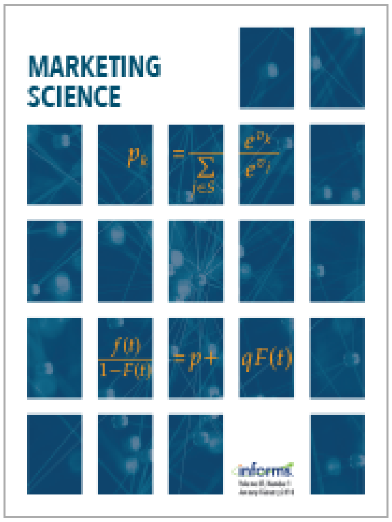

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Bidding Behavior in Descending and Ascending Auctions

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This research examines how individual differences and institutional practices influence consumer bidding in auctions. Bidders may be motivated by different goals, e.g., *thrill* (of winning the item, with minimal attention to what they pay for it) versus *prudence* (winning the item at a price at or below its perceived value). Also, innate or auctioneer-induced differences may exist in the *precision* and *salience* of bidder cognitions about the item's value. We report two studies on how these motivational and cognitive factors influence bids in descending and ascending auctions, respectively. Each study also manipulated a situational variable (*wait time* at each price step). The two auctions realized different average prices for the same item set. Average bids were higher in the descending (versus ascending) auction in several study conditions. In both auction formats, bidders primed with thrill (versus prudence) bid higher, but more precise and/or salient values attenuated this goal effect. Among other results, in the descending auction, longer wait times elicited higher bids from bidders primed with thrill (but not prudence). In the ascending auction, longer wait times produced lower bids for bidders primed with prudence (but not thrill). These findings on consumer bidding behavior have practical implications for auction design.

Key words: auctions; bidding; goals; pricing; value
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1. Introduction

Recent press releases (e.g., eBay Inc. 2012) report that during 2011, eBay Marketplace attracted over 100 million active Internet auction users who closed total transactions (excluding vehicles) in excess of $60 billion. This staggering volume and growth in auction transactions is the imperative for understanding how individual differences and institutional practices impact bidder responses and seller outcomes. Scholars from various disciplines including economics (e.g., McAfee and McMillan 1996, Lusk and Shogren 2007), management science (e.g., Rothkopf 1991, Rothkopf and Harstad 1994), and organizational behavior (e.g., Bazerman 2001a) have called for more research from a marketing perspective to guide auction theory and practice. Marketing scholars (e.g., Chakravarti et al. 2002, Cheema et al. 2005) have identified promising new research opportunities, noting the relative paucity of behavioral research on auctions. This paper addresses this gap by examining how psychological states induced by selected individual differences and institutional practices can influence consumer bids in auctions.

The large theoretical literature on the economics of auctions focuses mainly on normative bidding strategies. The focal bidder starts with a private value signal and a prior distribution on other bidders' value signals[1] and updates these based on how other bidders act during the auction. Game-theoretic intuition is used to make the bidding decision and develop the optimal bid function. In independent private value (IPV) models, the bidder's value depends only on her own signal. In common value (CV) models, the actual value is the same for all bidders, although each bidder has a private signal of this common value. Affiliated value (AV) models describe the case where these value signals exhibit (positive) dependencies.

This literature archives two key theoretical results regarding expected revenues in various auction formats. First, the revenue equivalence theorem for IPV and CV models (Vickrey 1961, Myerson 1981) asserts that open descending and ascending auctions (and

[1] Consistent with *Webster's Desk Dictionary* (1996 ed.) definition of "value" ("the monetary worth of something"), the auction item's value implies a monetary representation of the psychological pleasure derived from owning (consuming) it.

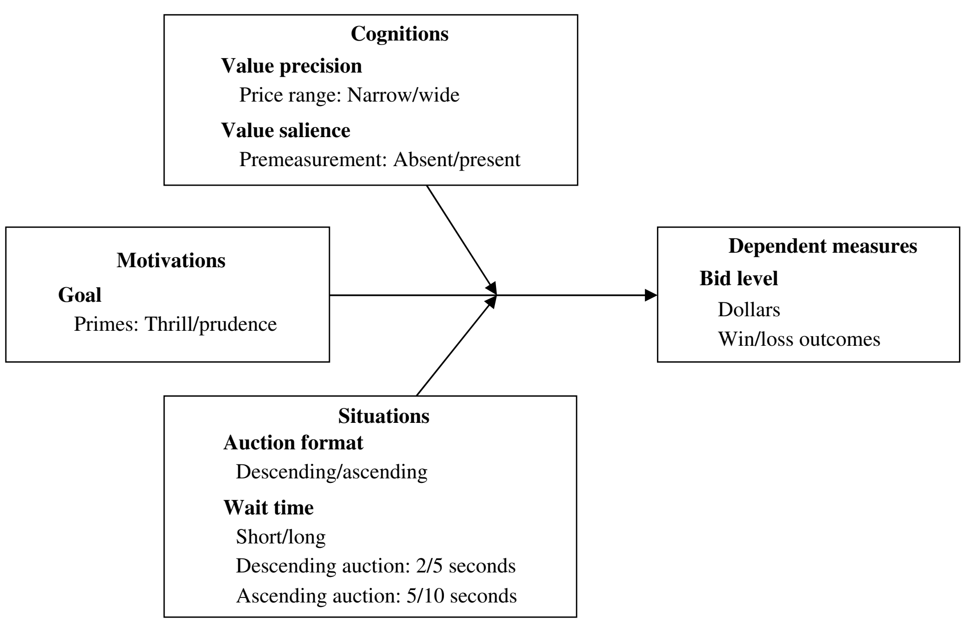
first- and second-price sealed-bid auctions) should yield identical expected revenues under some general conditions (Klemperer 1999). Second, Milgrom and Weber (1982) show that if bidders change their values contingent on other bidders' value signals (i.e., an AV model), ascending auctions should yield higher revenues than descending auctions. This result is derived for ascending auctions *with public and irrevocable exits*—the Japanese variant of an English auction (Cassady 1967). The Japanese variant is also the common ascending auction format used to test these predictions in experimental economics (Levin et al. 2002, Kagel 1995).

Experimental tests (e.g., Cox et al. 1982, Kagel 1995) show systematic departures from the above predictions. The departures often are attributed to bidders motivated or primed by goals other than surplus maximization (e.g., thrill of winning) or swayed by emotions (e.g., boredom, impatience, anxiety) induced by situational factors like the wait time at each price step (Ariely and Simonson 2003, Lucking-Reiley 1999, Smith and Dickhaut 2005). The violations may also have cognitive roots. Bidders may differ innately on how precisely they know an item's value or how salient an initial value is during the auction (Ariely et al. 2003). Auctioneers can affect value precision by supplying item price ranges that are wide or narrow (e.g., see the Christie's and Sotheby's websites) or alter value salience by encouraging bidders to consider their value prior to the auction. Auctioneers also control the auction format (descending or ascending) and the wait time at each price step. These situational factors may influence bidder opportunity to reflect on the exit/stay actions of other bidders (Sinha and Greenleaf 2000) and infer implications for their own value.

In contrast to the theory-testing tradition in experimental economics, the present paper focuses on a behavioral analysis of how such individual differences and institutional practice may influence bidder motivations and cognitions and drive bidding behavior in auctions. We examine the baseline effect of motivation (goal) differences on bidding behavior, distinguishing between bidders primed with *thrill* (winning the item, with minimal attention to what is paid for it) versus *prudence* (i.e., winning the item at a price at or below its perceived value). Guided by important and pragmatic auction design questions, we explore how this motivational effect is moderated by bidder cognition factors such as *value precision* and *value salience* and situational factors such as the *wait time* at each price step of the auction. We report two simulated online auction experiments that examine how these motivational and cognitive factors influence bids in a descending auction and an ascending auction, respectively. Both studies embed manipulations of wait time at each price step (see Figure 1).

This research makes five core contributions. First, we demonstrate the impact of motivational (goal) differences on how consumers bid in auctions. Priming a thrill (versus prudence) goal produces higher bids in both descending and ascending auctions, and this influence may occur below the threshold of subjective awareness. Second, we show how two cognitive factors (value precision and value salience) mitigate this effect. Values known more precisely and/or that

Figure 1 **Experiment Overview**



are more salient during the auction are less labile. Third, we show that the wait time at each price step of an auction influences the goal effect, which is attenuated when wait times are short. Fourth, we compare the descending and ascending auction results to outline practical steps that bidders and auctioneers can take to inhibit or amplify these motivational, cognitive, and situational influences on bids. Finally, we use a model incorporating thrill versus prudence goal differences to explore the welfare implications of our results.

The remainder of this paper is organized as follows. Section 2 outlines the descending and ascending auction formats, explains the rationale for choosing the focal factors for the study, and presents a set of hypotheses regarding how these factors would influence bids in the two auction formats. We report our empirical work in the next two sections. Section 3 presents the experimental procedures to the data analyses of and the results of the descending auction. Section 4 describes the corresponding aspects of the ascending auction experiment. Section 5 provides a synthesis of the results of the two studies, outlines an ex post theoretical analysis of the welfare implications of the goal effect, and discusses the implications of the results for consumers and auctioneers, with practical insights for auction design. Section 6 concludes with a discussion of future research opportunities.

2. Hypotheses Development

2.1. Descending and Ascending Auction Formats

The Dutch auction (used to sell flowers and agricultural produce in Holland) is the most common *descending auction* format (Cassady 1967). The auctioneer starts at a high price or *bid level* (Rothkopf and Harstad 1994) and lowers it in steps until one bidder bids and wins the item at the current bid level. The other bidders (who failed to bid) lose the auction. The English auction is a common ascending auction format. The auction starts at a low bid level (e.g., a reserve price) that rises as bidders place higher bids. The auction ends when no bidder bids at a bid level. The last remaining bidder wins the item and pays the previous bid amount (a coin toss breaks ties).

In the Japanese variant (Cassady 1967) of the ascending auction, the bid level rises in fixed increments. *All* bidders must indicate if they will bid at the current bid-level. A bidder who does not bid at a given level makes a *public and irrevocable* exit and cannot bid again. The last remaining bidder wins the auction at the second-highest bidder's exit price. A public and irrevocable exit admits the inference that a bidder's value has been exceeded (Klemperer 1999). The count of remaining competitive bidders signals the number whose values equal or exceed the current bid level—information that a focal bidder can use to adjust her own values and develop bidding strategy. Prominent in the theoretical literature on auctions (e.g., Milgrom and Weber 1982), the Japanese variant is commonly used in experimental studies of ascending auctions (Levin et al. 2002, Kagel 1995, Smith and Dickhaut 2005). Ascending auctions with *private and revocable* exits (common at auction houses such as Christie's and Sotheby's and even on eBay) allow no such control of information structure.

The experimental economics literature focuses on testing how actual bids compare with theoretical predictions regarding optimal bids, examining the efficiency of specific auction mechanisms. Our primary purpose is distinct and focuses on how relevant psychological and task factors affect bidding within descending and ascending auctions, respectively. We compare these effects informally across the two auction formats. Even though it is not our aim to test theoretical predictions regarding optimal bids, our use of the standard (Japanese) format for the ascending auction leaves room to compare our results with the extant literature.

2.2. Focal Factors and Study Hypotheses

Prior research shows that a variety of individual differences as well as task and contextual factors influence perceptions of posted prices (e.g., Adaval and Monroe 2002, Bettman et al. 1998). Such influences may be stronger in dynamic price formation settings such as auctions. In this section we describe our rationale for selecting the focal motivational, cognitive, and situational factors that we examine in the current paper. We also develop a set of hypotheses regarding their individual and selected interactive effects on bidding behavior.

2.2.1. Primed Goal. Goals refer to outcomes that people strive to approach or avoid (Markman and Brendl 2005). We select goals as the focal motivational factor because they are powerful drivers of behavior when there is conscious commitment to actions and end states (Baumgartner and Pieters 2008, Gollwitzer 1999, Higgins 1997). However, goals can also influence behavior without conscious awareness of such links (Bargh and Chartrand 1999). Thus, the underlying motive or goal for auction participation may have conscious or nonconscious influences on bidding. "Addiction to thrills" is one prominent motive for participating in online auctions (Herschlag and Zwick 2000), though many consumers participate in seeking bargains. Although motives are rarely cleanly partitioned, some consumers are driven mainly by the thrill of winning the item and attend only minimally to what they pay. For others, the dominant goal is a prudent purchase—to acquire the item at a price equal to or less than their assessment of its value.

Auctioneer ads routinely appeal to these motivations (thrill versus prudence). The website of a venerable auction house, Christie's, describes the "in-person" bidding experience: "... the real fun begins ... the auctioneer will bring down the gavel and you'll feel a rush of excitement" (Christie's 2012). In 2007–2008, eBay's multimedia campaign stressed the exhilaration of winning ("It's better when you win it") urging buyers to "shop victoriously" (TG Daily 2007). In an interesting contrast, the eBay website urges bidders to be cautious (eBay 2012): "Determine the maximum amount that you're willing to pay ... make every bid a serious one." Thus, the institutional and popular literature on auctions suggests that often, thrill seeking drives bidding, even as consumers are urged to exercise prudence. Thus, thrill and prudence goals are seen as important and contrasting regulators of bidding behavior in auctions.

The experimental economics literature has explored the "joy of winning" as an explanation for overbidding (relative to theoretically optimal bids) in private value auctions. Researchers exploring this idea (e.g., Cox et al. 1992, Goeree and Holt 2002) have concluded in favor of a risk aversion explanation based on the fit of a particular model of the "utility of winning" to their experimental data. However, we construe thrill (prudence) to be distinct from risk seeking (aversion) and view them as motivationally rooted experiential goals that may drive bidding in an auction, *irrespective of risk attitude*. We revisit this issue in the discussion section both from a conceptual standpoint and in light of our empirical results (which are based on primes that directly manipulate thrill and prudence goals).

Just as consumption goals influence various phases of consumer decision making (Austin and Vancouver 1996), the goal that a bidder brings into the auction may influence the evolution of bidder values and bids (whether consciously or nonconsciously). Smith and Dickhaut (2005) find that heart rate data (claimed as a proxy for emotions) are associated with bidding behavior in a Dutch (descending) auction. We argue that in a descending auction, bidders primed with thrill (versus prudence) may be less influenced by the inaction of other bidders. They may jump the gun and bid early, thus paying more for the item. In contrast, bidders primed with prudence are more likely to be guided by their own and other bidders' values. These bidders may tend to herd (Banerjee 1992, Dholakia et al. 2002) and emulate the inaction of other bidders, leading them to adjust their own value downward. In other words, bidders primed with thrill (versus prudence) should bid more aggressively (higher) in a descending auction.

In an ascending auction, exit/stay decisions are made sequentially at each bid level. Smith and Dickhaut (2005) found no association between participants' heart rate data and bidding behavior in their ascending auction (Japanese variant). However, participants' mental states were not manipulated in their study. In contrast, our study directly embeds a thrill/prudence prime. Bidders with a thrill prime are focused on winning and may not monitor closely the exit/stay behaviors of other bidders. To the extent that they do attend to these behaviors, research on motivated reasoning (Kunda 1990) and confirmation bias (Nickerson 1998) suggests that these bidders may be influenced more by bidders who stay (versus exit) because this is consistent with their primed "win" mind-set. Also, their commitment may escalate at each sequential price step (Bazerman 2001b, Chandran and Morwitz 2005) so that they bid higher to continue competing with the remaining bidders. In contrast, prudence-primed bidders are more likely to monitor both the exit and stay decisions of other bidders and infer implications for their own value. A more balanced consideration of other bidder exits and stays should make them less likely to escalate bids. Thus, as in a descending auction, bidders primed with thrill (versus prudence) in ascending auctions should bid more aggressively (higher).

Hypothesis 0 (H0). *Bidders primed with thrill will bid higher than those primed with prudence.*

This prediction is unsurprising when there is a conscious commitment to manipulated goals. However, bidders are not always conscious of their actions, and it is unclear whether the goal effect in either auction format can occur below the subjective awareness threshold. We address this issue in our study, using two versions of a fictitious article about eBay (Appendix A) to prime goals between participants (Bargh and Chartrand 2000, p. 266). One version primes thrill, emphasizing the excitement that bidders experience from winning the auction. The other primes prudence, cautioning against getting carried away and paying too much. Because both the prime and the decision are in auction contexts, goal effects may occur either above or below the awareness threshold. We assess the locus of the effect using post-auction self-reports.

2.2.2. Wait Time. Auctioneers control the wait time (WT) at each price step. Dutch flower auctions are examples of descending auctions with fast tick-down clocks, whereas descending auctions on the Internet usually have slow clocks. Experts (e.g., Cassady 1967, p. 107) suggest that fast-paced descending auctions "... keep would-be buyers alert and responsive ... and more vigorous bidding is likely." Based on the experimental economics literature (Cox et al. 1982) and our own pretests, we chose two seconds (*short*) and five seconds (*long*) as the levels of wait time manipulation for the descending auction study.

A long (versus short) wait time (WT) at each price step of a descending auction allows a focal bidder more processing opportunity—a key explanatory construct in consumer decisions (Bettman et al. 1998). The bidder has more time to process information signals, assess her own value, and formulate bid strategy. Given more time to assess the implications of the inaction of other bidders, the focal bidder may lower her estimate of other bidders' values and revise her own value downward. This matches the "probability miscalculation" reasoning (Cox et al. 1991) for why bids in descending auctions are lower than theoretical predictions.

However, we reason differently about the WT effect in a descending auction. Recent studies (e.g., Katok and Kwasnica 2008) show that the average revenue in Dutch auctions rises with slower clock speeds and, with a sufficiently slow clock (30 seconds), could exceed that in a first-price sealed-bid auction. The data comport with a model featuring impatient bidders. On the Internet, longer wait times slow down auctions and raise monitoring costs (Carare and Rothkopf 2005). Even with only a few seconds at each bid level, the cumulative wait in a descending auction may create boredom or stimulate anxiety (that another bidder may bid and end the auction). These influences are more likely to drive bidding than probability miscalculation (which requires counterfactual inferences of competitive value from the *absence* of bids). Hence, in descending auctions, long (versus short) wait times should elicit earlier (higher) bids as a main effect. We verify this reasoning using post-auction self-reports.

The goal instrumentality literature shows that unmet goals tend to gain strength (Baumgartner and Pieters 2008, Markman and Brendl 2005). Hence, even with a few seconds to wait at each price step, WT can interact with bidder goals to affect bids. Prudence-primed bidders attend more to the bid level and relatively less to the wait time because for them, the wait time does not inhibit goal attainment. In contrast, thrill-primed bidders, keen to attain their goal of winning the item, may become more impatient or anxious as their unmet goals become stronger. Long wait times should exacerbate this tendency. This would lead thrill-primed bidders to bid earlier (i.e., higher) when WT is *long* versus *short*.

For the ascending auction, short (long) wait times were set at 5 (10) seconds by design to equate subjective perceptions of available time to those in the descending auctions. A focal bidder in the ascending auction may reflect on bidder exits and prior bids as she decides whether or not to bid (other bidders' actions at the current bid level are known only after the wait time elapses and the participant declares her own decision). Although a long (versus short) WT allows more opportunity for the bidder to process others' behaviors and reassess her own value, it may induce boredom and prompt earlier exits.

Moreover, WT should moderate the goal effect in ascending auctions in a manner similar to that in descending auctions. With long (versus short) WT, bidders primed with prudence (versus thrill) will reflect more on the exit/stay actions of other bidders. This may generate greater boredom (or even induce caution influenced by others' exits) and prompt earlier exits at lower bid levels. Bidders primed with thrill are less likely to exit early. They attend less to others' behaviors and may focus selectively on those who remain (consistent with their own win mindset). They are also less likely to exit because the irrevocable exit implies a goal-incongruent loss (cf. an early bid in the descending auction produces a goal-congruent win). Hence, we predict the following for both descending and ascending auctions.

Hypothesis 1 (H1). *The bid difference between bidders primed with prudence versus thrill will be* smaller *for bidders who experience a short* (*versus long*) *wait time*.

2.2.3. Value Precision. Both online and off-line auctioneer catalogs (e.g., www.saffronart.com online, and Christie's and Sotheby's off-line) list estimated values for auction items. These firms also provide seller price estimates as a service. The information helps bidders to form an initial estimate of the item's value. Also, bidders may bring prior knowledge of an item's value into an auction. This initial value estimate may serve as a relevant anchor, and its *precision* will influence how it is updated during the auction. Bayesian reasoning, commonly used in auction theory (e.g., Kagel 1995, Klemperer 1999, McAfee and McMillan 1987), implies that the precision of a bidder's priors on an item's value will influence how it is updated with new information. We manipulate value precision in our studies by providing bidders with a *mean-centered* price range (PR) that is either narrow or wide.

In a descending auction, bidder values typically follow the bid level down. Greater precision implies a tighter subjective confidence interval around the initial value (i.e., it is less labile). Hence, a focal bidder with a *narrow* (versus *wide*) PR should bid higher because she is less likely to lower her value based on the inaction of other bidders. Beyond this main effect, value precision may also moderate the goal effect. With a narrow (more precise) PR, the initial value for both prudence- and thrill-primed bidders should be influenced less by bidder inaction. Hence, the goal effect should be relatively small. With a wide (less precise) PR, bidders primed with prudence are more likely to lower their bids. In contrast, thrill-primed bidders are less likely to lower bids because they are motivated to win. Thus, the goal effect will be relatively larger.

In an ascending auction, the bid level rises as bidders compete, and the focal bidder must raise value to compete. Because more precise values are less labile, bidders with a narrow (versus wide) PR are less likely to raise their value and will bid lower (a prediction opposite to that for the descending auction). However, value precision will also moderate the goal effect. With a narrow (more precise) PR, the initial value will be less labile for both prudence and thrill primes, i.e., a smaller goal effect. With a wide (less precise) PR, the initial value for both prudence- and thrill-primed bidders should track the rising bid level but more so for the latter because they want to win. The goal effect will be reinforced if prudence (thrill)-primed bidders attend selectively to exits (stays) consistent with their respective mind-sets. Thus, PR will moderate the goal effect similarly in descending and ascending auctions.

Hypothesis 2 (H2). *The bid difference between bidders primed with prudence versus thrill will be* smaller *for those who see a narrow (versus wide) price range.*

2.2.4. Value Salience. Some bidders have a salient initial value as they bid for an item in the auction. Many authors (e.g., Cassady 1967, p. 146) imply that a prospective buyer is wise to "establish a maximum price which he will not exceed." Internet auction sites also ask bidders to state a maximum price to guide an offered "proxy bidding" system. Naturally accessible and salient information receives more weight in judgment (Dick et al. 1990, Feldman and Lynch 1988, Morwitz et al. 1993). Also, salience can be prompted by premeasurement (PM). Asking bidders to report an initial value just prior to the auction (PM present) raises value salience relative to no premeasurement (PM absent). Articulation makes the initial value a salient anchor and affects how much it is adjusted in response to auction events. Stating one's willingness to pay has a similar effect (Simonson and Drolet 2004).

In a descending auction, a focal bidder is less likely to follow the bid level down when the initial value is salient (PM present) versus when it is not (PM absent). Bidders with a premeasured (versus not premeasured) value are less influenced by the inaction of other bidders. Moreover, value salience will also moderate the goal effect. With PM present, both thrill- and prudence-primed bidders are less likely to be influenced by the inaction of other bidders, and the goal effect should be relatively small. With PM absent, prudence-primed bidders will bid more cautiously (lower) than thrill-primed bidders. The win mind-set of thrill-primed bidders will dampen the effect. Hence, the goal effect will be larger when PM is absent.

In an ascending auction, a focal bidder with a salient preauction value (PM present) is less influenced by the rising bid level and will bid lower than one with a less salient value (PM absent). This premeasurement main effect is opposite to that predicted for the descending auction. However, value salience should moderate the goal effect quite similarly in ascending and descending auctions. With PM present, the initial value is less labile, and bidders with both prudence and thrill primes should adjust the initial value to a lesser degree. With PM absent, the initial value is less salient, and bidders with a thrill (versus prudence) prime should be more likely to raise bids, consistent with their win mind-set. This effect may be reinforced if a thrill (prudence) prime also draws selective attention to exit (stay) behaviors of competing bidders. Thus, for both descending and ascending auctions,

Hypothesis 3 (H3). *The bid difference between bidders primed with prudence versus thrill will be* smaller *if bidders' preauction values are measured versus not measured.*

In summary, we offer a baseline hypothesis (H0) for the goal (thrill/prudence) effect on bids. We then identify three key factors—wait time (WT), value precision (PR), and value salience (PM); outline their main effects; and develop formal hypotheses (H1, H2, and H3) on how they moderate the goal effect. Although our process reasoning differs, we predict similar moderating effects for descending and ascending auctions. We also empirically test for other main effects and higher-order interactions, but space constraints preclude formal discussion.

2.3. Empirical Approach

A common theme in experimental auction studies (Lusk and Shogren 2007) is how actual bids in various study conditions compare with equilibrium bids. In contrast, our objective in this paper is to test hypotheses on how average prices may differ as a function of the manipulated variables and selected interactions. As we explain shortly, our average price data cannot be interpreted as equilibrium bids because our payoff structure and use of "bot" bidders may have affected absolute bid levels, although these background factors were constant across study conditions.

We use laboratory experimental auctions to examine the effects of these manipulations, controlling for extraneous effects. In contrast to the tradition of using induced values for fictitious commodities to examine deviations from equilibrium bids, we use familiar products to add realism and raise participant involvement (Ding 2007, Hoffman et al. 1993). The focal participant bids against bot bidders programmed to mimic competing bidders. This allows us to control how price information is disseminated (via bidder entry and exits) and permits direct comparisons of average bids across study conditions within each experiment. This is not possible with human bidders in real auctions. However, note that bidding against bots (versus humans) may have altered focal bidder behavior in our studies (e.g., if participants imbued the bots with unusually high levels of rationality). However, such influences should be similar and should not affect comparisons across study conditions.

3. The Descending Auction Study

3.1. Procedure

A total of 339 undergraduates participated in the descending auction study for extra course credit and the possibility of winning the auctioned product and/or extra money. Participants sat at individual computers and a custom program managed the study procedures. Bidders in the *PM present* condition reported their values for the auction items, whereas those in the *PM absent* condition did not. All bidders then read one of two articles (see Appendix A) used to prime either thrill or prudence. A pretest with 35 students gauged the articles' emphasis on thrill/prudence. The thrill-primed article scored higher (5.75 versus 2.91, $p < 0.001$) on three 7-point thrill items ("...emphasized the thrill of winning in an auction," "...would make me more aggressive when bidding in an auction," and "...would increase my desire to win when participating in an auction"; $\alpha = 0.74$) versus three 7-point prudence items ("...emphasized the risk of paying too much," "...would make me more cautious while bidding," and "...would increase my desire to avoid paying too much when participating in an auction"; $\alpha = 0.80$). The prudence-primed article scored higher on the prudence items compared with the thrill items (6.43 versus 2.80, $p < 0.001$). Thus, the articles emphasized the desired mind-sets and primed the intended constructs.

The auction payoff instructions (see Appendix B, panel 1) were provided next. Bidders were endowed with $50 of "bidding money," and the payoff criteria were explained in detail. Several considerations guided our choice of payoff structure, which was identical across study conditions. First, we wished to use real products in contrast to inducing values for fictitious commodities and training bidders to maximize surplus. Second, we sought participant interest in the mundane auction items by using an attractive payoff structure. Third, because budget constraints precluded payment of winning payoffs to all participants, we used an incentive-compatible (probabilistic) conversion of winner payoffs to real money. Finally, we wanted to generate a spread in subjective values for the items (Harrison 1989), assuming that participants would maximize expected surplus (given the auction was picked for conversion).[2] The payoff structure cannot be used to generate equilibrium bidding strategy or test the efficiency of auction mechanisms. However, an analysis of the actual bids in the auctions (see §5.1) suggests that the payoff structure did not interact with study factors, allowing comparisons of bids across conditions.

Participants first bid in two practice descending auctions for unrelated products to become familiar with the computer interface and the bidding process. Next, they saw the set of auction items (see Appendix B, panel 2) and selected a product on which to bid in the real descending auction. This selection enhanced task realism and involvement. The between-participants PR manipulation was introduced next as a "quick survey of the market prices of comparable products." Participants in the narrow (wide) PR condition saw a mean-centered price range that was $\pm 30\%$ ($\pm 60\%$) of the mean (see Table C.1 in Appendix C).

Each bidder then participated in a descending auction with six other programmed bots. We avoided deception by telling participants that they were bidding against bots programmed to behave like regular bidders. The auction screen showed the bid status of the bot bidders (see Appendix D, panel 1). The bid-level started at a high price (see Table C.2 in Appendix C) and dropped in 50-cent steps. The WT at each bid level was manipulated between participants to be either short or long (two or five seconds, respectively). The first bid, either by a bot or by the participant, won the auction. Start and stop bid levels in the auction were preset (see Table C.2

[2] With our payoff structure, an auction selected for conversion provides a $5 payoff (i.e., $0.10 \times \$50$) if the focal bidder had lost. Winning a product of value ($\$y$) at a bid of ($\$x$) yields a payoff of $\{y + (50 - x)\}$. Let $q(x)$ be the probability of losing at a bid of $\$x$. Thus, a bidder indifferent between winning and losing may use a *bidding heuristic* obtained by solving $q(x) \cdot 5 = \{1 - q(x)\} \cdot \{y + (50 - x)\}$. Clearly, even a bidder who has no value for the product ($y = 0$) should bid $45 if indifferent between winning and losing. More generally, though, win probability is an endogenous function $G(x)$ of the bid, where $G(\cdot)$ is the bid distribution function and bidders maximize expected payoff. Here, the optimal bid depends on the bidder's subjective assessment of opponent bids, as captured in $G(x)$. To derive the optimal bid, note that the expected payoff is $EV = q(x) \cdot 5 + \{1 - q(x)\} \cdot \{y + (50 - x)\}$. The optimal bid x that maximizes EV is obtained from the first-order condition $45 - x + y = -\{1 - q(x)\}/q'(x)$, where $1 - q(x) = P(\text{winning}) = G^m(x)$, and m is the number of bot bidders. The optimal bid x^* is a solution to $45 - x^* + y = G(x^*)/\{mG'(x^*)\}$. With $m = 6$ (as in our studies), the solution is given by $45 - x^* + y = G(x^*)/\{6G'(x^*)\}$. Depending on the empirical bid distribution, the optimal bid can vary over a wide range. Thus, if $G(\cdot)$ is an extreme value distribution with means equal to the provided price range means, optimal bids may vary from $23 to above $45.

in Appendix C). If no participant bid before the stop bidlevel, a bot bid ended the auction. The program randomly picked a low or high level for the bot bid. This distributed the win/loss outcomes more evenly across the study conditions.

The use of bot bidders as competitors and preset background factors may have changed participant responses relative to competing with human bidders. However, using a simulated online auction with programmed bots ensured that all participants encountered the same auction environment, on average. This also created significant efficiencies in comparing participant behaviors across study conditions. Postauction, all participants answered questions on manipulation checks, demographics, auction experience, and a measure of susceptibility to interpersonal (informational) influence (SII) (Bearden et al. 1989). Participants worked through this study sequence at their own pace and could leave after completing the debriefing questionnaire. On average, the descending auction study took 25 minutes.

3.2. Descending Auction—Analyses and Results

Table 1 presents the proportion of focal bidder wins as well as their mean (estimated) bids by condition for the descending auction. These bids are based on underlying values, and participants who bid relatively high (low) are more (less) likely to win. Hence, the win proportions reflect the underlying distribution of the focal bidders' values. The only bid of record in a descending auction is that of the winning bidder (either a participant's bid or a preset bot bid). Although a winning bot bid does not reflect the focal bidder's value, one may infer that the bidder would have (prospectively) bid lower had the auction not ended with the bot bid. Thus, the winning bot bid is the lower-censoring point of the range of the bids from focal bidders who lost. When the focal bidder won, her winning bid was used as an uncensored observation. When a bot won, the winning bot bid was used as the left censor point of the bid distribution. We used the SAS PROC LIFEREG procedure (SAS 1999, SAS Online Documentation 2003) to analyze the bid data (see Dholakia and Morwitz 2002). The estimation procedure is explained in detail in the notes to Appendix E.

We now report the test results for the hypotheses regarding the focal bidder's *bid levels* in the descending auction. The tests are based on the estimated mean bids (see Table 1) computed from a full model (see Appendix E) that includes all the main and higher-order interactions of the focal manipulations (goal, WT, PR, and PM), as well as selected covariates (an estimate of participants' inferred value for other bidders, auction experience, and SII score). As expected, the inferred value covariate strongly affected the focal bidder's bid level ($\chi^2 = 2{,}063.29$, $p < 0.001$), reflecting the informational differences arising from the varying base price of the items, as well as the information inferred during the auction. The auction experience covariate was also significant ($\chi^2 = 48.00$, $p < 0.001$).

3.2.1. Primed Goal. Thrill-primed bidders bid higher than prudence-primed bidders ($M_{\text{thrill}} = 28.34$,

Table 1 **Descending Auction (Experiment 1) Focal Bidders' Win Percentage and Mean (Estimated) Bid**

			Thrill prime		Prudence prime		Marginal means				
			WT		WT		Prime		WT		
PM	PR	Outcome[a]	Long	Short	Long	Short	Thrill	Prudence	Long	Short	Pooled
PM present	Narrow	%	68	55	58	43	61	51	63	49	56
		E$	30.77	27.89	29.39	28.46	29.23	28.96	30.00	28.17	29.09
	Wide	%	79	55	59	63	66	61	68	59	63
		E$	29.59	27.27	28.14	30.74	28.35	29.34	28.81	28.88	28.85
PM absent	Narrow	%	77	56	45	48	66	46	62	52	57
		E$	29.75	26.82	28.10	26.53	28.19	27.30	28.96	26.69	27.77
	Wide	%	60	38	53	52	49	52	57	46	51
		E$	27.47	28.57	24.44	24.16	28.03	24.27	26.08	26.17	26.13
Marginal means	PM present	%	74	55	59	53	63	56	65	54	60
		E$	30.18	27.58	28.79	29.55	28.79	29.14	29.42	28.52	28.97
	PM absent	%	69	48	49	50	58	49	59	49	54
		E$	28.66	27.62	26.42	25.24	28.12	25.77	27.61	26.43	26.97
	PR narrow	%	73	55	52	45	64	49	62	51	56
		E$	30.23	27.32	28.81	27.50	28.67	28.17	29.49	27.40	28.42
	PR wide	%	69	47	56	57	57	57	63	52	57
		E$	28.50	27.90	26.52	27.00	28.19	26.78	27.51	27.45	27.48
	Pooled	%	71	51	54	51	61	53	63	51	57
		E$	29.39	27.60	27.73	27.24	28.44	27.48	28.54	27.42	27.96

[a]The upper number (%) is the percentage of winning focal bidders in that experimental condition. The lower number (E$) is the mean *estimated* focal bidder bid in that condition, from the model in Appendix E.

$M_{prudence} = 27.48$; $\chi^2 = 57.79$, $p < 0.001$), supporting the baseline hypothesis H0. This result is intuitive, but the bidder self-reports provide further insights. Although the former bid higher, the thrill- and prudence-primed bidders did not differ in their responses (1 = disagree, 9 = agree) to the two during auction mind-set measures "I really wanted to win the auction" ($M_{thrill} = 6.72$, $M_{prudence} = 6.60$; $p > 0.65$) and "I did not want to pay too much for the product" ($M_{thrill} = 7.85$, $M_{prudence} = 7.82$, $p > 0.80$). Also, the reported levels of either anxiety or excitement with the auction did not differ (all p-values > 0.10).

These dissociations between the bid levels and self-reported (during auction) mind-sets of the two groups are remarkable because the goal-priming articles are also in the auction domain and pretested as clearly different in their emphasis on thrill and prudence. Also, in the main study, postauction responses (1 = disagree, 9 = agree) to identical three-item thrill and prudence measures used in the pretests confirmed that the two priming articles were again seen as different in emphasis.[3] The thrill-primed article scored 6.21 (4.91), in contrast with the prudence-primed article, which scored 4.66 (7.16) on the thrill (prudence) measures, respectively (all relevant differences significant at $p < 0.001$). These data are consistent with the interpretation that the observed bid differences may have been driven by primed mind-sets below the threshold of awareness and were not a conscious response to the themes of the priming articles.

3.2.2. Wait Time. The $Goal \times WT$ interaction (H1) was significant ($\chi^2 = 20.76$, $p < 0.001$). As predicted, the goal effect was not significant for bidders with short wait times ($M_{thrill} = 27.60$, $M_{prudence} = 27.24$; $z = 1.12$, $p > 0.25$). Among bidders with long wait times, those primed with thrill (versus prudence) bid higher ($M_{thrill} = 29.39$, $M_{prudence} = 27.73$; $z = 2.86$, $p < 0.005$).[4] The WT main effect was significant but qualified by the above interaction. The WT main effect showed that bidders with long (versus short) wait times bid higher ($\chi^2 = 76.13, p < 0.001$; $M_{long} = 28.55$, $M_{short} = 27.42$).

Self-reports suggest that the long wait time did not induce more anxiety ($M_{long} = 5.91$, $M_{short} = 6.20$; $p > 0.10$). Yet those with long (versus short) wait times rated the auction as less exciting ($M_{long} = 5.50$, $M_{short} = 5.98$; $F(1, 334) = 4.68$, $p < 0.05$) and felt that the asking price changed too slowly ($M_{long} = 6.96$, $M_{short} = 4.78$; $F(1, 334) = 75.90$, $p < 0.0001$). This is surprising because the wait times were only a few seconds at each price step. Apparently, bidders with long (versus short) waits became impatient or bored and bid earlier (higher) to end the auction.

3.2.3. Value Precision. The goal effect was also moderated by the price range information. Goal had no effect on bids for bidders with a narrow price range ($M_{thrill} = 28.67$, $M_{prudence} = 28.17$; $z = 0.81$, $p > 0.40$). However, for bidders with a wide price range, thrill (versus prudence)-primed bidders bid higher ($M_{thrill} = 28.19$, $M_{prudence} = 26.78$; $z = 2.78$, $p < 0.01$). Thus, the predicted $Goal \times PR$ interaction (H2) was significant ($\chi^2 = 6.34$, $p < 0.05$). As expected, the goal effect was attenuated for bidders with more precise values. The main effect of price range was significant but qualified by the above interaction. Bidders with a narrow (versus wide) price range bid higher ($M_{narrow} = 28.42$, $M_{wide} = 27.48$; $\chi^2 = 3.96$, $p < 0.05$). The latter (whose value estimates were less precise) reported greater anxiety ($M_{narrow} = 5.75$, $M_{wide} = 6.39$; $F(1, 334) = 6.44$, $p < 0.05$) and may have been more hesitant to bid.

3.2.4. Value Salience. Premeasurement of bidders' values attenuated the goal effect on bids. The significant $Goal \times PM$ interaction shows that, consistent with H3, values made more salient and accessible during the auction impacted the goal effect ($\chi^2 = 48.56$, $p < 0.001$). Among bidders who did not report preauction values, bidders primed with thrill (versus prudence) bid higher ($M_{thrill} = 28.11$, $M_{prudence} = 25.77$; $z = 4.37$, $p < 0.001$). In contrast, the goal effect was not significant for bidders who reported preauction values ($M_{thrill} = 28.79$, $M_{prudence} = 29.14$; $z = 0.91$, $p > 0.30$). The value salience factor also had the anticipated main effect. Bidders who had reported preauction values bid higher than those who did not report preauction values ($\chi^2 = 155.68$, $p < 0.001$; $M_{present} = 28.97$, $M_{absent} = 26.98$). Indeed, initial values made salient by premeasurement were not as labile as values that were not premeasured.

Other significant two-way and higher-order interactions involving premeasurement show a systematic pattern in which salient (premeasured) values attenuated the effects of wait time and price range, more so for prudence (versus thrill)-primed bidders. Detailed results for these effects are available from the authors upon request.

3.3. Discussion

The results show that in the descending auction, bidders primed with thrill bid higher than those primed with prudence. Related self-report data suggest that this goal-priming effect may have worked below the subjective awareness threshold. Moreover, goal effects were attenuated for bidders with short (versus

[3] These measures, collected after the auction, may be interpreted as manipulation checks, keeping in mind that they could have been influenced by auction events and outcomes.

[4] As the data are not normally distributed, the z-scores and p-values for contrasts within an interaction are from nonparametric Wilcoxon two-sample tests on estimated bids in the respective cells (SAS NPAR1WAY procedure).

long) wait times. Even with wait times of just a few seconds, longer waits seem to have induced boredom or impatience that drove the observed goal effect. Even as they succumbed to boredom and bid earlier (and higher), thrill-primed bidders achieved a goal-consistent outcome. In contrast, prudence-primed bidders were unaffected by the wait time as an early high bid was inconsistent with their mind-set. Thus, motivational differences influenced bidder behavior and elicited different responses to situational factors.

Value precision and value salience affected bids in similar ways. Bids were higher with more precise values, suggesting that a more precise initial value estimate attenuated the influence of other bidders' inaction. Furthermore, with more precise values, the goal effect was not significant. But with less precise values, bidders with the prudence (versus thrill) prime bid lower. These bidders also reported greater anxiety, suggesting hesitance to bid. Value salience also had a sensitizing effect on bids. Bids were higher with premeasured values, implying that a more accessible initial value reduced the influence of others' inaction during the descending auction. Premeasurement also moderated the goal effect. When values were not salient, bidders with the prudence (versus thrill) prime bid significantly lower, but the effect was eliminated when values were salient. Thus, both cognitive factors moderated the motivational effect of thrill versus prudence goals.

Overall, these results are consistent with our hypotheses regarding the effects of the focal factors on bid levels in descending auctions. They show that bid levels are systematically affected by motivational (goals), cognitive (value precision and value salience), and situational (wait time) factors. We now examine these hypotheses for an ascending auction.

4. The Ascending Auction Study

4.1. Procedure

The ascending auction study manipulated the same motivational (bidder goals), cognitive (value precision and value salience), and situational (wait time) factors. We examined the main and interactive effects of these factors on bid values and also explored how the latter three factors moderate the goal effect. As with the descending auction, we also anticipated and tested for the main effects and other higher-order interactions, but we do not discuss them here due to space constraints. Except for the wait time levels, all other factors in this study were manipulated exactly as in the descending auction study. Pretests showed that focal bidders in the ascending auction needed more housekeeping time to bid at *each* bid level because the auction events were more complex (i.e., bids/exits of up to six bots at each level). Hence, based on pretests, the short (long) wait time for the ascending auction was set at 5 (10) seconds. This matched the subjective perceptions of wait time in the ascending and descending auctions.

The data for the ascending auction are from 305 undergraduates who participated for course credit and a chance to win one of the auctioned products and/or extra money. We used the same priming articles, auction items, and a similar sequence of computer-administered procedures for the PM (present/absent) and goal (prudence/thrill prime) manipulations (see Appendices A and B). The payoff instructions were also identical to those in the descending auction (see Appendix B, panel 1). Guided by the same logic, they share the same advantages and limitations. Two example auctions using the same unrelated products as the descending auctions familiarized participants with the interface. In the real auctions, participants selected an auction item from the set of three options (see Appendix B, panel 2). Next, we administered the PR manipulation (narrow versus wide; see Table C.1 in Appendix C) between participants.

Bidders participated in a computer-based auction with six other bot bidders via a Web interface (see Appendix D, panel 2). Bidding started at a low price, and the bid level rose in fixed 50-cent steps, with the WT manipulated between participants to be short or long (5 or 10 seconds, respectively). The fixed increments avoided "jump bids" and controlled for extraneous influences on wait times and signals of bidder aggressiveness. Bidders who did not bid at a bid level exited the auction irrevocably. The bot bidders dropped out at preset *high* or *low* bid levels (identical to those in the descending auction; see Table C.3 in Appendix C). A focal bidder who remained after the highest bot bidder's exit won the auction and paid the price at which the bot dropped out. If the focal bidder's exit preceded the bots, the auction continued as preset with the last remaining bot declared as winner. This simulated online ascending auction with programmed bots provided the same auction environment, on average, for all participants. After the auction, participants answered questions on manipulation checks, demographics, auction experience, and susceptibility to interpersonal influence (SII). They worked at their own pace and could leave after completing the debriefing questionnaire. The ascending auction study took 30 minutes on average.

4.2. Ascending Auction: Analyses and Results

Table 2 shows the proportion of focal bidder wins as well as the mean (estimated) highest focal bidder bid by study condition for the ascending auction. The ascending auction records the full sequence of bids. Thus data are available for the *highest bid* from each focal bidder. For a losing focal bidder, her highest bid is her exit level. For a winning focal bidder, the highest value to which the focal bidder was willing to bid is unobserved. Hence, the bid level at which no other (bot) bidder remained is the censoring level (right censored) for the bid distribution of winning focal bidders. Thus, for losing focal bidders, the highest bid is used as an uncensored observation. For winning focal bidders, the dropout level of the highest bot bidder is used as the right-censored observation. The SAS PROC LIFEREG procedure (SAS 1999, SAS Online Documentation 2003) was used for the analysis (see Appendix F).

We now report the results for the hypotheses regarding the focal bidder's *bid levels* in the ascending auction. Appendix F shows the effects associated with each formal hypothesis from a full model that includes all main effects and higher-order interactions of the focal manipulations (goal, WT, PR, and PM), as well as the selected set of covariates. The inferred value covariate, which controls for item price differences as well as different levels of bot bids, had a significant impact on the bid level ($\chi^2 = 8.39$, $p < 0.005$). The focal bidder's bid level was also affected by auction experience ($\chi^2 = 4.61$, $p < 0.05$) and SII ($\chi^2 = 6.06$, $p < 0.05$). As before, the hypotheses are tested based on the estimated mean bids (see Table 2) computed from the model in Appendix F.

4.2.1. Primed Goal. Bidders with the thrill prime bid higher than those with the prudence prime ($M_{\text{thrill}} = 25.77$, $M_{\text{prudence}} = 24.48$; $\chi^2 = 43.22$, $p < 0.001$) as predicted in H0. This intuitive result gains significance in light of participants' responses to two questions regarding their during-auction mind-set. There were no significant differences between bidders with thrill (versus prudence) primes in responses (1 = disagree, 9 = agree) to the items "I really wanted to win the auction" ($M_{\text{thrill}} = 6.35$, $M_{\text{prudence}} = 6.46$; $p > 0.70$) and "I did not want to pay too much for the product" ($M_{\text{thrill}} = 7.35$, $M_{\text{prudence}} = 7.67$; $p > 0.10$).

Although the priming articles were in the auction domain and pretested as different in judged emphasis on thrill and prudence, explicitly stated goals did not differ for bidders primed with thrill versus prudence. Postauction responses (1 = disagree, 9 = agree) to the thrill and prudence measures confirmed the different emphasis of the two priming articles. The thrill-primed article scored 5.88 (4.14) on the thrill (prudence) measures. In contrast, the prudence-primed article scored 4.27 (7.08) on the thrill (prudence) measures (relevant differences were significant at $p < 0.001$). Hence, these ascending auction data (as for the descending auction) suggest that the bid differences stemmed from primed mind-sets below the awareness threshold and were not conscious responses to the priming articles.

4.2.2. Wait Time. Consistent with H1, the *Goal* × *WT* interaction was significant ($\chi^2 = 11.87$, $p < 0.001$). Among bidders with long wait times, those with a thrill prime bid higher than those with a prudence prime, as predicted ($M_{\text{thrill}} = 25.71$, $M_{\text{prudence}} = 23.68$;

Table 2 Ascending Auction (Experiment 2) Focal Bidders' Win Percentage and Mean (Estimated) Highest Bid

			Thrill prime		Prudence prime		Marginal means				
			WT		WT		Prime		WT		
PM	PR	Outcome[a]	Long	Short	Long	Short	Thrill	Prudence	Long	Short	Pooled
PM present	Narrow	%	48	70	40	71	59	56	44	70	58
		E$	25.07	25.76	24.91	24.55	25.41	24.72	25.00	25.21	25.11
	Wide	%	63	56	50	33	59	41	57	44	50
		E$	25.69	25.46	24.70	25.31	25.58	25.02	25.21	25.38	25.30
PM absent	Narrow	%	73	75	50	75	74	63	62	75	68
		E$	26.17	25.69	23.95	25.67	25.97	24.81	25.11	25.68	25.38
	Wide	%	53	74	38	50	64	44	46	63	55
		E$	25.89	26.27	21.06	25.11	26.10	23.31	23.68	25.73	24.81
Marginal means	PM present	%	55	63	45	50	59	48	51	57	54
		E$	25.36	25.62	24.79	24.97	25.49	24.89	25.11	25.30	25.20
	PM absent	%	63	74	44	63	69	54	55	68	62
		E$	26.04	26.03	22.66	25.39	26.04	24.10	24.46	25.71	25.09
	PR narrow	%	60	72	46	73	66	60	54	73	63
		E$	25.63	25.73	24.36	25.16	25.68	24.77	25.06	25.44	25.24
	PR wide	%	58	66	44	41	62	43	51	54	53
		E$	25.79	25.92	22.98	25.21	25.86	24.20	24.47	25.56	25.05
	Pooled	%	59	69	45	56	64	51	53	63	58
		E$	25.71	25.83	23.68	25.18	25.77	24.48	24.78	25.51	25.15

[a]The upper number (%) is the percentage of focal bidders who won in that condition. The lower number (E$) is the mean *estimated* focal bidder's *highest* bid in that condition, from the model in Appendix F.

$z = 6.75$, $p < 0.0001$). Bidders with short wait times showed a smaller but significant goal effect ($M_{\text{thrill}} = 25.83$, $M_{\text{prudence}} = 25.18$; $z = 3.46$, $p = 0.001$). Thus, prudence (versus thrill)-primed bidders were more conservative when provided longer (versus shorter) wait times. Although qualified by the above interaction, the WT main effect was significant. Longer wait times elicited lower bids ($M_{\text{long}} = 24.78$, $M_{\text{short}} = 25.51$; $\chi^2 = 19.43$, $p < 0.001$).

Participants with long (versus short) wait times agreed more with the statement that the bid level "was changing too slowly" ($M_{\text{long}} = 7.63$, $M_{\text{short}} = 6.44$; $F(1, 301) = 20.70$, $p < 0.0001$). Moreover, self-reported anxiety and excitement with the auction decreased with long versus short wait times. This was true for both prudence-primed bidders (anxiety: $M_{\text{long}} = 3.94$, $M_{\text{short}} = 4.77$, $F(1, 301) = 4.42$, $p < 0.05$; excitement: $M_{\text{long}} = 3.86$, $M_{\text{short}} = 4.92$, $F(1, 301) = 7.88$, $p < 0.01$) and thrill-primed bidders (anxiety: $M_{\text{long}} = 3.68$, $M_{\text{short}} = 4.47$, $F(1, 301) = 4.33$, $p < 0.05$; excitement: $M_{\text{long}} = 3.26$, $M_{\text{short}} = 5.09$, $F(1, 301) = 24.98$, $p < 0.0001$). Thus, in the ascending auction, long wait times induced boredom or impatience for both prudence-primed and thrill-primed bidders. However, as one would expect, only the former (not the latter) made earlier exits (bid lower).

4.2.3. Value Precision. As predicted in H2, the *Goal* × *PR* interaction was significant ($\chi^2 = 7.10$, $p < 0.01$). Bidders with more (versus less) precise values were not as susceptible to goal effects. Thus, the goal effect was attenuated (but significant) for bidders with a narrow price range ($M_{\text{thrill}} = 25.68$, $M_{\text{prudence}} = 24.77$; $z = 4.83$, $p < 0.001$) relative to those with a wide price range ($M_{\text{thrill}} = 25.86$, $M_{\text{prudence}} = 24.20$; $z = 5.17$, $p < 0.001$). However, contrary to expectations, bidders with a narrow (versus wide) price range bid higher ($\chi^2 = 14.34$, $p < 0.001$; $M_{\text{narrow}} = 25.24$, $M_{\text{wide}} = 25.05$). This main effect of the PR manipulation is inconsistent with the idea that more precise values are less labile. We discuss a likely reason for this pattern of results in §4.3.

4.2.4. Value Salience. The main effect of value salience was not significant in the ascending auction ($\chi^2 = 0.15$, $p > 0.60$). However, there was a significant *Goal* × *PM* interaction ($\chi^2 = 11.55$, $p < 0.001$), as predicted in H3. For bidders who did not report a preauction value (PM absent), bids were higher for those primed with thrill versus prudence ($M_{\text{thrill}} = 26.04$, $M_{\text{prudence}} = 24.10$; $z = 6.62$, $p < 0.001$). With PM present (i.e., bidders reported a preauction value), the goal effect was attenuated but still significant ($M_{\text{thrill}} = 25.49$, $M_{\text{prudence}} = 24.89$; $z = 2.98$, $p < 0.01$).

Other significant higher-order interactions involving the premeasurement factor show a fairly systematic and consistent pattern. Salient values (PM present) attenuated the effects of wait time and value precision for the prudence-primed bidders but not for the thrill-primed bidders. Detailed results are available from the authors upon request.

4.3. Discussion

The ascending auction results show that bidders primed with thrill bid higher than those primed with prudence. The self-reported data suggest that the effects may be attributable to primed mind-sets below the threshold of subjective awareness. Wait time moderated the goal effect such that prudence-primed bidders bid even more conservatively when wait time was long. Longer wait times induced boredom or impatience among bidders regardless of whether they were primed with prudence or thrill. However, only the bidders primed with prudence made earlier exits (i.e., at lower bid levels). As expected, the thrill-primed bidders stayed longer in the auction (to higher bid levels). Note that for these bidders, an exit generates an irrevocable, goal-incongruent loss.

The unexpected value precision main effect (i.e., those with a narrow (versus wide) price range bid higher) bears discussion. Note that the ascending auction starts at a low bid level that increases sequentially. Some bidders who were uncertain about their value may have used the provided price range to create relevant reference points to compare their bids (see Chapman and Johnson 2002). As the initial value is adjusted upward, the supplied lower bound of the mean-centered price range provides a conservative reference point for explicit comparison (Dholakia and Simonson 2005). For bidders with a narrow (versus wide) price range, this lower bound is a higher number and may elicit higher bids if it is used as an anchor or reference point. This effect may also underlie a few discrepant orderings of mean bid levels and win proportions in Table 2. Notwithstanding this unexpected main effect of price range, both value precision and value salience moderated the goal effect in the ascending auction, attenuating it as predicted.

In summary, the ascending auction results also show that the motivational factor (primed thrill or prudence goal) significantly influenced bidder behavior and induced different responses to a situational factor (long/short wait times). The motivational effect was also moderated by both cognitive factors (value precision and value salience). These findings provide compelling evidence that bids are influenced by a variety of psychological and situational factors in an ascending auction. However, the processes that underlie these influences are different and produce different consequences for ascending and descending auctions.

5. General Discussion

The auction formats emerging on the Internet offer intriguing contexts in which researchers may examine how consumers participate in price formation processes versus reacting to sellers' posted prices (Chakravarti et al. 2002, Chandran and Morwitz 2005). The descending and ascending auctions differed not only in process but also the information observable during the auction. Bidders in the descending auction saw no bids from other bidders except the auction ending bid. However, those in the ascending auction observed the bids and the public and irrevocable exits for all bidders. There were operational differences in the wait time durations across the auctions. Although the two auctions used similar participant pools and similar procedures, they were conducted separately, and no subject participated in both studies.

5.1. Ramifications of the Payoff Structure

The payoff structure used in these auctions was discussed in §3.1. As noted, our aim was not to examine optimal bids or formally compare the efficiency of the auction mechanisms. However, we now examine the actual bids in order to assess how the payoff structure may have impacted our empirical results. By design, we started the descending auctions for each product at a price below \$45 (but \$1 above the upper bound of the wide price range). Had participants used a heuristic (see footnote 2) in which they were indifferent between winning and losing, the auctions should have ended quickly at prices close to the starting value. Yet for all products, even the *maximum* bid was at or below the upper bound of the wide price range.

As shown in Table G.1 in Appendix G, the median winning bids in the high (low) bot bid condition were calligraphy at \$30.00 (\$28.00), a glass bowl at \$25.50 (\$20.50), and bookends at \$24.50 (\$22.00). Moreover, there was a significant number of losing bidders (24%, 23%, and 25%) even when bots were set to bid low (\$20.50, \$16.50, and \$15.50 for the calligraphy, glass bowl, and bookends, respectively). These bids were even below the items' retail prices (\$24.00, \$19.50, and \$18.00, respectively; see Table C.1 in Appendix C). The payoff structure did not induce artificially high bids from the vast majority of descending auction participants.

For the ascending auction, the participant bids were bounded above by the preset bot bid, and we do not observe how much higher the winners would have been willing to bid. However, even when allowed to bid high (\$27.50, \$22.50, and \$20.50 for the calligraphy, glass bowl, and bookends, respectively), as many as 55%, 50%, and 39%, respectively, of the participants chose to exit at a lower price and lost the auction (see Table G.2 in Appendix G). Many of these bidders were unwilling to bid even the market price of the products. Overall, the data show no particular reason to suspect that the payoff structure had aberrant effects or impacted the study conditions differently. Histograms of actual winning bids by condition are available from the authors upon request.

5.2. Comparing Descending and Ascending Auctions

5.2.1. Average Bids. We first compare the average bids in the two studies. The bot bidders were preset to follow identical bid patterns in both auctions, and as intended, the overall proportions of focal bidders who won the descending and ascending auction were virtually identical (57% and 58%, respectively). Yet the average prices paid by winning focal bidders in the descending and ascending auction were different ($M_{\text{descending}} = \$25.10$, $M_{\text{ascending}} = \$20.44$; $F(1, 361) = 445.44$, $p < 0.0001$). The difference was observed both for thrill-primed bidders ($M_{\text{descending}} = \$25.38$, $M_{\text{ascending}} = \$20.67$; $F(1, 361) = 267.32$, $p < 0.0001$) and for prudence-primed bidders ($M_{\text{descending}} = \$24.77$, $M_{\text{ascending}} = \$20.14$; $F(1, 361) = 189.61$, $p < 0.0001$). The auction type $\times$ goal interaction was not significant ($F(1, 361) = 0.38$, $p > 0.50$).

Two study features must be kept in mind to make a fair comparison of average bids across the auction formats. First, in both studies, the price ranges were mean-centered, but were either wide or narrow. This can influence the values placed on the items and (hence) the choice of bidding strategy. Recall that the bids were left (right) censored for the descending (ascending) auction, and values were estimated using distribution assumptions. Second, bots were preset to bid high or low in each auction. When the bots were preset to bid high in the descending auction, the bid range available to focal bidders was restricted to higher values. Similarly, when the bots were preset to bid low in the ascending auction, the bid range for focal bidders was restricted to lower values. However, when the bots were preset to bid low (high) in the descending (ascending) auction, bidders could explore a broader range of bids, comparable across the two auction formats. Thus, the two auction formats may be meaningfully compared by contrasting average bids in the low bot bid conditions for the descending auction with those in the high bot bid conditions in the ascending auction, by narrow/wide price range.

Table 3 shows the six possible comparisons of the estimated mean bids (narrow and wide price range for the three products) assuming an extreme value distribution. These mean bids did not differ significantly across the two auctions for bookends (both wide and narrow PR) and the glass bowl (narrow PR condition). For the calligraphy item, the descending auction elicited higher estimated mean bids (both wide and narrow PR). The mean bid is higher in the ascending (versus descending) auction only for the

Table 3 Estimated Mean Bids (Descending and Ascending Auction) by Product, Price Range, and Bot Bid Level

Price range and auction condition	Products		
	Calligraphy	Glass bowl	Bookends
Narrow price range			
Ascending (high bot bid)	22.43	20.97	20.07
Descending (low bot bid)	26.36	21.28	19.91
Ascending − Descending	−3.93	−0.31	0.16
p-Value (two-tailed)	0.000	0.575	0.776
Wide price range			
Ascending (high bot bid)	22.01	22.48	20.55
Descending (low bot bid)	26.35	19.05	20.78
Ascending − Descending	−4.33	3.43	−0.22
p-Value (two-tailed)	0.000	0.007	0.850

glass bowl (wide PR condition). An analysis using estimated mean bids based on a uniform distribution shows parallel results.

Our controlled studies with real products used the Japanese variant for the ascending auction format. Although our payoff structure was not designed to elicit optimal bids, we note informally that our ascending (versus descending) auction bids were rarely higher (cf. the equilibrium bid order predicted by Milgrom and Weber 1982). However, our results parallel those of some Internet auction studies that used fewer informational controls and far slower clock times (Lucking-Reiley 1999). The sudden death property of the descending auction along with the aesthetic product set is a clue. It is suggestive that bids on the calligraphy item (perhaps evaluated most subjectively of the three products) are least consistent with theory. Perhaps the AV assumption that underlies the prediction did not hold well for this hedonic product. This conjecture matches the logic guiding exemplars that are used to illustrate IPV, CV, and AV situations in the auctions literature and deserves further study.

5.2.2. Motivational Effects and Wait Time. Motivational factors played a strong role in both auctions and elicited higher bids from thrill (versus prudence)-primed participants. However, these goal effects were moderated differently by situational and cognitive factors across the two auction formats. The WT results are particularly intriguing. In the descending auction, thrill-primed bidders with long (versus short) wait times bid higher ($M_{\text{long}} = 29.39$, $M_{\text{short}} = 27.60$; $z = 3.68$, $p < 0.001$), but bids from prudence-primed bidders did not differ ($M_{\text{long}} = 27.73$, $M_{\text{short}} = 27.24$; $z = 0.94$, $p > 0.30$). In the ascending auction, thrill-primed bidders were unaffected by WT ($M_{\text{long}} = 25.71$, $M_{\text{short}} = 25.83$; $z = 0.70$, $p > 0.40$), whereas prudence-primed bidders with long (versus short) wait times bid lower ($M_{\text{long}} = 23.68$, $M_{\text{short}} = 25.18$; $z = -5.37$, $p < 0.001$).

Participants were involved with the auctions ($1 =$ disagree, $9 =$ agree; $M_{\text{descending}} = 6.65$, $M_{\text{ascending}} = 6.32$). However, boredom/impatience resulting from longer wait times (even a few seconds at a price step) led participants to different decisions in the two auction formats, contingent on their goal. Unmet goals strengthen with time. In a descending auction, the thrill-primed bidder, more prone to act when bored or impatient, ends the auction by bidding early (high). The resulting win provides both thrill and a goal-congruent outcome. In an ascending auction, the thrill-primed bidder is less prone to act when bored or impatient because an early exit implies an irrevocable and goal-incongruent loss. Prudence-primed bidders (unaffected by wait time in the descending auction) bid lower in the ascending auction because a loss may be justified by prudence.

How would bidders behave if wait times are very small in each auction format? The descending auction results suggest that very small wait times may elicit lower bids because participants either remain engaged or have little time to react. However, very small wait times may induce anxiety and drive earlier (higher) bids. In ascending auctions, very small wait times restrict opportunity to consider auction events and revise values. The focal bidder may simply ignore auction events and bid up to her own a priori value, attenuating salience (and goal) effects. However, extreme time pressure can induce superficial inferences based on the most salient auction events. If stay-ins are salient, bidders may infer higher competitive valuations and revise value upward. Salient early competitive dropouts may drive down value. Our results imply that the propensity to act on such information may be contingent on bidder goals.

5.2.3. Effects of Cognitive Factors. The main effects of value precision were expected to differ between descending and ascending auctions. In the descending auction (falling bid level), bidders with a narrow (more precise) price range bid higher than those with a wide (less precise) price range. The ascending auction (rising bid level) showed an unexpected similar result, perhaps attributable to the use of the lower bound of the provided price range as a reference anchor. In both formats, the goal effect is stronger for bidders with less (versus more) precise values. Also, value salience induced by preauction measurement affected bid levels in the descending auction but not the ascending auction. The ascending format provides progressively more and richer information on other bidders' values. This may have attenuated the main effect of value salience. However, salient values attenuated the goal effect in both auction formats, as predicted.

5.2.4. Goal Primes and Risk Attitudes. We find that thrill and prudence goals are important and contrasting regulators of bidding behavior. At first glance, thrill (prudence) resembles risk seeking (aversion), suggesting very similar effects on bidding.

Indeed, risk aversion provides better fits to empirical bidding data (Goeree and Holt 2002) relative to some formulations of the "joy of winning" concept (Cox et al. 1992). We argue conceptually that thrill and prudence are motivationally rooted experiential goals that can drive bidding, irrespective of risk attitude.[5]

Our empirical results strengthen the argument that the thrill (prudence) constructs are distinct from risk seeking (aversion). The auctions literature (Klemperer 1999, p. 234) predicts that in descending auctions, risk aversion should elicit higher bids (relative to risk neutral bidders), whereas in ascending auctions, bids should reflect value and be unaffected by risk aversion. Prior empirical results on first-price auctions (here the descending auction) produce higher bids—a result consistent with risk aversion (Cox et al. 1988). Thus, if thrill (prudence) motivations map to risk seeking (aversion), auction theory predicts higher bids in the prudence (versus thrill) condition in the descending auction and no difference in the ascending auction. In contrast, we find that, on average, bids are *higher* in the thrill (versus prudence) condition for *both* descending and ascending auctions. Thus, despite a superficial resemblance, thrill (prudence) differs conceptually from risk seeking (aversion), and our empirical results on thrill–prudence effects cannot be explained based on risk attitudes.

5.3. Analytical Extensions

This paper addressed the behavioral impact of priming thrill and prudence goals on bidding in descending and ascending auctions and explored how this core motivational effect was moderated by factors such as wait times, value precision, and value salience. The supplementary appendix (at http://dx.doi.org/10.1287/mksc.1120.0730) builds on the core finding regarding the goal prime effects. We derive propositions exploring the equilibrium impact (under IPV) of thrill and prudence goals on the bidder's expected surplus, the number of participating bidders, and the seller's expected revenue. The propositions are similar for ascending and descending actions and are qualitatively summarized below.

Proposition 1. *Incorporating thrill value produces, in equilibrium,* (i) *an increase in bidder's expected surplus,* (ii) *an increase in the number of participating bidders,* (iii) *higher seller expected revenue, and thus* (iv) *Pareto dominance.*

Proposition 2. *Incorporating prudence value, in equilibrium, produces* (i) *an increase in bidder's expected surplus,* (ii) *an increase in the number of participating bidders,* (iii) *no change in seller expected revenue, and thus* (iv) *weak Pareto dominance.*

These propositions provide a roadmap for studies of the equilibrium impact of behavioral variables traditionally not discussed in the auctions literature. Together, they imply that when bidders seek the thrill of winning, the seller's expected revenue always increases along with the bidder's expected surplus, yielding a Pareto-dominant outcome. However, with prudent bidders, only the bidder's expected surplus increases, but not the seller's expected revenue, i.e., a case of weak Pareto dominance. Thus, it may be in the seller's interest to encourage bidders to seek the thrill of winning when participating in an auction. However, notwithstanding Pareto dominance, such actions may invite regulatory scrutiny. Managerially, though, it is significant that a multimedia ad campaign from a leading Internet auctioneer overtly emphasized the exhilaration of winning and urged buyers to "shop victoriously."

5.4. Auction Design Implications

These results convey several managerial insights. Although we cannot draw formal comparisons to equilibrium bids, the observed revenue orderings relative to theoretical predictions may guide real-world auctioneers in auction format choices. The motivational and cognitive profiles of auction participants carry useful information for auction design. Knowing *why* bidders are participating and *what* bidders know about market prices for focal items allows auctioneers to anticipate bidder responses to design parameters such as wait times (clock speeds) and exit rules. For example, our results suggest that shorter (longer) wait times in ascending (descending) auctions may produce higher average bids (see Cassady 1967) and that narrower (versus wider) price ranges raise average revenue in both auc-

[5] To see this, consider the traditional definitions of risk seeking, risk neutrality, and risk aversion as the willingness to pay an amount more than, equal to, or less than, respectively, the expected value E of a gamble. Let S ($S > E$) be the calibrated amount that a risk seeker is willing to pay (value) for a given risky gamble with expected value E. All else equal, if this risk seeker is motivated by prudence (without a qualitative change in risk attitude), she would be willing to pay only an amount in the interval $(E, S]$ to acquire a product of expected value E in the auction. However, if the risk seeker is motivated to experience thrill, she would be willing to pay an amount greater than S to win the same product. The risk-seeking orientation is preserved in each case. Similarly, let A ($A < E$) be the calibrated amount that a risk-averse person is willing to pay (value) for the risky gamble with expected value E. All else equal, if this risk-averse person is motivated by prudence, she would be willing to pay only an amount less than or equal to A to win a product of expected value E in the auction. However, if the risk-averse person is motivated to experience thrill (without changing risk attitude), she would be willing to pay an amount in the interval (A, E) to win the same product. Risk aversion is preserved in each case. Thus, despite a superficial resemblance, thrill (prudence) and risk seeking (aversion) are essentially different constructs that can move independently of each other. Moreover, the literature on risk orientation is generally silent on the emotional and experiential aspects that are embedded in our conceptualization of thrill and prudence.

tion formats. Auctioneers (and regulators) can also alter value salience by providing bidders with appropriate instructions and memory cues.

Our results show that bidders are less susceptible to motivational or situational influences when they explicitly state a price prior to the auction. Primers on bidding strategies in ascending auctions often suggest that bidders pick a reservation price (highest willingness to pay) for the item *and write it down* before entering the auction. Auction houses may also provide options that raise value salience (e.g., eBay invites bidders to enter their highest bid into a "bid manager" program that bids on their behalf). Such mechanisms lower monitoring costs (see Roth and Ockenfels 2002) and may mitigate motivational and situational influences.

6. Future Research Directions

Several features of our studies and the results suggest new research directions. First, our participants knew that competing bidders were just bots simulating other bidders. Recent research (e.g., McCabe et al. 2001) shows that bidding against human (versus computer-simulated) opponents differs because of various emotional and cognitive influences. Additional research on bidding behavior in face-to-face and computer-mediated situations and with real and simulated opponents will add both substantive and methodological value.

Second, research is needed on how informational differences and bidder sociology (perceived affiliation of values) affects bids and realized prices across auction formats. Contexts in which bidders take cues from social identity (e.g., other bidders' status/expertise) are of significant interest. Also, gaps between willingness to accept and pay could vary based on whether consumers perceive the auction as a sociocultural process for setting an item's consensual worth (Smith 1993).

Third, we used modestly priced ($10 to $30) and common items that participants found reasonably attractive. Many products sold in real (online and brick-and-mortar) auctions are more expensive or unique. Laboratory studies can reveal how consumers process information in various auction formats when the target item has special meaning that raises involvement and emotion (see List and Lucking-Reiley 2002).

Fourth, the public and irrevocable exit in the Japanese (ascending) auction allows inferences regarding bidder actions. However, with revocable exits, bidder values cannot be inferred cleanly from behavior at a given bid level. Also, the number of bidders in the auction at any stage remains unknown. Jump bids (Sinha and Greenleaf 2000) in these formats may prompt inferences about opponent competitiveness and influence how bidder values and bid strategy evolve. Our results provide a benchmark for studies examining bidding behavior in such ascending auction formats.

Finally, our studies focus on single auctions and do not address context and carryover effects (e.g., of product order and relatedness) that may occur in a sequence of auctions (Elmaghraby 2003). We control for prior auction experience and do not address the evolution of bidder understanding of own and others' bidding strategy. The extent to which experience in a given auction format transfers to other formats is relevant and important, given the many formats available on the Internet.

In summary, the research reported here provides an organizing framework for empirical studies of motivational, cognitive, and situational influences on bidding behavior and associated price formation processes in auctions. Marketers must consider these effects in using laboratory experimental auctions as part of a market research toolkit for assessing consumer willingness to pay for real products (Hoffman et al. 1993, Lusk and Shogren 2007). We need more research on consumer behavior in dynamic decision making contexts with structured information in order to realize this potential.

Electronic Companion

An electronic companion to this paper is available as part of the online version at http://dx.doi.org/10.1287/mksc.1120.0730.

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Appendix A. Articles Used to Prime Consumer Goals (adapted from Gutner 2000)[6]

Thrill Prime

Going, Going, Gone . . . You Win!

Businessweek Online: *January* 20, 2002

Robbin Sinclair used to sell collectibles at flea markets to help pay her college tuition. But she no longer wastes weekends sitting at a booth while she waits for buyers to plunk down their money. Sinclair, a 43-year old student from Casper, Wyo., has set up shop on eBay, the largest online auction site. Recently she pocketed $175 for a pair of 1950s vintage curtains with fluttering pink leaves that she couldn't give away at the flea market. eBay allows her to reach far more people and make more money than she did at any flea market.

Since their first appearance in 1995, Internet auctions have become one of the hottest phenomena on the web.

[6] Used with permission of Bloomberg L.P.

They offer buyers a "virtual flea market" with an endless range of merchandise from around the world—and they give sellers a "storefront" from which to market everything from sports memorabilia to computer systems to millions of international buyers. In this age of e-commerce overdo, online auctions are the ideal way to match buyers and sellers—fast, frictionless and perfectly fair. The public has certainly bought that message: online auction sites such as eBay, Yahoo!Auctions, and uBid.com are just a few websites that are thriving in the current economy in spite of the economic downturn. A recent study by Harris Interactive found that 35 million Americans, or 31% of the U.S. online population, participate in online auctions. Jupiter Research predicts that consumer-to-consumer online auction sales will exceed $15 billion in 2004.

Internet Auctions provide sellers and buyers a forum—and a community. eBay, for example, has 38 million buyers and sellers who trade on its site. These consumers participate in thousands of bulletin boards, chat rooms and email conversations about their collecting passions and interests. They have catapulted the website, in three short years, from a funky little online garage sale full of Beanie Babies and attic trash into a global marketplace for almost anything from a $1 baseball card to a $4.9 million Gulfstream jet. eBay's customers crowd the online discussion boards, posting 100,000 messages a week to share tips, point out glitches, and lobby for changes. eBay's customers even police the site by rating each other, keeping fraud minimal.

"The rush of winning the auction is what keeps bringing me back," says Jeff Schade, a 24-year old entrepreneur. "Staying up nights, competing with the other bidders, winning at the last minute—it sure beats shopping at a department store." Winning in online auctions is a thrill that's absent in shopping at brick-and-mortar stores. Bidders compete against other live bidders for something they really want. This thrill is multiplied manifold when the bidder wins the auction. If you don't want to compete, however, there is a way out. eBay allows the seller to specify a "Buy it Now" price—one at which you can buy the product right away, short-circuiting the auction. This is not a route that frequent bidders on eBay will take. "Buying it Now—now that's wimping out, if you ask me!" says one message poster on AuctionWatch.com's site. The hunt for the product and the joy of the win is a passion shared by most online auction participants.

Auction sites continue to thrive and their members grow in the current economic scenario, irrespective of the recent downturn. This is not in small part thanks to their loyal members and the thrill that auctions provide to the victorious bidder.

George Harris in New York

Prudence Prime

Going, Going, Gone . . . Sucker!

Businessweek Online: *January* 20, 2002

Robbin Sinclair used to sell collectibles at flea markets to help pay her college tuition. But she no longer wastes weekends sitting at a booth while she waits for buyers to plunk down their money. Sinclair, a 43-year old student from Casper, Wyo., has set up shop on eBay, the largest online auction site. Recently she pocketed $175 for a pair of 1950s vintage curtains with fluttering pink leaves that she couldn't give away at the flea market. eBay allows her to reach far more people and make more money than she did at any flea market.

Since their first appearance in 1995, Internet auctions have become one of the hottest phenomena on the web. They offer buyers a "virtual flea market" with an endless range of merchandise from around the world—and they give sellers a "storefront" from which to market everything from sports memorabilia to computer systems to millions of international buyers. In this age of e-commerce overdo, online auctions are the ideal way to match buyers and sellers—fast, frictionless and perfectly fair. The public has certainly bought that message: online auction sites such as eBay, Yahoo!Auctions, and uBid.com are just a few websites that are thriving in the current economy in spite of the economic downturn. A recent study by Harris Interactive found that 35 million Americans, or 31% of the U.S. online population, participate in online auctions. Jupiter Research predicts that consumer-to-consumer online auction sales will exceed $15 billion in 2004.

Internet Auctions provide sellers and buyers a forum—and a community. eBay, for example, has 38 million buyers and sellers who trade on its site. These consumers participate in thousands of bulletin boards, chat rooms and email conversations about their collecting passions and interests. They have catapulted the website, in three short years, from a funky little online garage sale full of Beanie Babies and attic trash into a global marketplace for almost anything from a $1 baseball card to a $4.9 million Gulfstream jet. eBay's customers crowd the online discussion boards, posting 100,000 messages a week to share tips, point out glitches, and lobby for changes. eBay's customers even police the site by rating each other, keeping fraud minimal.

But auctions aren't a perfect form of commerce—far from it. They're prone to a fundamental flaw: the winner's curse, which hurts buyers. Winner's curse is the bane of clueless newbies on auction sites like eBay's. It's what people suffer when they win an auction by overestimating how much something is worth and therefore bidding too much. It's a sucker's game, yet it's part of daily business in online consumer auctions. Collecting money from newbies who overbid because they're ill informed is "part of the business plan," says one message poster on AuctionWatch.com's site. "You always see rookies paying way too much!" says another. The soundest way to dodge the winner's curse is to gather more information about the true value of what's been sold. That's one of eBay's strengths—bidders can study past auctions of like items.

Auction sites continue to thrive and their members grow in the current economic scenario, irrespective of the recent downturn. But auctioneers who don't work on minimizing the flaws inherent in their auction mechanisms could wind up on the losing end of winner's curse.

George Harris in New York

Appendix B. Auction Stimuli

1. Payoff Instructions

You are given $50 in "bidding money" that you can use for bidding in EACH auction. The residual money from the first auction does not carry over to the second auction as the two auctions are separate. This "bidding money" is to be used to bid on the products. Note that you cannot bid higher than the amount of bidding money that you have. Also, this "bidding money" MAY translate into real money in some cases, as explained in the following paragraph.

After both the auction sessions are over, a total of thirty-two auctions across all subjects in all study conditions will be chosen at random to be "converted into a real transaction." If a specific auction you participated in is chosen to be converted, you will receive a "payoff." If you won the chosen auction, this payoff will include (a) the product you won and (b) the "bidding money" remaining with you after the auction is over. If you did not win the chosen auction, you will receive a dime for every dollar of bidding money given to you; i.e., you will receive a total of $5. A few example scenarios of this "payoff" are given below for illustration.

Scenario 1. An auction you participated in was not picked for conversion. In this case, you do not receive a payoff other than course credit for participating in the experiment.

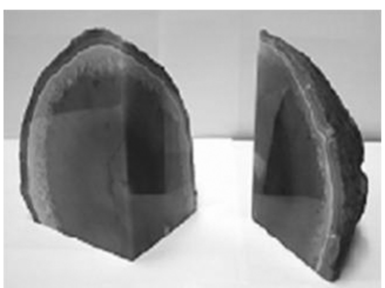
Scenario 2. An auction you participated in was picked for conversion, but you did not win that auction. In this case, you receive a payoff of a dime on every dollar of the unused bidding money, i.e., $5, in addition to course credit for participating in the experiment.

Scenario 3. An auction you participated in was picked for conversion, and you won, say, product "*X*," for, say, $20, in that auction. Your payoff will then be (a) the product "*X*" PLUS (b) the remaining "bidding money" = ($50 − $20) = $30, and course credit for participating in the experiment.

Scenario 4. An auction you participated in was picked for conversion, and you won, say, product "*Y*," for, say, $45, in that auction. Your payoff will then be (a) the product "*Y*" PLUS (b) the remaining "bidding money" = ($50 − $45) = $5, and course credit for participating in the experiment.

Make sure that you understand this payoff scheme well. It is designed to ensure that you act keeping the payoff in mind, since there is a good chance that an auction that you participated in will be chosen for conversion, and you will earn the payoff.

2. Auction Items



Bookends

Glass bowl

Calligraphy

Appendix C. Study Parameters

Table C.1 Narrow and Wide Price Range Manipulations

		Narrow range		Wide range		
Product ID	Product	Low	High	Low	High	Actual price
30	Calligraphy	17	31	10	38	24
31	Glass bowl	14	25	8	31	19.5
32	Bookends	13	23	7	29	18

Note. Narrow [wide] price ranges are ±30% [±60%] of the product's actual price.

Table C.2 Descending Auction Starting Bids and Bots' Bid Levels

Product ID	Product	Start bid	*High* stop bid[a]	*Low* stop bid	Price
30	Calligraphy	39.00	27.50	20.50	24.00
31	Glass bowl	32.00	22.50	16.50	19.50
32	Bookends	30.00	20.50	15.50	18.00

[a]If the focal bidder has not bid by the stop bid, one of the bots bids and ends the auction. Bidders are assigned to *high* and *low* bots bidding conditions at random. The *high* [*low*] stopping bids are +15% [−15%] of the product's retail price.

Table C.3 Ascending Auction Starting Bids and Dropout Patterns

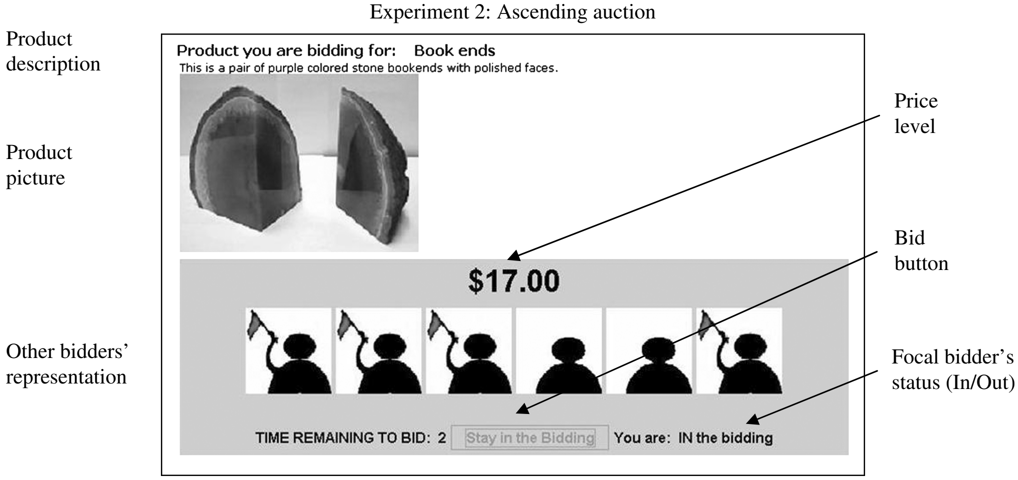
	Calligraphy		Glass bowl		Bookends	
Bots' bidding level	High	Low	High	Low	High	Low
Start bid level	9.00	9.00	7.00	7.00	6.00	6.00
Bidder A	26.00	19.00	21.00	15.00	19.00	14.00
Bidder B	**27.50**	**20.50**	**22.50**	**16.50**	**20.50**	**15.50**
Bidder C	25.00	18.00	20.00	14.00	18.00	13.00
Bidder D	22.00	15.00	17.00	11.00	15.00	10.00
Bidder E	23.50	16.50	18.50	12.50	16.50	11.50
Bidder F	26.00	19.00	21.00	15.00	19.00	14.00

Note. Bidder B is the highest bot bidder (denoted by boldface).

Appendix D. Auction Screen Layout

Experiment 1: Descending auction

Experiment 2: Ascending auction



Appendix E. Descending Auction (Experiment 1): Summary LIFEREG Results

Hypothesis	Effect (Type III)[a]	df	Wald χ^2	Pr > χ^2
H0	*Goal*	1	57.79	< 0.0001
	WT	1	76.13	< 0.0001
H1	*Goal* × *WT*	1	20.76	< 0.0001
	PR	1	3.96	0.0467
H2	*Goal* × *PR*	1	6.34	0.0118
	PM	1	155.68	< 0.0001
H3	*Goal* × *PM*	1	48.56	< 0.0001
	WT × *PR*	1	117.61	< 0.0001
	Goal × *WT* × *PR*	1	0.03	0.8659
	WT × *PM*	1	61.31	< 0.0001
	Goal × *WT* × *PM*	1	6.39	0.0115
	PR × *PM*	1	12.71	0.0004
	Goal × *PR* × *PM*	1	96.77	< 0.0001
	DT × *PR* × *PM*	1	0.39	0.5336
	Goal × *WT* × *PR* × *PM*	1	7.22	0.0072
	Inferred value[b]	1	2,063.29	< 0.0001
	SII	1	0.00	0.9955
	Auction experience	1	48.00	< 0.0001

Notes. The dependent measure is the focal bidder's bid level. When the focal bidder wins, we use the winning bid. When the focal bidder loses, the preset bot bid (at which the bot bids and wins) is treated as the left-censoring point. Total $n = 339$; left-censored n (focal bidder lost) $= 147$.

[a]The assumed response model is $\mathbf{y} = \mathbf{X}\beta + \sigma\varepsilon$; $\mathbf{y}$ is the dependent measure vector described above, $\mathbf{X}$ is the matrix of covariates and independent variables, β is the vector of regression parameters, σ is an unknown scale parameter, and ε is a vector of errors assumed to be from a specific class of distributions. Models using alternative error specifications were fit to estimate the main and interactive effects of the manipulations along with relevant covariates. The log-likelihood (LL) score of each error model was compared with the LL score for the generalized gamma model and the relevant χ^2 tests were used to assess fit. The one-parameter extreme value distribution produced the best fit (LL $= -1{,}804.59$) measured against the generalized gamma model (LL $= -54.20$; $\chi^2(2) = 3{,}500.78$, $p < 0.001$). This model is the basis of the results reported in the text.

[b]In a descending auction, the participant observes no new information on competitive values while the clock ticks down because any bot bid ends the auction. Here, the participant's estimate of the highest value among the other m competing bidders becomes her expected payment conditional on winning (Klemperer 1999). This estimate may be computed as the expected first-order statistic of the m bidders' values, assuming these to be uniformly distributed between the lower (L) and the upper (U) bound of the price range (Mean, or M) provided. To control for the effects of auction information (which includes the effects of auction item identity) we compute this expected first-order statistic as $L + [\{m/(m+1)\}(M - L)]$ and use it as the "inferred value" covariate.

Appendix F. Ascending Auction (Experiment 2): Summary LIFEREG Results

Hypothesis	Effect (Type III)[a]	df	Wald χ^2	Pr> χ^2
H0	*Goal*	1	43.22	< 0.0001
	WT	1	19.43	< 0.0001
H1	*Goal* × *WT*	1	11.87	0.0006
	PR	1	14.34	0.0002
H2	*Goal* × *PR*	1	7.10	0.0077
	PM	1	0.15	0.6996
H3	*Goal* × *PM*	1	11.55	0.0007
	WT × *PR*	1	1.32	0.2512
	Goal × *WT* × *PR*	1	2.29	0.1306
	WT × *PM*	1	11.02	0.0009
	Goal × *WT* × *PM*	1	14.58	0.0001
	PR × PM	1	6.66	0.0098
	Goal × *PR* × *PM*	1	5.98	0.0145
	WT × *PR* × *PM*	1	7.08	0.0078
	Goal × *WT* × *PR* × *PM*	1	0.42	0.5195
	Inferred value[b]	1	8.39	0.0038
	SII	1	6.06	0.0138
	Auction experience	1	4.61	0.0318

Notes. The dependent measure is the focal bidder's highest bid. When the focal bidder wins, the preset highest bid level (at which the last bot drops out of the bidding) is treated as the right-censoring point. When the focal bidder loses, we use the bid at which they drop out. Total $n = 305$; right-censored n (focal bidder won) $= 176$.

[a]As with the LIFEREG analysis for the descending auction, we tested various error specifications. A model that specified a one-parameter extreme value distribution for error fit best (LL $= -1{,}274.88$) compared to the generalized gamma model (LL $= -118.57$; $\chi^2(2) = 2{,}312.62$, $p < 0.001$). This model forms the basis of the reported results.

[b]In the ascending auction, the number of competing bidders remaining at any bid level contains new information on competing values (Milgrom and Weber 1982). Here, the estimate of the highest value among the other m bidders is the expected first-order statistic of these m bidders' values (Arnold et al. 1992) with the distribution left truncated at the current bid B lying between the lower (L) and upper (U) bound of the provided price range. We assume the values of *all* bidders to be uniformly distributed between L and U. To control for the effects of auction information (including auction item identity and the bots' exit pattern in the ascending auction), we compute this expected first-order statistic as $B + [\{m/(m+1)\}(U - B)]$ and use it as the "inferred value" covariate.

Appendix G. Bidding Information by Products

Table G.1 Descending Auction

Bidding information	Products					
	Calligraphy		Glass bowl		Bookends	
	High bot bid	Low bot bid	High bot bid	Low bot bid	High bot bid	Low bot bid
No. of bidders	54	58	58	60	57	52
No. of (%) winners	21 (39%)	44 (76%)	22 (38%)	46 (77%)	20 (35%)	39 (75%)
No. of (%) losers	33 (61%)	14 (24%)	36 (62%)	14 (23%)	37 (65%)	13 (25%)
Start/stop bid ($)	39.00–27.50	39.00–20.50	32.00–22.50	32.00–16.50	30.00–20.50	30.00–15.50
Narrow price range ($)	17.00–31.00		14.00–25.00		13.00–23.00	
Wide price range ($)	10.00–38.00		8.00–31.00		7.00–29.00	
Actual bids $ (*Winners*)						
Maximum	38	36	31	30.5	28.5	29
75 percentile	33	30	28	25	25.75	25
50 percentile	30	28.00	25.5	20.5	24.5	22
25 percentile	30	25	25	19	22.50	19.5
Minimum	28	22	23	17	21	16

Notes. The stop bid is the amount bid by the programmed bot in the high and low bot bid conditions, respectively. The descending auction winner is the one who bid *above* the stop bid value shown. Otherwise, the bidder loses and no bid is observed. Thus, the actual bids shown are those of winners.

Table G.2 Ascending Auction

Bidding information	Products					
	Calligraphy		Glass bowl		Bookends	
	High bot bid	Low bot bid	High bot bid	Low bot bid	High bot bid	Low bot bid
No. of bidders	65	67	40	54	46	33
No. of (%) winners	29 (45%)	41 (61%)	20 (50%)	37 (69%)	28 (61%)	21 (64%)
No. of(%) losers	36 (55%)	26 (39%)	20 (50%)	17 (31%)	18 (39%)	12 (36%)
Start/stop bid ($)	9.00–27.50	9.00–20.50	7.00–22.50	7.00–16.50	6.00– 20.50	6.00–15.50
Narrow price range ($)	17.00–31.00		14.00–25.00		13.00–23.00	
Wide price range ($)	10.00–38.00		8.00–31.00		7.00–29.00	
Actual bids $ (*Losers*)						
Maximum	27.5	20.5	22.5	16.5	20.5	15.5
75 percentile	20.5	20	22.5	16.5	20.5	15.5
50 percentile	15.5	19.5	20	16	20	15
25 percentile	9.5	13.5	16.5	15	14	15.00
Minimum	9.5	9.5	13	10	11	11.5

Notes. The stop bid is the amount bid by the programmed bot in the high and low bot bid conditions, respectively. The ascending auction winner is the one who outlasts the bot bid at the stop bid value shown. We observe only the bids of the losing bidders. Thus, the actual bids shown are those of the losers.

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