it is accomplished under two structural conditions:

- (1)  $\underline{A} < \varphi'(P_{o,t}^*) < \bar{A}$  ( $\underline{A} < 0$ ,  $\bar{A} > 0$ ), and
- (2)  $X_t > \underline{B}$  ( $\underline{B} > 0$ ).

(See Appendix 1 for  $\underline{A}$ ,  $\bar{A}$ , and  $\underline{B}$ .)

In other words, Proposition 1 requires that the derivative of the probability density function evaluated at the optimal bid be bounded from above and below, whereas the bidder's bidding threshold is bounded from below. This result is important because it limits the feasible probability distribution functions (PDF) that can satisfy Problem (9)–(11) not only to those with finite ranges, but also to PDF that meet another condition, as specified above. These can potentially include the uniform distribution (discussed in more detail in the next section) and some members of the family of beta distributions.

The condition presented in Proposition 1 with respect to bidder's propensity to bid is intuitive and quite insightful. It implies that the site will only induce bidders for whom the transaction benefit along with the excitement of potential bid acceptance, relative to the disappointment from potential bid rejection, must exceed a certain threshold. Note that changes in bidder's propensity to bid may be interpreted in one of two ways. First, the same bidder may have different  $X_t$  values over time, depending on the history of winning and losing bids. We refer to that as within-individual dynamic  $X_t$ . Alternatively,  $X_t$  may be interpreted across individual bidders.

### 3. Detailed Insights Under Uniform Probability Density Function

In this section, we develop theoretical predictions and insights under the uniform probability distribution that the bidder has with respect to the site's cost. The assumption of uniform distribution with respect to

product cost from a buyer's perspective has a long tradition in the bidding literature (Cox et al. 1982, Kagel et al. 1987, Kagel and Levin 2001, Weverbergh 1979, Wilson 1967), as well as in bilateral bargaining problems (Chattergee and Samuelson 1983, Holt and Sherman 1994, Samuelson and Bazerman 1985, Radner and Schotter 1989). Two advantages accrue by invoking such an assumption. First, it enables us to generate additional (and finer) theoretical insights. Second, as noted by Davis and Holt (1993, p. 69) "the uniform distribution is probably the most commonly used distribution in experiments, because it is easy to induce with dice, it is easy to explain to the subjects, and it often facilitates the calculation of the optimal or equilibrium decisions."

When the potential bidder (consumer) expects the cost of the product to the site to be uniformly distributed between  $[C_l, C_u]$ , the probability of winning a bid is

$$\int_{C_l}^{P_{o,t}} \varphi(C_l) dC_l = \frac{P_{o,t} - C_l}{C_u - C_l}. \quad (13)$$

If we substitute Equations (3), (7), (8), and (13) into Equation (5), the bidder's expected utility now can be represented as

$$E[U_t(P_{o,t})] = \theta(P_{m,t} - P_{o,t}) \frac{P_{o,t} - C_l}{C_u - C_l} + \alpha_t \frac{P_{m,t} - P_{o,t}}{P_{r,t}} \cdot \frac{P_{o,t} - C_l}{C_u - C_l} - \beta_t \frac{P_{o,t}}{P_{r,t}} \frac{C_u - P_{o,t}}{C_u - C_l}. \quad (14)$$

**PROPOSITION 2. THRESHOLD LEVEL FOR THE UNIFORM PROBABILITY DISTRIBUTION.** *For the uniform probability distribution function that the bidder has with respect to the product's cost, there always exists a unique threshold level for the individual's propensity to bid above which she/he will submit a price that is strictly lower than the best alternative market price and strictly higher than the minimum cost to the site. More specifically, the unique threshold level is given by*

$$\underline{B} = \left( \frac{\sqrt{P_{m,t}(C_u - C_l)} + \sqrt{C_l(C_u - P_{m,t})}}{P_{m,t} - C_l} \right)^2 > 1. \quad (15)$$

**PROOF.** See Appendix 1.

While the threshold  $\underline{B}$  identified in Proposition 1 represents a necessary condition for participation in the reverse-auction site, the threshold  $\underline{B}$  in Proposition 2 represents the necessary and sufficient condition under which a bidder will participate in the reverse auction with an optimal bid that is between  $C_l$  and  $P_{m,t}$ . Note that the threshold level specified in (15) under the uniform probability distribution is more restrictive than the level specified in Proposition 1. Also note that  $\underline{B}$  increases as  $C_u$  increases,  $C_l$  increases, or  $P_{m,t}$  decreases. This is quite intuitive, as such changes (in  $C_u$ ,  $C_l$ , and  $P_{m,t}$ ) decrease the attractiveness of the reverse-auction site and, as a result, fewer bidders will participate.

**PROPOSITION 3. OPTIMAL BID FOR THE UNIFORM DISTRIBUTION AND ITS PROPERTY.** *For the uniform probability distribution function that the bidder has with respect to the product's cost, the optimal bidding price is*

$$P_{o,t}^* = \frac{C_u - (P_{m,t} + C_l)X_t}{2(1 - X_t)}. \quad (16)$$

*Depending on the bidding scenarios, the submitted bid is monotonic with respect to the individual's propensity to bid ( $X_t$ ), and its behavior can be described as follows.*

The behavior of the optimal bidding strategy as a function of a bidder's propensity to bid ( $\underline{B} < X_t$ )	
Bidding scenario characteristics	
Scenario 1 ( $P_{m,t} < C_u - C_l$ )	Strictly concave and increasing over $X_t$ , and bounded between $(C_u - (P_{m,t} + C_l)\underline{B})/(2(1 - \underline{B}))$ and $(P_{m,t} + C_l)/2$
Scenario 2 ( $P_{m,t} > C_u - C_l$ )	Strictly convex and decreasing over $X_t$ , and bounded between $(P_{m,t} + C_l)/2$ and $(C_u - (P_{m,t} + C_l)\underline{B})/(2(1 - \underline{B}))$
Scenario 3 ( $P_{m,t} = C_u - C_l$ )	Constant over $X_t$ and equals to $(P_{m,t} + C_l)/2$

**PROOF.** See Appendix 1.

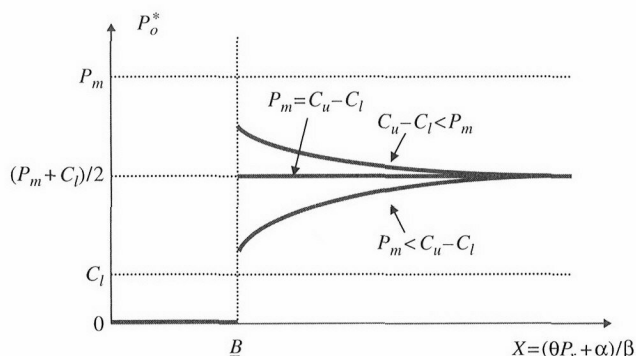
If one takes the within-individual dynamic perspective, then for a given reservation price, which is constant over time ( $P_{r,t} = P_r$ ), a consumer will increase her current period bid if her  $X$  increases from the previous period and decrease her bid if her  $X$  decreases under Scenario 1, decrease her current period bid if her  $X$  increases from the previous period and increase her bid if her  $X$  decreases in Scenario 2, and always bid  $(P_m + C_l)/2$  regardless of the results of prior bid-dings and how her sensitivities about winning/losing change in Scenario 3. In other words, under Bidding Scenario 1, the more the bidder becomes interested in bidding, the more emphasis she places on the winning probability. On the other hand, under Bidding Scenario 2, the more the bidder is interested in bidding, the more emphasis she places on the net gain from the bid.

**COROLLARY 1. IMPACT OF EMOTIONS ON OVERBIDDING AND UNDERBIDDING.** *Compared to the profit-maximizing strategy of bidding at  $(P_{m,t} + C_l)/2$  (where the emotional utility component is not considered), bidders in Scenario 1 tend to underbid, while bidders in Scenario 2 sites tend to overbid. Bidders in Scenario 3 or those with very high value of  $X_t$  (regardless of the bidding scenario) will bid close to  $(P_{m,t} + C_l)/2$ .*

**PROOF.** Follows directly from Proposition 3.

The intuition for Corollary 1 parallels the discussion that follows Proposition 3. In Scenario 1, a bidder is more interested in the amount of gain from winning, but such a preference gradually gives way to



**Figure 1** Optimal Bidding Strategy (Price) as a Function of a Bidder's Propensity to Bid

Note. The thicker line represents the optimal bidding strategies for different bidders under different conditions.

the emphasis on winning probability as she becomes more interested in bidding. On the other hand, a bidder in Scenario 2 is interested in the probability of winning; similarly, such a preference gradually gives way to emphasis on the amount of gain as she becomes more interested in bidding. As a result, she will underbid (relative to the benchmark classic bid) in Scenario 1 and overbid in Scenario 2.

The results in Propositions 2 and 3 and Corollary 1 are represented graphically in Figure 1.

As discussed earlier, two countering effects are at work upon each winning or losing. A win/lose will either sensitize the subject to future winning/losing, or it may make the subject become satiated/inert with future winning/losing. The actual effect of a win/lose, in our judgment, is an empirical issue and will likely be individual specific. We discuss some empirical evidence in the next session.

## 4. Empirical Testing and Analyses

In this section we present and discuss an experiment designed to test the major insights obtained in §3. Eighty-seven undergraduate business students at a major university participated in this experiment. We first describe the experimental procedure, followed by the analyses of the data.

### 4.1. Experimental Procedure

Subjects were recruited from the student-subject pool and were assigned to one of six sessions (each session had an average of 15 subjects). The experiment was conducted using a pencil-and-paper format. To allay beliefs that cutoff prices might be rigged against any individual, the cutoff price ( $C_l$ ) in each round was generated using Excel spreadsheet function and publicly projected onto the screen in the front of the room. The acceptance of the bids in each of these six sessions followed different random draws based on the probabilities assigned to respondents.

The subjects were told that this would be a money-making opportunity based on a hypothetical scenario

where there is a huge demand for a Spring break package (a trip to Florida for two, with all expenses included), and that people are willing to pay \$1,160 for this package. The subjects could choose one of two options to buy the package and profit by selling it at \$1,160. The two options are: (1) purchase the package from a travel agency for \$1,100 and (2) submit a bid to a reverse-auction site for the package. If the bid is rejected, they could still go to the travel agency and buy it for \$1,100. Notice that a person who is profit maximizing will never buy from the travel agency before bidding. Only a person who is deeply frustrated from losing will stop. Each subject participated in 20 rounds, and had the opportunity to purchase one package in each round. In the first 10 rounds, approximately half the respondents experienced a Scenario 1 auction site; in the next 10 rounds, they were assigned to a Scenario 2 auction site; for the remaining respondents, this order reverses. Scenario 3 was not considered in the experiment because it represents an asymptotic case of Scenarios 1 and 2, and it would increase the task required from the subjects.

The parameters of the two scenarios, shown in Table 1a, result in the bid's winning probabilities shown in Table 1b. As illustrated, for the same bid submitted, the probability of winning is higher under Scenario 1, relative to the probability of winning under Scenario 2.

In order to ensure that the subjects are incentive compatible with the experiment and that they are serious about the bidding, subjects were told that two of them from each session would be chosen to receive a cash award. For those chosen, one round out of the twenty would be randomly selected to determine the cash award as one-tenth of the actual profit from the round, resulting in a cash reward ranging from \$6 to \$106.

At each round, subjects were asked to make following decisions:

- (1) participate or not in the reverse-auction site;
- (2) if she/he decides to participate, what is his/her bid;
- (3) indicate excitement if this bid is accepted (1 = not excited at all, 10 = the highest excitement ever experienced)
- (4) indicate frustration if this bid is rejected (1 = not frustrated at all, 10 = the worst frustration ever experienced).

Our measures of excitement/frustration were chosen chiefly to minimize the amount of disruption in each round. In a similar setting, Mellers et al. (1999) have also used a similar single-measure procedure to assess the elation/disappointment of subjects immediately after they learned the outcome of the monetary gamble that they had participated in. They used a category rating scale that ranged from +50 (*extremely elated*) to -50 (*extremely disappointed*).

**Table 1a** Experimental Design, Parameters for the Two Auction Scenarios

	$P_r$	$P_m$	$C_u$	$C_l$
Scenario 1 (\$)	1,160	1,100	1,250	100
Scenario 2 (\$)	1,160	1,100	1,850	800

**Table 1b** Relationships Between Bids and Probabilities of Winning

Scenario 1 site											
Bid submitted (\$)	100	200	300	400	500	600	700	800	900	1,000	1,100
Probability of being accepted (win) (%)	0	9	17	26	35	43	52	61	70	78	87
Scenario 2 site											
Bid submitted (\$)	800	850	900	950	1,000	1,050	1,100				
Probability of being accepted (win) (%)	0	5	10	14	19	24	29				

These excitement and frustration scale values need to be linked to monetary compensation. To do so, respondents were asked, after completing all 20 auction rounds, to imagine a context of having bid 30 times for a friend with two possible outcomes. In the first outcome, all 30 bids are accepted. Respondents then filled the blank “I am really excited and had a lot of fun doing it; it’s almost as if you had paid me \$—— to do this.” Then they would rate their excitement on the same 1–10-point scale used in the earlier scale to rate excitement if a bid is won. Similarly, frustration and its monetary equivalence are measured. These relationships were used to transform the measurements of excitement and frustration into monetary equivalences during the experimental 20 rounds using the following equations:

$$u_{2, \text{accept}}(P_{o,t}) = \frac{\text{MonetaryEquivalence}(30 \text{ rounds})}{\text{Excitement}(30 \text{ rounds})} \text{Excitement}(P_{o,t}) \quad (17)$$

$$u_{2, \text{reject}}(P_{o,t}) = \frac{\text{MonetaryEquivalence}(30 \text{ rounds})}{\text{Frustration}(30 \text{ rounds})} \text{Frustration}(P_{o,t}). \quad (18)$$

The experimental settings were designed to ensure that the assumptions of our model were replicated. Consider first the random generation of responses to bids. Friedman and Sunder (1994) have emphasized the importance of limiting the suspicion that

the experimenter is manipulating the random number generation process by choosing each number after observing the results up to that point in the game. In our case, showing the numbers being generated in real time and applicable across heterogeneous respondents enhanced this aspect of the credibility of our experiment. Further, supplying a table that enlists the winning probabilities at different levels of bids (see Table 1b) ensured that the respondent understood the implications of a uniformly distributed cut-off. The payment procedure used in the experiment limited cumulative wealth effects (Thaler and Johnson 1990) to a minimal role in modifying the behavior of the bidder across all 20 rounds. Finally, by providing respondents with a clear selling price for the items won in the auction, and a nonauction alternative, we provide unambiguous profit estimates at each bid level.

## 4.2. Experimental Results

We first provide some summary statistics and key insights with respect to the experimental results, including whether subjects indeed changed their bids within the same scenario (classic theory predicts they will not) and, if they did, are there any regularities? We also test a key model assumption concerning the nonstationarity of the two emotions coefficients (excitement and frustration) and whether one observes any regularity. The specific analytical insights tested empirically involve Propositions 2 and 3, and Corollary 1. In general, the analyses follow a two-step process. First, we generate individual subject-level results, based on either all bids or adjacent bids submitted under the same scenario by a given subject. We follow with analyses across subjects, which are based on the individual-level results obtained in the first step. We believe that this is the most appropriate procedure to test our theoretical propositions, as it highlights individual heterogeneity while also providing population-level insights.

All of the analyses described below are based on the subjects who, according to the theoretical prediction (Proposition 2), would bid in the reverse auctions used in the experiment.<sup>2</sup> To identify these subjects, the average  $X$  was calculated for each individual in the 10 rounds (in either Scenario 1 or Scenario 2) and only subjects whose average  $X$  were above the threshold level  $\underline{B}$  (see Equation (15)) were retained for further analysis. This results in 69 subjects for Scenario 1 and 23 subjects for Scenario 2. Note that not all subjects

<sup>2</sup> The deleted subjects, who were predicted by the theory to not participate, might have chosen to bid because they somehow derive utility from simply participating in the auction, and it is thus not appropriate to include them with the rest of the subjects. We have also rerun the analyses with all respondents included, and the results are substantially unchanged.



**Table 2** Number of Bids Submitted by Subjects Retained for Analysis

Number of bids submitted	Number of subjects in Scenario 1	Number of subjects in Scenario 2
10	63	18
9	1	1
8	3	2
7	2	1
6	0	0
5	0	0
4	0	0
3	0	1
2	0	0
1	0	0
Total	69	23

made 10 bids, and of those who chose to make fewer than 10 bids, not all of them were consecutive. Table 2 presents the number of bids for each of the two scenarios, made by the subjects retained for further analysis. The results reported in the table indicate that the majority of the subjects did submit 10 bids.

We first investigate whether subjects indeed changed their bids under the same auction scenario—a fundamental property of our model. Without accounting for the bidder's dynamic nature of excitement and frustration, the classic theory predicts that a subject should always submit the same bid. Our model proposes that a bidder will revise the bid each time as his/her emotional state changes due to the outcome of previous bidding. In order to test this, we first divided all bids into two groups, those for which the previous bid submitted by the same subject have been accepted and those for which the previous bid have been rejected. We then counted, within each group, the number of bids that were higher, the same, or lower than the previous bid submitted by the same subject. The results are reported in Table 3. They clearly demonstrate a dynamic pattern of the bidding strategies that characterize the reverse-auction environment. Most bids reflect a change (592 out of 787 bids). Furthermore, we found that subjects were more likely to decrease the bid if their bids in the previous round were accepted (127 versus 66, chi-square test significant,  $p < 0.001$ ). On the other hand, there is a tendency to increase bids once the previous ones are rejected (250 versus 149, chi-square test significant,  $p < 0.001$ ). This result argues strongly against

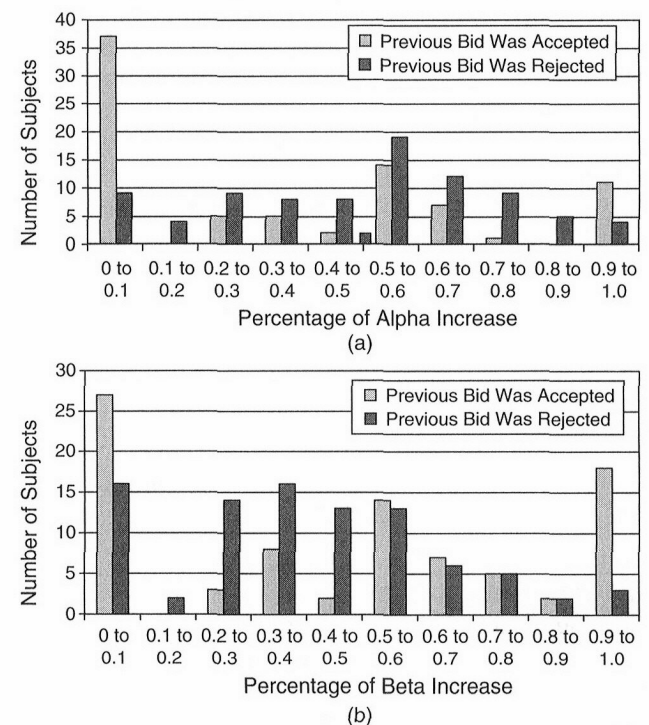
the classic (static) theory and supports the need for new models such as the one described in this paper. We will show that the direction of these changes typically follows the pattern predicted by a model that includes shifting emotions as arguments of the utility function.

A key assumption behind the model, which accommodates the observation noted above, is that the bidders' excitement and frustration coefficients are dynamic and that they will vary over bids (time periods). Unfortunately, however, the extant literature does not provide any guidance concerning the directionality of such changes in reverse-auction settings. In Figures 2a and 2b, we provide preliminary evidence with respect to this issue by testing (1) the general trends of changes for these two coefficients, conditional on winning or losing in the previous round, and (2) whether winning and losing induced statistically different trends. Bids of each individual were divided into two groups: those submitted after the previous bid was accepted and those submitted after the previous bid was rejected. We then calculate, for each individual and within each bid group, the percentages of bids where  $\alpha$  increased or  $\beta$  increased. The empirical distributions of these four summary percentages across all subjects are shown in Figures 2a and 2b.

It is clear from Figures 2a and 2b that there is a large degree of heterogeneity across subjects regarding

**Table 3** Changes in Current Bids Conditional on the Outcome of Previous Bid

	Current bid compared to the bid submitted in the previous round		
	Higher	Same	Lower
Outcome in previous round			
Bid was accepted	66	41	127
Bid was rejected	250	154	149

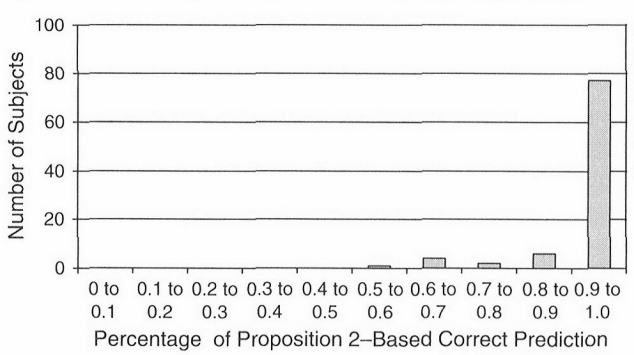
**Figure 2** (a) Percentage of Alpha Increase Across Subjects  
(b) Percentage of Beta Increase Across Subjects

changes in the excitement and frustration coefficients. Most subjects have both increased and decreased their coefficients for different rounds under the same outcome of previous bid (win or lose), a strong indication that the two counteracting forces (sensitization effect versus fading/adaptation effect) were at work. The average percentage of increasing  $\alpha$  when a previous bid has been accepted (0.33) is significantly ( $p = 0.002$ ) lower than when the previous bid has been rejected (0.47). This indicates that, on average, subjects are more likely to get more excited about winning in the current round after losing in the previous round. On the other hand, the average percentage of increasing  $\beta$  when a previous bid has been accepted (0.45) is significantly ( $p = 0.044$ ) higher than when the previous bid has been rejected (0.37). This indicates that subjects are more likely to get more frustrated about losing in the current round when a previous bid had been accepted. Note that the total number of subjects used in each situation is different, because not all subjects win or lose at least once in the first nine rounds under each scenario and there were several instances (3) where a subject omitted the excitement or frustration measurement (2) in all 10 rounds. The total number of subjects used for this analysis is 82 (with previous bid was accepted) and 87 (previous bid was rejected) for the excitement parameter ( $\alpha_i$ ), and 86 (previous bid was accepted) and 90 (previous bid was rejected) for the frustration parameter ( $\beta_i$ ).

To test Proposition 2, which predicts that bids will be submitted only by subjects whose  $X_t$  values are above  $\underline{B}$  in Equation (15), the following procedure was employed. For each subject, the percentage of times that the  $X_t$  values exceeded  $\underline{B}$ , given that a bid was submitted, was calculated. This individual-level score captures the correct predictions made by Proposition 2. For example, if subject  $i$  made the first eight bids under Scenario 1, for each of these bids, his/her  $X_1 \dots X_8$  were calculated and designated as above or below the threshold level, thereby determining the percentage of correct predictions at the individual level. Note that if the subject decided not to submit a bid in round  $t$ ,  $X_t$  could not be calculated. Hence, the base used here is the total number of bids submitted within the 10 possible rounds for which the value of  $X_t$  could be calculated. Because Proposition 2 is not scenario specific, the data were pooled over the two scenarios (there are two subjects who had indicated no frustration/omitted frustration measurement, resulting in a total of 90 data points). The histogram of the percentage of correct predictions is displayed in Figure 3.

Overall, the histogram indicates that Proposition 2 predicts well. The across-subject average correct prediction is 0.96, and the standard deviation is 0.11.

Figure 3 Percentage of Proposition 2–Based Correct Prediction



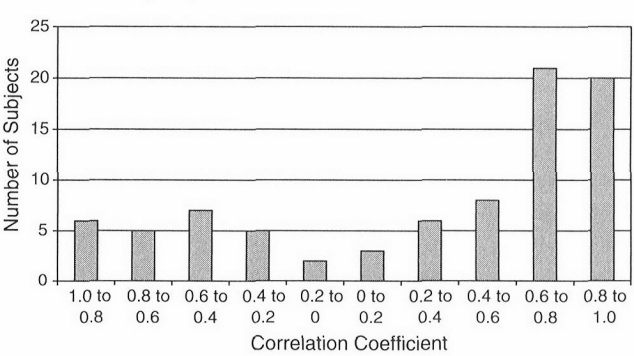
Proposition 3 addresses three issues that have been tested empirically: (1) the magnitude of bids submitted, (2) the change of the bid as a function of changes in  $X_t$  by scenario type, and (3) the concavity/convexity of bids submitted as a function of  $X_t$  and scenario type.

To test the first aspect of Proposition 3, which is independent of the scenario type, the following procedure was employed. We first calculated the magnitude of the bid predicted under Proposition 3 (see Equation (16)) for each subject in each round, and compared it to the actual bid submitted by the subject in each round. We next estimated the correlation between actual bid and the predicted bid for each subject over the rounds in which he/she actually submitted bids in each reverse-auction scenario. The data from 83 usable subjects (excluding eight subjects whose bids were the same in all rounds and one subject whose beta is zero) were then pooled across the two scenarios, and the empirical histogram of the correlations across subjects is shown in Figure 4.

The histogram and the average correlation across subjects of magnitude 0.3064 (statistically larger than zero based on  $t$ -test,  $p < 0.001$ ) suggest a fair degree of predictive capability for the bids magnitude aspect of Proposition 3.

The second aspect of Proposition 3 was the monotonicity (either increasing or decreasing, depending

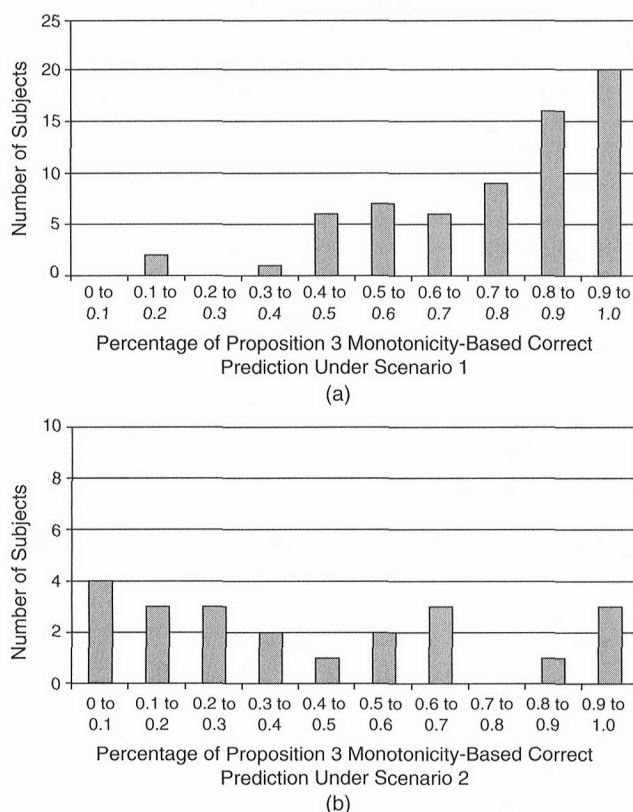
Figure 4 Correlation Between Actual Bids and Predicted Bids (Within Subjects)



on the bidding scenario) of the bids with respect to the behavior of the  $X_t$ . Here, two different tests have been employed. The first test is based on adjacent bids. It required organizing the data for each subject based on the change in  $X_t$  relative to  $X_{t-1}$  (increase/same/decrease) and the change in the magnitude of bid in round  $t$  relative to that in round  $t-1$  (increase/same/decrease). This creates nine ( $3 \times 3$ ) possibilities of which only three possibilities are addressed and predicted by Proposition 3. Under Scenario 1, the three possibilities of interest are:  $X_t$  increases and  $P_{o,t}$  increases;  $X_t$  remains the same and  $P_{o,t}$  remains the same;  $X_t$  decreases and  $P_{o,t}$  decreases. A subject under Scenario 1 whose  $X_t$  increased and  $P_{o,t}$  decreased or remained the same represents *incorrect* predictions derived from Proposition 3. The percentage correct prediction for each subject, and for each scenario, was then calculated.

The histograms of the percentage of correct predictions across subjects and within scenario are shown in Figures 5a and 5b for Scenario 1 (total number of subjects employed is 67, excluding one subject with no measurable adjacent  $X$  and one subject with no measurable  $X$ ), and for Scenario 2 (total number of subjects employed is 22, excluding one subject with no measurable  $X$ ), respectively.

**Figure 5** (a) Percentage of Correct Prediction Under Scenario 1  
(b) Percentage of Correct Prediction Under Scenario 2



The results suggest the model is capable of predicting well the monotonicity of the behavior of the bids under Scenario 1 (the average percentage of correct prediction across subjects is 0.78, significantly higher than an equal probability naïve prediction of 0.33), but predicting with far less degree of accuracy of the monotonicity behavior of the bids under Scenario 2 (the average percentage of correct prediction across subjects is 0.41).

The second test of monotonicity behavior predicted by Proposition 3 is based on the correlation between the  $X_t$  (not necessarily adjacent) and  $P_{o,t}$  for each subject and per scenario. Note that Proposition 3 predicts a positive correlation between the  $X_t$  and  $P_{o,t}$  for a subject submitting bids under Scenario 1, and a negative correlation under Scenario 2. The percentage of correct directional prediction can then be calculated in a straightforward manner across subjects. For 91% of the subjects bidding under Scenario 1 (59 out of 65, excluding 3 subjects who submitted the same bid for all 10 rounds and 1 subject with zero beta), the correlation is positive, as predicted, and for 22% of the subjects bidding under Scenario 2 (4 out of 18, excluding 5 subjects who submitted the same bid for all 10 rounds), the correlation is negative as predicted. This result is consistent with the first test of the monotonicity that examined the behavior of adjacent bids, that is, the model predicts the behavior accurately for bidding under Scenario 1, but mispredicts in Scenario 2.

The third aspect of Proposition 3 characterizes the concavity and convexity of bidding prices under the two bidding scenarios. In order to test this aspect of Proposition 3, a general quadratic function below was employed:

$$P_o = \gamma_0 + \gamma_1 x + \gamma_2 x^2. \quad (19)$$

The concavity/convexity properties can be tested by checking the empirical sign of  $\gamma_2$  via regression. Note that Proposition 3 predicts a concave relationship between  $P_{o,t}$  and  $X_t$  for a subject submitting bids under Scenario 1, and a convex relationship under Scenario 2. We thus expect the sign of  $\gamma_2$  to be negative for subjects bidding under Scenario 1 and positive under Scenario 2. Two different levels of analysis were conducted to test the predictions. We first estimated Equation (19) across all subjects and all rounds, under each scenario. The sign of the  $\gamma_2$  coefficient is indeed negative under Scenario 1, and is significantly different from zero ( $p = 0.016$ ). Also, as predicted, the coefficient's sign is positive under Scenario 2, though not significant. To obtain insight into the heterogeneity across subjects, we estimated the equation separately for each subject under each scenario. We found that 72% of the subjects (48 out of 67, excluding one subject with zero beta and one subject

whose data failed to satisfy the singular requirement in regression) under Scenario 1 indeed have negative  $\gamma_2$  as predicted by the model. The results for Scenario 2 are less satisfactory—only 32% of subjects (7 out of 22, excluding one subject with no beta) have positive  $\gamma_2$  as predicted by the model. The latter finding may very well be due to the small usable (those predicted by our theory to participate in such auction site) sample size on which it is based.

Finally, Corollary 1 predicts that compared to the classic profit maximization subjects will underbid under Scenario 1 and overbid in Scenario 2. To test this prediction, we first determined the average bid for each subject, calculated over all bids submitted by him/her under each scenario, and then calculated the percentage of subjects whose average bids conformed to the theoretical prediction (i.e., over- and underbidding). We found that 67% of subjects bidding under Scenario 1 underbid (their bid was lower than the profit-maximizing \$600 bid), while 43% of subjects bidding under Scenario 2 overbid (their bid was higher than the profit-maximizing \$950 bid). This result provides strong evidence to support the theoretical prediction under Scenario 1, but it does not lend support for the prediction made under Scenario 2. The evidence becomes much stronger, however, for both scenarios when we examine the average bids across all rounds. To do this, we first calculate the average bid for each round over the bids submitted by all subjects for that round, and then we calculate the percentage of rounds (out of 10 rounds under each scenario) where the average bids conform to the theoretical prediction. As shown in Table 4, the average bids in all 10 rounds under Scenario 1 are below the profit-maximizing \$600 (i.e., 100% correct prediction), while the average bids in 7 out of 10 rounds in Scenario 2 are above the profit-maximizing \$950 (i.e., 70% correct prediction).

## 5. Summary and Discussion

In this paper, we have developed and empirically tested a new analytical bidding model that contains both economic and behavioral constructs. The formal model generates fine-grained predictions about the bids people make as a function of their anticipated excitement given winning, and frustration

given losing. This model takes into explicit consideration the bidding environment in which these decisions are made. The empirical results reveal three major insights about the validity of the proposed model.

First, it is clear that the classic economic model did not capture the empirical behavior of bidders. Contrary to the static bidding strategy predicted by this benchmark model, we found that a bidder usually changed her bids after each round. Furthermore, the direction (increase or decrease) of such change is conditional on the outcome of previous bid. This result is unlikely to be due to learning, as we explicitly explained to the subjects before the experiment that they should not expect to learn anything from the outcome other than the probability table already stated to them. We also did not observe convergence in bids, as a learning mechanism implies.

Second, we found that emotions are an integral component of a bidder's decision state and bidding strategy. The empirical evidence indicates that there is indeed a strong emotion effect (specifically, excitement and frustration) associated with bidding, and such emotions change dynamically as a function of the outcome of the previous bid. It is also clear that the projected excitement and frustration have an impact on the bids made. Supporting evidence arises from the observed no-bids. From a classic profit-maximizing perspective, such default behavior has to arise from the frustration at losing, because any bid in the allowable range is as good as or better than the return of no-bid. Further, the overwhelming majority of bids submitted were associated with propensities to bid,  $X$ , that are above threshold, as predicted by our model.

Third, we show that, as predicted by our model, a bidder in a relatively favorable environment (Scenario 1) emphasizes more the amount of gain if she wins (thus make lower bids), but gradually puts more emphasis on the probability of winning as she becomes more interested in the bidding. Furthermore, we also show that a bidder in a relatively hostile environment (Scenario 2) emphasizes more the probability of a win (thus overbid), although this effect is not as strong as that observed under Scenario 1. We did not find, however, evidence that bidders under Scenario 2 will gradually put more emphasis on the amount of winning as they become more interested in the bidding.

The single most likely reason for the strong empirical support for Scenario 1 and weak empirical support for Scenario 2 lies in the role of our model as an enhanced normative model (instead of a pure descriptive model), as well as the design of the experiment. From the latter standpoint, examining again our criteria for Scenario 2, Scenario 2 is only marginally different from Scenario 1. Scenario 1(2) is defined to be any

**Table 4** Percentage of Underbidding (Scenario 1) and Overbidding (Scenario 2)

	Percentage of correct prediction (across subjects)	Percentage of correct prediction (across rounds)
Scenario 1	67% ( $n = 69$ )	100% ( $n = 10$ )
Scenario 2	43% ( $n = 23$ )	70% ( $n = 10$ )

sites whose range of distribution ( $C_u - C_l$ ) is larger (smaller) than the market price. In the experiment conducted here, Scenario 1's range is \$50 above and Scenario 2 site's range is \$50 below the market price of \$1,100 (see Table 1a). Future experiments could examine whether an environment strongly in the Scenario 2 camp (for example, the range is \$500 below the market price of \$1,100) results in substantially different behavior.

Ultimately, more models are needed that characterize bidders' behavior in the face of emotions. We have focused here on just two constructs, excitement and frustration, but there are others, such as an apparent desire to be part of an auction, or anger, that need to be incorporated into mathematical models and examined empirically. Such constructs are important not only to understand responses to auctions, but also to be able to develop predictive models of market response to such biddings.

An electronic companion to this paper is available at <http://mansci.pubs.informs.org/ecompanion.html>.

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