Subjective Assessments of Self and Competitor Expertise: Influences on Bidding and Post-Auction Product Valuation

Stephen Andrew Hood

Dissertation submitted to the faculty of the Virginia Polytechnic Institute and State University in partial fulfillment of the requirements for the degree of

Doctor of Philosophy in Executive Business Research

Dipankar Chakravarti, Chair
Rajesh Bagchi
Amar Cheema
Paul M. Herr

December 15, 2021
Falls Church, Virginia

Keywords: Auctions, Competitor Expertise, Participative Pricing

Subjective Assessments of Self and Competitor Expertise: Influences on Bidding and Post-Auction Product Valuation

Stephen Hood

ABSTRACT

This dissertation contains two essays focusing on how Self and Competitor Expertise influence valuation both during and post-auction. The first essay, “Competitor Expertise: Influences on bidding behavior and post-auction values in ascending auctions,” considers how a bidder’s perception of competitors’ expertise types and levels influences valuation both during (bid level), after (WTP/WTA), and over time (ΔWTP/ΔWTA). Generally, I find that despite normative predictions regarding bidding behavior in a competitive auction environment, bidders tend to bid higher and maintain higher post-auction valuations when competing against experts in the product domain, although not amateurs or experts in other domains (e.g., auction bidding strategies). Post-auction valuation patterns further depended on Auction Outcome. The second essay, “Assessed Self-Expertise: Influences on Bidding Behavior and Post-Auction Values Against Competitors of Varying Expertise Levels,” extends our investigation to consider how a bidder’s perception of their own expertise type and level also influences valuation both during and post-auction. Broadly, I find additional support that bidders post higher valuations both during and post-auction when competing against Experts vs. Amateurs, but that this behavior is primarily driven by bidders who assess themselves as Experts and further depends on Auction Outcome.

Subjective Assessments of Self and Competitor Expertise: Influences on Bidding and Post-Auction Product Valuation

Stephen Hood

GENERAL AUDIENCE ABSTRACT

This dissertation contains two essays that consider the influence of how one's own type and level of expertise (Self-Expertise) as well as one's perception of their competitors' expertise (Competitor Expertise) influence bidding behavior and post-auction product valuation. In the first essay, "Competitor Expertise: Influences on bidding behavior and post-auction values in ascending auctions," the issue of how bidders perceive Competitor Expertise levels is considered. Generally, bidders tend to bid higher and maintain higher post-auction valuations when competing against experts with expertise in the product category. Post-auction valuations and their durability further depend on whether bidders win or lose the auction. In the second essay, "Assessed Self-Expertise: Influences on Bidding Behavior and Post-Auction Values Against Competitors of Varying Expertise Levels," the issue of how one's self-assessment of their own type and level of expertise is further considered. Broadly, bidders tend to post higher valuations when they assess themselves as experts in the product category. Interestingly, this effect is largely driven by experts competing against other experts, although this also further depends on whether bidders won or lost.

Acknowledgements

First, I would like to express my deepest gratitude to my dissertation committee chair and advisor, Professor Dipankar Chakravarti, for his ongoing support, patience, and enthusiasm during the past five years. His guidance and mentorship have been invaluable during the research and writing of my thesis, and I cannot imagine a better advisor or mentor throughout my course of study.

Next, I would like to express my appreciation to the rest of my dissertation committee: Professors Rajesh Bagchi, Amar Cheema, and Paul Herr. Their encouragement, feedback, and insightful questions have played a pivotal role in the formation of this research as well as my development as a researcher.

I also wish to thank my instructors, and everyone with whom I was a doctoral student at Virginia Tech. Their camaraderie, encouragement, and shared long nights have made an otherwise long and difficult journey enjoyable and memorable.

Finally, I wish to thank my family: my parents, Roy Hood and Marilyn Tjaden, who raised me and encouraged me to develop my curiosity about the world around me; my grandfather, Dana Tjaden, who taught me the value of having an idea and bringing it to life; and not least, my wife, Chloe Song, without whose patience, support, and encouragement none of this would have been possible.

Table of Contents

Chapter 1: Introduction

Fueled by online platforms such as eBay, auctions have become popular as a marketplace mechanism for buying and selling products. Even as the economics literature (see, e.g., Klemperer, 1999; Krishna, 2010) provides rich normative models of buyer and seller behavior in auctions, experimental economists and consumer researchers have focused on consumer bidding behavior in auctions conducted in both live and online formats (Chakravarti et al., 2002; Cheema et al., 2005). Whereas normative models tend to assume buyers have fixed and immutable values for auctioned products, models focusing on bidding behavior find individual differences and institutional practices influence how consumers bid and the product valuations that subsequently emerge. Innate or auctioneer-induced differences in bidder goals and motivation, precision, and salience of bidder knowledge about the item's value, as well as situational factors such as clock speeds and wait time at each price step, have all been shown to influence bids in both descending and ascending auctions (Cheema, Chakravarti, & Sinha, 2012).

This dissertation reports the results of five experiments that focus on how the competitive settings in which auctions are conducted also influence consumer bidding behavior, post-auction product valuation, as well as the temporal stability of these valuations. The empirical work is organized in two essays. The first essay (Chapters 2 and 3) reports the results of three experiments that examine how bids and post-auction valuations (in an ascending Japanese auction) are influenced by the focal bidder's subjective assessments of the competitive environment (i.e., whether they perceive their competitors as amateurs or as experts, specifically with expertise related to the auction *process*, the focal *product* domain, or a *hybrid* of both). We also examine how the

Auction Outcome (win/loss) against such perceived experts influences bidder judgments of the auctioned product's immediate post-auction value and its stability over time.

How a focal bidder bids in an auction and their post-auction product valuations may also depend on their subjective self-assessment of their own expertise. The second essay (Chapter 4) reports two experiments examining how bidding and post-auction product valuation depends not only on the perception of Competitor Expertise but also on the assessment of one's own (self) expertise as well as Auction Outcome. In other words, these studies examined whether participants' assessed Self-Expertise moderated the effects of perceived Competitor Expertise on bidding and product valuation. The empirical work is based on two alternative auction formats: (i) the ascending Japanese auction where the focal bidder can observe and draw inferences from competitor exits and bidding behavior, and (ii) a sealed-bid auction where such information is not available.

In summary, the proposed research makes two primary empirical contributions to the body of knowledge regarding bidder behavior in auctions. First, we extend prior research to show that bidders are systematically influenced not merely by the number of competing bidders but also by their subjective perceptions of Competitor Expertise. Second, the results also show that a bidder's subjective assessment of their <u>own expertise</u> both has a direct effect on bidding behavior and moderates the effect of perceived Competitor Expertise on post-auction product valuation. Together, these findings reinforce the idea that how consumers bid and construct post-auction value in an auction is susceptible to competitive influences. Specifically, the price consumers pay for a product depends on psychological factors related to perceptions of Competitor Expertise as well as assessments of Self-Expertise (that bidders may self-generate, or auctioneers can influence systematically). Moreover, Auction Outcome also impacts judgments of product value which endure differently depending upon assessments of competitor and a bidder's own expertise.

In the remainder of this chapter, the auctions literature is situated within the larger context of participative pricing mechanisms along with a brief overview of relevant aspects of auction theory and constructs such as private values (PV) and common values (CV) products. The discussion embeds an overview of the normative literature on auctions along with a discussion of empirical findings from experimental economics, as well as marketing and consumer psychology literature. The latter literature suggests the possibility of systematic departures from normative predictions of bidding behavior driven by social (competitive) and environmental factors (auction setting).

1.1 Auctions as Pricing Mechanisms

Auctions have a longstanding history as a marketplace mechanism. As far back as in the fifth century BCE, Herodotus (ca. 425 BCE) recorded the auctioning of wives in a Babylonian marriage market. Apocryphal as the story might be (Rollinger, 1993) it suggests auctions were already well-known as an exchange mechanism at the time. This is further supported by records from Herodian (ca. 240 CE) in the second century CE who records that following the murder of Emperor Didius Julianus, the Roman praetorians proclaimed that "the empire [itself] was for [auction], promising to hand it over to the man who offered the highest price."

In modern times, auctions continue to be widely used as a pricing mechanism. Some institutional uses include governments using auctions to sell debt, communication agencies using auctions to sell spectrum bandwidth rights, and firms using auctions to award procurement contracts. And consumers participate in auctions to buy, sell, and exchange goods and services. As such, even before the advent of the internet, auctions have attracted the attention of academics from different disciplines, practitioners from various industries and from governments, and regulators focused on understanding, formulating, and enforcing the governance systems that facilitate the operation of auction markets.

Prior to the internet, consumer auctions were often seen as a unique and esoteric market space inhabited by art enthusiasts, antique aficionados, and hobbyists such as philatelists and numismatists. Sociologists have described auction markets in terms of in- and out-group membership, cultural codes, and social dynamics (Smith, 1989). However, the increased accessibility provided by the internet has not only situated auctions as a mainstream market mechanism but also kindled high levels of consumer participation. This, in turn, has sparked renewed academic and practitioner interest in this dynamic pricing mechanism. Only a rare consumer is unaware of auctions, and many consumers are active participants (Park & Wang, 2010). Indeed, while eBay comprises only a small fraction of the 2021 global e-commerce and online auction market of $645.2B, their transaction volume increased from $14.4B in 4Q 2006 to $22.1B in 2Q 2021 ($27.1B in pre-COVID 2Q 2020). With 159M active buyers (19M sellers) and 1.5B listings worldwide (51% international), the company posted 2Q 2021 revenues of $2.7B (https://investors.ebayinc.com/fast-facts/default.aspx).

Price setting in purchase transactions involves two contrasting systems. Posted price mechanisms (e.g., fixed-price retail) are one-way systems in which consumers make purchases based on preset, immutable prices. In contrast, participative pricing mechanisms are more interactive, and consumers play an active role in price formation (Spann, et al., 2018), and consumers select a mechanism that matches their desired level of involvement and time commitment. Some participative processes involve one-shot mechanisms. Thus, in a pay-what-you-want (PWYW) system, the buyer proposes a price that the seller then accepts. In a name-your-own-price (NYOP) system, the consumer names a price that is either accepted or rejected by the seller. And within auctions, there are sealed-bid formats in which buyers submit offers by a common deadline, and the item goes to the highest bidder who pays either the bid price (first-price auctions) or the price offered by the second-highest bidder (second-price auctions).

Other participative systems (e.g., haggling or negotiations) involve a buyer-seller dyad making offers and counteroffers that, if successful, converge to a mutually agreeable price. Auction mechanisms involve simultaneous engagement of multiple bidders and, depending on the specific format, provide a “bazaar-like competitive atmosphere[s]” full of emotion and excitement, as well as consumers looking for experiential variety in both duration and involvement (Bapna, Goes, & Gupta, 2001). This is particularly true of open auctions in ascending (English) or descending (Dutch) formats (Herschlag & Zwick, 2002). In the former situation, consumers often engage in herd-like behavior (Dholakia & Soltysinski, 2001), caught up in excitement stemming from frenzied bidding (Haubl & Popkowski Leszczyc, 2018). In the latter, descending format, tension and excitement build as the clock ticks down, and the “sudden death” nature of the auction can prompt a bidder to “jump the gun.”

Auction processes stimulate local and contextual dependencies that both influence consumer bidding behavior both during the auction as well as afterward as a function of whether they won (willingness to accept - WTA) or lost (willingness to pay - WTP), both immediately post-auction (t_1) as well as over time (Δt). Some dependencies that have previously been treated in the economics and marketing literature include increased salience of competition (Ku, Malhotra, & Murnighan, 2005), competitive reactivity (Haubl & Popkowski Leszczyc, 2018), time constraints (Malhotra, 2010), constraints on the amount of good for sale (Ariely & Simonson, 2003), as well as the social dynamics surrounding the auction event (Cheema, et al., 2005). Many of these lead to higher bids, usually through some type of arousal mechanism, above or below an awareness threshold. Often, normative economic theories posit outcomes based on model assumptions that ignore contextual dependencies. However, these can have subtle influences that moderate bidding and drive “non-normative” outcomes.

1.2 Normative Auction Theory

The economic tradition has traditionally dominated theoretical and empirical work in auctions. The priority in this tradition has been to establish and test normative theory. Normative models are mainly concerned with prescribing either how auctions should be designed to optimize their performance, or how rational buyers and sellers should transact considering various structural and environmental factors governing a given auction mechanism. Broadly, auctions may be distinguished along two dimensions.

The first dimension relates to the degree of affiliation (relatedness) of bidder values (value signals) (i.e., whether bidders' product values are independent and private or whether the object has a value that, when known, will be common for all bidders). A second classification dimension relates to the type of auction mechanism. The four standard (common) auction types include the ascending (English) auction, the descending (Dutch) auction, the First-Price, Sealed-Bid auction, and the Second-Price Sealed-Bid auction. These two dimensions are elaborated on below.

1.2.1 Private Value and Revenue Equivalence

In a Private Value (PV) model, each bidder is aware of their own private value for the product, which is *independent* of other bidders' values. One example might be a bottle of wine purchased explicitly for the purpose of one's own enjoyment (yielding a unique value that is known only to the focal consumer). The Revenue Equivalence Theorem (RET) is a key postulate for PV auctions: given risk-neutral bidders, independent and identically distributed values, and the item going to the highest bidder, expected seller revenues are identical for the ascending, descending, first- and second-price, sealed-bid mechanisms. First noted by Vickrey (1961), this celebrated result was later generalized for symmetric, independent PV models (Riley & Samuelson, 1981). In a seminal paper, Myerson (1981) proposed the revelation principle, showing that for any allocation mechanism, there exists a *direct* allocation mechanism in which, at equilibrium, buyers reveal their true values, and the allocation outcomes are identical to that of the original mechanism. This paper generalized the RET and set forth the core principles of optimal (incentive compatible and individually rational) mechanism design, including conditions under which the seller should maintain a reserve price.

The PV model also assumes bidders are risk-neutral (neither risk-averse nor risk-seeking), symmetric (their values or value signals are drawn from the same distribution), and they face no budget constraints (relative to bidding their value). Other auction models (see Klemperer, 2004) have derived results for a variety of departures from the canonical assumptions (e.g., see Holt, 1980 on risk-averse bidders; Bikhchandani, 1988 on bidder asymmetry involving "almost common" values; and Bulow & Klemperer 1996 on varying numbers of bidders. Important equilibrium results have been established for asymmetric bidders (Maskin & Riley, 2000) and for instances where bidders collude (McAfee & McMillan, 1992). Notwithstanding the elegant analytical accomplishments, experimental tests show mixed results even in tightly controlled settings closely matching normative theory assumptions (see, for example, Kagel, 1995; Chakravarti et al., 2002).

1.2.2 Common Value and the Winner's Curse

In contrast to PV models, under a Common Value (CV) model, the "true value" of the product is initially unknown. However, once revealed, the value is the same (common) for all participating bidders (e.g., a bottle of wine purchased explicitly as an investment for resale). However, *ex ante*, each bidder only has a signal of this common value (Klemperer, 2004) that typically varies across bidders but is drawn from the same common distribution. No bidder "knows" the *"common"* market value *ex ante*. It is revealed only following the purchase. In Affiliated Value (AV) models (see Milgrom and

Weber 1982), bidder value signals are allowed to be (positively) correlated, and any given bidder's value signal, therefore, provides information for other bidders.

A bidder's expectation of the auctioned product's value is based on their own value signal. In a CV context, winning implies the bidder, conditional on having won, has the highest value signal of all bidders. Thus, winning implies that this bidder, conditional on winning, had the highest value signal of all bidders. Even though each person's signal is an unbiased estimator of the object's value, the highest signal is obviously not an unbiased estimator. A bidder who fails to recognize and account for this pays more than the object's estimated worth. Thus, in a CV auction, the winning bidder "paid too much" because, regardless of the object's *ex post* common value, it could have been acquired for less.

Capen, Clapp and Campbell (1971) examined this empirically in their investigation of auctions for offshore drilling leases, and since then, this "winner's curse" has been shown in a variety of contexts (Thaler, 1988). Indeed, the larger the number of competing bidders, the larger the size of the winner's curse. However, note that the winner's curse is relevant only for first price CV auctions where the winner pays the bid price (but not for PV auctions where values are not market-driven). In second-price CV auctions, the winner pays a price equal to the bid of the second-highest bidder. Hence, the winner in such auctions is immune to the winner's curse. Knowledgeable bidders in a first-price CV auction may avoid the "winner's curse" by shading their bids appropriately. Thus, the "elation" that is often associated with winning should be tempered by the likely prospect of becoming a victim of the winner's curse.

1.2.3 Auction Mechanisms

A second classification dimension relates to the type of auction mechanism. The four standard auction types include the ascending (English) auction, the descending (Dutch) auction, the First-Price Sealed-Bid (FPSB) auction, and the Second-Price Sealed-Bid (SPSB) auction. Ascending open English auctions are the most familiar and commonly known. In these auctions, the auctioneer “cries out” a progressively increasing bid level, and one among the group of attending bidders must “bid” for the price level to hold. If a bid is placed, the auctioneer raises the bid level. The process continues until no one bids further, at which time the highest bidder wins and pays a value equal to that which she bid (first-price). In some formats, the winning bidder pays a price equal to the next highest bid (second-price). The descending (Dutch) auction is less well known and is known for its use in the flower (tulip) markets in the Netherlands. In this format, the auctioneer begins the auction with a high price and drops the price progressively according to fixed periods of time. The auction ends as soon as a bidder places a bid. This bidder wins the auction and pays the price at which they bid.

The FPSB and SPSB auctions are sealed-bid auctions in which bidders pick a value they are willing to pay for the focal product. This bid is then privately (sealed-bid) transmitted to the auctioneer. The bidder submitting the highest value wins the auction and pays either their bid price (first-price format) or the price bid by the next highest bidder (second-price format). The First-Price and Dutch auctions are seen as strategically equivalent, as are Second-Price and English auctions (Kagel J. H., 1995). Note that during these auctions, no bidder observes the behavior of competing bidders as the bids are sealed.

While there is substantial and seminal work in economics regarding normative models of auction mechanisms, recent empirical work suggests that much work remains to be done to capture actual bidder behavior in realistic settings. For example, normative theory predicts revenue equivalence between the four auction mechanisms. However, empirical research shows robust and systematic differences between the normative predictions and empirically observed bidding behavior. Thus, FPSB auctions yield higher revenues than Dutch auctions (Coppinger, Smith, & Titus, 1980). Also, Kagel et al. (1987) report failures of strategic equivalence between SPSB and English auctions. Although normative models assume that bidder values should be fixed and immutable, empirical work shows that a variety of auction features (e.g., see Cheema et al., 2012 on clock speed, bidder knowledge, and pre-commitment; Sinha & Bagchi, 2019 on situational factors such as ambient room temperature; and Haubl & Popkowski Leszczyc, 2018 for how the speed of competitor reactions influence product valuations and bidding behavior). In summary, normative economic models have done well at capturing how bidders in auctions *ought* to behave but fall short of capturing how bidders in auctions actually *do* behave.

The empirical work in Study Set 1 of this dissertation is based on a variant of the ascending (English) auction called the “Japanese auction” (Milgrom & Weber, 1982). In this Japanese variant, the bid level rises over time, and bidders are assumed to remain in the auction until they make a *public* and *irrevocable* exit. Thus, once a bidder exits the auction, they may not reenter (Klemperer, 2004). The Japanese variant has an advantage in that researchers can obtain active bidding information at each bid level. In an ascending English auction, researchers can only record bids as they are entered.

Typically, only one bid is recorded before an auctioneer raises the bid level to the next price. Thus, researchers know only the final sale price and do not know how many bidders were interested in the product at each bid level. This makes it difficult to develop, test, and interpret theoretical models of bidding behavior. In a Japanese auction, all bidders must indicate their interest in the product at each bid level. An exit at any stage is irrevocable, making bidder value information more complete and less ambiguous. This permits systematic modeling (Milgrom & Weber, 1982) and unambiguous interpretation of competitive behavior during the auction, allowing empirical study of a focal bidder's reactions to anticipated/realized competitive moves.

In Study Set 2, we report two studies examining how subjective bidder assessments of Self-Expertise moderate the influence of perceived Competitor Expertise. The first uses a Japanese auction mechanism similar to those in Study Set 1 and provides comparative insights regarding bidder behavior when they may observe and react to competitor actions during the auction. The second study uses a FPSB auction in which the focal bidder cannot observe competitor bids and exit behaviors during the auction. Hence, bidders must rely on their subjective judgments of Competitor Expertise and assessments of own expertise based on merely bidder presence rather than observations of competitor behavior during the auction.

1.3 Auctions in Marketing and Psychology

Perhaps the most critical differences between normative economic models of auction bidding and the empirical studies of bidding behavior in economics, psychology, and marketing stem from assumptions regarding the nature of bidder values. Normative theories rest on assumptions that bidders carry fixed and immutable values for focal products based on *a priori* value signals. However, empirical work suggests these values, if they exist at all (Fischoff, 1991), are influenced by contextual factors (Watson & Buede, 1991). The findings suggest that whereas consumers may enter an auction with some prior notion of the product's value, these values are neither fixed nor immutable. Rather, consumers *construct* these values both during the auction based on auction features and events (including competitive behavior) as well as post-auction based on outcomes (wins/losses). Post-auction values may even change over time depending on the psychological (e.g., dissonance and regret) and sociological processes (e.g., retrospective competitive perceptions) that consumers set in motion to interpret and cope with Auction Outcomes.

Sociologists have noted that not all individuals who choose to bid in auctions do so with pure product acquisition goals. In many cases, an auction is used to settle questions of ownership when value or some other critical aspect of the product is in question. In such contexts, auctions confer and support social legitimacy regarding both the product's value and allocation, as well as the process by which ownership transfer occurs (Smith, 1989). For other participants, auctions provide emotional value (excitement) via social interaction with competitive overtones (Herschlag & Zwick, 2002). Auctions, particularly those implemented via online platforms (e.g., eBay), play an important sociological role by instituting feedback mechanisms that create trust and establish reputation in marketplaces with diverse and distributed buyers and sellers (Chen, et al., 2020).

Psychologists (Fischoff, 1991) have argued that consumer values are rarely fixed or immutable and are instead context-sensitive and malleable. Chakravarti et al., (2002) discuss numerous auction contexts where psychological reasoning and inferences may alter consumer value for a focal item. Bidders may then *construct* values that reflect various cognitive and emotional implications of auction events such as competitor bids, entries, and exits. Moreover, such context-dependence may reflect the mindset that bidders bring to the auction. For example, Cheema et al. (2012) found that a priming manipulation (excitement/prudence) influenced bidder goals and bid levels. Also, varying clock speed (i.e., the deliberation time available at each bid level) influenced bid levels in a descending auction. And Haubl and Popkowski-Leszczyc (2018) found that speed of competitive reactions raises perceptions of competitive intensity and increases WTP. Findings such as these suggest bidder inferences regarding a product's value may rest on perceptions of Competitor Expertise and observed competitor entry/exit during an auction. Moreover, post-auction value assessments may rest not only on inferences about Competitor Expertise but also on whether bidders won or lost.

1.4 Competitor Expertise

The normative auctions literature has examined the role of focal bidders' adversaries in determining optimal bidding behavior and seller revenues. Several authors have considered the issue of the number of bidders. Harstad, Kagel and Levin (1990) derived the equilibrium bidding strategies in different auctions when the number of bidders is uncertain. However, the same author team (Kagel, Levin, & Harstad, 1995) showed that in second-price common value auctions, bidders fail to reduce their bids in response to public information regarding increased numbers of bidders (and the product's value). Thus, bidders do not seem to recognize and account for the likelihood of adverse selection inherent in such auctions. As the authors point out, this failure to support Nash equilibrium predictions cannot be attributed to bidders' risk aversion.

Other developments in the normative literature have typically focused on information asymmetries. Maskin and Reilly (2000) develop the theory of asymmetric auctions, addressing instances where bidder values are drawn from different distributions. Each bidder has essentially the same information about the product, but they have differences in their value signals (i.e., differences in the extent to which a bidder's value signal is comprised of common and private value components). The authors show that given such asymmetry, revenue equivalence no longer holds. Furthermore, depending on the nature of the asymmetry, expected revenue may vary for the open English and the SPSB auctions. Maskin and Riley (2000) further characterize information asymmetry by defining strong and weak bidders based on "conditional stochastic dominance" over the supports of the value distribution. Their results suggest that a disadvantaged bidder should bid more aggressively against an advantaged (versus a disadvantaged) bidder. They also derive a symmetric result that an advantaged bidder should bid less aggressively against a disadvantaged (versus an advantaged) bidder.

As noted earlier, bidders view other bidders as competitors (Ariely & Simonson, 2003; Heyman, Orhun, & Ariely, 2004) and experience auctions as intensely competitive events (Ku, Malhotra, & Murnighan, 2005). Thus, in contrast with the above abstract characterizations of advantaged and disadvantaged bidders, we argue that consumers in auctions may view competing bidders in terms of both the nature and level of their expertise. Viewed in this way, the competitive context may influence bidders to bid differently during the auction and to value the auction object differently post-auction. Post-auction values may be based not just on the type and level of competition but also on the outcome (win/loss) obtained. Indeed, these post-auction values need not be fixed but may change over time at rates that depend on the competitive circumstances of the auction.

In normal settings, consumers may enter auctions based on heuristic and subjective assessments of Competitor Expertise. First, a bidder may view a competing bidder as an expert on auction *Processes*. This expertise inference in competitive bidding strategies could be subjective or stem from data or prior informal observations of a given competitor in a variety of auction settings. Other competitors may be assessed as *Product Experts, or* category experts, with the inference once again based on prior knowledge or observations. Still, other competing bidders may be categorized as *Hybrid Expert*s, possessing expertise in both auction processes and the product category. Finally, some competing bidders may be assessed as possessing neither process nor Product Expertise and would be assessed as Amateurs. While such subjective judgments need not be veridical or even grounded in reality, they may still be held with conviction and acted upon. Note that an auctioneer could (within legal bounds) create perceptions of differential expertise for attendees at an auction event by framing the event in different ways (e.g., embellishing invitations to the auction or with ostensibly "preferred" seating arrangements for specific customers).

The expertise literature, in general, has contrasted the decision behaviors of experts and novices in a variety of problem-solving tasks (e.g., see Chi, Feltovich, &

Glaser, 1981; Charness, 1981; Guss, Edelstein, Badibanga, & Bartow, 2017. Indeed, some researchers (e.g., List, 2003, 2004) have claimed that increased decisionmaker experience and domain expertise tends to attenuate contra-normative phenomena such as endowment effects in the marketplace. Thus, Prospect Theory may be seen as describing the behavior of inexperienced decision makers. However, in a study contrasting the bidding behavior of experts and amateurs in internet auctions, Wilcox (2000) demonstrated that while increased domain expertise leads to bidding behavior that is more consistent with neoclassical theory (e.g., bids closer to the expected Nash bidding strategies), experts continue to violate rational bidding norms.

Despite the volume of research contrasting differences in decision making between experts and amateurs, there is a surprising dearth of academic research examining bidder behavior as a function of their assessments of Competitor Expertise. Several questions remain unanswered. First, do bidders behave differently when they face competitive bidders that they subjectively assess as experts versus amateurs? How might such behaviors differ when the assessed expertise varies along various dimensions of expertise (e.g., auction processes, the product category, or a hybrid of the two)? Do bidders follow the behavior of these experts differently and vary their bid levels based on their subjective assessments of Competitor Expertise? Second, do bidders' post-auction estimates of product value vary not only as a function of whether they won or lost, but also against whom they won or lost? Third, do these outcome-dependent values change over time at different rates as a function of bidders' subjective assessments of Competitor Expertise? Finally, this research also examines the extent the answers to the above questions are moderated by bidders' subjective self-assessments of their own expertise.

This dissertation addresses the above and related questions. The study designs allow for exploratory variation, but the findings are interpreted in the light of and contrasted with prior theoretical and empirical results. A brief overview of the dissertation follows.

1.5 Overview of the Dissertation

This dissertation presents the results of two sets of studies that examine how the competitive setting in which auctions are conducted influences consumer bidding behavior, post-auction product valuation, as well as the temporal stability of these valuations. Study Set 1 (described in Chapters 2 and 3) shows how bidding and Auction Outcomes are influenced by bidders' subjective assessment of Competitor Expertise. Chapter 2 provides a more detailed discussion of the Competitor Expertise categories, the procedures used to manipulate Auction Outcomes, as well as the alternative measures of post-auction product valuation elicited from participants. We report the details of the experimental work in Chapter 3. Specifically, we report three experiments that use Japanese auction settings to examine how subjective assessments of the type and level of Competitor Expertise (e.g., amateurs or competitor experts, and whether perceived Competitor Expertise relates to the auction *process*, the focal *product* being auctioned, or a *hybrid* of both) as well as the Auction Outcome (win/loss) influence post-auction values of the auctioned product as well as the stability of these values.

The second essay (described in Chapter 4) shows that auction bidding, the level of post-auction valuation and its temporal stability, rests not only on the focal bidders' subjective assessment of Competitor Expertise and Auction Outcome but also on the bidder's subjective assessment of their own expertise. In other words, we examine how a focal bidder's assessment of their own expertise moderates the effects of perceived Competitor Expertise. Since most participants started out at low expertise levels, we implemented the expertise manipulation by providing participants with an information set and a follow-up test providing false feedback. These procedures were implemented similarly for the two studies in Study Set 2. The first experiment uses a Japanese auction (similar to those in Study Set 1) where participants can observe and draw during auction inferences from their competitors' bidding behavior. The second experiment uses a first-price, sealed-bid auction in which the focal bidder is unable to observe dynamic competitive bids and exits during the auction, and instead must rely on a snapshot of the relative proportion of competitor experts attending the auction. Hence, their (sealed) bids are based on their subjective assessments of competitor and own expertise, without inferences drawn from observing their competitors' bidding behavior.

Across all studies, we measure participants' levels of auction involvement as well as regret and satisfaction with the Auction Outcome. These are used as covariates in interpreting the results of the first auction and as potential moderators of the temporal stability of the product valuations obtained. The details of these analyses are explained in the chapters that follow. Chapter 2 reports the conceptual background and the general empirical setting, whereas Chapter 3 presents detailed procedures, analyses, as well as results for all three experiments in Study Set 1 (effects of Competitor Expertise). Chapter 4 uses a similar presentation for the two experiments in Study 2. Chapter 5 concludes the dissertation with a summary of the two sets of studies, a unified discussion of the two sets of studies, a discussion of the implications of the findings, and directions for future research.

Chapter 2: Perceived Competitor Expertise: Influences on Bidding Behavior and Post–Auction Values in Ascending Auctions

2.1 Introduction and Overview

This chapter develops the conceptual platform on which we build our empirical investigation of how bidders' subjective assessments of Competitor Expertise influences bidding behavior during an auction. We also examine how, along with the Auction Outcome (win/loss), these assessments influence post-action value of the auctioned product and the stability of these values over time. Study Set 1 consists of three experiments that examine these issues in Japanese auction settings. Specifically, we attempt to answer the following three questions:

1. How does bidder behavior vary during an ascending auction when the bidder has different subjective assessments of Competitor Expertise?

2. How do bidders' immediate post-auction estimates for an auctioned product's value differ as a function of perceived Competitor Expertise and Auction Outcome (win or loss)?

3. How does a bidder's estimate of post-auction value change *over time* as a function of perceived Competitor Expertise and the Auction Outcome (win or loss)?

We first contrast our work with previous research in general decision contexts. Next, we define and discuss the treatment conditions within the Competitor Expertise variable, which is relatively more granular than previous treatments in either the auctions or expertise literature. Following this, we broadly define our objectives and the specific propositions that we examine and then sequentially describe the three experimental studies. For each study, we first describe the manipulations of perceived Competitor Expertise, then describe the experimental auction mechanism and procedure used to manipulate Auction Outcomes (win/loss). Finally, we describe our dependent measures: (i) bid levels; and (ii) three alternative measures of post-auction product value, elicited both immediately following the auction as well as after a short, interpolated task.

2.2 Literature Review

2.2.1 Decision Making by Experts and Novices

2.2.1.1 Knowledge Factors

Wikipedia defines an expert as someone with "broad and deep competence in terms of knowledge, skill, and experience through practice and education in a particular field." They are widely acknowledged as a "reliable source of technique or skill whose faculty for judging or deciding rightly, justly, or wisely is accorded authority and status by peers or the public" in a focal domain. This "extensive knowledge or ability" arises from research, experience, or occupation and in a particular area of study (https://en.wikipedia.org/wiki/Expert*)*. In contrast, an amateur (or novice), by definition, is a beginner (i.e., an individual lacking experience in the subject domain).

Prior expertise research has largely focused on comparing the decision behaviors of experts and novices in problem-solving contexts ranging from business to sports (see, e.g., Chi, Feltovich, and Glaser, 1981; Gobel & Charness, 2006; Guss et al., 2017). Not surprisingly, this literature shows that across task domains, experts generally tend to perform better than novices. The difference is attributed to more elaborate knowledge, both declarative and procedural. Experts are generally better than novices at problem framing (i.e., selecting aspects of a problem to examine and the appropriate focal cues). They are better at identifying potential solutions and tend to develop better heuristic paths to these solutions. Also, given their superior procedural knowledge, experts are presumably better at identifying key decision points, the best options within a decision set, as well as how to adapt their decision making approach based on possible contingencies (Ericcson, 2014).

With respect to the role of bidder experience, Wilcox (2000) contrasted the bidding behavior of experts and amateurs in second-price, ascending internet auctions. He found that when strategic dominance was strong (i.e., there was relatively more uncertainty or a larger common value component surrounding the product value), more (versus less) experienced bidders were more (less) likely to follow Nash equilibrium bidding strategies (i.e., bid their maximum WTP at the last possible moment). This was presumably to avoid revealing the common value component of their own value signal. Experience had less impact when strategic dominance was weak (i.e., there was relatively less uncertainty or a smaller common value component surrounding the product value). Interestingly, Wilcox (2000) also found that nonprofessional (i.e., amateur) bidders did not bid in a manner consistent with game theoretic auction models. Presumably, experience allows bidders to collate information on strategies that are more likely to be successful and then act on this knowledge. Thus, the influence of experts may be consequential and result in both real and perceived value differences for those who choose (or not) to follow them.

2.2.1.2 Trust Factors

Thus far, our discussion has focused on reasoning based on knowledge and the influence this may have on subsequent value perception people may have when interacting with experts vs. novices. Another consideration is the extent people trust experts' knowledge and actions and whether this subsequently influences the choice of whether to follow them. Note that differences in trust may stem from two lines of reasoning.

First, participants may hold differing levels of trust regarding the signaling credibility of actions taken by experts. For example, while experts do generally make better decisions (Ericcson, 2014) and such decisions may carry value, it may be in an expert's interest to conceal or mislead potential observers by engaging in denial or deception. There are specific examples of this in the auctions literature and are treated in investigations actions such as jump bidding (Easley & Tenorio, 2004), shill bids (Chakraborty & Kosmopoulou, 2004), or situations in which auctioneer credibility (and subsequently any agents they may employ) are in question (Akbarpour & Li, 2020; Hildesley, 1984).

Alternatively, experts may hold differing levels of trust regarding the reliability of experts' value signals. In a survey of both students and domain experts within their chosen discipline, Hansson et al. (2017) showed that while domain experts and novices did perceive the *anticipated* differences in their levels of ignorance and knowledge, tests of *actual* knowledge revealed no differences between the two groups. This did vary by discipline. Other research (Ericsson, 2008) has shown that traditional expertise indicators (e.g., self-assessment or length of experience, or practice in the target domain) may not always predict performance quality. Examples of such expertise failures have been documented in both firms' board rooms (Almandoz & Tilcsik, 2016) as well as in scientific settings (Kehoe & Tzabbar, 2015). Nevertheless, it is likely that a reputation of expertise creates a credible basis for participants to follow the behavior of experts, particularly if the premises of such expertise are made salient.

Experts may, however, engage in opaque bidding strategies (e.g., sniping) or deception to gain a strategic advantage. While Hybrid and Product Experts are expected to have the advantage of product knowledge, Process Experts may attempt to conceal their value or mislead other participants regarding value in an effort to extract a surplus. Amateurs, by definition, are likely to have low credibility regarding both product category knowledge and bidding strategy. As such, participants may prefer to follow Hybrid and Product Experts over Process Experts and Amateurs. Our descriptions of the characteristics of these expert types are designed to reinforce such inferences (e.g., "Process Experts are *experts in auctions* [and] *auction bidding strategies*" in Appendix A).

The research reported in this dissertation differs from the above work on expertise in two fundamental ways. First, rather than conceptualizing expertise dichotomously (experts versus novices), we take a more context-relevant view (see the following section) based on the institutional literature on auctions. Second, rather than focusing on contrasting the decision behavior of experts and novices, we seek to understand differences in bidder behavior when competing against perceived experts with varying capabilities (i.e., competitors with expertise in the product domain, auction process domain, or a mixture of both product and auction process domain expertise). The substantive context of auction events, as we clarify in the next section, makes these expertise distinctions salient. Therefore, these are expected to influence bidding behavior and post-auction valuations in different ways. We discuss these Competitor Expertise categories next.

2.2.2 Varieties of Competitor Expertise

Perceptions of Competitor Expertise may rest objectively on factors such as prior knowledge and identification of competing bidders. On the other hand, such perceptions may be subjective and rest on heuristic assessments of observable competitive characteristics or inferences created by auctioneer manipulations of the auction context (exclusivity cues, bidder badges, preferred seating, etc.). A review of the institutional literature suggests bidders attending auctions for products in a specific product category may create subjective assessments of four different types of Competitor Expertise based on such information.

First, *Product Experts* are most easily recognized as collectors or aficionados who have relatively greater expertise with the focal product category. Such individuals may participate in product auctions relevant to their own interests, represent institutional buyers, or provide consultative services to auction houses. Auction houses, institutions, and private buyers often employ Product Experts to help create catalog descriptions, set presale estimates, starting bids and reserve prices, as well as provide actuarial product appraisals. These entities tend to seek experts with specialized private information to differentiate both their venue and auctioned products and take great care to ensure that their retinue of Product Experts is properly vetted and qualified (Hildesley, 1984; Kauffman & Wood, 2005). The presence of competing Product Experts may therefore lead a focal bidder to infer higher product quality and value. Such positive value signals may subsequently influence bidding strategy.

Second, *Process Experts* are generally seen as professional buyers who make a living based on their auction purchases and may engage in subsequent resale. Such expertise is synthesized through experience across countless auctions and an accumulated, intuitive understanding of successful bidding strategies (Wilcox, 2000). In other words, Process Experts understand how to acquire the target product at a favorable price (enhance their own resale profits) or to drive up competitors' prices (reduce the competitors' resale profits). These individuals may participate as a buyer's agent or for themselves as collectors or resellers, and practitioner evidence suggests buyers ignore their services at their peril. Such expertise is critically important in common value auctions where there is uncertainty regarding the product's value until the market clears and in which bidders are susceptible to overbidding and vulnerable to the "winner's curse" (Hildesley, 1984). Although the presence of Process Experts may be suggestive of market value, their presence may also suggest a commodity orientation for the target product category. As such, a focal bidder with a genuine interest in the auctioned product may perceive a competitive disadvantage against a Process Expert and subsequently withdraw from the auction earlier.

Third, Hybrid Experts are competing bidders who have significant experience with both the product category and the auction process. Some Product Experts may have participated in auctions often enough to acquire an intuitive sense for dominant bidding strategies and processes. By the same token, some Process Experts may have overcome entry barriers to accrue sufficient experience in specialized product categories. The signal embedded in the presence of such Hybrid Experts may be ambiguous. Their Product Expertise attribute might invite other bidders to follow their bidding behavior and result in subsequently higher bids, but their Process Expertise attribute might create apprehension and result in reduced bids. Although normative theory would predict either bidding value or somewhat reduced bids (McClellan, 2017; Milgrom & Weber, 1982), when object values are uncertain, we suggest the focal bidder is more likely to follow the Hybrid Expert bidder for their Product Expertise and discount the competitive disadvantage stemming from the latter's Process Expertise.

The fourth and final expertise category consists of *Amateurs*. The presence of such bidders simply reflects interest and curiosity. They lack product category expertise and are also inexperienced with the auction process. From the focal bidder's standpoint, competing last against an Amateur bidder who remains in the auction may not seem attractive, particularly if Process and Product Experts have already dropped out. Bids from Amateurs signal no particular knowledge of the auctioned product nor sophistication with respect to bidding strategy and subsequent commodity orientation. Hence, focal bidders have little incentive to follow Amateur competitors and may quit bidding soonest when competing in an ascending auction against amateurs (versus other competitors with some form of expertise).

2.3 Propositions

In an ascending auction where the seller steadily raises the price and bidders gradually exit until the winning bidder remains, the winner pays the price at which the last bidder drops out. In this “second-price ascending auction” (the common internet auction format on eBay), the focal bidder should remain in the auction until the bid level reaches their true value. Remaining in the auction beyond this bid level may result in the focal bidder paying an amount higher than their true value. Dropping out earlier risks forgoing a surplus if the remaining competitors withdraw before the bid level reaches the focal bidder’s true value. Thus, bidding one’s true value (remaining until this bid level is reached) is the dominant (Nash) strategy. However, bidding true value may not remain the dominant strategy in a first-price auction because a true value bid yields a surplus of zero irrespective of win or loss. Hence it is optimal for the bidder to “shade,” or slightly reduce, their bid. The degree of shading involves balancing two opposite forces: bidding too close to value leaves little (or even negative) surplus given a win, but bidding too low reduces the probability of winning and may leave the bidder without any surplus.

A common value auction introduces additional considerations. Even if a bidder bids their true value, conditional on winning, their value estimate is the highest of all bidders (and hence a likely overestimate of the common value). With many bidders, the next highest bid (the second-price) is also likely to be an overestimate. Hence rational bidders in a common value auction should shade their bids even in a second-price format.

In a first-price format, they should shade their bids even further. We return to these cases in Chapter 3, but for now focus on situations in which bidders do not have fixed, preexisting values for the auctioned product, but instead infer such values based on the behavior of competing bidders during the auction (Cheema, Chakravarti, & Sinha, 2012; Fischoff, 1991). In such situations, perceived Competitor Expertise (veridical or not) may play an important role.

A competing bidder who is perceived to be an Amateur is unlikely to serve as a referent because they lack attributes that may serve as justification for following their bidding behavior. Also, a Process Expert may be evaluated as a bargain seeker, and their strategic behavior, laced with strategic considerations, may not index the auction item's true worth (common value). On the other hand, the Product Expert's bidding behavior may be seen as a reliable signal of the product's true worth. Hence a focal bidder seeking to interpret competitor behavior to formulate their own value for the product may follow competitors with product expertise up the ascending price ladder. There may be a similar expectation for a bidder with Hybrid Expertise. So long as they remain in the auction (even given a strategic incentive to shade bids), a bidder perceived to be a Hybrid Expert may be seen as worth following up the ascending price ladder.

2.3.1 Propositions: Bidding Behavior

The above suggests that differences in competitor bidding behavior may influence consumer perceptions regarding the reliability of different competitor experts' value signals and that this may subsequently influence their own bid levels. Thus:

P1. Bidders are more likely to follow Hybrid and Product Experts up the ascending price ladder (than Process Experts and Amateurs).

2.3.2 Propositions: Post-Auction Values

As suggested earlier, the focal bidder's value for the auctioned product may be influenced by events that occur during the auction such as competitor decisions to remain (stays) or irrevocably withdraw (exits). For the focal bidder who remains in the auction, perceived expertise of competitors that remain is likely to influence the construal of value of the auctioned product. Such value construal may not conform to economic notions of rationality for those entering the auction with a well-formed assessment of the product's value. Thus, when values are not well-defined, perceptions of Competitor Expertise may be a meaningful inference heuristic. Subsequently, in this context, those who bid last against Hybrid or Product Experts may bid higher and have higher post-auction product value assessments.

In addition to Competitor Expertise, Auction Outcome may also influence the focal bidder's value inferences. Focal bidders that win the auction know the price at which they won and are therefore familiar with the market clearing bid level. As such, their immediate post-auction assessment of what they would be willing to pay the auctioneer in a direct purchase (not mediated by an auction) may be anchored by this price. Similar to a "buy it now" price, we term this measure WTPDIR1. However, the fact that they won and now own the product may lead to endowment effects that change their <u>willingness to accept</u> (WTA1) an offer for the product that they won. Moreover, this WTA1 measure may differ as a function of the perceived expertise level of their most persistent competitor. The bidder may reason that Hybrid/Product Experts are better judges of product value than Process Experts or Amateurs. They may also feel some pride for having acquired the product in competition against true connoisseurs. Hence, WTA1 value may be higher for those who had a Hybrid/Product Expert versus a Process Expert or an Amateur as their most enduring competitor. Thus:

> P2. Auction winners' immediate post-auction value measures of the product's <u>direct purchase value</u> (WTPDIR1) will <u>not</u> differ by perceived Competitor Expertise.

> P3. Auction winners' immediate post-auction willingness to accept (WTA1) measures will be higher for those who won against Hybrid/Product Experts versus Process Experts/Amateurs.

In contrast to winners, auction participants who lose do not observe the winning bid level. Hence, their post-auction assessments of product value should be higher than that of winners irrespective of whether the measure is of direct purchase value (WTPDIR1) or willingness to pay (WTP1) for the item they could not acquire in the auction. Also, if these bidders follow similar reasoning as the winners, their WTP1 should show a similar pattern of differences as a function of perceived Competitor Expertise (i.e., higher when they lose to Hybrid/Product Experts versus Process Experts/Amateurs). Alternatively, their WTP1 estimates may be influenced by how they choose to manage experienced regret. As such, they may attempt to devalue the product by arguing that the winner "paid too much." However, such rationalization may be less compelling for losses against Hybrid/Product Experts versus Process Experts/Amateurs.

> P4. Auction losers' immediate post-auction measures of <u>direct purchase</u> value (WTPDIR1) will be higher than that of auction winners.

> P5. Auction losers' immediate post-auction willingness to pay (WTP1) measures will be higher for those who lost to Hybrid/Product Experts versus Process Experts/Amateurs.

Bidders who lose in our auction come from two pools. One pool consists of those who exhaust their budgets and can bid no higher. Another group consists of those who quit of their own volition (perhaps because they did not value the product enough or were impatient). One would expect the second group of losers to have lower product valuations than the former. While Proposition 6 reflects this, differential regret management efforts in the two groups could drive other results. Thus:

> P6. Auction losers' immediate post-auction willingness to pay (WTP1) measures will be higher for those who lost because their budget was exhausted versus those who quit volitionally.

2.3.3 Propositions: Temporal Stability of Post-Auction Values

Immediate post-auction value measures may reflect a transient sense of elation (for winners) and dejection (for losers). However, the passage of time should allow the opportunity for reflection and adjustment. Measures of direct purchase value (ΔWTPDIR) should remain relatively stable. However, auction winners may show changes in ΔWTA as a function of whom they won against. If perceived Competitor Expertise signals the reliability of values, those who won against Hybrid/Product Experts should exhibit stable (or even increased) ΔWTA relative to those who won against Process Experts/Amateurs. The latter may show a decrease in valuation with time once the elation of winning wears off, and reflection suggests that they may have paid too much to win against competitors with relatively less knowledge of product value.

> P7. Auction winners' post-auction measures of <u>direct purchase</u> value (ΔWTPDIR) will (a) remain stable over time and (b) not vary as a function of perceived Competitor Expertise.

> P8. Auction winners' post-auction ΔWTA measures (a) will be relatively stable for those who won against hybrid/Product Experts, but (b) decrease for those who won against Process Experts/Amateurs.

Focal bidders who lost the auction may have more opportunity to engage in regret management with time. Although they may exhibit higher value assessments relative to winners (P5), these values are likely to be unstable and influenced by perceived

Competitor Expertise. Direct purchase value measures (ΔWTPDIR) may be relatively more stable, but ΔWTP measures of value may drop as losing bidders mentally devalue the product. However, as noted, such devaluation may be less compelling for losses against Hybrid/Product Experts versus Process Experts/Amateurs.

P9. Auction losers' post-auction measures of direct purchase value (ΔWTPDIR) will (a) remain relatively stable over time, and (b) not vary as a function of perceived Competitor Expertise.

P10. Auction losers' post-auction ΔWTP measures will decrease over time. However, the decrease will be smaller for those who lost against Hybrid/Product Experts versus those who lost against Process Experts/Amateurs.

Our propositions do not make sharp distinctions for wins or losses against Hybrid versus Product Experts. In comparing Hybrid and Product Experts, one might reason that Product Experts' bids are more reliable indicators of value, but the influence of auction Process Expertise is unclear. Process Experts' bids may not reliably indicate value, but one might anticipate that *ceteris paribus* Process Experts are more likely than Amateurs to bid lower. Relying on bids from Amateurs may be perceived as unreliable, and bidders who lose to Amateurs may therefore post values that are highly variable. Lacking theoretical clarity on these issues, we wait to examine our empirical results for an exploratory understanding of the differences, if any.

Next, we report three experiments examining the above propositions. The studies were driven by the same conceptual framework with sequential procedural refinements after each study. The software platform for the studies was custom designed to enable seamless implementation of study instructions, expertise manipulation, the auction bidding exercise, collection of dependent measures (valuations), and other ancillary measures both immediately after the auction and following a time delay (via an interpolated task).

2.4 General Procedure

The auction mechanism used for these three experiments is an ascending Japanese auction. In a Japanese auction, the bid level increases based on predetermined increments or bid levels. At each bid level, participants must indicate whether they wish to remain in the auction by actively submitting a bid (Cassady, 1967). Failure to bid at one of the bid levels constitutes immediate and irrevocable withdrawal from the auction, and a participant's bid is recorded at their last bid level. The last remaining bidder wins the auctioned product and pays a price equal to the previous (second-highest) bid level (Klemperer, 2004; Milgrom & Weber, 1982). The procedure differs from the more common, ascending English auction: at each bid level, bidders must indicate whether they wish to stay in the auction. In contrast with other common auction mechanisms (e.g., ascending "English" and descending "Dutch" auctions), the Japanese auction has each participant confirm their willingness to stay in at the current bid level. This allows assessment of each participant's value for the auction object, except for the winning bidder (Kagel J. H., 1995; Kagel & Levin, 2015) whose true value is not observed.

The propositions above were examined using a custom-designed auction software that nested within the Qualtrics survey platform. The software was developed using a combination of JavaScript, CSS, and HTML. This software allowed participants, who were members of the Amazon Mechanical Turk (M-Turk) and Prolific web panels, to move seamlessly between study instructions, expertise manipulation, the auction bidding exercise, and the post-auction survey that captured valuation and other psychological measures at two different points of time. These are described in greater detail as we present each study.

Following recruitment, participants were directed to the online auction where they received study instructions and provided informed consent. The study instructions included a description of the Competitor Expertise types (Product Experts: experts in the product category and discerning in product quality; Process Experts: experts at auctions and auction bidding strategies; Hybrid Experts: possessing both product and Process Expertise; or Amateurs: possessing neither Product nor Process Expertise). The graphics used different shirt colors to facilitate easy participant identification of expertise types. The focal bidder wore a red shirt, and Product, Process, and Hybrid Experts each wore gold, blue, and green shirts, respectively. Amateurs wore a white shirt (see Appendix A). Following the instruction set, a knowledge check tested participants' grasp of the features of each competitor expert type. Participants who failed the test were required to review the instruction material and pass the check before they could proceed.

The instructions also explained the auction incentive structure which was structured to encourage bidding. The specific incentive structures and related parameters varied by study and are shown in Appendix B. An illustrative example of the text used to explain the auction payouts is shown in Appendix C. Participants were endowed with a budget with which to bid. They could quit voluntarily at any time (a self-imposed loss), bid until they won, or lose because they exceeded their budget. The product's market value was announced at the very end of the study. Those designated to win (assigned randomly) received this market value (unknown at the time of bidding) reduced by their bid for the product. Those who lost (either because they quit voluntarily or because the bid level exceeded their budget) kept their unspent budget. The actual payments to participants were at conversion rates that slightly favored those who won (versus lost).

Participants first bid in a practice auction (for a watch) to gain familiarity with the auction interface. Following the practice auction, participants selected a bottle of wine to bid on (Appendix D, Panel 1). The purpose of the selection task was to increase participant involvement with the product. During the actual auction, participants viewed the bidding interface which showed the product (the bottle they chose), the number and type of competitor experts against whom they were bidding, a bidding timer, and the current bid level (Appendix D, Panel 2). At each bid level, participants had ten seconds to click the "Bid" button to place a bid. Once the time counted down to zero, participants either saw the next bid level (if they had bid) or the auction end (if they did not bid).

Bidder dropout patterns at each bid level were varied systematically so that the focal bidder (participant) last competed against a remaining bidder of the assigned expertise type. For Study Set 1 (Chapter 3), the bidder dropout patterns for Studies 1-3 are shown in Appendix E, F, and G, respectively. For each round, the bid level increased by preset increments. Thus, as the auction progressed, bidders assigned to compete against a given expert type observed all other competitors drop out, leaving just one competitor of the assigned expertise type. The dropout patterns ensured that the focal bidder saw their final opponent (per their assigned Competitor Expertise condition) by either the second or third round of bidding and stayed with them until they quit, lost, or won.

Auction Outcome (i.e., whether the focal bidder won or lost) was also manipulated. Some participants were randomly designated to win (lose) the auction. Those designated to win saw the final competitor drop out of the auction at a preset bid level (that varied by study), allowing them to bid and win. Those designated to lose could continue bidding and experience a forced loss once the bid level exceeded their budget. Participants were unaware of their designated win/loss condition. Moreover, to ensure mundane realism, participants were permitted to quit the auction at any time. Since the bid level was endogenously determined, win-designated bidders who chose not to bid to the preset win level could also lose the auction. Lose-designated bidders could also quit at any time but experienced a forced loss when their budget was exceeded. This design compromises experimental control. However, apart from the benefits of mundane realism, it allows us to explore how bidders who quit at different bid levels value the auction object.

At the end of the auction, participants answered questions about their valuation of the item's direct purchase value (WTPDIR), willingness to accept for winners (WTA), and willingness to pay for losers (WTP), as well as their evaluation of the auction experience (experienced regret, satisfaction with bidding, and felt excitement). They answered these questions once immediately after the auction (at T_1) and then again, following a short, interpolated task (at T_2). They also provided their demographic details at the very end of the study. In summary, the three studies followed a similar basic procedure but varied in detail. The focal manipulations were perceived Competitor Expertise and Auction Outcome (both between subjects). The dependent measures were (a) the actual bid level; (b) perceived product valuation (direct purchase value, WTPDIR, for all participants, WTA for winners, and WTP for losers); and (c) the auction experience measures. The measures of product valuation and auction experience were obtained twice from each participant. Thus, measurement time was a within-participant factor. Appendix O provides details of the questions used to elicit the value measures as well as the measures of auction experience. Each auction experience measure (excitement, regret, and satisfaction) was constructed by multiple relevant items (Appendix O).

2.5 Post-Auction Valuation Measures

The bid level data that were generated during the auction are a measure of the focal bidder's assessment of the product's value. This value may have been constructed during the auction and then evolved based on the bidder's observation of the actions of other competing bidders. This revealed measure of value represents the highest price a bidder is willing to pay at the time of the auction (Klemperer, 1999) and is the primary focus of both theoretical (Milgrom & Weber, 1982) and experimental auctions (Lusk & Shogren, 2007) literature. Elicited from participants who have "skin in the game" (Hanley, Shogren, & White, 2006), it is arguably an effective and incentive compatible price revelation tool (Hoffman, Menkhaus, Chakravarti, Field, & Whipple, 1993; Lusk & Shogren, 2007).

In contrast, values may also be elicited by asking participants hypothetical questions about the maximum they are willing to pay to purchase (WTP) or the least they are willing to accept to sell (WTA) the product. WTP and WTA have played a central role in understanding consumer pricing decisions in both practice and research (Anderson, Jain, & Chintagunta, 2008; Jedidi & Jagpal, 2009), and bracket the synthetic valuation measure known as the "endowment effect." From a normative perspective, a person's WTP and WTA should not differ significantly (Willig, 1976). However, researchers have demonstrated non-trivial discrepancies between WTP and WTA in both the laboratory (Knetsch & Sinden, 1984) and the field (Brookshire, Randall, & Stoll, 1980). These results suggest that WTP, WTA, and the gap between them are persistent and robust to learning (Kahneman, Knetsch, & Thaler, 1990), as well as market mechanisms, such as negotiations (Galin, 2013) and auctions (Loureiro, Umberger, & Hine, 2003). The endowment effect gap can predict felt emotions toward a product (Murata, 2015) and drive economically consequential differences in returns (Wang, 2009). Thus, post-auction WTP, WTA, and the Endowment Effect (WTA-WTP) bear careful scrutiny as value measures in our research context.

The "Buy-it-Now" (BIN) price was initiated in 2000 by online auction houses like eBay and Yahoo! Although BIN procedures vary across auction houses, it is of conceptual and pragmatic interest because it allows buyers to short circuit the gap between participative and fixed-price retail mechanisms (Durham, Roelofs, & Standifird, 2004). As of 2018, most online auction house listings include the BIN option, offering both fixed and participative pricing at the same time (Einav, Farronato, Levin, & Sundaresan, 2018). Apart from the institutional features of BIN options (Hsiao, 2019), researchers have also examined why such options provide efficiency levels and revenues that are different (usually higher) than those generated in auctions (Grebe, Ivanova-Stenzel, & Kroger, 2021).

In addition to traditional WTP and WTA measures, we also develop a retrospective measure of value that we label the product's "direct purchase value" to the bidder. We ask focal bidders to retrospectively indicate the maximum they would have been willing to pay had the auctioneer given them an option to name a direct purchase price at the start of the auction. Thus, bidders can state their direct purchase value for the product (WTPDIR) without undertaking the stresses and strains of the participative auction. Their response may differ from the post-auction WTP (for losers) and WTA (for winners) and is collected retrospectively and <u>after</u> the WTA (WTP) measure. Given that it is collected retrospectively, the WTPDIR measure of value may be influenced by the auction experience, and it is conceptually distinct from WTA or WTP. We decided not to collect this measure prior to the auction to avoid fixing an *ex ante* value for the auction object prior to the auction, as this may have influenced bidding (see Cheema et al., 2012).

We also examine how these valuation measures change over time. Even though normative theory suggests that intertemporal preferences (and by extension, valuations) should be generally stable (Brouwer, 2012), behavioral research shows that they are sensitive to multiple contextual factors (Redelmeier & Kahneman, 1996), regret (Graham & Sugden, 1983), and the relative salience of various product attributes (Tsetso, Usher, & Chater, 2010). In our auction context, we examine the possibility that with bidder reflection, these valuation measures may change over time as a function of perceived Competitor Expertise. Thus, the value of an auctioned object may rest not only on the

Auction Outcome (win/loss) but also on the perceived expertise of the competition against which the outcome is obtained.

2.6 Conclusion

This chapter provides a discussion of our core independent variable: perceived Competitor Expertise (Product Expertise, Process Expertise, Hybrid Expertise, and Amateurs) and how it may affect bidding in an ascending auction. We identify a set of key dependent measures: (a) the amount bid in the auction; (b) post-auction measures of the auction object's value; and (c) the stability of these value measures over time. We also examine how the Auction Outcome (win or loss) may moderate the perceived value measures and their stability over time. We provide a set of initial propositions regarding these effects as a benchmark for interpreting the results from our empirical studies. We also outline the general procedures of the three experimental studies that we describe next in Chapter 3.

Chapter 3: Perceived Competitor Expertise: Three Ascending Auction Experiments

This chapter presents three studies that examine the influences of perceived Competitor Expertise on bidding in ascending auctions as well as post-auction valuation and its stability over time. We describe these studies in sequence next.

3.1 Study 1 Procedure

Study 1 was originally designed to examine the set of propositions described earlier. A programming error rendered post-auction valuation data unusable. However, the Competitor Expertise manipulation and auction bidding procedure was completed successfully and allowed us to examine Proposition P1 that pertains to bidding behavior during the auction. This initial study focused on bidding against competitors perceived as Product Experts, Process Experts, or Amateurs. Hybrid Experts were not considered in this study.

A total of 303 M-Turk panelists were recruited to participate in an online auction for a base pay of $0.50 and the opportunity to earn an additional bonus depending on auction performance. One individual failed to complete the study. Of the remaining 302 participants, 99, 99, and 104 were assigned to compete against Product Experts, Process Experts, and Amateurs, respectively (recall that these labels refer to the perceived expertise of the last remaining competitor), and 152 (150) participants were designated to win (lose) the auction. Of the 152 participants assigned to win, 86 won, and 66 quit the auction before reaching the winning bid level. Of the 150 assigned to lose, 67 stayed until their budget ran out, and 83 quit at intermediate bid levels. In summary, a total of 216 participants lost the auction (149 quit by choice and 67 because their budget ran out).

The study simulated a hypothetical auction for an expensive bottle of wine, and participants were endowed with a $145.00 budget for the auction. Bidding began at $100.00 and proceeded in $5.00 increments. Designated winners could win the auction at a bid level of $130.00 (paying $125.00 since the last competitor dropped out at the $125.00 level). For designated losers, the final competitor bid to $150.00, a bid level at which the focal bidder's budget was exceeded. The product's market value was announced post-auction as $152.50. The incentive structure encouraged budding: the unspent budget was converted at $0.003 on the dollar, whereas the product surplus (market value less the winning payment of $125.00) was converted at $0.005 on the dollar. Ostensibly, losers made $0.94, and winners made $1.32 on the game. Appendix B summarizes these details. However, for equity reasons, we used a lottery mechanism to ensure that all participants were paid $1.32. As noted earlier, valuation data in this study were unusable due to a programming error.

3.1.1 Study 1 Results

The expertise manipulation checks were successful. Focal bidders competing against Amateurs reported significantly more amateurs competing than other expert types ($M_{CAmateur} = 5.16, SE_{CAmateur} = 0.16; M_{CProcess} = 3.35, SE_{CProcess} = 0.17; M_{CProduct} = 3.29, SE_{CProduct} = 0.17$), F(2, 299) = 41.26, p < 0.001. Those competing against Process Experts reported significantly more Process Experts competing versus others ($M_{CAmateur} = 3.43, SE_{CAmateur} = 0.18; M_{CProcess} =$

$4.90, SE_{CProcess} = 0.18; M_{CProduct} = 3.93, SE_{CProduct} = 0.18$), F(2, 299) = 17.14, p < 0.001. Finally, those competing Product Experts also reported more Product Experts ($M_{CAmateur} = 3.55, SE_{CAmateur} = 0.17; M_{CProcess} = 3.89, SE_{CProcess} = 0.17; M_{CProduct} = 5.44, SE_{CProduct} = 0.17$), F(2, 299) = 35.49, p < 0.001).

Among those designated to win, focal bidders stayed in the auction longer (bid higher) when competing against Product Experts (70.00% stayed until the winning bid level) versus either Process Experts (50%) or Amateurs (50%), $\chi^2(2) = 5.46, p = 0.07$. Thus, these data support Proposition P1. Among bidders designated to lose, those competing against Product Experts also tended to bid highest (53.06% stayed until their budget ran out), versus those competing with Amateurs (51.92%) or against Process Experts (28.57%), $\chi^2(2) = 7.64, p = 0.02$. Somewhat unexpectedly, the stay percentage did not differ for Product Expert or Amateur competition, but both were significantly higher than for Process Expert competition. Appendix H provides the full set of results. We do not pool the data for winners and losers because the levels to which they could bid ($130.00 and $150.00, respectively) were different.

3.1.2 Study 1 Discussion

Bid level results from Study 1 show that auction participants bid differently depending on the perceived Competitor Expertise type they last competed against. Among those who won, participants bid higher when competing against Product Experts than either Process Experts or Amateurs. Among those who lost (recall that this is at a higher bid level), bidders quit soonest when competing against Process Experts, next when competing against Amateurs, and stayed the longest when competing against Product Experts.

These results are interesting for two reasons. First, auction theory suggests that in the absence of information about competitor valuations, bidders should bid their value (Milgrom & Weber, 1982) or shade them somewhat to avoid the winner's curse (Thaler, 1988; Wilson, 1977). This notion was violated for bidders who won or lost. Second, the results show that bidders bid higher when competing against Product Experts. This suggests that bidders followed the bidding actions of Product Experts as more reliable signals of the product value.

Unexpectedly, focal bidders bid higher when biding against Amateurs versus against Process Experts. It may be that they anticipated that Process Experts would bid strategically, irrespective of the product's value. Hence, they may have been more willing to take their cues from Amateurs who may be less likely to commoditize the item. Study 2 explores these expertise effects further.

3.2 Study 2

The design of Study 2 was guided by observations and findings from Study 1. First, the programming error was corrected so that we obtained valuation data in addition to the bidding data. Second, although we retained a participant-selected bottle of wine as the auctioned product, the price was lowered to a level conforming to a somewhat less indulgent purchase for average M-Turk workers with incomes between $20,000 and $30,000 (Ross, Irani, Silberman, Zaldivar, & Tomlinson, 2010). Hence, (see Appendix B) the bidding range was lowered to between $40.00 - $50.00, with bidding increments set at $1.00, and the budget endowment at $50.00. Third, the winning bid level for designated winners was $45.00 (pays $44.00). Designated losers could bid to $51.00 before their budget ran out. Fourth, we elicited the value measures using a slider scale anchored by a low of $40.00 and a high of $90.00 to avoid unreasonable estimates that emerge in open-ended elicitation. Finally, we modified the incentive structure. The base compensation was lowered to $0.30. However, the conversion rates were raised: unspent budget converted at $0.005 on the dollar, and product (market value = $66.00) converted at $0.01 on the dollar). Ostensibly losers (winners) made $0.55 ($0.99), but all participants were paid $0.99 for equity reasons.

3.2.1 Study 2 Procedure

Participants were 346 M-Turk panelists recruited for the base pay and performance bonus outlined above (participants from Study 1 could not participate in Study 2). Of these, 172 (174) were randomly assigned to win (lose). Of the assigned winners, 98 won and 74 lost (quit before reaching the winning bid level). Of the 174 assigned to lose, 60 stayed until their budget ran out, and 114 quit at intermediate bid levels. Thus, a total of 258 participants lost the auction (198 quit by choice and 60 because their budget ran out). As in Study 1, participants could quit the auction at any time during bidding. The 346 panelists, 116, 115 and 115 were randomly assigned to compete against Product Experts (n = 116), Process Experts (n = 115), and Amateurs (n = 115), respectively. This study also did not include Hybrid Experts.

The instruction sets used to implement the Competitor Expertise perceptions were similar to those used in Study 1 with variations reflecting the changes outlined. The auction interface was adjusted to reflect the new auction characteristics, improved graphics, and more clear instructions. As in Study 1, participants gained experience with the platform via a practice auction, selected the bottle of wine that they would bid on, and proceeded to the main auction. Bidding started at $40.00 and proceeded in $1.00 increments. As noted above, the winning bid level for designated winners was $45.00 (pay $44.00). A bidder could quit at any time during the auction, but those designated to lose could bid up to $51.00, after which their budget ($50.00) ran out.

Appendix O shows the details of all measures collected in the study. We collected three measures of the auctioned item's value immediately after the auction was concluded. The first was a measure of "direct purchase value" (WTPDIR) of the bottle of wine. The second, collected from those who won the auction, was a traditional willingness to accept (WTA) measure for the bottle of wine they had won. The third measure, collected from those who lost the auction, was a traditional willingness to pay (WTP) measure for the bottle of wine that they had failed to acquire in the auction. These measures were collected using a slider scale set between $40.00 - $90.00. We elaborate on these valuation measures in the next section.

In addition, all participants (focal bidders) provided responses to questions that assessed experienced regret, excitement, and satisfaction during the auction. Participants then completed an interpolated task (watching a video) that required approximately two minutes. Following the interpolated task, participants once again provided the three valuation measures. The market value of the auctioned item ($66.00) was then announced. Participants were then paid their study earnings (losers were given a token prize) so that all participants received $0.99.

3.2.2 Study 2 Results

The expertise manipulation worked as intended. Bidders competing last against Amateurs reported significantly more Amateurs competitors in the auction than other expert types ($M_{CAmateur} = 6.10, SE_{CAmateur} = 0.17; M_{CProcess} = 2.18, SE_{CProcess} = 0.0.17; M_{CProduct} = 2.20, SE_{CProduct} = 0.17$), F(2, 343) = 169.17, p < 0.001). Those competing last against Process Experts reported significantly more Process Expert competitors ($M_{CAmateur} = 2.60, SE_{CAmateur} = 0.20;\ M_{CProcess} = 6.11, SE_{CProcess} = 0.20; M_{CProduct} = 3.00, SE_{CProduct} = 0.19$), F(2, 343) = 96.9, p < 0.001. Finally, those who competed with Product Experts as their final opponents reported significantly more Product Expert competitors ($M_{CAmateur} = 2.57, SE_{CAmateur} = 0.19; M_{CProcess} = 2.40, SE_{CProcess} = 0.19; M_{CProduct} = 5.89, SE_{CProduct} = 0.19$), F(2, 343) =105.17, p < 0.001.

3.2.2.1 Bid Level

The bid level results (Appendix I) provide additional support for Proposition P1. Win-designated bidders who competed last against Product Experts showed a greater propensity to remain in the auction (70.18%) than those competing against Process Experts (50.00%) or Amateurs (50.88%). The proportions are significantly different ($\chi^2(2) = 6.77, p = 0.03$. Also, lose-designated bidders who last competed against Product Experts also had a higher propensity (47.5%) to remain in the auction than those competing against Process Experts (26.3%) or Amateurs (29.3%). These proportions are also significantly different, $\chi^2(2) = 6.07, p = 0.05$. As in Study 1, we avoid pooling data for the winners and losers because their maximum bid levels were different.

3.2.2.2 Post-Auction Valuations

As shown in Appendix O, three measures of post-auction valuation were collected immediately following the auction. Auction winners indicated the lowest amount they would be willing to accept for the bottle of wine (WTA1). Auction losers indicated the highest amount they would be willing to pay (WTP1) to acquire the bottle in the auction. Next, all participants also provided their "direct purchase value" (i.e., what they would have been willing to pay for the bottle if they could have bought it directly from the auctioneer - WTPDIR1).

Participants then worked on an interpolated task that lasted about two minutes. Following this, they provided the value assessments once again allowing us to calculate how value changed over time (ΔWTA, ΔWTP, and ΔWTPDIR). Thus, we obtained two sets of post-auction valuation measures from each participant, separated by a time delay. At each of the two measurement points, participants also indicated their level of satisfaction (SAT) and regret (REG) regarding how they had bid in the auction, as well as the extent to which they found the auction exciting (EXC).

3.2.2.2.1 Post-Auction Valuations - Immediate

We examined how each of the immediate post-auction value measures (WTPDIR1, WTA1, WTP1) were influenced by perceived Competitor Expertise (Product/Process/Amateur) and the Auction Outcome (Win/Loss). Participants indicated their responses on a sliding scale left-anchored at $40.00 and right-anchored by $90.00. These bounds were provided to guide subjects to make reasonable value assessments. However, this also created a possibility that the value estimates were left- or right-censored. Examination of the data for responses that were either at the lower or upper bounds of the provided range showed no such observations for the WTA1 measure. However, the WTP1 data showed both left (3.47%) and right (0.58%) censoring. Interestingly, 13.58% of the WTPDIR1 measures were left censored.

Also, note that for bidders who lost due to a budget constraint and for bidders who won the ascending auction because all competitors dropped out, we do not observe the value they would have been willing to bid. Although the valuation measures may not reflect censoring attributable to this issue, we acknowledge the possibility of censoring due to the use of a bounded numerical scale for value measurement.

Given potential censoring, these post-auction valuation measures were analyzed using a maximum likelihood censored Tobit model available within the SAS PROC LIFEREG procedure. Model fit was tested using several continuous conditional outcome distributions available within SAS PROC LIFEREG as well as covariate combinations. Final distribution and covariate selection were based on each model's AIC score and likelihood ratio tests. The normal distribution fit poorly. Generalized gamma was retained as the best fitting distribution for all dependent measures in both studies 2 and 3. Also, a comparison of nested models using likelihood ratio tests suggested using satisfaction, excitement, regret, age, and gender as covariates. Summaries of these analyses for each dependent measure of value are provided in Appendix J (Panel 1: WTPDIR1; Panel 2: WTA1; Panel 3: WTP1, respectively). Note that reported mean valuations are tabulated under each regression and are reported as unlogged transformations derived from the exponentiated Tobit model coefficients (i.e., means are reported in dollars).

Participants were randomly assigned to two groups, respectively, designated to either win the auction at $45.00 (pay $44.00) or lose at $50.00. This was implemented by creating a predetermined competitor bidder dropout schedule (see Appendix F for Study 2). However, this designation was known only to experimenters and participants were not privy to it. Thus, to retain mundane realism, participants were allowed to quit the auction at any time (Cheema, Chakravarti, & Sinha, 2012). A significant number of participants in both win and lose-designated groups quit the auction at various bid levels. One group of participants quit before the bid level reached $44.00 (regardless of whether they were designated to win or lose). A second group, designated to lose at $50.00, quit at various bid levels between $44.00 and $49.00. The third group played as designated and consequently lost at $50.00 when their budget was exceeded. Since the auction experience (and perhaps game involvement levels) differed based on the bid level at which individuals quit, the Auction Outcome variable was created as a four-level factor: winners at $50.00 (n = 98), losers at $50.00 (n = 43), losers between $44.00 - $49.00 (n = 85), and those who lost below $44.00 (n = 120). No participants were dropped from the analysis based on their auction bidding behavior.

WTPDIR1. A censored regression analysis was used to model WTPDIR1 (the direct purchase value measure) as a function of Competitor Expertise type (Product Expert, Process Exert, Amateur), Auction Outcome (Win at $50.00, lose at $50.00, lose at $44.00 - $49.00, lose at <$44.00) and the interaction of these two factors. Age, gender, satisfaction, regret, and excitement were used as covariates. As shown in Appendix J, Panel 1, Auction Outcome ($\chi^2 = 23.467, p < 0.001$) and the interaction of Competitor Expertise and Auction Outcome was significant ($\chi^2 = 14.111, p = 0.028$). Among the covariates, higher levels of regret (p = 0.001) and excitement (p = .001) and lower age (p = 0.006) were associated with higher WTPDIR1 values. The table of relevant means is provided below the regression results.

First, the data show that consistent with Proposition 2, the WTPDIR1 measure for winners did not differ by Competitor Expertise level ($M_{CProduct} = \$41.91, M_{CProcess} = \$43.02, M_{Amateur} = \$42.73$), p's > 0.10. Second, consistent with Proposition 4, bidders who lost the auction at \$50.00 (designated losers) reported higher WTPDIR1 values than those who won ($M_{Losers} = \$48.25$ versus $M_{Winners} = \$42.55$), p < 0.001. Notably, this difference was largest for bidders who lost to Amateurs ($M_{Losers} = \$51.52$ versus $M_{Winners} = \$42.73$), p < 0.001), next for those who lost to Process Experts ($M_{Losers} = \$48.13$ versus $M_{Winners} = \$43.02$, p < 0.001) and smallest for those who lost to Product Experts ($M_{Losers} = \$45.10$ versus $M_{Winners} = \$41.91$, p < 0.001). We note that since winners could bid only to \$45.00, whereas lose-designated bidders could bid to \$50.00, these comparisons of WTPDIR1 may not be fair. Study 3 allows win and lose-designated bidders to either win or lose at the same bid level (\$50.00), and this provides a more impartial test of this proposition. Finally, for the bidder group that lost at \$50.00, those competing with Amateurs (M = \$51.52) provided significantly higher values than those competing against Product Experts (M = \$45.10), p = 0.003. Those who quit between \$44.00 and \$49.00, as well as those who quit before the bid level reached \$44.00, also reported significantly lower WTPDIR1 values (\$43.48 and \$41.62; p's < 0.001).

WTA1. A censored regression analysis was used to model WTA1 (the willingness to accept measure for auction winners) as a function of Competitor Expertise type (Product Expert, Process Exert, Amateur). As before, age, gender, satisfaction, regret, and excitement served as covariates. As Appendix J, Panel 2 shows, Competitor Expertise had a significant effect ($\chi^2 = 13.203, p = 0.001$). Also, higher levels of excitement (p = 0.04) and lower age (p < 0.001) were associated with higher WTA1 values. The table of relevant means is provided below the regression results.

Focal bidders who won against amateurs ($49.64), as well as those who won against Product Experts ($48.76), reported higher WTA1 values (p < 0.001) than those who won against Process Experts ($46.85). These data for the Product Expert group provide partial support for Proposition 3. However, the result with respect to Amateurs is unexpected. It may be that bidders who won against Amateurs felt some level of conflict and quoted a higher WTA1 to (self) justify their acquisition of the product.

WTP1. A similar censored regression analysis was used to model WTP1 (losers' willingness to pay for the auction object that they did not win) as a function of Competitor Expertise type (Product Expert, Process Exert, Amateur), Auction Outcome (lose at $50.00, lose at $44.00 - $49.00, lose at < $44.00) and the interaction of these two factors. As previously, age, gender, satisfaction, regret, and excitement were used as covariates. Appendix J, Panel 3 shows that Auction Outcome ($\chi^2 = 26.566, p < 0.001$) had a significant effect, and Competitor Expertise was marginally significant ($\chi^2 = 5.592, p = 0.061$). The interaction was not significant (p = 0.123). Among the covariates, higher levels of excitement were associated with increased WTP1 (p = 0.002).

No other covariates were significant. The relevant means are tabulated below the regression results.

Focal bidders who lost at \$50.00 against Amateurs (\$50.44), as well as those who lost against Product Experts (\$48.73), reported higher WTP1 values than those who lost against Process Experts (\$44.65), $p < 0.001$. These data for the Product Expert group provide additional partial support for Proposition 5. However, the results for those who competed against Amateurs (\$50.44) were once again unexpectedly high. Both the WTA1 and WTP1 results for Amateurs are inconsistent with our knowledge-based reasoning and suggest that motivated reasoning and justification processes may have been in play in assessing value when competing with Amateurs. Focal bidders who quit at bid levels between \$44.00 and \$49.00 assessed similar values regardless of Competitor Expertise (Product: \$43.55; Process: \$43.68; Amateurs \$44.14). In contrast, and, consistent with Proposition 6, pooled across expertise levels, bidders designated to lose at \$50.00 reported the highest overall WTP1 values (\$47.94), significantly higher than those who quit between \$44.00 and \$49.00 (\$43.79) or below \$44.00 (\$42.12), p's < 0.001.

3.2.2.2.2 Post-Auction Valuation: Durability

We used a set of Difference-in-Differences analyses (Warton, Parker, & Karter, 2016) to examine change in post-auction valuation over time as a function of Time interacted with Competitor Expertise, Auction Outcome, and the interaction of these two factors. We used SAS PROC GLIMMIX for this analysis.

ΔWTPDIR. The results of the analysis for changes in WTPDIR are shown in Appendix K, Panel 1. The omnibus tests for Competitor Expertise, Auction Outcome, and the interaction of these two factors were not significant (respective p's = 0.606, 0.756 and 0.739). Among the covariates, higher levels of regret ($p < 0.001$), excitement ($p = 0.022$ and satisfaction ($p < 0.001$), and lower age ($p = 0.007$) were associated with an increase in ∆WTPDIR. The table means are reported below the regression results.

Proposition 7 guided our examination of the simple effects for the auction winners. A test of these differences for those who won at $45.00 revealed that ∆WTPDIR changes for those who won against Product Experts ($0.49) and Amateurs ($0.11) were stable (i.e., not significantly different from zero). This is consistent with Proposition 7A. However, the valuation for those who lost against Process Experts ($1.40) increased significantly, $p < 0.001$. This increase in value for those won against Process Experts was also significantly greater than for those bidders who won in competition against Product Experts (0.49), $p < 0.001$, and Amateurs (0.11), $p < 0.001$. The increase in value for those who won against Process Experts was unexpected (Proposition 7B) and suggests that, upon reflection, focal bidders may have felt that Process Experts had bid conservatively and that the auctioned product's value was probably higher than what they had initially believed.

Proposition 9 guided our examination of the simple effects for the auction losers. Focusing on bidders who lost at $50.00, ∆WTPDIR changes for those who lost against Product Experts ($0.37) and Process Experts (-$0.73) were not significantly different from zero, p's > 0.10. However, the value for those who lost against Amateurs increased significantly ($1.13, $p = 0.02$). Bidders who quit between $44.00 and $49.00 also showed similar patterns of changes in their WTPDIR. For these bidders, change for those who lost against Product Experts ($0.02), Process Experts (-$0.11), and amateurs ($0.88) were not significantly different from zero, p's > 0.10. This is consistent with Proposition 9A. However, Proposition 9B was not supported. Values increased more for those who lost against Amateurs ($0.88) than for those who lost against Process Experts (-$0.11, p = 0.001) or against Product Experts ($0.02, p = 0.001).

ΔWTA. Appendix K, Panel 2 shows the results for the analysis of the change in WTA for those who won the auction at $45.00. The omnibus tests showed no significant effects of Competitor Expertise (p = 0.164). Also, none of the covariates were significant. The table of means is reported below the regression. Analysis of the simple effects showed that post-auction values were relatively stable for those who lost against Product Experts (-$0.35, p = 0.09) but fell significantly for those who lost against Process Experts (-$2.56, p < 0.001) and Amateurs (-$1.66, p < 0.001). Furthermore, the difference in change for those who competed against Process Experts and Amateurs was significantly lower than for those who competed against Product Experts, p < 0.001. These data are consistent with Proposition 8.

ΔWTP. Appendix K, Panel 3 shows the analysis for change in post-auction WTP measures for those who lost the auction. The table of means is below the regression. The omnibus tests showed no significant change in post-auction WTP as a function of Competitor Expertise (p = 0.894), Auction Outcome (p = 0.390), or the interaction between them (p = 0.64). Among the covariates, higher levels of regret (p = 0.002), satisfaction (p = 0.016) and excitement (p = 0.001) were associated with greater increases with ΔWTP. Men posted larger increases in value. Proposition 10 guided our examination of the simple effects. Focusing on bidders who lost at $50.00, we observe the overall predicted decrease in value (-$1.26), p = 0.01. However, the decrease was largest for those who lost against Product Experts (-\$2.41), $p < 0.001$, followed by those who lost against Process Experts (-\$1.07), $p = 0.01$. The decrease for those who last competed against Amateurs (-\$0.29) was not significant, $p > 0.10$. Bidders who quit between \$44.00 and \$49.00 showed a very different pattern. Valuation increased for those who lost against Product Experts (\$1.03, $p = 0.001$) and decreased for those competing against Process Experts (-\$0.74, $p = 0.05$). Competition against Amateurs did not produce a significant difference in value change over time. These data did not provide support for Proposition 10.

3.2.3 Study 2 Discussion

Study 2 replicated the bid level results obtained in Study 1. Consistent with Proposition 1, focal bidders who competed last against Product Experts tended to remain in the auction the longest, following those who competed against Process Experts and Amateurs. Turning to the results for the post-auction values, Proposition 2 was supported: winners' assessment of the products' direct purchase value did not differ as a function of Competitor Expertise (admittedly a null hypothesis test). Proposition 4 was also supported: auction losers reported higher post-auction measures of direct purchase value than winners. Propositions 3 and 5 involving the post-auction measures of WTA1 (winners) and WTP1 (losers) respectively received partial support. Those competing against Product Experts reported higher direct purchase value than those competing against Process Experts. However, contrary to expectations, both WTA1 and WTP1 measures were highest for those competing against Amateurs. We speculate that this may reflect motivated reasoning in which high values were reported to justify a win or a loss against amateurs.

The propositions for value durability received mixed support. Proposition 8 was supported. Those who won against Product Experts showed stable post-auction ΔWTAs, whereas values dropped significantly for those who won against Process Experts and Amateurs. However, support for the remaining proposition was tenuous. The ΔWTPDIR results showed inconsistent support for Proposition 7. Changes were unexpectedly high for those who won against Process Experts. Perhaps reflection led focal bidders to believe that the Process Experts may have bid conservatively, and the auctioned product was worth more than they had initially believed. There was a similar inconsistency in results for Proposition 9. Focal bidders who lost against Amateurs unexpectedly increased their valuations. It may be these bidders felt that their initial estimates were too low because they wished to justify their loss and that reflection led them to feel that the auction item may be worth more. Proposition 10 related to value changes for those who lost the auction. Although the predicted decreases in valuation were observed, the magnitude of the decreases was not ordered as expected by Competitor Expertise types. Thus, Proposition 10 was not supported.

3.3 Study 3

Study 3 was designed as an extended replication of Studies 1 and 2. The design of Study 3 was adjusted such that win- and lose-designated bidders could win or lose randomly at the same maximum bid level ($50.00) rather than at different bid levels. Thus, both groups had equal opportunity to experience the entire auction. However, bidders in either group could still quit at any time during the auction regardless of this assignment (unknown to the participants). We also added an additional type of competitor expert, “Hybrid: Experts, who possess both Product and Process Expertise.

3.3.1 Study 3 Procedure

Referring to Appendix A, we used the standard instruction set to introduce the Hybrid Experts (green shirts) along with the Product and Process Experts as well as Amateurs. This instruction set was very similar to those used in Studies 1 and 2. Also, Appendix G shows the dropout schedule of the virtual expert participants, such that by the time the bid level reached $44.00, the focal bidder was competing exclusively against an opponent from the designated expertise condition. To avoid some issues encountered with participants’ use of the slider scale, the slider scale was replaced with a free-text, numeric entry field, restricted to lie in the range between $25.00 and $75.00.

A total of 397 participants were recruited from the Amazon M-Turk web panel. The base fee for participation was set at $0.25 and the opportunity to earn an additional incentive based on auction performance. The same conversion rates were used as in Study 2 (unspent budget at $0.005 on the dollar, and the product (market value = $66.00) was converted at $0.01 on the dollar. Ostensibly losers (winners) made $0.50 ($0.92), but all participants were paid $0.92 for equity reasons. Other aspects of the ascending Japanese auction procedure (a bottle of wine as the auction object, bid increment levels of $1.00) were identical to those for Study 2.

Participants were randomly assigned to compete last against Hybrid Experts (n = 100), Product Experts (n = 100), Process Experts (n = 98), or Amateurs (n = 99), and were also randomly assigned to win (n = 201) or lose (n = 196). Of those assigned to win 102 won and 99 lost, and so a total of 295 participants lost the auction. The same three measures of post-auction value were collected immediately following the auction (winners: WTA; losers WTP; all participants: WTPDIR). After an interpolated task that lasted approximately two minutes, they provided their value assessments once again. Thus, as in the previous experiment, each participant provided two sets of post-auction valuation measures, separated by a time delay, allowing for analysis of how valuation changed over time. At each of the two measurement points, participants indicated their satisfaction and regret levels about how they had bid in the auction and the extent to which the auction was exciting (see Appendix O), as well as other demographic measures.

3.3.2 Study 3 Results

Manipulation checks were successful. In particular, bidders assigned to compete last against Amateurs reported that there were significantly more Amateurs competing than other types: ($M_{CAmateur} = 6.29,\ SE_{CAmateur} = 0.16;\ M_{CProcess} = 1.96,\ SE_{CProcess} = 0.17;\ M_{CProduct} = 2.41, SE_{CProduct} = 0.17; M_{CHybrid} = 2.44, SE_{CHybrid} = 0.17$), F(3, 393) = 104.85, p < 0.001. Bidders assigned to compete last against Process Experts reported competing against significantly more Process Experts in the auction ($M_{CAmateur} = 1.94, SE_{CAmateur} = 0.18; M_{CProcess} = 6.33, SE_{CProcess} = 0.18; M_{CProduct} = 2.64, SE_{CProduct} = 0.18$); $M_{CHybrid} = 2.21, SE_{CHybrid} = 0.19$), F(3, 393) = 119.12, p < 0.001. Bidders assigned to compete last against Product Experts reported competing against significantly more Product Experts ($M_{CAmateur} =$

$2.11, SE_{CAmateur} = 0.17; M_{CProcess} = 1.95, SE_{CProcess} = 0.17; M_{CProduct} = 5.75, SE_{CProduct} = 0.17; M_{CHybrid} = 2.18, SE_{CHybrid} = 0.17$),), F(3, 393) = 89.27 p < 0.001. And bidders assigned to compete last against Hybrid Experts also reported competing against significantly more Hybrid Experts ($M_{CAmateur} = 2.08, SE_{CAmateur} = 0.18; M_{CProcess} = 1.81, SE_{CProcess} = 0.17; M_{CProduct} = 2.56, SE_{CProduct} = 0.17; M_{CHybrid} = 6.17, SE_{CHybrid} = 0.19$),), F(3, 393) =120.98 p < 0.001.

3.3.2.1 Bid Level

The bid level results (Appendix L) provide strong support for Proposition 1. Specifically, focal bidders competing against Hybrid Experts remained in the auction the longest (bid higher). Of 100 bidders in this condition, 58 (58.00%) remained and bid the maximum their budget allowed. Those who competed against Product Experts were next. Of 100 bidders assigned to this condition, 54 (54.00%) bid the maximum their budget allowed. Interestingly, those competing against the Process Experts were next. Of the 98 participants assigned to this condition, 51 (52.04%) bid the maximum their budget allowed. Among the 99 participants competing against Amateurs, only 33 (33.33 %) remained. These differences are statistically significant $\chi^2(3) = 14.30, p = 0.003$). Overall, these results are consistent with the findings of Studies 1 and 2.

3.3.2.2 Post-Auction Values

As in Study 2, given that we restricted the range in which participants could indicate their post-auction valuations (WTPDIR1, WTA1, and WTP1), we examined the data for evidence of left and right censoring at \$25.00 and \$75.00). For Study 3, WTPDIR1 was left- (4.76%) and right-censored (2.08%), WTA1 was right-censored (8.33%), and WTP1 was left- (3.49%) and right-censored (3.93%). As for Study 2, each post-auction valuation measure was analyzed using a censored regression model as a function of Competitor Expertise and the Auction Outcome group and their interaction. Regret, satisfaction, excitement, Age, and Gender were used as covariates. We report these results next.

3.3.2.2.1 Post-Auction Values Immediate

WTPDIR1. Appendix M, Panel 1 shows a significant omnibus effect of Auction Outcome ($p < 0.001$) on the WTPDIR1 measures. However, the omnibus tests were not significant for either Competitor Expertise or the interaction of Competitor Expertise and Auction Outcome. Among the covariates, higher levels of regret ($p = 0.001$) and lower age ($p = 0.006$) were associated with higher WTPDIR1 values. Males tended to post higher ($p = 0.040$) values than females. The table of relevant means is provided below the regression results.

First, replicating support for Proposition 2, the WTPDIR1 measure for winners did not differ by Competitor Expertise level ($M_{CHybrid} = \$48.10, M_{CProduct} = 51.10, M_{CProcess} = \$52.43, M_{CAmateur} = \$50.60$), p's > 0.10. Note that the lack of significance is subject to power considerations. Second, consistent with Proposition 4, bidders who lost the auction at \$50.00 (designated losers) reported higher WTPDIR1 values than those who won ($M_{Losers} = \$55.30$ versus $M_{Winners} = \$50.53$), $p < 0.001$. However, contrary to Proposition 5, this gap was largest for bidders who lost to Product Experts ($M_{Losers} = \$59.31$ versus $M_{Winners} = \$51.01$), $p < 0.001$), next largest for those who lost to Hybrid Experts ($M_{Losers} = \$54.50$ $v$ersus $M_{Winners} = \$48.10$), p < 0.001) and smallest for those who lost to Process Experts ($M_{Losers} = \$54.78$ versus $M_{Winners} = \$52.43$), p = 0.001) and Amateurs ($M_{Losers} = \$52.60$ versus $M_{Winners} = \$50.60$), p = 0.02). These results, which reflect valuation differences between winners and losers at the same bid level ($50.00), are better indicators of valuation as a function of Auction Outcome (losing versus winning). Also, for the bidder group that lost at $50.00, those competing against Product Experts reported the highest values ($59.31, all p's < 0.001), again perhaps reflecting their confidence in these bidders' expertise). Interestingly, on average, valuations provided by focal bidders who quit between $44.00 and $49.00 were lower than those who lost at $50.00 ($48.41 and $50.53 respectively), p = 0.02. Those who quit before the bid level reached $44.00 reported significantly lower valuations ($42.80), p < 0.001.

WTA1. A censored regression analysis was used to model WTA1 (the willingness to accept measure for auction winners) as a function of Competitor Expertise type (Product Expert, Process Expert, Amateur). Age, gender, satisfaction, regret, and excitement served as covariates. As shown in Appendix M, Panel 2, the omnibus Competitor Expertise effect was not significant ($\chi^2 = 5.067, p = 0.167$). Also, higher levels of satisfaction (p = 0.050) were associated with higher WTA1 values. The table of relevant means is provided below the regression results.

Guided by Proposition 3, we examined the simple effects of winners' WTA scores as a function of the competing expert type. Consistent with Proposition 3, those who won in competition against Product Experts ($57.77) reported higher WTA1 values than those who won against Process Experts ($53.26), p < 0.001. However, inconsistent with our proposition, but consistent with the Study 2 results, focal bidders who won against Amateurs reported the highest WTA1 values on average ($59.36), and together with those who won against Product Experts, these were significantly higher than for those who won against either Process Experts or Hybrid Experts ($54.04), p's < 0.001. The fact that this unexpected finding replicates across Studies 2 and 3 lends credence to our speculation that motivated reasoning may underlie this result. It may be that focal bidders who won against Amateurs reported a high WTA1 value to self-justify their acquisition of the product and mitigate cognitive dissonance.

WTP1. A similar censored regression analysis was used to model WTP1 (losers' willingness to pay for the auctioned product that they did not win) as a function of Competitor Expertise type (Hybrid Expert, Product Expert, Process Exert, Amateur), Auction Outcome (lose at $50.00, lose at $44.00 - $49.00, lose at < $44.00) and the interaction of these two factors. As before, age, gender, satisfaction, regret, and excitement were used as covariates. Appendix M, Panel 3 shows that Auction Outcome ($\chi^2 = 49.576, p < 0.001$) and the interaction with Competitor Expertise ($\chi^2 = 14.233, p = 0.027$) had significant effects. However, the omnibus Competitor Expertise effect was not significant (p = 0.846). Among the covariates, higher levels of regret (p = 0.005), excitement (p = 0.001) and lower age (p = 0.036) were associated with increased WTP1. Also, males tended to report higher WTP1 (p = 0.016). The relevant means are shown below the regression results.

Support for Proposition 5 was weak. Among focal bidders who lost at $50.00, Product Experts ($49.01) reported directionally higher WTP1 values than those who lost to amateurs ($48.91), although this did not reach significance (p > 0.10). Those who lost to Hybrid Experts ($51.86) did report higher valuations than those who lost against Amateurs ($48.91), although they also reported higher values than those who lost against Product Experts ($49.01), all p's < 0.001. Those who lost to Process Experts had intermediate WTP1 values ($51.16) that were also not significantly different from the other expert types or Amateurs (p's > 0.10). Thus, reported WTP1 values did not vary by Competitor Expertise. Focal bidders who quit at bid levels between $44.00 and $49.00 reported values that were directionally consistent with Proposition 5 (Hybrid: $50.82; Product: $49.42; Process: $47.11; Amateurs: $47.56). Those who lost against Hybrid Experts reported higher values than those who lost against Process Experts (p = 0.03) and Amateurs (p = 0.04). The remaining differences were not significant. In contrast, and consistent with Proposition 6, pooling across expertise levels, the designated losers at $50.00 reported the highest overall WTP1 values ($50.47), significantly higher than those who quit between $44.00 and $49.00 ($48.66, p < 0.001), but only directionally higher than those who quit below $44.00 ($50.26, p > 0.10). These results replicate the findings of Study 2.

3.3.2.2.2 Post-Auction Valuation: Durability

As in Study 2, we used a set of Difference-in-Differences analyses (Warton, Parker, & Karter, 2016) to examine relative change in post-auction valuation <u>over time</u> as a function of Competitor Expertise, Auction Outcome, and the interaction of these two factors. As in Study 2, SAS PROC GLIMMIX was used to conduct this analysis.

ΔWTPDIR. The results of the analysis for changes in WTPDIR are shown in Appendix N, Panel 1. The omnibus tests for Time * Competitor Expertise, Auction

Outcome, and the interaction between Competitor Expertise and Auction Outcome were not significant, p's = 0.077, 0.439, and 0.543, respectively. Among the covariates, higher levels of regret ($p = 0.001$) and excitement ($p = 0.001$) and lower age ($p = 0.005$) were associated with an increase in ΔWTPDIR. The table of means is reported below the regression.

Proposition 7 guided our examination of the simple effects for auction winners. A test of these differences for those who won (at $50.00) revealed that WTPDIR changes ($0.26) were generally stable over time (i.e., not significantly different from zero). This is consistent with Proposition 7A and is corroborated by the WTPDIR change data for those won against Product Experts ($0.19), Process Experts (-$0.43), and Amateurs (-$0.84). However, unexpectedly, the increase in ΔWTPDIR ($1.72) was significant for those who won against Hybrid Experts, $p < 0.001$, as well as significantly different from the other Competitor Expertise types, p's < 0.001. Thus, Proposition 7B was only partially supported. Whereas the data were consistent with those of Study 2 for Product Experts and Amateurs, we did not observe the increase in value noted for Process Experts. ΔWTPDIR for those who won against Process Experts (and Amateurs) decreased, though not significantly.

The simple effects for change in WTPDIR for auction losers were examined against Proposition 9. Focusing on bidders who lost at $50.00, ΔWTPDIR remained stable regardless of whether the loss was in competition against Hybrid Experts ($0.06), Product Experts (-$0.34), Process Experts ($0.06), or Amateurs ($0.51) (i.e., not significantly different from zero). Bidders who quit between $44.00 and $49.00 also showed a generally stable ΔWTPDIR pattern for those who lost against Hybrid Experts

($0.47) and Process Experts (-$0.02), although those who lost against Product Experts (-$0.95) and Amateurs (-1.21) did significantly decrease their valuations, p's < 0.01. Thus, apart from Amateurs and Process Experts who bid and lost between $44.00 – $49.00, these data are generally consistent with Proposition 9A. In summary, both Propositions 9A and 9B were generally supported for those who lost at $50.00 against Hybrid, Product, and Process Experts, as well as Amateurs. However, those who quit at bid levels between $44.00 and $49.00 reported significant reductions in the value of the auctioned product following the delay. It may be these bidders felt that their original assessments of the product's worth were inflated (given the Amateur competition). Upon reflection, they lowered these estimates.

ΔWTA. Appendix N, Panel 2 shows the results for the analysis of the change in WTA for those who won the auction at $45.00. The omnibus tests showed that Competitor Expertise (p = 0.543) did not have a significant effect on change in WTA. Also, no covariates other than gender (p < 0.048) were significant. The means are reported in the table below the regressions. Analysis of the simple effects show that post-auction values were relatively stable for those who won against Product Experts (-$0.53) and Process Experts (-0.54), both p's > 0.10. This is partially consistent with Proposition 8A. However, at the same time, and contrary to expectations, ΔWTA decreased significantly for those who last competed against Hybrid Experts (-$2.41), p < 0.001. Also, ΔWTA decreased for those who last competed against Amateurs (-1.61, p = 0.01). This is only partially consistent with Proposition 8B.

ΔWTP. Appendix N, Panel 3 shows the analysis for change in post-auction WTP for those who lost the auction. The omnibus test shows that value change was jointly influenced by a significant interaction of Competitor Expertise and Auction Outcome with time ($\chi^2 = 15.720, p = 0.015$). The interaction of Competitor Expertise with Time ($p = 0.311$) and Auction Outcome with Time ($p = 0.341$) were not significant. Among the covariates, higher levels of excitement ($p < 0.001$) and lower age ($p < 0.024$) were associated with increases in ΔWTP. The relevant mean changes are tabulated by condition below the regression table.

Proposition 10 guided our examination of the simple effects. Focusing on bidders who lost at \$50.00, we observed an overall decrease in value (-\$0.93), $p < 0.001$. The decrease was primarily driven by those who lost against Process Experts (-\$4.45, $p < 0.001$). However, contrary to Proposition 10, there were no significant decreases in ΔWTP associated with losses against Hybrid Experts, Product Experts, or Amateurs (all p's > 0.10). For bidders who quit between \$44.00 and \$49.00, only Hybrid Experts (-\$2.11) decreased their valuations over time, $p < 0.001$. Interestingly, among those who withdrew from the auction below a bid level of \$44.00, those who competed against Product Experts (\$3.31) and Process Experts (\$2.04) posted significant increases, but those competing against Amateurs posted a significant decrease (-\$2.38), all p's > 0.001. These data are inconsistent with Proposition 10 and uninterpretable within the reasoning framework underlying the proposition.

3.3.3 Study 3 Discussion

Study 3 replicated the bid level results obtained in Studies 1 and 2. Consistent with Proposition 1, focal bidders who competed last against Hybrid and Product Experts tended to remain in the auction the longest, following those who competed against

Process Experts and Amateurs. Turning to the results for the post-auction values, Proposition 2 was supported: winners' assessment of the products' direct purchase value did not differ as a function of Competitor Expertise (admittedly a null hypothesis test). There was partial support for Proposition 3: those who won against Product Experts, as well as those who won against Hybrid Experts, reported higher WTA1 values relative to those who won against Process Experts. However, focal bidders who won against Amateurs reported the highest WTA1 values on average. This result, though inconsistent with our proposition, replicates a similar finding in Study 2. The replication lends credence to our earlier conjecture suggesting motivated reasoning. It may be that focal bidders who won against Amateurs reported a high WTA1 to self-justify their acquisition of the product and mitigate cognitive dissonance. Additional analyses of the regret and satisfaction measures may provide further insights.

Second, consistent with Proposition 4, bidders who lost the auction at \$50.00 (designated losers) reported higher WTPDIR1 values than those who won. However, contrary to Proposition 5, this gap was largest for bidders who lost to Product Experts, next largest for those who lost to Hybrid Experts, and smallest for those who lost to Process Experts and Amateurs. Although unexpected, these results, which reflect valuation differences between winners and losers at the same bid level (\$50.00), may reflect relatively more accurate comparisons for how Auction Outcomes (losing versus winning) influence judgments of post-auction value. At the same time, the observed pattern is contrary to expectation within a reasoning framework that assigns credibility to competitive bids based on expertise. Again, further exploratory analysis that assigns formal moderating or mediating roles to variables we have thus far treated as covariates may yield insights into these seemingly anomalous results. These may be tested in future research.

Third, support for Proposition 6 was essentially replicated across Studies 2 and 3. In Study 3, pooling across expertise levels, bidders designated to lose at \$50.00 reported higher overall WTP1 values than those who quit at bid levels between \$44.00 and \$49.00 or even at bid levels below \$44.00. These results generally replicate those reported earlier in Study 2.

Finally, the propositions for value durability received mixed support. Proposition 7 related to changes in ΔWTPDIR for auction winners (at \$50.00). Overall, ΔWTPDIR was stable on average and was corroborated by the data for those won against Product Experts, Process Experts, and Amateurs (consistent with Proposition 7A). However, there was a significant increase for those who won against Hybrid Experts. Thus, Proposition 7B was only partially supported. Note that the data were consistent with the findings of Study 2 for Product Experts and Amateurs. However, the increase in value noted for Process Experts in Study 2 was not observed in study 3. ΔWTPDIR for those who won against Process Experts and Amateurs decreased, though not significantly.

Support for Proposition 8 was mixed. Partially consistent with Proposition 8A, post-auction values were relatively stable for those who won against Product Experts (-\$0.53), $p > 0.10$. However, contrary to expectations, ΔWTA decreased significantly for those who lost against Hybrid Experts (-\$2.41), $p < 0.001$. Consistent with Proposition 8B, ΔWTPDIR decreased significantly for those who won against Amateurs (-\$1.61, $p = 0.01$), but only directionally for Process Experts (-\$0.54), $p > 0.10$. Thus, Proposition 8 was partially supported except for the unexpected decrease in ΔWTA for those who won against Hybrid Experts. This result is difficult to reconcile within our expertise-driven propositions for value credibility assessments.

Proposition 9 related to change in WTPDIR for those who lost the auction. For bidders who lost at $50.00, ∆WTPDIR was stable regardless of whether the loss was against Hybrid Experts, Product Experts, Process Experts, or Amateurs. Bidders who quit between $44.00 and $49.00 also reported generally stable ∆WTPDIR for those competing against Hybrid, Product, and Process Experts, although a significant decrease was observed for those who competed against Amateurs. A similar pattern was obtained for those who quit below a bid level of $44.00, with values generally stable for those who competed against Product, Process, and Hybrid Experts but decreasing significantly for those who competed against Amateurs. These results are generally aligned with Proposition 9A. Thus, both Propositions 9A and 9B were supported for those who lost at $50.00 against Hybrid, Product, and Process Experts, as well as Amateurs. However, reported values were lower following the delay for those who competed last against Amateurs and quit at bid levels between $44.00 and $49.00, as well as below $44.00. Given the nature of Amateur competition, it may be these bidders felt their original assessments of the object's value were too high. Hence, upon reflection, they lowered their estimates.

Support for Proposition 10 was mixed at best. Focusing on bidders who lost at $50.00, we see the predicted drop in value for those competing against Process Experts. However, contrary to Proposition 10, ∆WTP did not fall after the delay for those who lost against Hybrid Experts, Product Experts, or Amateurs. For bidders who quit between $44.00 and $49.00, ∆WTP decreased only when the loss was against a Hybrid Expert.

For those who quit below $44.00, those who competed against Product and Process Experts posted significant increases, but those competing against Amateurs posted a significant decrease. These data are inconsistent with Proposition 10 and uninterpretable within the reasoning framework underlying the proposition.

3.4 General Discussion

The three studies reported in this chapter addressed how perceived Competitor Expertise influences bid levels in an ascending Japanese auction. We also explore how perceived Competitor Expertise and Auction Outcome influence assessments of auction item value both immediately after the auction and following a delay. Studies 1 and 2 manipulated perceived Competitor Experience at three levels (Product Experts, Process Experts, and Amateurs). Study 3 introduced a fourth level, Hybrid Experts with both Product and Process Expertise.

Interestingly the introduction of Hybrid Experts appears to have attenuated the relative attraction of bidding higher when competing against Product Experts compared to Process Experts. Thus, in Studies 1 and 2, focal bidders tend to bid higher when competing against Product Experts, whereas, in Study 3, they bid higher when competing against experts in general (Hybrid, Product, and Process Experts). One might attribute this to the idea that Hybrid Experts reflect the best of both worlds in evaluating product value. Thus, Hybrid Experts' knowledge of both the product domain and auction process may make their value signals the most credible among expert competitors attenuating the salience of differences between Process and Product Experts. Our data seems to suggest that, for the most part, participants tended to view Hybrid Experts' value signals as the most credible, and this subsequently influenced perception of the relative difference (and thus credibility) of Product and Process Experts. However, future research may explore boundary conditions under which Product Experts, Process Experts, or even Amateurs may influence the bid level to which participants remain in the auction.

An issue that has not been discussed so far is focal bidders' perceptions of their own expertise levels. Just as they may perceive their competition as having different levels of expertise, they may also view themselves as Amateurs, Process Experts, Product Experts in the auctioned product's category, or Hybrid Experts possessing expertise regarding both the product category and the auction process. Given the significant and largely systematic variations that we found in Study Set 1, it stands to reason that a focal bidder's assessment of their own level of expertise (Self-Expertise) may influence how they bid against competitors whom they perceive as having different levels of expertise. We address this issue in the next chapter with Study Set 2.

Chapter 4: Assessed Self-Expertise: Influences on Bidding Behavior and Post-Auction Values Against Competitors of Varying Expertise Levels

The propositions and the empirical work (the three experiments in Study Set 1) presented in Chapters 2 and 3 focused on bidder perceptions of Competitor Expertise. Our results showed that bidders were generally more likely to bid higher when competing against Product and Hybrid Experts than when competing against Process Experts and Amateurs. Also, post-auction valuation (i.e., WTPDIR, WTA, and WTP, both immediately following the auction and over time) differed systematically as a function of Competitor Expertise and Auction Outcome.

However, just as bidders may perceive their competition as having different levels of expertise, they may also vary in how they assess their own type and level of expertise regarding both the product category and the auction process (i.e., Self-Expertise). In other words, bidders may also assess themselves as Amateurs, auction Process Experts, Product Experts in the auctioned product category, or Hybrid Experts. Given the significant and generally systematic variations observed in Study Set 1, it is plausible that focal bidders' assessment of their own level of expertise will also influence how they bid against Competitor Experts. In this chapter, we begin with a conceptual discussion benchmarked against the propositions and the findings of Study Set 1 and report two additional empirical studies that further explore the topic of Competitor Expertise within the context of the focal bidder's assessed Self-Expertise.

4.1 Overview

The research presented in this chapter tests the general proposition regarding the role of bidders' assessed Self-Expertise regarding the auction process and the auctioned product category. We expect that how bidders bid in auctions, their level of post-auction valuations of the auction object, and the temporal stability of those values will rest not only on the focal bidders' subjective assessments of Competitor Expertise and the Auction Outcome but in addition, on the bidder's subjective assessment of their own expertise. In other words, we explore how a focal bidder's assessment of own expertise level moderates the effects of perceived Competitor Expertise.

Based on our experience in Study Set 1, we expected most participants to have a low assessment of Self-Expertise, and that a credible manipulation of Self-Expertise would require using informational input and perhaps false feedback on test performance. As we describe later, these procedures were designed and implemented similarly for the two studies in Study Set 2. In this second set of studies, the first experiment uses a Japanese auction (similar to those in Study Set 1) where participants may observe and draw inferences from competitors' bidding and exit behaviors during the auction. The second experiment uses a First-Price, Sealed-Bid auction format in which focal bidders cannot observe competitive bids and exits. Hence, (sealed) bids are based on bidders' subjective assessments of Self-Expertise and how it relates to Competitor Expertise, with no observations of competitor bidding behavior during the auction.

Findings from the expertise literature have shown that experts and amateurs process information differently and that this may lead to significant differences in decision making (Klein, 1998). Interestingly, it remains unclear from the expertise literature whether these processing and decision making differences are driven by actual differences in expertise level (e.g., objective domain knowledge as well as hours of practiced study and hands-on experience) or subjective self-assessments of one's own expertise that may be influenced by phenomena such as availability (Fox, 2006). Thus, consistent with our goal to further understand the influence of expertise on decision making and valuation in an auction setting (cf. Chapter 1.4), we now turn our attention to the influence of assessed type and level of one's own expertise and how this jointly influences bidding behavior and post-auction valuation.

The discussion and the empirical work (Study Set 2) reported in this chapter contribute to the literature in several ways. Relative to the sparse literature on how bidders behave in competition with opponents with different levels of expertise, we show

how these behaviors are affected by bidders' subjective assessment of their own expertise (Self-Expertise). Extant research on the influence of assessed Self-Expertise in auctions focuses on focal bidder behavior given actual valuation advantages, such as "insider information" (Wilson, 1977) or a small private value advantage in a common value "wallet game" auction (Avery & Kagel, 1997). In contrast, we focus on the focal bidders' *perception* of their own expertise, which may or may not be veridical (i.e., relative to objective expertise). Such subjective perceptions of self-expertise level, akin to the notion of the subjective knowledge construct in the consumer knowledge literature (Alba & Hutchinson, 1987; Brucks, 1985), are expected to condition bidding against various types of Competitor Experts, as well as yield differences in post-auction valuation (WTA, WTP, and WTPDIR) both immediately after the auction, as well as their lability following a time-delay.

In Study 1, we manipulate participant assessed Self-Expertise at four levels (Amateurs, Process Experts who have greater expertise in auction processes, Product Experts that have deep knowledge of the auctioned product category, and Hybrid Experts who have expertise spanning both the auction process and the product category. However, for design parsimony, we manipulate Competitor Expertise at only two levels (Amateurs and Hybrid Experts). In Study 2, we manipulated assessed Self-Expertise at two levels (Amateurs and Hybrid Experts).

4.2 Propositions

We provide three sets of propositions related to how focal bidder behavior may be jointly influenced by participant assessed Self-Expertise, Competitor Expertise, as well as

Auction Outcome. These relate to the actual bid level, immediate post-auction product values (WTA1, WTP1, and WTPDIR1), and their temporal durability (ΔWTA, ΔWTP, and ΔWTPDIR). Our initial propositions are driven by the impact of objective/subjective knowledge, which we believe governs actual bidding behavior. The empirical results in Study Set 1 suggest that post-auction valuation is also likely to rest on lay reasoning driven by perceptions of assessed Self and Competitor Expertise and motivated reasoning (Epley & Gilovich, 2016; Kunda, 1990) stemming from experienced regret. Satisfaction or excitement may also drive immediate post-auction valuation and influence their temporal durability

4.2.1 Bid Level

The results of Study Set 1 provide a starting point for propositions regarding Study Set 2. Focal bidders (likely who assess themselves as Amateurs) were prone to follow the bidding behavior of Hybrid and Product Experts and stay longer (bid higher) in the auction relative to competition against Process Experts or Amateurs. Study Set 2 contrasts only Hybrid Experts and Amateurs. We expect to observe similar effects (i.e., focal bidders will bid higher when bidding against Hybrid Experts versus Amateurs). However, we also expect these effects will be qualified by focal bidders' assessment of their own expertise. We expect that such tendencies to remain longer will be strongest for Amateurs and weakest (or non-existent) for those who assess themselves as all-around "Hybrid" Experts. Product Experts are more likely to bid higher against Hybrid Expert competitors than Amateurs. We do not offer a proposition for those who assess themselves as Process Experts. Although, like the others, they may bid higher against

Hybrid Experts vs. Amateurs, alternatively, they may bid lower and shade their bids regardless of Competitor Expertise. Thus:

P1A. Focal bidders who bid against Hybrid Experts will bid higher than those who bid against Amateurs.

P1B. Self-Expert Hybrid and Product Experts will bid higher than Process Experts and Amateurs.

P1C. Differences in the propensity to bid higher against Hybrid Expert versus Amateur competitors will be highest for bidders who assess themselves as Amateurs vs. Product Experts and lowest for those who assess themselves as Hybrid Experts. *Ex ante*, likely behavior against Process Experts is ambiguous.

4.2.2 Post-Auction Values – Immediate

As observed in Chapter 3 (Study Set 1), we anticipate Auction Outcome is likely to have a significant impact on the post-auction values that bidders have for the auctioned product. We build our propositions based on our initial premises regarding value inferences that rely on expertise (objective or perceived) as a credibility signal. Hence, wins and losses and their implications for product value are likely to be interpreted in the frame of who was the competitor as well as the focal bidder's assessment of their own expertise. Values may be reported as logically inferred from expertise cues. At the same time, motivated reasoning may play a role in shaping what is reported or even perceived through a motivational lens (Epley & Gilovich, 2016; Kunda, 1990). Our propositions are therefore presented separately for auction winners and losers. We acknowledge the exploratory orientation of these propositions. Also, they embed multiple comparisons intended to guide an initial interpretation of our experimental outcomes. The robustness of these interpretations should be examined in future research through both replication and a more focused design.

Winners. Participants who win the auction know the winning bid level. Although their direct purchase value (WTPDIR1) should not differ as a function of Competitor Expertise, the results of Study 2 suggest the likelihood of some variation based on Competitor Expertise (higher for those who win against Hybrid Experts relative to Amateurs). By the same token, auction winners' immediate post-auction WTA1 valuations should be higher for those who won against Hybrid Experts than for those who won against Amateurs. Also, participants who assess themselves as Product and Hybrid Experts are likely to be more confident about their bids and therefore post higher values than those who assess themselves as Process Experts and Amateurs who may be less confident about their bids. These ideas are captured in the following propositions:

> P2A. Focal bidders who win against Hybrid Experts will have higher WTPDIR1 and WTA1 values than those who win against Amateurs.

> P2B. Participants who assess themselves as Hybrid and Product Experts who won will report higher WTPDIR1 and WTA1 values than those who assess themselves as Process Experts and Amateurs.

P2C. The difference in (a) WTPDIR1 and (b) WTA1 Values reported by those who assess themselves as Hybrid and Product Experts' and win against Competitor Expert Hybrid Experts versus Amateurs will be larger than the corresponding differences for those who assess themselves as Process Experts and Amateurs.

Losers. Participants who lose the auction will not have observed the market value of the product (only that they lost at $50.00 or the bid level at which they exited). Since they are unaware of the market clearing bid level, they are likely to report higher WTPDIR1 and WTP1 values than those who won. To the extent they also believe Hybrid Experts have a better sense of value than Amateurs, these reported values may be higher for those who lost to Hybrid Experts versus Amateurs. The influence of assessed Self-Expertise on product values may be fairly subtle. Ordinarily, and as we propose below, Hybrid and Product Experts who lose (particularly at $50.00) would report relatively higher estimates of the auctioned product's value. In contrast, Process Experts and Amateurs may be less confident (particularly when bidding against Amateurs) and provide lower values. However, as discussed previously, we acknowledge the possibility that Hybrid and Product Experts may engage in motivated reasoning (Epley & Gilovich, 2016; Kunda, 1990), in order to justify their loss and actively devalue the product. However, such reasoning may be less compelling for losses against Hybrid Experts versus Amateurs. Participants who assess themselves as Process Experts and Amateurs may reconcile more readily with such losses (even if less so against Competitor Expert

Amateurs than Hybrid Experts). We present the following propositions to capture these ideas:

P3A. Focal bidders who lose against Hybrid Experts will report higher WTPDIR1 and WTP1 values than those who lose against Amateurs.

P3B. Participants who assess themselves as Hybrid and Product Experts who lose will report higher WTPDIR1 and WTP1 values than those who assess themselves as Process Experts and Amateurs.

P3C. The difference in (a) WTPDIR1 and (b) WTP1 Values reported by those who assess themselves as Hybrid/Product Experts' who lose against Competitor Expert Hybrid Experts versus Amateurs will be larger than the corresponding differences for those who assess themselves as Process Experts/Amateurs.

4.2.3 Post-Auction Values – Temporal Durability

Winners. In the previous section, we proposed that auction winners' immediate post-auction WTPDIR1 and WTA1 valuations will be higher for those who won against Hybrid Experts than for those who won against Amateurs. Also, those who assess themselves as Product and Hybrid Experts are likely to be more confident about their bids and should post higher values than those who assess themselves as Process Experts and Amateurs who may be less confident about their bids. We expect that similar ideas will govern how post-auction values change over time. Valuations that are held with greater confidence will remain stable or increase over time. Those valuations for which confidence is lower will tend to decline over time. Thus, we propose:

> P4A. Focal bidders who win against Hybrid Experts will have stable or increasing ΔWTPDIR and ΔWTA values over time. Values for those who win against Amateurs are likely to decrease over time.

> P4B. The ΔWTPDIR and ΔWTA values reported by participants who assess themselves as Hybrid and Product Experts who won will increase over time. Those reported by Process Experts and Amateurs who won are likely to decrease over time.

Given the directional differences in our predictions, we offer no propositions regarding the magnitude of these temporal differences over time. Bidders may also engage in motivated reasoning that influences what they perceive and report as the auctioned product's value (Epley & Gilovich, 2016; Kunda, 1990).

Losers. Participants who lose the auction will not have observed the market clearing bid level of the product in the auction (only that they lost at $50.00 or the bid level at which they exited). We predicted that because these participants did not observe this market clearing bid level, losing bidders are likely to report higher WTPDIR1 and WTP1 values than those who won. However, over time we expect that those who lost against Hybrid Experts (Amateurs) would increase (reduce) this value. The effect of assessed Self-Expertise on product values may be fairly subtle. Reasoning based on expertise and associated credibility suggests that like winners, Hybrid and Product Experts who lose (particularly at $50.00) would raise their estimates of the product's value. In contrast, Process Experts and Amateurs may be less confident (particularly when bidding against Amateurs) and reduce their estimate of product value over time.

However, we acknowledge the possibility Hybrid and Product Experts may engage in motivated reasoning (Epley & Gilovich, 2016; Kunda, 1990) in order to justify their loss and thus actively devalue the product over time. However, such reasoning may be less compelling for losses against Hybrid Experts versus Amateurs. Participants who assess themselves as Process Experts and Amateurs may reconcile more readily with such losses (even if less so against Competitor Expert Amateurs than Hybrid Experts). As such, changes in their values may be shaped less by motivated reasoning and more by expertise-driven credibility. We present the following propositions to capture these ideas:

> P5A. Focal bidders who lose against Hybrid Experts will report increasing ΔWTPDIR and ΔWTP values over time. Those who win against Amateurs will decrease their values over time.

> P5B. The ΔWTPDIR and ΔWTP values for participants who assess themselves as Hybrid and Product Experts and lose will remain stable or increase over time. The ΔWTPDIR and ΔWTP values for those who assess themselves as Process Experts and Amateurs and lose will decrease over time.

As for winners, given the directional differences proposed, we offer no propositions regarding the magnitude of these differences over time. We also note that losing bidders may engage in motivated reasoning that may influence the value they report or even their perceptions of value in order to mitigate cognitive dissonance or justify the Auction Outcome to themselves or others (Epley & Gilovich, 2016; Kunda, 1990).

4.3 General Procedure

A custom software package was designed for Study Set 2 (Studies 1 and 2) using a blend of JavaScript, CSS, and HTML. Consistent with the package used for Study Set 1, this version was also designed to work within the Qualtrics survey platform and allowed seamless implementation of specific study instructions, the auction platform, the collection of dependent measures, covariates, and demographic data. The instruction sets for Study Set 2 were modified based on results from Study Set 1 and reflect the modified study goals. First, to make the Competitor Expertise types more accessible to participants, we renamed the Competitor Expertise labels: "Hybrid Expert" to "Wine-Auction Expert," "Product Expert" to "Wine Expert," and the "Process Expert" to "Auction Expert." The Amateur label was retained. These expertise categories were introduced via an instruction set (Appendix P). Second, although four levels of Competitor Expertise were described, we used only two of them ("Wine-Auction Expert" and "Amateurs") in the actual auctions for design parsimony. While we renamed the various expertise labels in the actual auction that we implemented, we retained the original superordinate labels (e.g., Product Expert, Process Expert, Hybrid Expert, and Amateur) in our discussion of the results.

Third, the software incorporated an assessed Self-Expertise manipulation at all four assessed Self-Expertise levels using a knowledge test with false feedback procedure described below. Finally, the base compensation was lowered to \$0.25. Other conversion rates were identical to those in Study 3: the unspent budget was converted at \$0.005 on the dollar, and product value (provided a win Auction Outcome) was converted at \$0.01 on the dollar. However, the announced market value for the product was reduced to \$55.00. Ostensibly auction losers (winners) made \$0.50 (\$0.81), but all participants were paid \$0.81 for equity reasons. Appendix R provides a summary of the payoffs for winners and losers for both studies in Study Set 2. Appendix S shows the explanation of the payoff structure that was provided to the participants.

For Study 1, following the expertise manipulations, the software implemented an ascending, Japanese auction like that described in Chapter 3 (Study Set 1). The bid level was progressively raised in \$1.00 increments, and participants bid at each bid level to remain in the auction (Cheema, Chakravarti, & Sinha, 2012). Failure to bid constituted immediate and irrevocable removal from the auction and recording of the last bid level at which the participant bid. The valuation measures and behavioral data (Excitement, Satisfaction, and Regret) were also collected as before, once immediately after the auction and then again after an interpolated task that took approximately two minutes. Participants were then debriefed and returned to the M-Turk platform. For Study 2, the software's bidding interface was modified to conduct a First-Price, Sealed-Bid (FPSB) auction in which participants were asked to submit their highest bid for the selected product immediately after the expertise manipulations. Prolific panelists were used in this study. The three valuation measures and behavioral measures were collected as before, once immediately after the auction and then after a short, interpolated task. Participants were debriefed and returned to the Prolific platform. The two studies allowed a contrast of how subjective assessments of own (Self) and Competitor Expertise influenced bidding under different auction mechanisms. Participants could observe competitor bidding and exits in the Japanese auction, but not in the FPSB auction. We discuss additional implications of this issue in our discussion of future research in Chapter 5.

4.4 Study 1

4.4.1 Design and Procedure

598 M-Turk panelists were recruited to participate in this study for a base fee of $0.25 and the opportunity to earn an additional bonus depending on their performance. Participants read the study instructions which introduced them to the task (Appendix P), asked them for their informed consent, outlined the auction payoff structure (Appendix S), and detailed the different types of Competitor Experts they would encounter during the auction. We also tested their understanding of the Competitor Expertise types using a knowledge check. Note, participants were not excluded based on performance on the knowledge check. However, participants who did not score accurately on this test were asked to review the information and retake the test to verify their understanding of the Competitor Expertise types. Data from 14 participants who did not receive the intended Assessed Self-Expertise manipulation due to a computer error were discarded.

Self-Expertise. Results from our previous studies signaled the likelihood that most panelists were Amateurs with respect to both auction processes and the product category in question (wine). We confirmed this in a test with 201 Prolific panelists for whom we measured the extent to which they believed they were experts in the auction process (Process Experts) and auction product domain (Product Experts). The questions (Likert Scale, 1-7, Disagree to Agree) were: Auction Process: (1) “I am an expert in auctions,” (2) “I am an expert with competitive bidding strategies” (r =.91); Product Domain: (1) “I am an expert on wine,” (2) “I am an expert on discerning wine quality” (r = 0.92). Average scores on these self-reported measures showed participants rated themselves as low in both auction Process Expertise ($M_{Process} = 2.56, SE_{Process} = 1.92$) and wine Product Expertise ($M_{Product} = 2.40; SE_{Product} = 1.79$). We, therefore, implemented the assessed Self-Expertise manipulation using a combination of provided information sets and a knowledge test followed by false feedback.

Participants were provided with “tips” purportedly on how to do well in the auction (Appendix T). The tips pertained either to auction processes (shown), the wine product category (not shown), or some general information on internet auctions. Participants were told that prior research shows that experts (versus non-experts) have better recall and comprehension of information related to their expertise domain. They were asked to review the information in expectation of a knowledge/intuition test and informed about their own expertise type ostensibly “based on their performance.” The tips differed across the Self Expertise conditions such that it would be easier or more difficult to answer domain-specific (e.g., wine Product or auction Process Expertise) questions depending on intended participant assignment. Appendix U shows the test. Irrespective of test performance, all participants were provided feedback that assigned an assessed Self-Expertise level consistent with their assigned condition. To reinforce the manipulation, participants were asked to acknowledge/affirm their expertise type (Appendix V).

Following the assessed Self-Expertise manipulation, participants worked through an auction demonstration designed to familiarize them with the auction bidding interface. Next, they selected the type of wine they wished to bid on (Appendix W, Panel 1) and proceeded to bid in the actual auction (Appendix W, Panel 2). Bidding started at $42.00 and proceeded in $1.00 increments (See Appendix R). During the actual auction, the bidding behavior of the intended Competitor Expert assignment (Amateur or Hybrid Expert) was manipulated using the competitor dropout pattern shown in Appendix X. As in Study 3 (Study Set 1), we manipulated Auction Outcome by randomly designating participants to either win or lose at the $50.00 bid level (when their budget was exhausted). This assignment was not known to participants. However, as before, participants in the present study could quit at any time during the auction for mundane realism considerations. Thus, in the final dataset, we had bidders who bid to $50.00 and won as designated. The bidders who lost the auction were a mix of those who lost after bidding to $50.00 as designated (the budget was exhausted), as well as those who quit on their own volition before the bid level reached $50.00. As in previous analyses, we further divided this latter group into those who lost because they ran out of their budget at $50.00, those who quit at bid levels between $44.00 and $49.00, and those who quit at bid levels below $44.00 (and were not fully exposed to the Competitor Expertise manipulation).

Thus, the overall study design was a 4 (Assessed Self-Expertise Type: Amateur vs. Process Expert vs. Product Expert vs. Hybrid Expert) x 2 (Competitor Expertise Type:

Amateur vs. Hybrid Expert) x 4 (Auction Outcome: Win at $50 vs. Lose at $50 vs. Lose at $44-49 vs. Lose below $44). We conducted three sets of analyses that examined the effects of these variables and their interactions on (1) bid levels, (2) immediate post-auction product valuations, and (3) durability of post-auction product valuations. As before, behavioral measures of Excitement, Regret, and Satisfaction were collected, along with demographic measures including participant age and gender. The specific valuation questions and the scale items used for Excitement, Regret, and Satisfaction are shown in Appendix O.

4.4.2 Study 1 Results

The assessed Self-Expertise manipulations were checked by asking participants to indicate their level of agreement with statements regarding their assessed Self-Expertise type: "I am a(n) Amateur/Wine Expert/Auction Expert/Wine-Auction Expert). Their responses on 7-point, Likert scale manipulation checks revealed a high agreement with statements corresponding to their assigned expertise type ($M_{Amateur} = 6.60, M_{Wine} = 5.67, M_{Auction} = 5.23, M_{WineAuction} = 5.43$). Similar statements regarding their final opponent: "My final opponent was a(n) Amateur / Wine Auction Expert" were used to check recall of their Competitor Expertise condition. High levels of agreement indicated accurate recall ($M_{Amateur} = 6.19, M_{WineAuction} = 5.80$) of their assigned competitor type. Agreement levels with incorrect statements were low (well below the scale mid-point), and all relevant contrasts were significant ($p < 0.001$). Appendix Y provides all relevant details.

4.4.2.1 Bid Level

The results of the bid level analysis are shown in Appendix AA. Panel 1 reports the data for all participants who bid to $50.00 and then won or lost as a function of perceived Competitor Expertise. Consistent with Proposition 1A, a higher proportion of focal bidders who competed against Hybrid Experts (51.71%) versus Amateurs (39.04%) remained until the $50.00 level (the budget limit). This difference was significant: $X^2(1) = 8.95, p = 0.003$. There was a significant main effect for assessed Self-Expertise, $X^2(3, N = 584) = 9.46, p = 0.02$, although the means were not aligned as predicted with Proposition 1B. Process Experts bid highest, a majority (54.86%), followed by Product Experts (47.95%) and Amateurs (40.94%). Surprisingly, Hybrid Experts (38.62) bid lowest.

The test of Proposition 1C provides interesting insights. Appendix AA, panel 3, tabulates the proportion of each type of assessed Self-Expertise type that remained in the auction until the $50.00 bid level when competing against a Hybrid Expert versus an Amateur. The data show that all assessed Self-Expert types (except for Process Experts) tended to bid lower against Amateurs vs. Hybrid Experts (Amateurs: 32.39%, p = 0.04; Product Experts: 36.99%, p = 0.15; and Hybrid Experts: 32.88%, p = 0.008). On the other hand, all assessed Self-Expertise types tended to bid highest against Hybrid Experts vs. Amateurs. This gap was lowest for Process Experts (55.07% – 54.67% = 0.40%; p > 0.10), higher for Hybrid Experts (67.12% – 55.56% = 12.44%, p = 0.15), Amateurs (48.72% – 32.39% = 16.33%; p = 0.043), and Product Experts (58.90% - 36.99% = 21.91%; p = 0.008). The data suggest that the Process Experts were the least influenced by Competitor Expertise. Interestingly, Product Experts were influenced most by competing against Hybrid Experts.

The behavior of assessed Self-Expertise Process Experts was enigmatic. These bidders followed both Amateurs and Hybrid Experts to equally high levels (55.07% and 54.67%, respectively). Contrary to our expectation that these bidders would shade their bids, they bid highest on average. The high bids against Hybrid Experts may reflect logical faith in the latter's expertise. However, the high bids when competing with Amateurs is either an anomaly or stems from a misplaced escalated commitment strategy to extract a surplus when bidding against Amateurs.

4.4.2.2 Post-Auction Valuation

As before, post-auction valuation data were gathered as numerical entries using a numeric, free-response field. However, the range of answers was restricted to a range between $25.00 and $75.00 to avoid careless and inappropriate responses. An examination of responses continued to show both left- and right-censoring. Specifically, WTPDIR1 was both left- (7.18%) and right-censored (2.91%), WTA1 was right-censored (10.40%), and WTP1 was both left- (2.36%) and right-censored (3.56%). To account for this, immediate post-auction values were analyzed using a maximum likelihood censored Tobit model available within the SAS PROC LIFEREG procedure to assess distribution fit and covariate inclusion.

As in Study Set 1, model fit was tested using continuous conditional outcome distributions available within SAS PROC LIFEREG as well as covariate combinations. Final distribution and covariate selection were based on each model's AIC as well as likelihood ratio tests. The generalized gamma distribution was retained as the best fitting distribution. Furthermore, a comparison of nested models using likelihood ratio tests suggested using Satisfaction, Excitement, Regret, age, gender, and income as covariates. For parsimony, all analyses of immediate post-auction values use generalized gamma as the response distribution, and the set of covariates is noted. The tabulated mean values are derived using unlogged transformations from the exponentiated Tobit model (i.e., participant valuations are reported in dollars).

4.4.2.2.1 Post-Auction Values Immediate

WTPDIR1. Results from the censored regression of immediate post-auction direct purchase valuations (WTPDIR1) are shown in Appendix AB, Panel 1. The analysis revealed a significant omnibus effect for Competitor Expertise ($\chi^2 = 4.480, p = 0.034$) as well as Auction Outcome ($\chi^2 = 18.616, p < 0.001$) on the WTPDIR1 measures. However, the two-way interaction of these factors (Competitor Expertise x Auction Outcome) was not significant. Also, the omnibus tests were not significant for assessed Self-Expertise as well as associated two- and three-way interactions. Among the covariates, only higher levels of excitement ($p < 0.001$) and lower age ($p = 0.006$) were associated with higher WTPDIR1 values. Males posted marginally higher WTPDIR1 values than females ($p = 0.06$). The relevant means are tabulated below the regression results.

Proposition 2 was used to guide us in our examination of the simple effects observed for the WTPDIR1 measure reported by <u>winning</u> bidders. As Appendix AB, Panel 3 shows, consistent with Proposition 2A, focal bidders who won against Hybrid

Expert competitors reported significantly higher values $\left(M_{CHybrid} = \$48.87\right)$ than those who won against Amateur competitors ($M_{CAmateur} = \$47.12$), p < 0.001. However, as shown in Panel 2, the WTPDIR1 measure for winners did not differ by Assessed Self-Expertise level ($M_{SProduct} = \$48.52, M_{SProcess} = \$48.42, M_{SAmateur} = \$48.89; p's > 0.10$) with the exception of participants who assessed themselves as Hybrid Experts ($M_{SHybrid} = \$46.16$) who curiously posted significantly lower valuations than the other assessed Self-Expertise types, p < 0.001. These data do not align with Proposition 2B.

Finally, an examination of the data in Panel 4 shows that consistent with Proposition 2C, the WTPDIR gap between those who won against Hybrid Experts vs. Amateurs was largest for participants who assessed themselves as Hybrid Experts ($48.30 - $44.01 = $4.29), p < 0.001; directionally less for those who assessed themselves as Product Experts ($48.97 - $48.07 = $0.90), p = 0.43; and directionally negative for those who assessed themselves as Process Experts ($47.97 - $48.88 = -$0.91), p = 0.44. However, contrary to Proposition 2C, the gap was also significantly positive for those who assessed themselves as Amateurs and who won against Hybrid Experts versus Amateurs ($50.26 - $47.52 = $2.74), p = 0.01. In retrospect, this is understandable as it may reflect greater confidence in Hybrid Experts versus Amateurs.

Proposition 3 guided our examination of the simple effects observed for the WTPDIR1 measure reported by <u>losing</u> bidders. As Appendix AB, Panel 3 shows, focal bidders who lost against Hybrid Expert competitors at $50.00 reported significantly higher values than those who lost against Amateurs ($M_{CHybrid} = \$54.61, M_{CAmateur} = \$52.07, p < 0.001$). This was also true for those who quit between $44.00 and $49.00 ($M_{CHybrid} = \$49.79, M_{CAmateur} = \$48.36, p < 0.001$) as well as for those who quit below \$44.00 $M_{CHybrid} = \$48.10, M_{CAmateur} = \$45.09, p < 0.001$). These data are generally consistent with Proposition 3A.

Proposition 3B was also supported. The data in Appendix AB, Panel 2 show that bidders who lost at \$50.00 and assessed themselves as Hybrid and Product Experts reported higher values ($M_{SHybrid} = \$55.16, M_{SProduct} = \$56.18$) than those reported by those who assessed themselves as Process Experts and Amateurs ($M_{SProcess} = \$51.95, M_{SAmateur} = \$50.07$), p’s < 0.001. The values reported by those who quit below \$44.00 also generally conform to this pattern with those who assessed themselves as Product Experts ($M_{SProduct} = \$49.30$) posting significantly higher values than the other expertise types, which were not significantly different from one another, $\left(M_{SHybrid} = \$46.73, M_{SProcess} = \$45.87, M_{SAmateur} = \$44.47\right)$P’s ≤ 0.001. Note that those who quit below \$49.00 did not encounter the winning bid. Thus, in contrast to those who lost at \$50.00, their reported product values are significantly lower than \$50.00. Clearly, experiencing the Auction Outcome affected the product valuation of the losing bidders.

Proposition 3C was supported for focal bidders who lost the auction at \$50.00. Thus, Appendix AB, Panel 4 shows that the WTPDIR1 gap between those who lost against Hybrid Experts versus against Amateurs was largest for participants who assessed themselves as Hybrid Experts (\$58.73 - \$51.59 = \$7.14), p < 0.001; and not significantly different for those who assessed themselves as Product Experts (\$52.88 - \$51.02 = \$1.86), Process Experts (\$56.30 - \$56.05 = \$0.25), or Amateurs (\$50.51 - \$49.62 = \$0.89), all p’s > 0.10. The proposition was also generally supported for those who quit below \$44.00 and for those who quit between \$44.00 and \$49.00. Detailed results are available in Appendix AB, Panel 4.

WTA1. A similar censored regression analysis was used to model WTA1 (the willingness to accept measure for auction winners) as a function of Competitor Expertise (Hybrid Expert, Amateur), assessed Self-Expertise (Hybrid Expert, Product Expert, Process Expert, Amateur). Age, gender, satisfaction, regret, and excitement served as covariates. As shown in Appendix AB, Panel 6, none of the omnibus effects were significant. The covariates also did not attain significance. The table of relevant means is provided below the regression results.

Guided by Proposition 2, we examined the simple effects of winners' WTA1 scores as a function of the Competitor Expert type. As Appendix AB, Panel 8 shows, focal bidders who won against Hybrid Expert competitors surprisingly reported <u>lower</u> values ($M_{CHybrid} = \$55.68$) than those who won against Amateur competitors ($M_{CAmateur} = \$58.04$). However (see Appendix AB, Panel 7), the WTA1 score for winners was ordered as predicted for assessed Self-Expertise. In particular, valuations reported by participants who assessed themselves as Hybrid Experts, Product Experts, and Process Experts ($M_{SHybrid} = \$58.67, M_{SProduct} = \$58.96, M_{SProcess} = \$57.46$), which although not significantly different from one another, were significantly higher than those reported by Amateurs ($M_{SAmateur} = \$52.36$), all p's < 0.001. These data are generally consistent with Proposition 2B but should be interpreted in the light of the results for Proposition 2C (see below).

The results for Proposition 2C (Panel 9) were surprising. The valuation gap for participants who assessed themselves as Hybrid Experts ($55.34 - $62.00 = -$6.66, p < 0.001) and Product Experts ($54.21 - $63.72 = -$9.51, p < 0.001) who won against Hybrid Experts vs. Amateurs were directionally opposite our predictions. In contrast, the valuation gap for Process Experts ($58.83 - $56.09 = $2.74, p < 0.001) and Amateurs ($54.36 - $50.37 = $3.99, p < 0.001) who won against Hybrid Experts versus Amateurs matched our predictions. The valuations reported by those who assessed themselves as Hybrid and Product Experts who won against Amateurs $M_{SHybrid} = \$62.00, M_{SProduct} = \$63.72$) are unusually high. A similar anomaly was also noted for the WTPDIR1 results. It is possible that these data stemmed from careless participant responses. However, they may also have emerged from motivated reasoning engaged by these assessed Self-Experts to mitigate dissonance created by wins against Amateurs (i.e., the reported product value justified the bid).

WTP1. Appendix AB, Panel 10 reports a similar censored regression analysis that modeled WTP1 (losers' willingness to pay for the auctioned product that they did not win) as a function of assessed Self-Expertise type (Hybrid Expert, Product Expert, Process Expert, Amateur), Competitor Expertise type (Hybrid Expert, Amateur), Auction Outcome (lose at $50.00, lose at $44.00 - $49.00, lose at < $44.00) and the interaction of these three factors. As before, age, gender, satisfaction, regret, excitement, and income were used as covariates. The results show that Competitor Expertise ($\chi^2 = 5.276, p < 0.022$), Auction Outcome ($\chi^2 = 68.196, p < 0.001$) and the interaction between assessed Self-Expertise and Auction Outcome ($\chi^2 = 12.805, p = 0.046$) predicted WTP1 significantly. Among the covariates, higher levels of regret (p = 0.038) and excitement (p = 0.021) were associated with higher WTP1. The relevant means are tabulated below the regression results in a series of panels.

Proposition 3 guided our interpretation of the simple effects. The data in Appendix AB, Panel 12, are consistent with Proposition 3A. Among focal bidders who lost at $50.00, those who lost to Hybrid Experts ($57.38) reported higher WTP values than those who lost to Amateurs ($55.25), p < 0.001. Similar results were observed for focal bidders who quit at bid levels between $44.00 and $49.00 ($M_{CHybrid} = \$53.27, M_{CAmateur} = \$51.27$), p < 0.001. And, for those who quit below $44.00 $\left(M_{CHybrid} = \$46.92, M_{CAmateur} = \$44.57\right)$, p < 0.001.

Proposition 3B was examined using the means reported in Appendix AB, Panel 11. Assessed Self-Expert Hybrid Experts ($55.46), Product Experts ($60.47), and Process Experts ($55.59) who lost reported equal or higher valuations relative to those who assessed themselves Amateurs ($53.74), all p's < 0.001. Thus, these valuations appear consistent with an expertise-credibility based inference. We do not see reported valuations that suggest participants who assessed themselves as Hybrid or Product Experts deliberately lowered product valuations to justify their loss. However, some of the reported WTA1 scores (e.g., by Product and Process Experts) do appear to be on the high side. These higher valuations may reflect auction losers' efforts to justify the loss by attributing it to an insufficient budget and thus mitigate experienced regret.

Significantly, for the group that lost at $50.00, those who assessed themselves as Hybrid Experts, Product Experts, and Process Experts each indicated higher WTP1 than those who assessed themselves as Amateurs. This suggests they may have experienced greater regret. Future analysis of this data will test this conjecture. Arguably, losing at $50.00 because their budget ran out would generate greater regret for participants with expertise than earlier volitional exits. We note that those who quit the auction below $44.00 did not post significantly different WTP1 values as a function of assessed Self-Expertise. This pattern is similar for those who bid between $44.00 and $49.00, with the exception of participants who assessed themselves as Process Experts ($54.16) whose WTP1 values were significantly higher than any of the other expertise types ($M_{SAmateur} = \$52.82, M_{SProduct} = \$50.63, M_{SHybrid} = \$51.46$), all p's < 0.001. These exploratory results suggest more focused studies of the role of experienced regret for losing bidders.

The data used to examine Proposition 3C are in Appendix AB, Panel 13. As predicted, the difference in WTP1 for participants who assessed themselves as Hybrid Experts and lost at $50.00 to Hybrid Experts versus Amateurs is highest ($60.29 - $50.63 = $9.66, $p < 0.001$). Surprisingly, the difference in valuation for those who assessed themselves as Product Experts ($59.96 - $60.99 = -$1.03, $p = 0.14$) was not significant. The corresponding differences for those who assessed themselves as Amateurs ($55.09 - $52.39 = $2.70, $p = 0.01$) and Process Experts ($54.17 - $57.00 = -$2.83, $p < 0.001$) was smaller than for those assessed themselves as Hybrid Experts. This is consistent with Proposition 3C. However, the fact that those who assessed themselves as Product and Process Experts reported a higher valuation when they lost to an Amateur (versus Hybrid Expert) is difficult to explain within our reasoning framework. A closer examination of the data for those who quit at bid levels between $44.00 and $49.00 and below $44.00 shows no significant anomalies. However, we note that the motivated reasoning patterns of Hybrid Experts, Product Experts, and Process Experts require further study, with a particular focus on the mediating role of endogenous regret in determining post-auction valuation. As noted earlier, future analyses of these data will address this issue.

4.4.2.2.2 Post-Auction Valuation: Durability

We used a set of Difference-in-Differences analyses (Warton, Parker, & Karter, 2016) to examine relative change in post-auction valuation over time as a function of assessed Self-Expertise, Competitor Expertise, Auction Outcome, as well as the 2- and 3-way interactions of these two factors. SAS PROC GLIMMIX was used to conduct these analyses for the three valuation measures (ΔWTPDIR, ΔWTA, and ΔWTP) that we collected in this study.

ΔWTPDIR. The results of the analysis for change in WTPDIR over time are shown in Appendix AC, Panel 1. The omnibus tests for the influence of the core factors on change in WTPDIR (i.e., the interactions with time) were not significant: Assessed Self-Expertise ($p = 0.168$), Competitor Expertise ($p = 0.093$), and their interaction ($p = 0.065$), as well as Auction Outcome ($p = 0.682$), its interaction with Assessed Self-Expertise ($p = 0.886$), Competitor Expertise ($p = 0.100$), as well as the 3-way interactions were not significant ($p = 0.123$), respectively. Among the covariates, higher levels of regret ($p = 0.014$) and excitement ($p = 0.001$) were associated with greater changes in WTPDIR. The relevant tables of means are reported below the regression.

Proposition 4 guided our focus on the simple effects for auction winners. As shown in Appendix AC, Panel 3, change in WTPDIR for those who won against Hybrid Experts (-\$0.15) remained stable, $p > 0.10$; however, those who won against Amateurs decreased (-\$0.37), $p = 0.01$. These data provide partial support for Proposition 4A. However, Proposition 4B was not supported. WTPDIR decreased for participants who assessed themselves as Hybrid Experts (-\$0.79), $p < 0.001$, and remained stable for those who assessed themselves as Product Experts (-\$0.04), $p > 0.10$. It decreased as predicted for assessed Self-Expert Process Experts (-$0.38, p = 0.001) but remained stable for those who assessed themselves as Amateurs ($0.14, p < 0.10). Thus, there was little support for Proposition 4 regarding ΔWTPDIR movements.

Appendix AC, Panel 3 also shows that in the group that lost the auction at $50.00, ΔWTPDIR decreased for those competing against Hybrid Experts (-$0.27), p = 0.001, and increased for those who won against Amateurs ($0.34), p < 0.001. In the group that quit the auction at bid levels between $44.00 and $49.00, valuations increased directionally ($0.25 and $0.17), p's > 0.10. Those who quit at bid levels below $44.00 showed a pattern similar to those who lost at $50.00: against Hybrid Experts (-$0.87), p < 0.001, and against Amateurs ($0.95), p < 0.001. Thus, support for Proposition 5B was tenuous. The data show that ΔWTPDIR values mostly remained stable for both auction winners and losers, regardless of their assessed Self-Expertise type or their perceptions of Competitor Expertise. Overall, there was little systematic support for our propositions regarding the change in WTPDIR over time.

ΔWTA. Appendix AC, Panel 8 shows the results for the difference-in-differences analysis for change in WTA for those who won the auction at $50.00. The omnibus tests for Competitor Expertise (p = 0.978), Assessed Self-Expertise (p = 0.601) and their interaction (p = 0.264) were not significant. Also, no covariates were significant. The means are reported in the table below the regressions. An analysis of simple effects showed mixed support for Proposition 4A. Contrary to expectation, ΔWTA decreased over time for bidders who won against Hybrid Experts (-$1.64), p < 0.001. However, the decrease in ΔWTA for those who won against amateurs (-$1.67), p < 0.001, was as expected. Support for Proposition 4B was also mixed (Appendix AC, Panel 7). Contrary to expectations, ΔWTA decreased for those who assessed themselves as Hybrid Experts (-\$1.76), $p < 0.001$, but remained stable (-\$0.31), $p > 0.10$, for those who assessed themselves as Product Experts. However, as expected, the auctioned product's value decreased over time for both those who assessed themselves Process Experts (-\$1.54), $p < 0.001$, as well as Amateurs (-\$3.01), $p < 0.001$.

Taken together, these results suggest a potential problem with the effectiveness of the expertise manipulation. Although the manipulation checks self-reports implied successful manipulations for designated Hybrid Experts and Product Experts (Appendix Y), changes in their reported values did not correspond to expectation. Their values remained stable when they won against Amateurs but decreased when they won against Hybrid Experts (see Appendix AC, Panel 9).

ΔWTP. Appendix AC, Panel 10 shows the details of the difference-in-differences analysis for change in post-auction WTP measures for those who lost the auction. The omnibus test for Auction Outcome (the three loser groups) was significant ($\chi^2 = 9.52$, $p = 0.009$). The remaining omnibus tests for the influence of the core factors on change in WTP (i.e., the interactions with time) were not significant: assessed Self-Expertise ($p = 0.463$), Competitor Expertise ($p = 0.172$) and their interaction ($p = 0.525$), the interaction of Auction Outcome with assessed Self-Expertise ($p = 0.834$) and Competitor Expertise ($p = 0.505$) and the 3-way interaction were not significant ($p = 0.552$), respectively. Among the covariates, higher levels of excitement ($p < 0.001$) were associated with greater change in WTPDIR. The relevant tables of means are tabulated below the regression.

Our examination of the simple effects was guided by Proposition 5. Tests of Proposition 5A are based on the data reported in Appendix AC, Panel 12. Contrary to expectation, for bidders who lost at \$50.00, ΔWTP decreases following competition against Hybrid Experts (-\$2.10), $p < 0.001$). On the other hand, consistent with 5A, competition last against Amateurs did result in a decrease in ΔWTP (-\$2.27), $p < 0.001$. This pattern repeats for those who quit between \$44.00 and \$49.00. WTP unexpectedly drops for those who lost to assessed Self-Expert Hybrid Experts (-\$3.32), $p < 0.001$. The expected drop for those who lost to Amateurs is observed (-\$1.22), $p < 0.001$, although it is relatively smaller. For those who quit below \$44.00, those who last competed against Amateurs moderately increased their valuations (\$1.12), $p < 0.001$; however, those who last competed against Hybrid Experts (\$0.29) did not change their valuation, $p > 0.10$. Overall, the results reflect mixed support for Proposition 5A. While ΔWTP decreases as expected for those who lost to Amateurs, ΔWTP also unexpectedly decreases for those who lost to Hybrid Experts as well.

Tests of Proposition 5B are based on the data reported in Appendix AC, Panel 11. For bidders who lost at \$50.00, participants who assessed themselves as Hybrid Experts (-\$0.82) and Product Experts (-\$0.86) reported somewhat lower values over time, p’s = 0.04 and $p = 0.01$, respectively. However, those who assessed themselves as Process Experts (-\$3.56) and Amateurs (-\$3.52) reported significant decreases in value over time, p’s < 0.001. A similar pattern of change in reported value over time was noted for those who withdrew from the auction between \$44.00 and \$49.00. Unexpectedly, those who assessed themselves as Hybrid Experts (-\$1.48) and Product Experts (-\$2.74) reported a decrease in value, p’s < 0.001. However, those who assessed themselves as Process

Experts (-$2.63) and Amateurs (-2.23) also reported significant drops in value as expected, p’s < 0.001. For those who quit below $44.00, value changes were not significant except for those who assessed themselves as Product Experts (1.58) who significantly increased their valuation over time, $p < 0.001$. Overall, the results reflect mixed support for Proposition 5B. ΔWTP drops across the board, contrary to expectation for assessed Self-Expert Hybrid Experts and Product Experts but consistent with expectations for Process Experts and Amateurs.

Taken together, the ΔWTP results (and the ΔWTA results) may reflect problems with the expertise manipulation. The manipulation checks self-reports implied successful manipulations for those who assessed themselves as Hybrid Experts and Product Experts (Appendix Y). However, the direction of changes in their reported values was unexpected. The decreases in value for those who assessed themselves as Process Experts and Amateurs were as expected.

4.5 Study 1 - Discussion

Study 1 was designed to examine how the level and type of assessed Self-Expertise (Hybrid Expert, Product Expert, Process Expert, and Amateur) influenced bidding behavior in an ascending Japanese auction when bidders were pitted against Competitor Experts perceived as Hybrid Experts or Amateurs. Assessed Self-Expertise was manipulated using a knowledge test and false feedback procedure. Perceptions of Competitor Expertise were manipulated using an instruction set like that used in Study Set 1. We examined the effects of these variables and their interactions on (1) bid levels,

(2) immediate post-auction valuation of the auctioned product, and (3) durability of the auctioned product's post-auction valuation.

Bid Levels. Proposition 1 guided our examination of the bid level data. First, a significantly greater proportion of focal bidders who competed against Hybrid Experts (versus Amateurs) remained in the auction until their $50.00 budget was exhausted. Second, bid level also differed by assessed Self-Expertise, but the means were not ordered as expected. Participants who assessed themselves as Process Experts bid highest (54.86%), followed by Product Experts (47.95%) and Amateurs (40.94%). Surprisingly, Hybrid Experts (38.62%) bid lowest.

Third, all assessed Self-Expertise types (except Process Experts) bid lower against Amateurs and higher against Hybrid Experts. The difference was lowest for those who assessed themselves as Process Experts and highest for Product Experts (58.90% - 36.99% = 21.91%, $p = 0.008$). As one may expect, Hybrid Experts were least influenced by Competitor Expertise (44.44%). In contrast, Product Experts were influenced most and relied greatly on Hybrid Experts (58.90%).

Finally, Process Experts' bidding was enigmatic. They followed Amateurs and Hybrid Experts to equally high bid levels (and bid highest on average). Their faith in Hybrid Experts is logical, but their high bids in competing with Amateurs may reflect a misplaced escalation of commitment, perhaps based on a belief that they could extract a surplus when bidding against Amateurs.

Immediate Post-Auction Values – Winners. Proposition 2 guided our assessment of the direct purchase WTPDIR1 measure for winning bidders. First, consistent with expectations, those who won against Hybrid Experts reported higher values than those who won against Amateurs. Second, this gap in WTPDIR1 was positive and larger for those who assessed themselves as Hybrid Experts, next largest for those who assessed themselves as Product Experts, but negative for those who assessed themselves as Process Experts. Unexpectedly, those who assessed themselves as Amateurs also showed a significant positive gap. This may reflect their greater faith in Hybrid Experts versus Amateurs as competitors. Finally, reported WTPDIR1 values did not differ by assessed Self-Expertise level except for those reported by those who assessed themselves as Hybrid Experts, which were lower.

Auction winners' WTA1 scores showed some unexpected patterns. First, contrary to expectation, focal bidders who won against Hybrid Experts reported lower values than those who won against Amateurs. This pattern also appeared in the corresponding WTA1 gap reported by those who assessed themselves as Hybrid Experts. Notably, Hybrid Experts and Product Experts who won against Amateurs reported unusually high WTA1. These data may reflect careless responses but could have been driven by motivated reasoning to mitigate cognitive dissonance created by wins against Amateurs. In contrast, the corresponding WTP1 gap for Auction Experts who won against Hybrid Experts versus Amateurs aligns with our expectations. Second, the ordering of the winners' WTA1 values by Assessed Self-Expertise is also as expected. The valuations reported by both those who assessed themselves as Hybrid and Product Experts were higher than those reported by those who assessed themselves as Process Experts and Amateurs.

Immediate Post-Auction Values – Losers. Proposition 3 guided our interpretation of the WTPDIR1 measure reported by losing bidders. First, among focal bidders who lost at $50.00, those who lost against Hybrid Experts reported higher values than those who lost against Amateurs. This pattern was also observed for those who withdrew from bidding at lower bid levels. Second, as expected, those who assessed themselves as Hybrid and Product Experts reported higher WTPDIR1 values than those who assessed themselves as Process Experts and Amateurs. Note that those who withdrew from the auction below $44.00 did not observe the market clearing bid level. Thus, consistent with expectation, these bidders reported lower product values. Clearly, bidders who lost because their budget ran out had different value assessments than those who quit volitionally. Third, the WTPDIR1 data for the various assessed Self-Expertise types were as expected. For those who lost at $50.00, the gap in WTPDIR1 between those who lost to Hybrid Experts versus Amateurs was largest for those who assessed themselves as Hybrid Experts, next largest for Product Experts, and smaller for Process Experts and Amateurs. The pattern generally replicated for those who volitionally withdrew from bidding at lower bid levels.

The WTP1 (willingness to pay – losers) data show mixed results relative to Proposition 3. First, as expected, for focal bidders who lost at $50.00, those who lost to Hybrid Experts reported higher WTP1 values than those who lost to Amateurs. Similar patterns emerged for focal bidders who withdrew from the auction at lower bid levels of their own volition. Second, also as predicted, the difference in WTP1 was highest for those who assessed themselves as Hybrid Experts who lost at $50.00 to other Hybrid Experts versus Amateurs. However, the fact that those who assessed themselves as Product Experts and Amateurs reported higher WTP1 following a loss to a competing Amateur (versus a Hybrid Expert) is difficult to explain within our reasoning framework. The data for those who quit volitionally show no significant anomalies. However, the possibility of motivated reasoning among losing assessed Self-Expert Hybrid Experts, Product Experts, and Process Experts requires further study, with a particular focus on the mediating role of regret.

WTP1 data for assessed Self-Expert Hybrid Experts and Product Experts who lost were equal or higher relative to Process Experts and Amateurs. These valuations are consistent with an expertise/credibility framework. There is no evidence that Hybrid and Product Experts deliberately tried to lower their WTP1 values to denigrate the product and justify their loss. Rather, some of the valuations (e.g., by Product and Process Experts) are on the higher side. These higher valuations may reflect efforts to justify the loss and mitigate experienced regret by attributing it to an insufficient budget.

Nevertheless, bidders who lost at $50.00 and competed against Hybrid Experts posted higher WTP1 values than when they competed against Amateur bidders, suggesting greater experienced regret. Arguably, losing at $50.00 because of a budget constraint may generate greater regret than volitional exits at lower bid levels. Thus, for those who quit volitionally, WTP1 does not differ much by assessed Self-Expertise type. If anything, those who assess themselves as Process Experts report higher WTP1, perhaps reflecting greater regret for exiting too quickly. Overall, these exploratory results suggest a more focused study of the mediating role of experienced regret for losing bidders.

Post-Auction Values: Durability. Propositions 4 and 5 guided our analysis of the results on the temporal durability of focal bidders' valuations as a function of Self and Competitor Expertise, as well as their joint interaction with Auction Outcome. We partition the discussion by auction winners and losers, and within each contrast results for WTPDIR1 and WTA1 (WTP1).

Temporal Durability - Winners. The results for assessed Self-Expertise were not systematic. ΔWTPDIR decreased for those who assessed themselves as Hybrid and Process Experts but remained stable for Product Experts and Amateurs. Thus, the observed changes in ΔWTPDIR over time were not systematic.

Interestingly, ΔWTA also decreased over time both for bidders who won against Hybrid Experts and those who assessed themselves Hybrid Experts. Although ΔWTA also decreased over time as expected for those who assessed themselves as Process Experts and for Amateurs, the absence of systematic effects for assessed Self-Expertise raises interpretability concerns.

Temporal Durability - Losers. As with the ΔWTPDIR data for winners, ΔWTPDIR values for auction losers also did not show systematic patterns. Most of the changes were not significant and, in some cases, were directionally contradictory to our propositions. For example, among those who lost the auction at $50.00, ΔWTPDIR unexpectedly decreased for those who lost against Hybrid Experts and increased for those who lost against Amateurs.

The ΔWTP valuation durability results also raised questions regarding the overall interpretability of the results. ΔWTP decreases across the board, surprisingly even for those who lost to Hybrid Experts, but consistent with expectation for those who lost to Amateurs. Also, we did not observe systematic results by assessed Self-Expertise. For example, for those who lost at $50.00, ΔWTP decreases irrespective of assessed Self-Expertise. Furthermore, the decreases are smaller for those who assess themselves as Hybrid and Product Experts relative to Process Experts and Amateurs.

In our review of the Study 1 effects, we report a useful set of exploratory findings regarding how assessed Self-Expertise moderates bidding behavior against different types of perceived Competitor Experts. We also obtain insight into immediate post-auction value stemming from such competition and further explore their temporal stability as a function of Auction Outcome. At the same time, the pattern of results for ∆WTA and ∆WTP (and for ∆WTPDIR) points to a potential problem with the assessed Self-Expertise manipulation. Although the manipulation checks implied successful manipulations for designated Hybrid and Product Experts (Appendix Y), the changes in reported values did not correspond to expectations, particularly for Hybrid and Product Experts. Neither were the reported values consistent as one would expect across the various assessed Self and Competitor Expertise conditions.

4.6 Study 2

In Study Set 2, the first study (Study 1) examined the influence of assessed Self- and Competitor Expertise on bidding behavior in a Japanese, ascending auction, as well as the higher-order moderating influence of Auction Outcome on auctioned product valuations both immediately after the auction as well after the passage of an interval of time. We used three measures of product value: a retrospective direct purchase value (WTPDIR1) for all bidders, a willingness to accept measure (WTA1) for auction winners, and a willingness to pay measure (WTP1) for auction losers. The Japanese ascending auction allowed bidders an opportunity to observe competitor entry and exit, and within Auction Outcome assignment endogenously make decisions to continue bidding or to withdraw from the auction. For those who bid up to their budget limit, the win or lose outcome was determined by a random designation.

Manipulations for both assessed Self and Competitor Expertise were the same as those used in Study 1. However, rather than manipulating four levels of assessed Self-Expertise, in Study 2, we manipulated only two: Hybrid Experts and Amateurs. A key departure from Study 1 was the auction mechanism we employed. In contrast to Study 1's Japanese Ascending auction, in Study 2, we used a First-Price, Sealed-Bid auction to examine bid value. In this auction mechanism, the focal bidder does not have access to other bidder decisions to stay or quit. Rather, they must decide on a bid based solely on assessed Self-Expertise as well as the relative presence of different types of Competitor Experts. Use of this auction mechanism allowed us to explore how auction mechanism impacts the effects of both assessed Self and Competitor Expertise on the dependent variables.

4.6.1 Study 2 Procedure

We recruited 425 participants from the Prolific web panel to participate in an online auction. Their base compensation was $2.17, and they had the opportunity to earn an additional bonus based on their auction performance. Except for the change to auction format and the reduction in the number of assessed Self-Expertise levels, all auction procedures remained the same as in Study 1. A custom-designed software package seamlessly implemented the study procedures. Participants were provided descriptions of the two Competitor Expert types (Appendix AD) and their comprehension was tested as before. Assessed Self-Expertise was manipulated using a knowledge test and false feedback procedure as before (Appendices T, U, and V). Both manipulations were checked as described below.

Participants were told that they had a $50.00 budget, and an instruction set explained the payoff structure (Appendix AE). The conversion rate used for budget savings ($0.005 per game dollar) and product value ($0.01 per game dollar) were the same as those used in Study 1. Appendix AF shows the product selection page on which participants could choose a preferred bottle of wine (Panel 1) as well as the modified auction user interface (Panel 2). Panel 2 illustrates the auction interface depicting four competing bidders (all with the same expertise type) and the focal bidder (with shirt colors coded to depict both assessed Self and Competitor Expertise type). The bidding procedure for the FPSB auction was straightforward: participants chose a product to bid on and then submitted a sealed-bid (in a numeric, free-text entry field). Bids were restricted between $42.00 (starting bid value) and $50.00 (the provided budget). Note that these matched the starting bid level and the budget in Study 1. However, unlike in the ascending auction experiment, all participants submitted a bid, and all outcomes (win/loss) were determined exogenously. After a participant submitted their bid, the pre-designated Auction Outcome was revealed. The number of participants assigned to each cell of the 2 (Competitor Expertise: Wine Auction Expert/Amateur) x 2 (Assessed Self-Expertise: Wine Auction Expert/Amateur) x 2 (Auction Outcome: Win/Lose) study design is shown in Appendix AG.

4.6.2 Study 2 Results

Manipulation check results showed assessed Self and Competitor Expertise manipulations were successful. For Competitor Expertise, the bidders assigned to compete against Hybrid Experts reported competing against more Hybrid Experts than Amateurs ($M_{CHybrid} = 6.23, SD_{CHybrid} = 0.11;\ M_{CAmateur} = 2.02, SD_{CAmateur} = 0.11;$ $F(1, 422) = 748.97$, $p < 0.001$). Also, those assigned to compete against Amateurs reported competing against more Amateurs than Hybrid Experts ($M_{CHybrid} = 1.65, SD_{CHybrid} = 0.10;\ M_{CAmateur} = 6.01, SD_{CAmateur} = 0.10$); $F(1, 422) = 886.67$, $p < 0.001$). For the Assessed Self-Expertise manipulation, those assigned to bid as Hybrid Experts reported having greater Hybrid Expertise ($M_{SHybrid} = 5.51, SD_{SHybrid} = 0.10;\ M_{SAmateur} = 1.17, SD_{SAmateur} = 0.11;$ $F(1, 422) = 847.89$, $p < 0.001$). Also, those assigned to bid as Amateurs rated themselves as Amateurs ($M_{SHybrid} = 2.57, SD_{SHybrid} = 0.11;\ M_{SAmateur} = 6.83, SD_{SAmateur} = 0.11;$ $F(1, 422) = 742.95$, $p < 0.001$). These ratings of assessed Self-Expertise also significantly exceeded the respective scale midpoints, suggesting a strong manipulation.

4.6.2.1 Bid Level Results

In this sealed-bid auction, each participant could submit bids in the same way regardless of the study condition. Nevertheless, since we constrained bids to lie between \$42.00 and \$50.00, the possibility of differential censoring across conditions remained. The data confirm bid amounts were censored from both the left (17.22%) and the right (6.13%). Hence, we used a similar maximum likelihood censored Tobit model (SAS PROC LIFEREG) to analyze the bid level results.

As shown in Appendix AH, Panel 1, bids were analyzed as a function of Competitor Expertise, assessed Self-Expertise, and the interaction between them. Although the omnibus test for the interaction was not significant, both assessed Self-Expertise ($\chi^2 = 5.87, p = 0.02$) and Competitor Expertise ($\chi^2 = 8.46, p = 0.004$) affected the bid level. The mean bid levels are tabulated below the regression results. Providing additional support for Proposition 1A, participants bid higher when competing against Hybrid Experts ($M_{CHybrid} = 44.57$) than Amateurs ($M_{CAmateur} = 43.79$), $\chi^2 = 8.46, p = 0.004$. Also providing additional support for Proposition 1B, participants bid higher when they assessed themselves as Hybrid Experts ($M_{SHybrid} = 44.51$) vs. Amateurs ($M_{SAmateur} = 43.84$), $\chi^2 = 5.87, p = 0.02$. Although the omnibus interaction was not significant, an analysis of the simple effects showed that those who assessed themselves as Hybrid Experts bid significantly higher when competing against other Hybrid Experts versus against Amateurs, p = 0.006. The bids from those who assessed themselves as Amateurs did not differ by Competitor Expertise (p = 0.16). These results show that both assessed Self and Competitor Expertise affected the bids submitted. However, we note that the results in this study are not entirely consistent with those in Study Set 1, assuming most of the Study Set 1 bidders likely considered themselves Amateurs and were influenced by Competitor Expertise. We discuss this seeming anomaly in the discussion of our results for Study Set 2.

4.6.2.2 Post-Auction Valuation:

The Auction Outcome (win/loss) was announced immediately following the auction's conclusion. As in earlier studies, we asked participants to indicate three measures of product valuation: willingness to pay in a direct purchase from the auctioneer (WTPDIR1), willingness to accept – winners (WTA1), and willingness to pay – losers (WTP1). We elicited these measures once immediately after the auction results were announced and then again following a short, interpolated task.

As in Study 1, post-auction valuation data were gathered as numerical entries in an open field, and participants were constrained to provide responses between $25.00 and $75.00 to avoid careless and inappropriate responses. This again introduced the possibility of left and right censoring, and examination of the responses confirmed that WTPDIR1 was both left- (6.60%) and right- (1.42%) censored, WTA1 was left- (1.40%) and right- (8.88%) censored, and WTPL1 was both left- (4.29%) and right- (4.76%) censored. Hence, as before, the post-auction value data were analyzed using a maximum likelihood censored Tobit model available within the SAS PROC LIFEREG procedure to assess distribution fit (generalized gamma) and covariate inclusion.

4.6.2.2.1 Post-Auction Valuations - Immediate

WTPDIR1. Results from the censored regression of immediate post-auction direct purchase valuation (WTPDIR1) are shown in Appendix AI, Panel 1. The analysis reveals a significant omnibus effect for Auction Outcome ($\chi^2 = 51.873, p < 0.001$) as well as an interaction of assessed Self and Competitor Expertise ($\chi^2 = 3.995, p = 0.046$) on the WTPDIR1 measures. The effects of assessed Self-Expertise ($\chi^2 = 3.138, p = 0.077$), as well as the three-way interaction between assessed Self and Competitor Expertise with Auction Outcome ($\chi^2 = 3.5014, p = 0.0613$) were marginally significant. Among the covariates higher levels of regret (p = 0.017), excitement (p <

0.001), satisfaction (p = 0.001), and lower income (p = 0.059) were associated with higher WTPDIR1 values. The relevant means are tabulated below the regression results.

Bidders who won the auction reported significantly lower WTPDIR1 than those who lost ($M_{Winners} = \$46.72, M_{Losers} = \$55.24, \text{X}^2 = 51.87, p < 0.001$), seemingly consistent with the winner's curse for this FPSB auction. Inconsistent with Propositions 2A and 2B, as shown in Appendix AI, Panel 8, WTPDIR1 values reported by winners did not vary by Competitor Expertise for those who assessed themselves as Amateurs ($(M_{CAmateur} = \$47.84, M_{CHybrid} = \$47.77), p > 0.10$, or those who assessed themselves as Hybrid Experts ($(M_{CAmateur} = \$45.57, M_{CHybrid} = \$45.70), p > 0.10$. However, the reported WTPDIR1 values did differ for losers. Inconsistent with 3A, those who assessed themselves as Amateurs and lost to other Amateurs posted higher values than when they lost against Hybrid Experts ($(M_{CAmateur} = \$56.80, M_{CHybrid} = \$53.83), p < 0.001$. However, consistent with 3B, for participants who assessed themselves as Hybrid Experts, the pattern was reversed ($(M_{CAmateur} = \$54.12, M_{CHybrid} = \$56.21), p < 0.001$. These WTPDIR1 data suggest that assessed Self-Expertise mattered little following an auction win. On the other hand, following an auction loss, higher values are reported when competing against one's own expertise type.

WTA1. Appendix AI, Panel 5 shows the censored regression results for WTA1. Inconsistent with Proposition 2, the influence of Competitor Expertise on WTA1 was not significant (p = 0.367); however, the influence of assessed Self-Expertise on WTA1 was marginally significant, $\chi^2 = 2.98, p = 0.084$). The interaction between assessed Self and Competitor Expertise was not significant (p = 0.205). Among the covariates, only income (p = 0.0346) and age (p = 0.01) had an effect such that lower levels of income were associated with increased post-auction WTA1, and younger participants were more likely to post higher WTA1 values. The mean scores are tabulated in Appendix AI, Panels 6 through 8. Inconsistent with Proposition 2B, there weren't any differences in WTA1 scores reported by participants who assessed themselves as Amateurs and won the auction after competing against other Amateurs ($50.49) or Wine-Auction Experts ($50.11), $p > 0.10$. However, consistent with Proposition 2B, those who assessed themselves as Hybrid Experts and won reported higher WTA1 following a win against other Hybrid Experts ($53.58) than against Amateurs ($51.38), $p < 0.001$. In other words, participants reported higher WTA1 when they won against their own kind. This provides mixed support for Proposition 3.

WTP1. Appendix AI, Panel 9 shows the censored regression results for WTP1. Results revealed that neither Assessed Self-Expertise ($p = 0.393$), nor Competitor Expertise ($p = 0.468$) nor their interaction ($p = 0.488$) were significant. The mean scores are tabulated in Appendix AI, Panels 10 through 12. Among covariates, satisfaction ($p = 0.0061$), excitement ($p = 0.0071$), and age ($p = 0.005$) had significant effects. Regret had a marginally significant effect ($p = 0.093$). Examination of the coefficients revealed higher levels of satisfaction produced lower post-auction WTP1, whereas higher levels of excitement produced higher post-auction WTP1, and an increase in regret produced lower WTP1. Furthermore, an increase in age resulted in decreased WTP1.

Inconsistent with Proposition 3A, an examination of the simple effects on WTP1 reveals that for participants who assessed themselves Amateurs, a loss resulted in similar post-auction WTP1 for both those who competed last against Amateurs ($57.14) and Hybrid Experts ($57.17), $p > 0.10$. However, consistent with Proposition 3A, participants who assessed themselves as Hybrid Experts and lost reported higher WTP1 scores following competition against Hybrid Experts ($56.89) relative to Amateurs (54.77), p = 0.001. Thus, similar to the results for those who won (WTA1), participants reported higher WTP1 valuations when they lost against their own expertise type. Support for Proposition 3A was therefore mixed.

4.6.2.2.2 Post-Auction Valuation: Durability

Post-auction WTPDIR, WTA, and WTP measures were elicited once again after a short, interpolated task. Comparing these measures to those elicited earlier (immediately after announcement of the Auction Outcome) allowed an examination of how these measures changed over time. As with Study 1, we used a set of Difference-in-Differences analyses (Warton, Parker, & Karter, 2016) to examine these relative changes in post-auction values <u>over time</u> as a function of Assessed Self-Expertise, Competitor Expertise, Auction Outcome, as well as the two and three-way interactions between them. SAS PROC GLIMMIX was used to conduct these analyses for the three valuation measures ΔWTPDIR, ΔWTA (winners), and ΔWTP (losers).

ΔWTPDIR. The results for changes in WTPDIR are shown in Appendix AJ, Panel 1. The omnibus tests do not show any significant effects for the core factors: assessed Self-Expertise ($p = 0.778$), Competitor Expertise ($p = 0.207$) and their interaction ($p = 0.591$); Auction Outcome ($p = 0.770$) and its two-way interactions with assessed Self-Expertise ($p = 0.360$) and Competitor Expertise ($p = 0.713$) as well as the three-way interaction were similarly not significant ($p= 0.394$). Among the covariates, higher levels of regret ($p = 0.021$), excitement ($p < 0.001$), and lower age ($p = 0.018$)

were associated with increases in ΔWTPDIR. The relevant tables of means are reported below the regression.

As shown in Appendix AJ, Panel 4, the change in WTPDIR was generally directionally negative. Participants who assessed themselves as Amateurs posted decreasing values irrespective of whether they won against Hybrid Experts (-$0.85; p = 0.005) or lost against competing Amateurs (-$0.71, p = 0.01). This pattern is difficult to reconcile within our expertise/credibility framework, and Propositions 5A and 5B are therefore only partially supported. No other change was significant. Nevertheless, these results suggest a need to examine how factors such as regret and excitement may have mediated these changes.

ΔWTA. Appendix AJ, Panel 5 shows the results for the difference-in-differences analysis for the change in WTA for auction winners. The omnibus tests show that Competitor Expertise ($\chi^2 = 3.01, p = 0.083$) had a marginally significant effect. However, assessed Self-Expertise (p = 0.683) and its interaction with Competitor Expertise (p = 0.565) did not significantly influence the durability of ΔWTA over time. Also, covariates were not significant. The relevant means are reported below the regression results in Appendix AJ, Panels 6–8. Inconsistent with Proposition 4B, analyses of the simple effects show that Amateurs (-$0.81) who won had relatively more stable ΔWTA scores than Hybrid Experts (-$1.19), p < 0.001. Also inconsistent with Proposition 4B, an examination of the interaction reveals that participants who assessed themselves as Amateurs had stable values irrespective of whether they competed against other Amateurs (-$0.28) or Hybrid Experts (-$0.13), p > 0.10. However, Hybrid Experts unexpectedly decreased their valuations after competition against other Hybrid Experts

(\$-2.25) relative to Amateurs (\$-1.35), $p < 0.01$. Thus, Propositions 4A and 4B remain unsupported.

ΔWTP. Finally, Appendix AJ, Panel 9 shows the overall difference-in-differences analysis for change in post-auction WTP measures for those who lost the auction. The omnibus tests for the influence of the core factors on change in WTP (i.e., the interactions with time) were not significant: assessed Self-Expertise ($p = 0.558$), Competitor Expertise ($p = 0.234$), and their interaction ($p = 0.473$). Among the covariates, higher levels of excitement ($p < 0.003$) and lower age were associated with increases in ΔWTPDIR. The relevant tables of means are below the regression in Appendix AJ, Panels 10-12.

An examination of the simple effects shows that participants who assessed themselves as Amateurs lowered their ΔWTP when they lost against other Amateurs (-\$1.45, $p = 0.005$). Those who lost against Hybrid Experts reduced their ΔWTP values, but not significantly (-\$0.36, $p > 0.10$). These results are consistent with expectation under Proposition 5A. Participants who assessed themselves as Hybrid Experts and lost (whether to Amateurs or other Hybrid Experts) did not show a significant change in their ΔWTP. These results are consistent with Proposition 5B. This stability is consistent with an expertise rationale and inconsistent with motivated reasoning to reduce ΔWTP in an effort to reconcile with their loss in the auction.

Taken together, these durability results show that the value measures (ΔWTPDIR, ΔWTA, and ΔWTP) showed a preponderance of value decreases. Although this is consistent with our expectations of how Amateurs would adjust their values given wins or losses against other Amateurs, decreases in value are unexpected for Hybrid Experts, particularly given wins against competitors who are also Wine-Auction Experts. Whereas value decrease following a loss may be attributed to motivated reasoning, the results do raise questions about whether the Hybrid Experts did indeed behave like experts when bidding (even though they responded to the manipulation check as expected).

4.7 Study 2 Discussion

Study 2 examined bidding behavior and post-auction valuation as a function of assessed Self and Competitor Expertise, each at two levels (Hybrid Expert and Amateur) in a First-Price, Sealed-Bid auction. In this auction, all focal bidders (participants) were required to bid without access to the entry/exit behavior of competing bidders. Auction Outcomes (win/lose) were determined exogenously. Assignments to all conditions were random. Participants provided post-auction measures of the auctioned product's value (WTPDIR, WTA, and WTP both immediately after the Auction Outcome was announced and again after a short delay).

First, the submitted bids were affected by both assessed Self and Competitor Expertise. Examination of simple effects revealed participants who assessed themselves as Hybrid Experts bid significantly higher when competing against other Hybrid Experts relative to when they competed against Amateurs, $p = 0.006$. The bids from those who assessed themselves as Amateurs were similar, regardless of Competitor Expertise ($p = 0.16$). Thus, participants who assessed themselves as Hybrid Experts used the Competitor Expertise cue more than those who assessed themselves as Amateurs. This unexpected result could be attributed to the possibility that Hybrid Experts experienced different levels of arousal when competing against other Hybrid Experts vs. Amateurs (Ku, Malhotra, & Murnighan, 2005). Also, in the absence of bid level data in the FPSB auction, Amateur bidders lacked the competitor bidding cue that they relied upon in the ascending auction studies.

Second, immediate post-auction WTPDIR1 assessments showed that bidders who won the auction reported WTPDIR1 values that were significantly lower than those who lost. Values reported by winners did not vary by Competitor Expertise for either those who assessed themselves as Amateurs or Hybrid Experts. However, these values differed for auction losers. Participants who assessed themselves as Amateurs and lost to other Amateurs posted higher values relative to when they lost to Hybrid Experts. The pattern was reversed for bidders who assessed themselves as Hybrid Experts. Thus, for both participants who assessed themselves as Hybrid Experts and Amateurs and <u>won</u>, it did not matter whom they <u>won</u> against. However, it did matter whom bidders <u>lost</u> against. Both those who assessed themselves as Hybrid Experts and Amateurs reported higher values when they lost against their own kind.

Third, the willingness to accept (WTA1) measure of value showed a different pattern. For participants who assessed themselves Amateur and won, it did not matter whether they won against Amateurs or Hybrid Experts. However, those who assessed themselves as Hybrid Experts and won reported higher WTA1 scores when they won against other Hybrid Experts. These latter bidders reported higher WTA1 when they won against their own kind.

Fourth, the reported WTP1 values showed that for participants who assessed themselves as Amateurs, it did not matter whether they lost against other Amateurs or Hybrid Experts. However, those who assessed themselves as Hybrid Experts and lost reported marginally higher WTP1 scores when they lost to other Hybrid Experts. In other words, they reported higher WTP1 when they lost against their own kind.

Fifth, observed changes in reported direct purchase value (ΔWTPDIR) were directionally negative. For participants who assessed themselves as Amateurs, ΔWTPDIR decreased irrespective of whether they won against Hybrid Experts or lost against other Amateurs. These changes are difficult to reconcile within our expertise/credibility framework. ΔWTPDIR decreased as expected for Hybrid Experts. More insight may emerge by examining how factors such as regret and excitement may have mediated these changes.

Sixth, an examination of ΔWTA durability patterns revealed that Amateurs who won exhibited temporally stable ΔWTA values irrespective of whether they competed against Amateurs or Hybrid Experts. However, consistent with expectations for Hybrid Experts, their ΔWTA decreased when they won against Amateurs. However, unexpectedly, they showed an even larger decrease when they won against other Hybrid Experts.

Finally, participants who assessed themselves as Amateurs decreased their ΔWTP when they lost against other Amateurs, but those who lost against Hybrid Experts reported stable ΔWTP values. These results also align with expectations. Also, Hybrid Experts who lost (whether to Amateurs or other Hybrid Experts) did not show a significant change in their WTP. This stability is consistent with an expertise rationale and inconsistent with motivated reasoning. Thus, observed changes in WTP over time generally match expectations.

4.8 Conclusion

The findings reported above show that assessed Self and Competitor Expertise do indeed influence bidding behavior, as well as post-auction valuation both immediately following the auction as well as after a short period of time. However, the nature of the effects are not always interpretable using a straightforward expertise/credibility framework. More insights into these data may emerge from examining the mediating and moderating effects of collateral movements in regret, satisfaction, and excitement. These analyses are part of our future research agenda. We recognize that past research has both proposed and shown such effects in auction situations (Ariely & Simonson, 2003; Cheema, Chakravarti, & Sinha, 2012) even when the nature of assessed Self and Competitor Expertise were not as salient as in our present studies.

In concluding this chapter, we note that each of our temporal durability value measures (ΔWTPDIR, ΔWTA, and ΔWTP) showed a tendency to decrease over time. Although this is consistent with our expectations for how Amateurs would adjust their values given wins or losses against other Amateurs, decreases in value are unexpected for those who assessed themselves as Hybrid Experts, particularly following wins against competitors who are other Hybrid Experts. Whereas value decreases following losses may be attributed to motivated reasoning, the results do raise questions about whether those assigned as Hybrid Experts did indeed <u>behave</u> like experts when bidding (despite responding as expected to the manipulation checks used).

In the next chapter, we conclude this dissertation with an integrative summary of the findings of both study sets. We discuss the limitations of the work and point to the areas where it appears fruitful to focus future research.

Chapter 5: General Discussion

This dissertation reports the results of five experiments that focused on how the competitive setting in which an auction is conducted may influence bidding behavior, bidders' post-auction product valuations, and the temporal stability of these valuations. Specifically, the research explored the effects of assessed Self and perceived Competitor Expertise on valuation during the auction (bidding behavior), as well as how these factors jointly interacted with Auction Outcome to influence post-auction valuation both immediately after the auction's conclusion as well as over time. The empirical work is organized in two essays. The first essay (Chapters 2 and 3) reports the results of Study Set 1, consisting of three experiments that explored how bids and post-auction valuation (in an ascending Japanese auction) is influenced by the focal bidder's subjective assessments of Competitor Expertise (i.e., whether they perceive their competitors as amateurs or as experts, with expertise related to the auction *process*, the focal *product* (auctioned product), or a *hybrid* of both). We also examine how Auction Outcome (win/loss) against such perceived experts influences judgments of the auctioned product's immediate post-auction value and its stability over time.

The second essay (Chapter 4) reports two experiments that examine how bidding and post-auction product valuation depend not only on perceptions of Competitor Expertise but also on the focal bidder's subjective assessment of their own expertise as well as the Auction Outcome. In other words, these studies examined how participants' assessed Self-Expertise in conjunction with perceived Competitor Expertise influenced bidding and product valuations. The first experiment used an ascending Japanese auction where the focal bidder could observe and draw inferences from competitor exits and bidding behavior. The second experiment used a first-price, sealed-bid mechanism where competitor exit information was not available.

5.1 Summary of Findings

Economic auction theory makes a normative assertion that people have fixed values for products, and absent additional information, should bid these values when bidding against competing bidders (Klemperer, 2004; Milgrom & Weber, 1982). The logic of bidding one's value signal is fairly straightforward – bidding lower than one's signal risks losing the product to a competitor at an otherwise acceptable bid level. Bidding higher risks having to pay more than one's signal. In the case of common value auctions, bidders may reasonably lower their bid when competing against a greater number of competitors to avoid the possibility of adverse selection (i.e., avoid the winner's curse) (Thaler, 1988; Wilson, 1977), and when competing against experts (who may have more reliable value signals for the product), this is especially important (Kagel & Levin, 1999).

The present research is rooted in a contrasting conceptual premise that rather than having fixed and immutable values, bidder values are constructed and evolve based on the auction environment and auction events. First, we develop and test propositions (Study Set 1) suggesting that bidders are influenced systematically not merely by the number of competing bidders, but also by *subjective perceptions of their competitors' expertise* (i.e., whether they are amateurs, knowledgeable about auction processes and bidding strategy, knowledgeable about the product category being auctioned, or whether they possess both product and process domain knowledge or hybrid expertise). Second, we also develop and test propositions (Study Set 2) suggesting that a focal bidders' *subjective assessment of their own expertise type and level* has both a direct effect on bidding behavior and moderates the effect of perceived Competitor Expertise. Our propositions rest on a framework that argues that bidding behaviors and value assessments rest on the credibility that stems from perceived expertise. We summarize the key findings below.

5.1.1 Study Set 1

Perceived Competitor Expertise had a strong effect on bidding behavior. Focal bidders who competed against Hybrid and Product Experts tended to bid the highest, followed by those who competed against Process Experts and Amateurs. The results for the immediate post-auction values were mixed relative to our expectations. First, as expected, auction winners' valuations did not differ by Competitor Expertise. In contrast, higher WTAs were reported by those who won against Product and Hybrid experts versus those who won against Process Experts. However, focal bidders who won against Amateurs reported the highest WTA values on average (a result consistent across both studies 2 and 3 in Study Set 1). Perhaps, focal bidders who win against Amateurs report a high WTA to self-justify their acquisition. Extended analysis of the mediating role of regret and satisfaction may confirm that even winning may lead to experiences of regret if the competition is not credible.

Second, also as expected, bidders who lost the auction at $50.00 (designated losers) reported higher direct purchase values (WTPDIR1) than those who won.

However, this gap was largest for bidders who lost to Product and Hybrid Experts and smallest for those who lost to Process Experts and Amateurs. This data pattern is difficult to explain in a framework where expertise is the cue to the credibility of competitive bids. Analyses exploring the moderating/mediating roles of the regret, excitement, and satisfaction measures may yield further process insights. On the other hand, pooling across expertise levels, designated losers at the $50.00 bid level reported higher overall WTP1 values than those who quit at lower bid levels.

Third, the value durability results for Study Set 1 were mixed. The ΔWTPDIR values were stable over time for those who won against Product Experts, Process Experts, and Amateurs but also showed a significant increase for those who won against Hybrid Experts. Among those who lost, ΔWTPDIR values were stable for those who competed against Product Experts and fell, as expected, for those who competed against both Process Experts and Amateurs. The key anomaly here was the unexpected decrease in ΔWTA for those who won against Hybrid Experts. There was also a similar significant decrease in ΔWTP when bidders lost against Hybrid Experts. Both these results are difficult to explain within our rationale that competitor expertise drives value credibility. However, as we note later, the interpolated task may have interfered with the deliberative evaluation of values between Time 1 and Time 2.

Finally, comparing the results across the three experiments in Study Set 1, it appears that the introduction of Hybrid Experts into the competitor mix appears to have attenuated the relative attraction of bidding higher when competing against Product Experts versus Process Experts. In Studies 1 and 2, the focal bidders followed Product Experts, whereas, in Study 3, they followed Hybrid Experts. Perhaps the focal bidder felt that hybrid expertise reflects the best of both knowledge domains (product and auction) and makes their value signals the most credible. Yet, Hybrid Experts may bid conservatively since their process expertise drives them to bid strategically in order to acquire the product below its true worth. Our results provide a foundation for further examinations of how focal bidders navigate the auction environment and construct value from observing and interpreting the behavior of competitors using lay reasoning.

5.1.2 Study Set 2

The two studies in Study Set 2 were designed to examine how the level and type of assessed Self-Expertise interacted with Competitor Expertise to influence both bidding and (contingent on Auction Outcome) post-auction behavior. In implementing these experiments, we renamed the expertise types from Hybrid Expert, Product Expert, Process Expert, and Amateurs to Wine-Auction Expert, Wine Expert, Auction Expert, and Amateur, respectively. This facilitated participant interpretation of the study conditions. The first study in this set used an ascending Japanese auction mechanism with focal bidders competing against either Hybrid Experts or Amateurs. Assessed Self-Expertise was manipulated using a knowledge test and false feedback procedure. Perceptions of Competitor Expertise were manipulated using an instruction set similar to Study Set 1. As before, we examined the effects of these variables and their interactions on (1) Bid levels; (2) Immediate Post-Auction values of the auction object (WTPDIR1, WTA1, WTP1); and (3) Durability of the Post-Auction values (ΔWTPDIR, ΔWTA, ΔWTP).

5.1.2.1 Study Set 2, Study 1

First, the level at which focal bidders bid differed by Assessed Self-Expertise, but the means were not ordered as expected. Process Experts bid highest, followed by Product Experts and Amateurs. Surprisingly, Hybrid Experts bid the lowest. Also, all assessed Self-Expert types (except Process Experts) followed Amateurs the least and Hybrid Experts the most. Participants who assessed themselves as Hybrid Experts were least influenced by Competitor Expertise. In contrast, Wine Experts were influenced most and relied greatly on Hybrid Experts. Those who assessed themselves as Process Experts followed Amateurs and Hybrid Experts and bid highest on average. Their faith in Hybrid Experts is expected, but their high bids against Amateurs may reflect a misplaced strategic effort to extract surplus.

Second, among the auction winners, those who won against Hybrid Experts reported higher WTPDIR1 values than those who won against Amateurs. The gap in WTPDIR1 was positive and larger for participants who assessed themselves as Hybrid Experts and Product Experts but negative for Process Experts. Unexpectedly, participants who assessed themselves as Amateurs showed a significant positive gap, perhaps reflecting their greater faith in Hybrid Experts versus Amateurs as competitors.

Third, the winners’ WTA1 scores showed some unexpected patterns. Focal bidders who won against Hybrid Experts reported lower WTA1 than those who won against Amateurs. Indeed, Hybrid Experts and Product Experts who won against Amateurs reported unusually high WTA1. However, the corresponding WTA1 change for Process Experts who won against Hybrid Experts versus Amateurs aligned with expectations, as did the ordering of the winners’ WTA1 values by Assessed Self-

Expertise: valuations reported by participants who assessed themselves as Hybrid and Product Experts were higher than those who assessed themselves as Process Experts and Amateurs.

Fourth, among losing focal bidders, those who lost against Hybrid Experts reported higher values than those who lost against Amateurs. Also, participants who assessed themselves as Hybrid and Product Experts reported higher WTPDIR1 than those who assessed themselves as Process Experts and Amateurs. WTPDIR1 data for those who assessed themselves as one of the expert types were as expected. The value gap between those who lost to Hybrid Experts versus Amateurs was largest for those who assessed themselves as Hybrid Experts, next largest for those who assessed themselves as Product Experts, and smaller for those who assessed themselves as Process Experts and Amateurs.

Fifth, the WTP1 data for auction losers were mixed. As expected, those who lost to Hybrid Experts reported higher WTP1 than those who lost to Amateurs. Also, the difference in WTP1 was highest for participants who assessed themselves as Hybrid Experts who lost to Hybrid Experts versus Amateurs. However, the fact that assessed Self-Expert Product Experts and Amateurs reported a higher WTP1 after they lost to a competing Amateur (versus a Hybrid Experts) is difficult to explain within our reasoning framework. The possibility of motivated reasoning among losing Hybrid Experts, Product Experts, and Process Experts requires further study, with a particular focus on the mediating role of endogenous regret.

Sixth, WTP1 data for participants who assessed themselves Hybrid Experts and Product Experts who lost were equal or higher relative to participants who assessed themselves as Process Experts and Amateurs. There is no evidence to suggest that Hybrid and Product Experts tried to lower their WTP1 values to denigrate the product and justify their loss. Rather, some of the valuations (e.g., by Product and Auction Experts) are on the higher side. These may reflect efforts to justify the loss by attributing it to an insufficient budget. Losing expert type bidders posted higher WTP1 values than the Amateur bidders, suggesting greater experienced regret. Arguably, losing at $50.00 due to a budget constraint may generate greater regret than volitional exits at lower bid levels. Overall, these exploratory WTP1 results suggest a more focused study of the mediating role of endogenously experienced regret for losing bidders.

Finally, as noted in Chapter 4, the results for temporal durability of valuations as a function of assessed Self and Competitor Expertise and Auction Outcome were not systematic. For example, ∆WTPDIR decreased over time for Hybrid Experts and Process Experts but remained stable for Product Experts and Amateurs. ∆WTA decreased over time for bidders who won against Hybrid Experts. The observed decrease in ∆WTA for participants who assessed themselves as Hybrid Experts was also unexpected. Although ∆WTA decreased over time as expected for those who assessed themselves as Process Experts and for Amateurs, the absence of a systematic pattern of effects complicates interpretation. This is also true for the losing bidders. Most of the changes over time were not significant and sometimes contrary to our expectations.

In summary, Study 1 revealed a useful set of exploratory findings regarding how assessed Self and Competitor Expertise jointly influence bidding behavior and subsequent post-auction product valuations contingent on Auction Outcome. We explore post-auction valuation both immediately following the auction as well as its durability over time. However, several anomalous valuation results suggest a potential problem with the assessed Self-Expertise manipulation. Although manipulation checks suggested a successful manipulation of Wine-Auction and Wine Expertise, it is possible that participants may not have fully internalized the manipulation during the bidding and valuation tasks.

5.1.2.2 Study Set 2, Study 2

Study 2 examined bidding behavior and post-auction values as a function of assessed Self and Competitor Expertise, each at two levels (Hybrid Experts and Amateur) in a First-Price, Sealed-Bid auction. The results confirmed that assessments of Self and Competitor Expertise influence bidding and post-auction valuation. Participants submitted a sealed bid and provided three post-auction measures of the item's value (WTPDIR1, WTA1, and WTP1) once immediately after the auction outcome was announced and then again after a short, interpolated task (ΔWTPDIR, ΔWTA, and ΔWTP).

First, the submitted bids were affected by both assessed Self-Expertise and perceived Competitor Expertise. Participants who assessed themselves as Hybrid Experts bid significantly higher when competing against other Hybrid Experts versus Amateurs. The bids from those who assessed themselves as Amateurs were similar regardless of Competitor Expertise assignment. Thus, those who assessed themselves as Hybrid Experts used Competitor Expertise as a cue more than those who assessed themselves as Amateurs.

Second, immediate post-auction WTPDIR1 assessments show that bidders who won the auction reported significantly lower values than those who lost. Auction winners' values did not vary by Competitor Expertise for either those who assessed themselves as Amateurs or Hybrid Experts. However, for auction losers, those competing against Amateurs reported higher values than those competing against Hybrid Experts. However, for those who assessed themselves as Hybrid Experts, the pattern was reversed. Thus, for both those who assessed themselves as Hybrid Experts and Amateurs who won, it did not matter whom they won against. However, it did matter for the bidders who lost. Both those who assessed themselves as Hybrid Experts and Amateurs reported higher WTPDIR1 when they lost against their own kind.

Third, the pattern was different for the WTA1 measure. For auction winners who assessed themselves as Amateurs, it did not matter whether the competition was Amateurs or Hybrid Experts. However, those who won and assessed themselves as Hybrid Experts reported higher WTA1 scores when they won against Hybrid Experts versus Amateurs. These bidders reported higher WTA1 when they won against their own kind.

Fourth, auction losers' WTP1 values showed that for those who assessed themselves as Amateurs, it did not matter whether they lost against Amateurs or Hybrid Experts. However, those who lost and assessed themselves as Hybrid Experts reported marginally higher WTP1 scores when competing against Hybrid Experts. Thus, they reported higher WTP1 when they lost against their own kind.

Fifth, the changes in reported direct purchase (ΔWTPDIR) values were directionally negative. For those who assessed themselves as Amateurs, ΔWTPDIR decreased if they had won against Hybrid Experts or lost against Amateurs. These changes are difficult to reconcile within our expertise-based credibility rationale. For Hybrid Experts, ΔWTPDIR decreased, as expected, if they won against Amateurs but was stable in all other conditions. More research is needed on how factors such as regret and excitement may mediate these changes.

Sixth, changes in the ΔWTA patterns of the auction winners showed that winning Amateurs had temporally stable ΔWTA scores irrespective of whether they competed against Amateurs or Hybrid Experts. For Hybrid Experts, ΔWTA decreased when they won against Amateurs. However, unexpectedly, they showed an even larger decrease when they won against Hybrid Experts.

Finally, participants who lost and assessed themselves as Amateurs lowered their ΔWTP after competing against other Amateurs, but as expected, maintained stable values after competing against Hybrid Experts. Also, Hybrid Experts who lost (whether to Amateurs or Hybrid Experts) did not show a significant change in their ΔWTP. This stability is consistent with an expertise rationale and inconsistent with motivated reasoning. Thus, the observed changes in ΔWTP over time generally match expectations.

5.2 Study Limitations

There are several limitations in the actual conduct of the study that should condition our interpretation of the results. First, as we noted earlier, some of our results raise questions about the extent Hybrid Experts internalized the expertise manipulation. The average web panelist has limited auction expertise, and the knowledge test and false feedback mechanism may have had limited success in creating a real sense of wine and auction domain expertise. This suggests a need to explore additional procedures.

Second, the somewhat scattered findings regarding the durability of values may require a rethinking of the interpolated task. The present tasks were cognitively taxing and were designed to reduce the likelihood of participants simply recalling the initial valuation. In retrospect, participants could have been asked to reflect on the valuation they submitted previously and be given an opportunity to revise it.

Third, the use of bots as competing bidders raises the question of whether participants' bidding behaviors would be influenced in bidding against bots versus human competitors. Cheema et al. (2012) provide a discussion of these and related issues in using this methodology for behavioral studies of auctions. Note also we did not use an incentive compatible incentive structure. This was an intentional design choice to encourage bidding for the product. Our goal was not to test economic models of auction bidding but simply to contrast the bids that emerged conditional on our manipulations of assessed Self and Competitor Expertise with a basic level of mundane realism (allowing bidders to quit the auction at any time they wished).

Finally, we note that our analyses so far have not explored the impact of the competitor dropout patterns that were incorporated in our study to implement the Competitor Expertise manipulations. It is possible that some of the early quitting behaviors of participating bidders may have been driven by inferences they made from observations of exits of the Competitor Expert bidders. Additional analyses of the quitting behavior data at various bid levels should provide additional insight regarding how the study implementation methodology may have influenced participant behavior.

Since such behaviors are normal in real-world ascending auctions, these findings would be of significant managerial interest in auction contexts.

5.3 Implications and Future Research

Conceptual Contributions. While much research has contrasted the decision behaviors of experts and novices, the literature on how experts and novices compete when confronting each other is sparse. Our studies provide initial insight into this issue and show that competitive behavior is shaped not merely by perceptions that experts may have about their own skill but also that of their competitors. As such, outcomes of competitive engagements (e.g., negotiations, participative pricing) may rest on both objective and subjective perceptions of players (agents) and how their tactics unfold.

Specific to the case of the auction, our results show that assessments of Self and Competitor Expertise can have a systematic impact on bidder behavior, auction outcomes, and subsequent value assessments both during and post-auction. Although our studies were limited to ascending Japanese and First-Price Sealed-Bid auction formats, we may anticipate similar direct and joint effects in other formats (e.g., Open English and Dutch/descending auctions, and other sealed-bid mechanisms). To the extent that various auction mechanisms allow different levels of opportunity for bidders to observe, interact, imitate, contrast, and signal, assessed Self and Competitor Expertise differences can lead to sharply different outcomes.

Our propositions regarding the likely effects were based on a straightforward cognitive rationale that assumed that expertise (whether perceived or veridical) along various dimensions would enable bidders to participate advantageously in auctions (relative to amateurs). Such expertise would strengthen confidence in bidding behavior and understanding of product value for the bidders themselves as well as for competitors looking for cues in these behaviors. We find significant support for our propositions in these experiments, but also a variety of unexpected results that suggest the need to augment our conceptual framework.

A fruitful future research direction would be to consider how expertise may also have motivational dimensions that compel bidders to engage in reasoning that allows them to justify bidding actions and auction outcomes. For example, whether a bidder bids conservatively or aggressively, the outcome leaves room for justification processes, regret management, and experienced satisfaction with an auction engagement. While we allude to such processes in the context of some of our results, there is room to examine how factors such as regret and excitement further mediate or moderate bidding behaviors during the auction and the value assessments that evolve and follow. More nuanced propositions that rest on such motivational concepts may provide insights into some of our unexpected results. The current studies have relevant data (i.e., regret, excitement, and satisfaction measures) that may provide a start in examining underlying moderation and mediation processes.

Most extant theoretical and experimental auctions research consider bidder behavior until the auction ends. Research that does consider behavior post-auction is generally focused on sequential auctions (McAfee & Vincent, 1993) or auctions in which several different products are sold (Weber, 1983). Our research asks what happens after the auction concludes. Much exchange occurs post-auction to include reselling to individuals as well as broader secondary markets (Smith, 1989). Such markets are not insignificant, and auction research would benefit from an improved understanding of behavioral factors that may influence valuation by post-auction secondary market decisionmakers. Our efforts to examine post-auction valuation movements over time are a step in this direction.

Finally, on the conceptual front, we acknowledge the possibility that economic reasoning regarding the winner's curse may lead bidders (particularly those who are more experienced) to infer that winning may imply having paid too much. In particular, it is possible that such reasoning leads them to believe that winning against experts may exacerbate the winner's curse relative to wins against Amateurs. This, of course, implies a pattern of reasoning that might suggest a reverse pattern of post-auction values than what is implied by our expertise-credibility driven reasoning. Although we observed relatively little evidence of such sophisticated economic reasoning, future research may examine the boundary conditions on expertise that lead to such inferential patterns and consequent post-auction value assessments.

Methodological Contributions. Several methodological contributions emerged collateral to the present research. First, we developed a computerized, homegrown auction simulation that allowed us to seamlessly implement the study procedures. This simulation was developed using a combination of JavaScript, CSS, and HTML and is deployable within the Qualtrics survey platform. This enabled us to employ online panelists as participants. The setup allows quick changes in study parameters, instruction sets, and different auction mechanisms, as well as to integrate task instructions, psychological manipulations, participant randomization, and survey items as needed. Originally designed by Cheema et al., (2012), this approach using bots offers an efficient approach to study individual bidding behavior. Custom software integration with a survey platform for use with web panelists offers significant and flexible research opportunities. In conjunction with potential graphics and voice embellishments, the possibilities are endless.

Second, the software and study design allowed examination of the behavior of individual bidders (auction participants) against computerized bots. The bots may be programmed to exhibit predetermined bidding behaviors (entry and exits), alternative skill sets (expert types, resellers, or amateurs), and alternative persona (dress, facial features, etc.). Although the use of bots as competitors may induce differences in behaviors relative to human competitors (Campbell, 2007), this also reduces the level of extraneous error variance induced by unpredictable behaviors that may influence auction experiments using real participants. One may also use different auctioned products (e.g., hedonic versus utilitarian) as well as alternative incentive structures (whether or not incentive compatible) to examine impacts on bidding behavior.

Managerial Contributions. Our results on expertise-driven valuation differences both during and post-auction may inform auction design choices for auction managers and prudent bidding decisions for consumers. Auctioneers may benefit from an enhanced understanding of the psychological factors that influence participant bid levels. Thus, if participants bid higher when competing against perceived Hybrid or Product Experts, a visible designation via a moniker may influence auction revenues. Consumers may also recognize the downside of bidding based on subjective knowledge that makes them overconfident regarding an item’s value. The finding that simple manipulations of assessed Self and Competitor Expertise can raise bids should alert regulators invested in consumer protection.

Our results also suggest that once an object is acquired (or lost) in an auction, its value may evolve based on more than just its intrinsic features. In fact, our research shows that the object's value may well depend on whom it was won (or lost) against. This value may vary immediately following the auction as the bidder faces the cognitive and motivational tension of reconciliation with the win/loss outcome. Also, these effects may accentuate or attenuate with reflection regarding the competitive circumstances. Nurturing these behavioral processes is an "after auction" managerial marketing task akin to after-sales service.

References

Adam, M., Kramer, J., & Muller, M. (2015). Auction fever! How time pressure and social competition affect bidders' arousal and bids in internet auctions. *Journal of Retailing*, 468-85.

Akbarpour, M., & Li, S. (2020). Credible Auctions: A Trilemma. *Econometrica*, 425-67.

Alba, J. W., & Hutchinson, J. W. (1987). Dimensions of Consumer Expertise. *Journal of Consumer Research*, 411-54.

Almandoz, J., & Tilcsik, A. (2016). When Experts Become Liabilities: Domain Experts on Boards and Organizational Failure. *Academy of Management Journal*, 1124-49.

Anderson, J. C., Jain, D. C., & Chintagunta, P. K. (2008). Customer Value Assessment in Business Markets: A State-of-Practice Study. *Journal of Business-to-Business Marketing*, 3-29.

Ariely, D., & Simonson, I. (2003). Buying, Bidding, Playing, or Competing? Value Assessment and Decision Dynamics in Online Auctions. *Journal of Consumer Psychology*, 113-23.

Avery, C., & Kagel, J. H. (1997). Second-Price Auctions with Asymmetric Payoffs: An Experimental Investigation. *Journal of Economics & Management Strategy*, 573-603.

Bapna, R., Goes, P., & Gupta, A. (2001). Insights and analyses of online auctions. *Communications of the ACM*, 42-50.

Bikhchandani, S. (1988). Reputation in Repeated Second-Price Auctions. *Journal of Economic Theory*, 97-119.

Brookshire, D. S., Randall, A., & Stoll, J. R. (1980). Valuing Increments and Decrements in Natural Resource Service Flows. *American Journal of Agricultural Economics*, 478-88.

Brouwer, R. (2012). Constructed preference stability: a test-retest. *Journal of Environmental Economics and Policy*, 70-84.

Brucks, M. (1985). The effects of product class knowledge on information search behavior. *Journal of Consumer Research*, 1-16.

Bulow, J. I., & Klemperer, P. D. (1996). Auctions vs. Negotiations. *American Economic Review*, 180-94.

Campbell, M. C. (2007). "Says Who?!" how the Source of Price Information and Affect Influence Perceied Price (Un)fairness. *Journal of Marketing Research*.

Capen, E. C., Clapp, R. V., & Campbell, W. M. (1971). Competitive Bidding in High-Risk Situations. *Journal of Petroleum Technology*, 641-53.

Cassady, R. (1967). *Auctions and Auctioneering.* Los Angeles: University of California Press.

Chakraborty, I., & Kosmopoulou, G. (2004). Auctions with Shill Bidding. *Economic Theory*, 271-87.

Chakravarti, D., Greenleaf, E., Sinha, A., Cheema, A., Cox, J. C., Friedman, D., . . . Zwick, R. (2002). Auctions: Research Opportunities in Marketing. *Marketing Letters*, 281-96.

Charness, N. (1981). Search in chess: Age and skill differences. *Journal of Experimental Psychology: Human Perception and Performance*, 467-76.

Cheema, A., Chakravarti, D., & Sinha, A. R. (2012). Bidding Behavior in Descending and Ascending Auctions. *Marketing Science*, 779-800.

Cheema, A., Popkowski-Leszczyc, P. T., Bagchi, R., Bagozzi, R. P., Cox, J. C., Dholakia, U. M., . . . Zeithammer, R. (2005). Economics, Psychology, and Social Dynamics of Consumer Bidding in Auctions. *Marketing Letters*, 401-13.

Chen, K.-P., Liang, T.-P., Yin, S.-Y., Chang, T., Liu, Y.-C., & Yu, Y.-T. (2020). How Serious is Shill Bidding in Online Auctions? Evidence from eBay Motors. *In work*, 1-51.

Chi, M. T., Feltovich, P. J., & Glaser, R. (1981). Categorization and Representation of Physics Problems by Experts and Novices. *Cognitive Science*, 121-52.

Coppinger, V. M., Smith, V. L., & Titus, J. A. (1980). Incentives and Behavior in English, Dutch and Sealed-Bid Auctions. *Economic Inquiry*, 1-22.

Dhar, R., & Wertenbroch, K. (2000). Consumer Choice between Hedonic and Utilitarian Goods. *Journal of Marketing Research*.

Dholakia, U. M., & Soltysinski, K. (2001). Coveted or Overlooked? The Psychology of Bidding for Comparable Listings in Digital Auctions. *Marketing Letters*.

Dholakia, U. M., Basuroy, S., & Soltysinski, K. (2002). Auction or agent (or both)? A study of moderators of the. *International Journal of Research in Marketing*, 115-30.

Durham, Y., Roelofs, M. R., & Standifird, S. S. (2004). eBay's Buy-It-Now Function: Who, When, and How. *Topics in Economic Analysis & Policy*, 1-22.

Dyer, D., Kagel, J. H., & Levin, D. (1989). A Comparison of Naive and Experienced Bidders in Common Value Offer Auctions: A Laboratory Analysis. *The Economic Journal*, 108-15.

Easley, R. F., & Tenorio, R. (2004). Jump Bidding Strategies in Internet Auctions. *Management Science*, 1407-19.

Einav, L., Farronato, C., Levin, J., & Sundaresan, N. (2018). Auctions versus Posted Prices in Online Markets. *Journal of Political Economy*, 178-215.

Epley, N., & Gilovich, T. (2016). The Mechanics of Motivated Reasoning. *Journal of Economic Perspectives*.

Ericcson, K. A. (2014). The road to excellence: The acquisition of expert performance in the arts and sciences, sports, and games. *Psychology Press*.

Ericsson, K. A. (2008). Deliberate Practice and Acquisition of Expert Performance: A General Overview. *Academic Emergency Medicine*, 988-94.

Fischoff, B. (1991). Value elicitation: is there anything in there? *American Psychologist*, 835-47.

Fox, C. R. (2006). The availability heuristic in the classroom: How soliciting more criticism can boost your course ratings. *Judgment and Decision Making*, 86-90.

Galin, A. (2013). Endowment Effect in negotiations: group versus individual decision-making. *Theory and Decision*, 389-401.

Gobel, F., & Charness, N. (2006). Expertise in Chess. In K. A. Ericsson, N. Charness, P. J. Feltovich, & R. R. Hoffman, *The Cambridge Handbook of Expertise and Expert Performance* (pp. 523-38). Cambridge: Cambridge University Press.

Graham, L., & Sugden, R. (1983). A Rationale for Preference Reversal. *The American Economic Review*, 428-32.

Grebe, T., Ivanova-Stenzel, R., & Kroger, S. (2021). How do sellers benefit from Buy-It-Now prices in eBay auctions? *Journal of Economic Behavior & Organization*, 189-205.

Guss, C. D., Edelstein, H. D., Badibanga, A., & Bartow, S. (2017). Comparing Business Experts and Novices in Complex Problem Solving. *Journal of Intelligence*, 1-18.

Hanley, N. J., Shogren, J. F., & White, B. (2006). *Introduction to Environmental Economics.* Oxford: Oxford University Press.

Hansson, I., Buratti, S., & Allwood, C. M. (2017). Experts' and Novices' Perception of Ignorance and Knowledge in Different Research Disciplines and Its Relation to Belief in Certainty of Knowledge. *Frontiers in Psychology*.

Harstad, R. M., Kagel, J. H., & Levin, D. (1990). Equilibrium bid functions for auctions with an uncertain number of bidders. *Economics Letters*, 35-40.

Haubl, G., & Popkowski Leszczyc, P. T. (2018). Bidding Frenzy: Speed of Competitor Reaction and Willingness to Pay in Auctions. *Journal of Consumer Research*, 1-21.

Herschlag, M., & Zwick, R. (2002). Internet Auctions - Popular and Professional Literature Review. *Quarterly Journal of Electronic Commerce*, 161-86.

Heyman, J., Orhun, Y., & Ariely, D. (2004). Auction fever: The effect of opponents and quasi-endowment on product valuations. *Journal of Interactive Marketing*, 7-21.

Hildesley, C. H. (1984). *Sotheby's Guide to Buying and Selling at Auction.* New York: K.S. Giniger Company, Inc.

Hoffman, E., Menkhaus, D., Chakravarti, D., Field, R., & Whipple, G. (1993). Using Laboratory Experimental Auctions in Marketing Research: A Case Study of New Packaging for Fresh Beef. *Marketing Science*, 318-338.

Holt, C. A. (1980). Competitive Bidding for Contracts Under Alternative Auction Procedures. *Journal of Political Economy*, 433-45.

Hsiao, A. (2019, July 17). *eBay Auction vs. Buy-it-Now Options: The Disadvantages of One and the Benefits of the Other*. Retrieved from thebalance smallbusiness: https://www.thebalancesmb.com/choose-ebay-listing-format-1140527

Jedidi, K., & Jagpal, S. (2009). Willingness to pay: measurement and managerial implications. In V. R. Rao, *Handbook of Pricing Research in Marketing* (pp. 37-60). Cheltenham: Edward Elgar Publishing Ltd.

Kagel, J. H. (1995). Auctions: A Survey of Experimental Research. In J. H. Kagel, & A. E. Roth, *The Handbook of Experimental Economics* (pp. 501-586). Princeton: Princeton University Press.

Kagel, J. H., & Levin, D. (1999). The Winner's Curse and Public Information in Common Value Auctions. *The American Economic Review*, 329-34.

Kagel, J. H., & Levin, D. (2015). A Survey of Experimental Research. In J. H. Kagel, & A. E. Roth, *The Handbook of Experimental Economics, Vol. 2* (pp. 563-637). Princeton: Princeton University Press.

Kagel, J. H., Harstad, R. M., & Levin, D. (1987). Information impact and allocation rules in auctions with affiliated private values: A laboratory study. *Econometrica*, 1275-1304.

Kagel, J. H., Levin, D., & Harstad, R. (1995). Comparative Static Effects of Number of Bidders and Public Information on Behavior in Second-Price Common Value Auctions. *International Journal of Game Theory*, 293-319.

Kagel, J., & Levin, D. (1992). *Revenue raising and information processing in English common value auctions. Mimeograph.* University of Pittsburgh.

Kahneman, D., Knetsch, J. L., & Thaler, R. H. (1990). Experimental Tests of the Endowment Effect and the Coase Theorem. *The Journal of Political Economy*, 1325-48.

Kane, M. (2005, November 28). *'Buy it Now' clicks with eBay sellers*. Retrieved from CNET: https://www.cnet.com/news/buy-it-now-clicks-with-ebay-sellers/

Kauffman, R. J., & Wood, C. A. (2005). The Effects of Shilling on Final Bid Prices in Online Auctions. *Electronic Commerce Research and Applications*, 21-34.

Kehoe, R. R., & Tzabbar, D. (2015). Lighting the Way or Stealing the Shine? An Examination of the Duality in Star Scientists' Effects on Firm Innovative Performance. *Strategic Management Journal*, 709-27.

Klein, G. A. (1998). *Sources of Power.* Cambridge: MIT Press.

Klemperer, P. (1999). Auction Theory: A Guide to the Literature. *Journal of Economic Surveys*.

Klemperer, P. (2004). *Auctions: Theory and Practice.* Princeton: Princeton University Press.

Knetsch, J. L., & Sinden, J. A. (1984). Willingness to Pay and Compensation Demanded: Experimental Evidence of an Unexpected Disparity in Measures of Value. *The Quarterly Journal of Economics*, 507-21.

Krishna, V. (2010). *Auction Theory.* Burlington: Elsevier.

Ku, G., Malhotra, D., & Murnighan, J. K. (2005). Towards a Competitive Arousal Model of Decision-Making: A Study of Auction Fever in Live and Internet Auctions. *Organizational Behavior and Human Decision Processes*, 89-103.

Kunda, Z. (1990). The case for motivated reasoning. *Psychological Bulletin*, 480-98.

List, J. A. (2003). Does market experience eliminate market anomalies? *The Quarterly Journal of Economics*, 41-71.

List, J. A. (2004). Neoclassical theory versus prospect theory: Evidence from the marketplace. *Econometrica*, 615-25.

Loureiro, M. L., Umberger, W. J., & Hine, S. (2003). Testing the initial endowment effect in experimental auctions. *Applied Economics Letters*, 271-75.

Lusk, J. L., & Shogren, J. F. (2007). *Experimental Auctions.* Cambridge: Cambridge University Press.

Malhotra, D. (2010). The desire to win: The effects of competitive arousal on motivation and behavior. *Organizational Behavior and Human Decision Processes*, 139-46.

Maskin, E., & Riley, J. (2000). Asymmetric Auctions. *Review of Economic Studies*, 413-38.

McAfee, R. P., & McMillan, J. (1992). Bidding Rings. *American Economic Review*, 579-99.

McAfee, R. P., & Vincent, D. (1993). The Declining Price Anomaly. *Journal of Economic Theory*, 191-212.

McClellan, A. (2017). Knowing Your Opponent: An Experiment on Auction Design with Asymmetries. *Presented at Stanford Institute for Theoretical Economics, 2017*, (pp. 1-27). Palo Alto.

Milgrom, P. R., & Weber, R. J. (1982). A Theory of Auctions and Competitive Bidding. *Econometrica*, 1089-1122.

Murata, A. (2015). On Persistency of Endowment Effect--Relationship Between Affection and Endowment Effect. *Psychological Research*, 287-91.

Myerson, R. B. (1981). Optimal Auction Design. *Mathematics of Operations Research*, 58-73.

Park, Y.-H., & Wang, X. (2010). Online and name-your-own-price auctions: a literature review. In V. R. Rao, *Handbook of Pricing Research in Marketing* (pp. 419-34). Cheltenham: Edward Elgar Publishing, Inc.

Rafaeli, S., & Noy, A. (2002). Online auctions, messaging, communication and social facilitation: a simulation and experimental evidence. *European Journal of Information Systems*.

Redelmeier, D. A., & Kahneman, D. (1996). Patients' memories of painful medical treatments: real-time and retrospective evaluations of two minimally invasive procedures. *Pain*, 3-8.

Riley, J. G., & Samuelson, W. F. (1981). Optimal Auctions. *The American Economic Review*, 381-92.

Rollinger, R. (1993). *Herodots babylonischer Logos: Eine kritische Untersuchung der Glaubwürdigkeitsdiskussion.* Innsbruck: Innsbrucker Beitrage zur Kulturwissenschaft.

Ross, J., Irani, L., Silberman, M., Zaldivar, A., & Tomlinson, B. (2010). Who are the Crowdworkers? : Shifting Demographics in Amazon Mechanical Turk. *CHI EA 2010* (pp. 2863-2872). ACM CHI.

Sinha, J., & Bagchi, R. (2019). Role of Ambient Temperature in Influencing Willingness to Pay in Auctions and Negotiations. *Journal of Marketing*, 121-38.

Smith, C. W. (1989). *The Social Construction of Value.* New York: Free Press.

Spann, M., Zeithammer, R., Bertini, M., Haruvy, E., Jap, S. D., Koenigsberg, O., . . . Thomas, M. (2018). Beyond Posted Prices: The Past, Present, and Future of Participative Pricing Mechanisms. *Customer Needs and Solutions*, 121-36.

Thaler, R. H. (1988). Anomalies: The Winner's Curse. *Journal of Economic Perspectives*, 191-202.

Tsetso, K., Usher, M., & Chater, N. (2010). Preference Reversal in Multiattribute Choice. *Psychological Review*, 1275-93.

Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *Science*, 1124-31.

Vickrey, W. (1961). Counterspeculation, Auctions, and Competitive Sealed Tenders. *The Journal of Finance*, 8-37.

Wang, X. (2009). Retail Return Policy, Endowment Effect, and Consumption Propensity: An Experimental Study. *The B.E. Journal of Economic Analysis & Policy*.

Warton, E. M., Parker, M. M., & Karter, A. J. (2016). *How D-I-D you do that? Basic Difference-in-Differences Models in SAS.* Retrieved from https://www.lexjansen.com/wuss/2016/49_Final_Paper_PDF.pdf

Watson, S., & Buede, D. (1988). *Decision Synthesis.* New York: Cambridge University Press.

Weber, R. J. (1983). Multiple-Object Auctions. In R. Engelbrecht-Wiggans, M. Shubik, & R. M. Stark, *Auctions, Bidding, and Contracting: Uses and Theory* (pp. 165-91). New York: New Yrok University Press.

Wilcox, R. T. (2000). Experts and Amateurs: The Role of Experience in. *Marketing Letters*, 363-74.

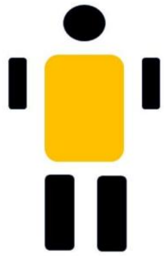
Willig, R. D. (1976). Consumer's Surplus without Apology. *American Economic Review*, 589-97.

Wilson, R. (1977). A bidding model of perfect competition. *Review of Economic Studies*, 511-18.

Xin, W., Yanping, S., & Tan, L. (2021). Small farmer planting confidence and willingness to pay for leguminous green fertilizer: environmental attributes perspective. *International Food and Agribusiness Management Review*, 1-19.

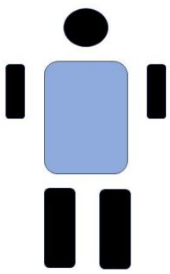
Appendices

Appendix A., Description of Competitor Expertise Types (Study Set 1)



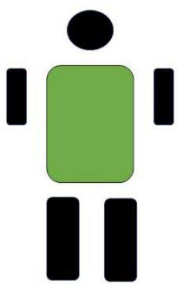
Product Experts

Key Descriptors:
- Wear ORANGE shirts
- Are experts in the product category
- Are experts in discerning product quality
- Are NOT experts in auctions
- Are NOT experts with auction bidding strategies



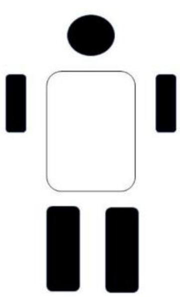
Process Experts

Key Descriptors:
- Wear BLUE shirts
- Are experts in auctions
- Are experts with auction bidding strategies
- Are NOT experts in the product category
- Are NOT experts in discerning product quality



Hybrid Experts

Key Descriptors:
- Wear GREEN shirts
- Are experts in the product category
- Are experts in auctions
- Are experts in discerning product quality
- Are experts with auction bidding strategies



Amateurs

Key Descriptors:
- Wear WHITE shirts
- Are NOT experts in the product category
- Are NOT experts in auctions
- Are NOT experts in discerning product quality
- Are NOT experts with auction bidding strategies

Notes:
Study Set 1, Studies 1 and 2 featured Product Experts, Process Experts, and Amateurs only. Study 3, in addition, featured Hybrid Experts.

Appendix B., Study Set 1, Studies 1-3, Key Auction Parameters and Task Earnings

	Study 1	Study 2	Study 3
Key Auction Values			
Budget Amount	$145.00	$50.00	$50.00
Starting Bid	$100.00	$40.00	$42.00
Bid Increment	$5.00	$1.00	$1.00
Announced Product Market Value	$152.50	$66.00	$66.00
Winning Bid Level	$130.00	$45.00	$50.00
Amount Paid by Winners	$125.00	$44.00	$49.00
Resulting Task Earnings			
Task Base Pay	$0.50	$0.30	$0.25
Conversion Rate - Residual Budget	$0.003	$0.005	$0.005
Conversion Rate - Product	$0.005	$0.01	$0.01
Residual Budget Earnings (Win/Loss)	$0.06 / $0.44	$0.03 / $0.25	$0.01 / $0.25
Product Earnings (Win/Loss)	$0.76 / $0.00	$0.66 / $0.00	$0.66 / $0.00
Total Earnings (Win/Loss)	$1.32 / $0.94	$0.99 / $0.55	$0.92 / $0.50

Notes:

- Conversion rates per game dollar
- Total earnings = Task Base Pay + Residual Product Earnings + Residual Budget earnings

Appendix C., Illustrative Example for Auction Incentive Structure (Study 3)
As we indicated earlier, your performance bonus will depend on whether or not you win in the auction, how carefully you bid and manage your budget, as well as the product's assessed market value which may be higher or lower than what you bid for it. Your payoff will be determined as follows:

Base pay ($0.25)
+ Budget Savings bonus: (Budget savings * 0.005)
+ Product Value bonus if you win: (Product's Market Value * 0.01)

Please review the following example scenarios for payoff calculations

Example 1:
Assume your budget is $50.00
Say you bid $47 and WIN. You pay $46 as no competitor bid above that.
Your budget saving is $4
Your Budget Savings bonus is $4*.005 = $0.02

A. If the appraised market value for the product turns out to be $56 ($10 more than what you paid), your Product Value bonus is $56*.01 = $0.56
Your TOTAL PAYOUT is: $0.25 + $0.02 + $0.56 = $0.83

B. If the appraised market value for the product turns out to be $46 (same as what you paid) your Product Value bonus is $46*.01 = $0.46
Your TOTAL PAYOUT is: $0.25 + $0.02 + $0.46 = $0.73

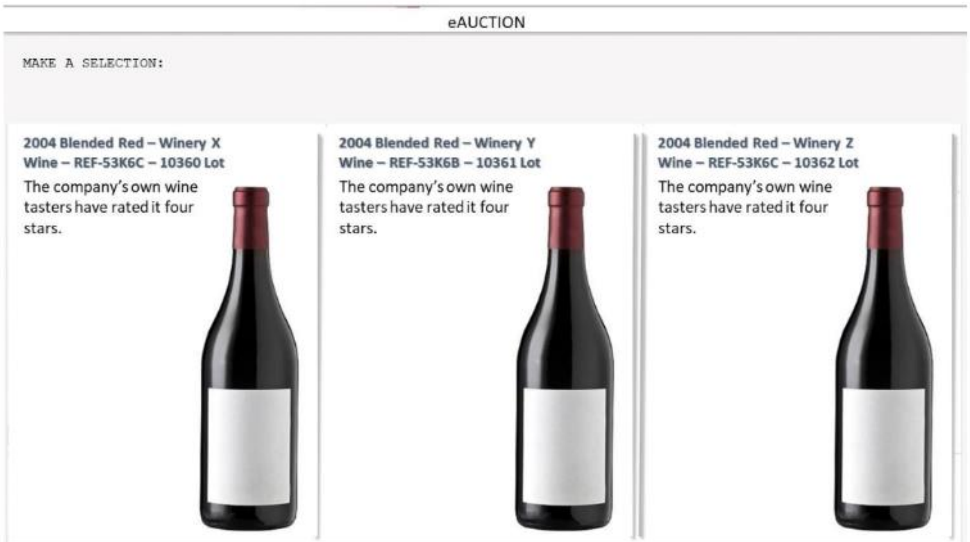
C. If the appraised market value for the product turns out to be $36 ($10 less than what you paid) your Product Value bonus is $36*.01 = $0.36
Your TOTAL PAYOUT is: $0.25 + $0.02 + $0.36 = $0.63

Example 2:
Assume your budget is $50.00
Say you LOST either because you quit or you bid to $50 and ran out of budget
Your pay nothing because you lost. Your budget saving is $50
Your Budget Savings bonus is $50*.005 = $0.25

The product's market value does not matter to you because you did not win it.
Hence, your Product Value bonus is $0

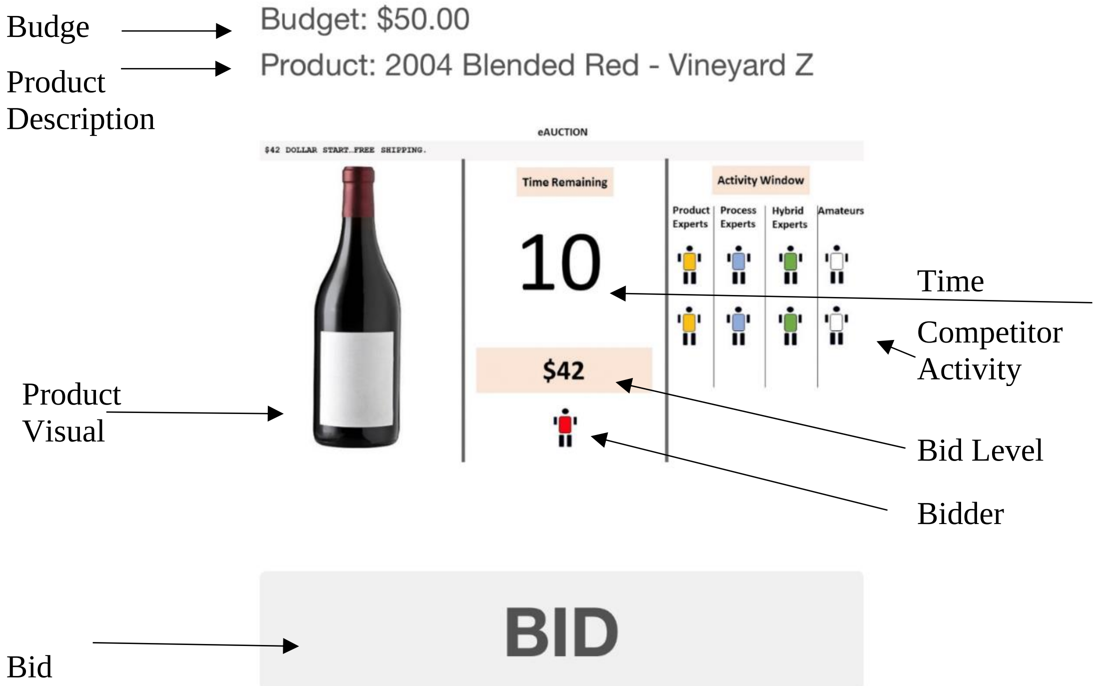
Your TOTAL PAYOUT is: $0.25 + $0.25 = $0.50

Appendix D., Study Set 1, Studies 1-3, Product Selection and Bidding User Interface
Panel 1: Illustrative Product Selection Interface



Today's auction is sponsored by three local wineries that wish to explore an initial price for one of three new blends. Because this is a blind test we will label the wines with "X," "Y," or "Z." The wines are from different wineries although they are rated very similar in quality.
Each of the wines are of very good quality that you would use for special occasions, and all are of equivalent quality but may suit different tastes. You will select one of the wines and will compete against others who have made the same selection. Bidding will start at $42.00 for a bottle. The eventual market price will be determined by experts based on consumer surveys.
Click --> to proceed.

Panel 2: Illustrative Bidding User Interface



Appendix E., Study Set 1, Study 1, Schedule of Participant Exposure to Focal Conditions by Bidding Round

Round	Bid Level	Amateur Competitors	Product Expert Competitors	Process Expert Competitors
0	$100	A Pc Pd	A Pc Pd	A Pc Pd
		A Pc Pd	A Pc Pd	A Pc Pd
1	$105	A Pd	Pc Pd	Pc Pd
		A	Pd	Pc
2	$110	A	Pd	Pc
		A	Pd	Pc
3	$115	A	Pd	Pc
4	$120	A	Pd	Pc
5	$125	A	Pd	Pc
6a	$130	A	Pd	Pc
6b	$130			
7a	$135	A	Pd	Pc
8a	$140	A	Pd	Pc
9a	$145	A	Pd	Pc
10a	$150	A	Pd	Pc

Notes: Please read the Amateur Competitors column as follows.

1. In round 0 (bid level $100), all participants begin the auction competing against two Amateurs (A), two Process Experts (Pc) and two Product Experts (Pd).
2. In round 1 (bid level $105), two Process Experts and one Product Expert drop out. Two Amateurs remain.
3. In round 2 (bid level $110), only the Amateur competitors remain, and participants are fully exposed to their assigned Amateur condition.
4. In round 3 (bid level $115), only one Amateur competitor remains.
5. In round 6 (bid level $130), for bidders assigned to win (6b) the final Amateur competitor drops out. The winning focal bidder pays $125 for the product.
6. In round 6a-10a (bid level $130), for bidders assigned to lose the final Amateur competitor remains in the auction until the focal bidder’s budget ($150) runs out (10a).

The dropout sequence for Product and Process Expert Competitors are interpreted similarly as above.

Appendix F., Study Set 1, Study 2, Schedule of Participant Exposure to Focal Conditions by Bidding Round

Round	Bid Level	Amateur Competitors	Product Expert Competitors	Process Expert Competitors
0	$40	A Pc Pd	A Pc Pd	A Pc Pd
		A Pc Pd	A Pc Pd	A Pc Pd
1	$41	A Pc Pd	A Pc Pd	A Pc Pd
		A	Pd	Pc
2	$42	A Pd	Pc Pd	Pc Pd
		A	Pd	Pc
3	$43	A	Pd	Pc
4	$44	A	Pd	Pc
5a	$45	A	Pd	Pc
5b	$45			
6a	$46	A	Pd	Pc
7a	$47	A	Pd	Pc
8a	$48	A	Pd	Pc
9a	$49	A	Pd	Pc
10a	$50	A	Pd	Pc

Notes: Please read the Amateur Competitors column as follows.

1. In round 0 (bid level $40), all participants begin the auction competing against two Amateurs (A), two Process Experts (Pc) and two Product Experts (Pd).
2. In round 1 (bid level $41), one Process Expert and one Product Expert drop out. Two Amateurs remain.
3. In round 2 (bid level $42), two Amateurs and a Product Expert remain.
4. In round 3 (bid level $43), only one Amateur competitor remains, and participants are fully exposed to their assigned Amateur condition.
5. In round 5 (bid level $45), for bidders assigned to win (5b) the final Amateur competitor drops out. The winning focal bidder pays $44 for the product.
6. In round 5a-10a (bid level $45), for bidders assigned to lose the final Amateur competitor remains in the auction until the focal bidder's budget ($150) runs out (10a). The dropout sequence for Product and Process Expert Competitors are interpreted similarly as above.

The dropout sequence for Product and Process Expert Competitors are interpreted similarly as above.

Appendix G., Study Set 1, Study 3, Schedule of Participant Exposure to Focal Conditions by Bidding Round

Bid Round	Bid Level	Amateur Competitors	Product Expert Competitors	Process Expert Competitors	Hybrid Expert Competitors
0	$42	A Pc Pd Hb	A Pc Pd Hb	A Pc Pd Hb	A Pc Pd Hb
		A Pc Pd Hb	A Pc Pd Hb	A Pc Pd Hb	A Pc Pd Hb
1	$43	A Pc Pd Hb	A Pc Pd Hb	A Pc Pd Hb	A Pc Pd Hb
		A Hb	Pc Pd	Pc Pd	A Hb
2	$44	A	Pd	Pc	Hb
		A	Pd	Pc	Hb
3	$45	A	Pd	Pc	Hb
4	$46	A	Pd	Pc	Hb
5	$47	A	Pd	Pc	Hb
6	$48	A	Pd	Pc	Hb
7	$49	A	Pd	Pc	Hb
8a	$50	A	Pd	Pc	Hb
8b	$50				

Notes: Please read the Amateur Competitors column as follows.

1. In round 0 (bid level $42), all participants begin the auction competing against two Amateurs (A), two Process Experts (Pc), two Product Experts (Pd), and two Hybrid Experts (Hb).
2. In round 1 (bid level $43), one Process Expert and one Product Expert drop out. Two Amateurs and two Hybrid Experts remain.
3. In round 2 (bid level $44), two Amateurs remain, and participants are fully exposed to their assigned Amateur condition.
4. In round 8 (bid level $50), for bidders assigned to win (8b) the final Amateur competitor drops out. The winning focal bidder pays $49 for the product.
5. In round 8 (bid level $50), for bidders assigned to lose the final Amateur competitor remains in the auction until the focal bidder's budget ($50) runs out (8a).

The dropout sequence for Product, Process, and Hybrid Expert Competitors are interpreted similarly as above.

Appendix H., Study Set 1, Study 1, Number of Participants Staying/Quitting

Assigned to Win at $130

	Total	**Stay #**	**Stay %**	**Quit #**	**Quit %**
Product	50	35	70.00%	15	30.00%
Process	50	25	50.00%	25	50.00%
Amateur	52	26	50.00%	26	50.00%

$X^2(2) = 5.46, p = 0.07$

Assigned to Lose at $150

	Total	**Stay #**	**Stay %**	**Quit #**	**Quit %**
Product	49	26	53.06%	23	46.94%
Process	49	14	28.57%	35	71.43%
Amateur	52	27	51.92%	25	48.08%

$X^2(2) = 7.64, p = 0.02$

Appendix I., Study Set 1, Study 2, Number of Participants Staying/Quitting

Assigned to Win at $45

	Total	**Stay #**	**Stay %**	**Quit #**	**Quit %**
Product	57	40	70.18%	17	29.82%
Process	58	29	50.00%	29	50.00%
Amateur	57	29	50.88%	28	49.12%

$X^2(2) = 6.77, p = 0.03$

Assigned to Lose at $50

	Total	**Stay #**	**Stay %**	**Quit #**	**Quit %**
Product	59	28	47.46%	31	52.54%
Process	57	15	26.32%	42	73.68%
Amateur	58	17	29.31%	41	70.69%

$X^2(2) = 6.07, p = 0.05$

Appendix J., Study Set 1, Study 2, Regression Results

Panel 1: Study Set 1, Study 2 (WTPDIR1): Censored Regression Results

Effect (Type III)	**Df**	**Wald χ^2**	**Pr > χ^2**
Competitor Expertise	2	2.129	0.345
Auction Outcome	3	23.467	<.001
Competitor Expertise*Auction Outcome	6	14.111	0.028
SAT1	1	0.023	0.881
REG1	1	10.501	0.001
EXC1	1	11.244	0.001
AGE	1	7.575	0.006
GENDER	1	3.582	0.058

Notes: Model estimation relied on maximum likelihood within SAS PROC LIFEREG, and several alternative Tobit models were analyzed using distributions appropriate for continuous data. Subsequent model selection relied on likelihood ratio tests using -2LL values to determine best distributional fit, and a comparison of AIC values was used to determine final covariate selection. Ultimately, generalized gamma was the retained distribution (-2LL = 2336.908) along with the above covariates (Satisfaction, Regret, Excitement, Age, and Gender; AIC = 2374.908). Note that here and elsewhere in this analysis all means are provided as unlogged transformations of the exponentiated Tobit model (i.e., provided valuations are in dollars). Examination of the coefficients show that higher levels of regret (REG1) and excitement (EXC1) lead to an increase in WTPDIR. Furthermore, an increase in age (AGE) leads to lower WTPDIR. Furthermore, males tended to post higher post-auction WTPDIR than females.

Table of Means

Outcome	**Overall**	**Product**	**Process**	**Amateur**
Win at $45	42.55 (1.26)	41.91 (1.71)	43.02 (1.72)	42.73 (1.75)
Lose at $50	48.25 (1.86)	45.10 (2.04)	48.13 (2.92)	51.52 (1.92)
Lose at $44-49	43.48 (1.11)	45.26 (1.57)	41.24 (1.57)	43.93 (1.52)
Lose at < $44	41.62 (1.51)	43.41 (2.27)	40.58 (1.76)	40.86 (1.79)
Lose $44-50	44.16 (1.07)	44.90 (1.33)	42.25 (1.42)	43.90 (1.43)

Notes: Sample sizes by outcome: Win at $45 (n = 98), Lose at $50 (n = 43), Lose below $44 (n = 120), Lose between $44-49 (n = 85), Lose $44-50 (n = 128). Total number of participants, n = 346.

Panel 2: Study Set 1, Study 2 (WTA1): Censored Regression Results

Effect (Type III)	Df	Wald χ^2	Pr > χ^2
Competitor Expertise	2	13.203	0.001
SAT1	1	1.041	0.308
REG1	1	0.378	0.539
EXC1	1	4.071	0.044
AGE	1	15.310	<.001
GENDER	1	1.082	0.298

Notes: Model estimation relied on maximum likelihood within SAS PROC LIFEREG, and several alternative Tobit models were analyzed using distributions appropriate for continuous data. Subsequent model selection relied on likelihood ratio tests using -2LL values to determine best distributional fit, and a comparison of AIC values was used to determine final covariate selection. Ultimately, generalized gamma was the retained distribution (-2LL = 700.715) along with the above covariates (Satisfaction, Regret, Excitement, Age, and Gender; AIC = 720.715). Examination of the coefficients show that higher levels of excitement (EXC1) lead to an increase in WTA. Furthermore, an increase in age (AGE) leads to lower WTA.

Table of Means

Outcome	Product	Process	Amateur
Win at $45	48.76 (0.89)	46.85 (0.74)	49.64 (0.87)
Lose at $50	--	--	--
Lose at < $44	--	--	--
Lose at $44-49	--	--	--
Lose $44-50	--	--	--

Notes: Sample sizes by outcome: Win at $45 (n = 98), Lose at $50 (n = 43), Lose below $44 (n = 120), Lose between $44-49 (n = 85), Lose $44-50 (n = 128). Total number of participants, n = 346.

Panel 3: Study Set 1, Study 2 (WTP1): Censored Regression Results

Effect (Type III)	Df	Wald χ^2	Pr > χ^2
Competitor Expertise	2	5.592	0.061
Auction Outcome	2	26.566	<.001
Competitor Expertise * Auction Outcome	4	7.255	0.123
SAT1	1	1.195	0.274
REG1	1	0.142	0.707
EXC1	1	9.288	0.002
AGE	1	1.417	0.234
GENDER	1	0.227	0.634

Notes: Model estimation relied on maximum likelihood within SAS PROC LIFEREG, and several alternative Tobit models were analyzed using distributions appropriate for continuous data. Subsequent model selection relied on likelihood ratio tests using -2LL values to determine best distributional fit, and a comparison of AIC values was used to determine final covariate selection. Ultimately, generalized gamma was the retained distribution (-2LL = 1738.467) along with the above covariates (Satisfaction, Regret, Excitement, Age, and Gender; AIC = 1770.467). Examination of the coefficients show that higher levels of excitement (EXC1) lead to an increase in WTP.

Table of Means

Outcome	Overall	Product	Process	Amateur
Win at $45	--	--	--	--
Lose at $50	47.94 (1.25)	48.73 (1.23)	44.65 (2.31)	50.44 (1.44)
Lose at < $44	42.12 (0.93)	43.39 (1.53)	41.62 (1.27)	41.36 (1.28)
Lose at $44-49	43.79 (0.87)	43.55 (1.29)	43.68 (1.07)	44.14 (1.21)
Lose $44-50	45.18 (0.79)	45.53 (1.05)	44.27 (1.03)	45.73 (1.06)

Notes: Sample sizes by outcome: Win at $45 (n = 98), Lose at $50 (n = 43), Lose below $44 (n = 120), Lose between $44-49 (n = 85), Lose $44-50 (n = 128). Total number of participants, n = 346.

Appendix K., Study Set 1, Study 2, Difference-in-Difference Analysis

Panel 1: Study Set 1, Study 2 (ΔWTPDIR): Difference-in-Difference Results

Effect (Type III)	**Num Df**	**Den Df**	**Chi-Sq**	**F Val**	**Pr > χ^2**	**Pr > F**
Competitor Expertise	2	326	2.640	1.320	0.267	0.267
Auction Outcome	3	326	30.520	10.170	<.001	<.001
Competitor Expertise * Auction Outcome	6	326	10.800	1.800	0.095	0.095
time	1	326	4.960	4.960	0.026	0.026
Competitor Expertise * time	2	326	1.000	0.500	0.606	0.606
Auction Outcome *time	3	326	1.190	0.400	0.756	0.756
Competitor Expertise * Auction Outcome * time	6	326	3.540	0.590	0.739	0.739
REG	1	326	14.860	14.860	<.001	<.001
SAT	1	326	13.270	13.270	<.001	<.001
EXC	1	326	5.270	5.270	0.022	0.022
AGE	1	326	7.190	7.190	0.007	0.007
GENDER	1	326	2.180	2.180	0.140	0.140

Notes: Model estimation relied on maximum likelihood within SAS PROC GLIMMIX, and several alternative models were analyzed using distributions appropriate for continuous data. For parsimony the same covariates were retained from the previous analysis. The preferred distribution was selected by identifying the Generalized Chi-Square/DF closest to 1, and ultimately the retained distribution was generalized gamma ($\frac{\chi^2}{d.f.}$) = 2.49). Examination of the coefficients show that higher levels of regret (REG), excitement (EXC), and satisfaction (SAT) lead to an increase in WTPDIR.

Table of Means (ΔWTPDIR)

Outcome	Overall	Product	Process	Amateur
Win at $45	0.67 (0.42)	0.49 (0.63)	1.40 (0.76)	0.11 (0.78)
Lose at $50	0.14 (0.62)	0.37 (0.80)	-0.73 (1.17)	1.13 (1.17)
Lose at < $44	0.93 (0.48)	0.34 (1.01)	1.03 (0.75)	1.43 (0.69)
Lose at $44-49	0.45 (0.43)	0.02 (0.82)	-0.11 (0.67)	0.88 (0.74)
Lose $44-50	0.34 (0.34)	0.19 (0.57)	-0.09 (0.58)	0.91 (0.62)

Notes: Sample sizes by outcome: Win at $45 (n = 98), Lose at $50 (n = 43), Lose below $44 (n = 120), Lose between $44-49 (n = 85), Lose $44-50 (n = 128). Total number of participants, n = 346.

Panel 2: Study Set 1, Study 2 (ΔWTA): Difference-in-Difference Results

Effect (Type III)	Num Df	Den Df	χ^2	F-Value	Pr > χ^2	Pr > F
Competitor Expertise	2	92	0.640	0.320	0.727	0.727
time	1	92	3.720	3.720	0.054	0.054
Competitor Expertise *time	2	92	3.610	1.810	0.164	0.164
REG	1	92	0.240	0.240	0.623	0.623
SAT	1	92	0.570	0.570	0.452	0.452
EXC	1	92	0.070	0.070	0.784	0.784
AGE	1	92	0.240	0.240	0.628	0.628
GENDER	1	92	1.260	1.260	0.261	0.261

Notes: Model estimation relied on maximum likelihood within SAS PROC GLIMMIX, and several alternative models were analyzed using distributions appropriate for continuous data. For parsimony the same covariates were retained from the previous analysis. The preferred distribution was selected by identifying the Generalized Chi-Square/DF closest to 1, and ultimately the retained distribution was generalized gamma ($\frac{\chi^2}{d.f.} = 1.24$).

Table of Means (ΔWTA)

Outcome	Product	Process	Amateur
Win at $45	-0.35 (1.06)	-2.56 (1.18)	-1.66 (1.24)
Lose at $50	--	--	--
Lose at < $44	--	--	--
Lose at $44-49	--	--	--
Lose $44-50	--	--	--

Notes: Sample sizes by outcome: Win at $45 (n = 98), Lose at $50 (n = 43), Lose below $44 (n = 120), Lose between $44-49 (n = 85), Lose $44-50 (n = 128). Total number of participants, n = 346.

Panel 3: Study Set 1, Study 2 (ΔWTP): Difference-in-Difference Results

Effect (Type III)	Num Df	Den Df	χ^2	F-Value	Pr > χ^2	Pr > F
Competitor Expertise	2	234	2.860	1.430	0.239	0.239
Auction Outcome	2	234	31.480	15.740	<.001	<.001
Competitor Expertise* Auction Outcome	4	234	9.750	2.440	0.045	0.045
time	1	234	0.470	0.470	0.494	0.494
Competitor Expertise*time	2	234	0.220	0.110	0.894	0.894
Auction Outcome *time	2	234	1.880	0.940	0.390	0.390
Competitor Expertise * Auction Outcome *time	4	234	2.530	0.630	0.640	0.640
REG	1	234	9.430	9.430	0.002	0.002
SAT	1	234	5.800	5.800	0.016	0.016
EXC	1	234	11.140	11.140	0.001	0.001
AGE	1	234	0.260	0.260	0.612	0.612
GENDER	1	234	7.830	7.830	0.005	0.005

Notes: Model estimation relied on maximum likelihood within SAS PROC GLIMMIX, and several alternative models were analyzed using distributions appropriate for continuous data. For parsimony the same covariates were retained from the previous analysis. The preferred distribution was selected by identifying the Generalized Chi-Square/DF closest to 1, and ultimately the retained distribution was generalized gamma ($\frac{\chi^2}{d.f.} = 4.02$). Examination of the coefficients show that higher levels of regret (REG), excitement (EXC), and satisfaction (SAT) lead to an increase in WTP. Furthermore, the effect of gender was such that men tended to post higher WTP than women.

Table of Means (ΔWTP)

Outcome	Overall	Product	Process	Amateur
Win at $45	--	--	--	--
Lose at $50	-1.26 (0.94)	-2.41 (1.30)	-1.07 (1.79)	-0.29 (1.77)
Lose at < $44	0.08 (0.71)	-0.03 (1.53)	0.48 (1.06)	-0.22 (1.04)
Lose at $44-49	0.27 (0.64)	1.03 (1.19)	-0.74 (1.01)	0.50 (1.11)
Lose $44-50	-0.38 (0.52)	-0.55 (0.88)	-0.80 (0.88)	0.19 (0.94)

Notes: Sample sizes by outcome: Win at $45 (n = 98), Lose at $50 (n = 43), Lose below $44 (n = 120), Lose between $44-49 (n = 85), Lose $44-50 (n = 128). Total number of participants, n = 346.

Appendix L., Study Set 1, Study 3, Number of Participants Staying/Quitting

Assigned to Win at $50

	Total	Stay #	Stay %	Quit #	Quit %
Amateur	49	18	36.73%	31	63.27%
Hybrid Expert	50	32	64.00%	18	36.00%
Process Expert	51	24	47.06%	27	52.94%
Product Expert	51	28	54.90%	23	45.10%

$X^2(3) = 7.99, p = 0.05$

Assigned to Lose at $50

	Total	Stay #	Stay %	Quit #	Quit %
Amateur	50	15	30.00%	35	70.00%
Hybrid Expert	50	26	52.00%	24	48.00%
Process Expert	47	27	57.45%	20	42.55%
Product Expert	49	26	53.06%	23	46.94%

$X^2(3) = 8.99, p = 0.03$

Assigned to Win or Lose (Pooled)

	Total	Stay #	Stay %	Quit #	Quit %
Amateur	99	33	33.33%	66	66.67%
Hybrid Expert	100	58	58.00%	42	42.00%
Process Expert	98	51	52.04%	47	47.96%
Product Expert	100	54	54.00%	46	46.00%

$X^2(3) = 14.30, p = 0.003$

Appendix M., Study Set 1, Study 3, Censored Regression Results

Panel 1: Study Set 1, Study 3 (WTPDIR1): Censored Regression Results

Effect (Type III)	**Df**	**Wald χ^2**	**Pr > χ^2**
Competitor Expertise	3	1.137	0.768
Auction Outcome	3	45.190	<.001
Competitor Expertise * Auction Outcome	9	9.475	0.395
SAT1	1	2.103	0.147
REG1	1	18.387	<.001
EXC1	1	2.815	0.093
AGE	1	7.618	0.006
GENDER	1	4.225	0.040

Notes: Model estimation relied on maximum likelihood within SAS PROC LIFEREG, and several alternative Tobit models were analyzed using distributions appropriate for continuous data. Subsequent model selection relied on likelihood ratio tests using -2LL values to determine best distributional fit, and a comparison of AIC values was used to determine final covariate selection. Ultimately, generalized gamma was the retained distribution (-2LL = 2744.761) along with the above covariates (Satisfaction, Regret, Excitement, Age, and Gender; AIC = 2790.761). Examination of the coefficients show that higher levels of regret (REG) produced higher post-auction WTPDIR1. Furthermore, older participants posted lower post-auction WTPDIR1, and males tended to post higher post-auction values for WTPDIR1.

Table of Means (WTPDIR1)

Outcome	Overall	Product	Process	Hybrid	Amateur
Win at $50	50.53 (1.11)	51.01 (1.78)	52.43 (1.96)	48.10 (1.89)	50.60 (2.05)
Lose at $50	55.30 (1.50)	59.31 (3.35)	54.78 (2.51)	54.50 (2.29)	52.60 (2.45)
Lose at < $44	42.80 (1.28)	39.77 (2.29)	43.12 (2.19)	43.78 (3.24)	44.54 (1.93)
Lose at $44-49	48.41 (0.82)	50.17 (1.41)	47.83 (1.51)	48.12 (1.48)	47.50 (1.57)
Lose $44-50	49.60 (0.78)	51.12 (1.35)	49.22 (1.36)	49.57 (1.31)	48.49 (1.38)

Notes: Sample sizes by outcome: Win at $50 (n = 102), Lose at $50 (n = 94), Lose below $44 (n = 68), Lose between $44-49 (n = 133), Lose $44-50 (n = 287). Total number of participants, n = 397.

Panel 2: Study Set 1, Study 3 (WTA1): Censored Regression Results

Effect (Type III)	Df	Wald χ^2	Pr > χ^2
Competitor Expertise	3	5.067	0.167
REG1	1	0.014	0.905
SAT1	1	3.836	0.050
EXC1	1	< 0.001	0.989
AGE	1	2.487	0.115
GENDER	1	2.961	0.085

Notes: Model estimation relied on maximum likelihood within SAS PROC LIFEREG, and several alternative Tobit models were analyzed using distributions appropriate for continuous data. Subsequent model selection relied on likelihood ratio tests using -2LL values to determine best distributional fit, and a comparison of AIC values was used to determine final covariate selection. Ultimately, generalized gamma was the retained distribution (-2LL = 754.82) along with the above covariates (Satisfaction, Regret, Excitement, Age, and Gender; AIC = 776.82). Examination of the coefficients show that higher levels of satisfaction (SAT) produced higher post-auction WTA1.

Table of Means (WTA1)

Outcome	Product	Process	Hybrid	Amateur
Win at $50	57.77 (2.21)	53.26 (2.79)	54.04 (2.75)	59.36 (2.67)
Lose at $50	--	--	--	--
Lose at < $44	--	--	--	--
Lose at $44-49	--	--	--	--
Lose $44-50	--	--	--	--

Notes: Sample sizes by outcome: Win at $50 (n = 102), Lose at $50 (n = 94), Lose below $44 (n = 68), Lose between $44-49 (n = 133), Lose $44-50 (n = 287). Total number of participants, n = 397.

Panel 3: Study Set 1, Study 3 (WTP1): Censored Regression Results

Effect (Type III)	Df	Wald χ^2	Pr > χ^2
Competitor Expertise	3	0.814	0.846
Auction Outcome	2	49.576	<.001
Competitor Expertise * Auction Outcome	6	14.233	0.027
SAT1	1	0.027	0.870
REG1	1	7.803	0.005
EXC1	1	11.192	0.001
AGE	1	4.404	0.036
GENDER	1	5.831	0.016

Notes: Model estimation relied on maximum likelihood within SAS PROC LIFEREG, and several alternative Tobit models were analyzed using distributions appropriate for continuous data. Subsequent model selection relied on likelihood ratio tests using -2LL values to determine best distributional fit, and a comparison of AIC values was used to determine final covariate selection. Ultimately, generalized gamma was the retained distribution (-2LL = 1965.170) along with the above covariates (Satisfaction, Regret, Excitement, Age, and Gender; AIC = 2003.170). Examination of the coefficients show that higher levels of Regret (REG) and Excitement (EXC) produced higher post-auction WTP1. Furthermore, as AGE increased this resulted in lower WTP1. Lastly, males tended to post higher WTP1 than females.

Table of Means (WTP1)

Outcome	Overall	Product	Process	Hybrid	Amateur
Win at $50	--	--	--	--	--
Lose at $50	50.47 (1.31)	49.01 (2.15)	51.16 (2.31)	51.86 (2.19)	48.91 (2.27)
Lose at < $44	50.26 (1.71)	45.67 (3.11)	51.43 (2.61)	49.91 (3.84)	53.15 (2.59)
Lose at $44-49	48.66 (0.83)	49.42 (1.30)	47.11 (1.54)	50.82 (1.45)	47.56 (1.49)
Lose $44-50	49.97 (0.78)	50.52 (1.26)	49.39 (1.38)	48.53 (1.19)	48.23 (1.32)

Notes: Sample sizes by outcome: Win at $50 (n = 102), Lose at $50 (n = 94), Lose below $44 (n = 68), Lose between $44-49 (n = 133), Lose $44-50 (n = 287). Total number of participants, n = 397.

Appendix N., Study Set 1, Study 3, Differences-in-Difference Analysis

Panel 1: Study Set 1, Study 3 (ΔWTPDIR): Difference-in-Difference Results

Effect (Type III)	Num Df	Den Df	χ^2	F Val	Pr > χ^2	Pr > F
Competitor Expertise	3	372	2.110	0.700	0.550	0.550
Auction Outcome	3	372	41.360	13.790	<.001	<.001
Competitor Expertise * Auction Outcome	9	372	8.580	0.950	0.477	0.477
time	1	372	0.120	0.120	0.733	0.733
Competitor Expertise * time	3	372	6.860	2.290	0.077	0.077
Auction Outcome * time	3	372	2.710	0.900	0.439	0.439
Competitor Expertise * Auction Outcome *time	9	372	7.910	0.880	0.543	0.543
REG	1	372	10.430	10.430	0.001	0.001
SAT	1	372	0.080	0.080	0.773	0.773
EXC	1	372	11.780	11.780	0.001	0.001
AGE	1	372	7.740	7.740	0.005	0.005
GENDER	2	372	3.860	1.930	0.145	0.145

Notes: Model estimation relied on maximum likelihood within SAS PROC GLIMMIX, and several alternative models were analyzed using distributions appropriate for continuous data. For parsimony the same covariates were retained from the previous analysis. The preferred distribution was selected by identifying the Generalized Chi-Square/DF closest to 1, and ultimately the retained distribution was generalized gamma ($\frac{\chi^2}{d.f.} = 3.12$). Examination of the coefficients show that higher levels of regret (REG) and Excitement (EXC) produced higher post-auction WTPDIR. However, higher levels of age produced lower post-auction WTPDIR.

Table of Means (ΔWTPDIR)

Outcome	Overall	Product	Process	Hybrid	Amateur
Win at $50	0.26 (0.42)	0.19 (0.80)	-0.43 (0.99)	1.72 (0.69)	-0.84 (0.87)
Lose at $50	0.32 (0.64)	-0.34 (1.73)	0.06 (1.01)	0.06 (0.95)	0.51 (1.06)
Lose at < $44	-0.49 (0.51)	0.40 (0.80)	-0.10 (0.86)	0.24 (1.52)	-2.49 (0.69)
Lose at $44-49	-0.43 (0.32)	-0.95 (0.62)	-0.02 (0.63)	0.47 (0.63)	-1.21 (0.67)
Lose $44-50	-0.27 (0.28)	-0.80 (0.59)	0.09 (0.55)	0.25 (1.53)	-0.71 (0.57)

Notes: Sample sizes by outcome: Win at $50 (n = 134), Lose at $50 (n = 132), Lose below $44 (n = 99), Lose between $44-49 (n = 219), Lose $44-50 (n = 351). Total number of participants, n = 598 (14 dropped due to a glitch resulting in lack of assignment to focal conditions).

Panel 2: Study Set 1, Study 3 (ΔWTA): Difference-in-Difference Results

Effect (Type III)	Num Df	Den Df	χ^2	F-Value	Pr > χ^2	Pr > F
Competitor Expertise	3	98	6.290	2.100	0.099	0.099
time	1	98	1.720	1.720	0.189	0.189
Competitor Expertise*time	3	98	2.150	0.720	0.543	0.543
REG	1	98	2.240	2.240	0.134	0.134
SAT	1	98	0.010	0.010	0.904	0.904
EXC	1	98	0.020	0.020	0.891	0.891
AGE	1	98	1.540	1.540	0.215	0.215
GENDER	2	98	6.080	3.040	0.048	0.048

Notes: Model estimation relied on maximum likelihood within SAS PROC GLIMMIX, and several alternative models were analyzed using distributions appropriate for continuous data. For parsimony the same covariates were retained from the previous analysis. The preferred distribution was selected by identifying the Generalized Chi-Square/DF closest to 1, and ultimately the retained distribution was generalized gamma (χ^2/(d.f.) =2.19). Examination of the coefficients show that higher levels of age produced lower post-auction WTA. Furthermore, males tended to post higher post-auction WTA than females.

Table of Means (ΔWTA)

Outcome	Product	Process	Hybrid	Amateur
Win at $50	-0.53 (1.55)	-0.54 (1.54)	-2.41 (1.29)	-1.61 (1.80)
Lose at $50	--	--	--	--
Lose at < $44	--	--	--	--
Lose at $44-49	--	--	--	--
Lose $44-50	--	--	--	--

Notes: Sample sizes by outcome: Win at $50 (n = 134), Lose at $50 (n = 132), Lose below $44 (n = 99), Lose between $44-49 (n = 219), Lose $44-50 (n = 351). Total number of participants, n = 598 (14 dropped due to a glitch resulting in lack of assignment to focal conditions).

Panel 3: Study Set 1, Study 3 (ΔWTP): Difference-in-Difference Results

Effect (Type III)	Num Df	Den Df	χ^2	F-Value	Pr > χ^2	Pr > F
Competitor Expertise	3	270	1.250	0.420	0.742	0.742
Auction Outcome	2	270	45.040	22.520	<.001	<.001
Competitor Expertise*AuctionOutcome	6	270	9.240	1.540	0.161	0.161
time	1	270	0.310	0.310	0.576	0.576
Competitor Expertise*time	3	270	3.580	1.190	0.311	0.311
Auction Outcome*time	2	270	2.150	1.070	0.341	0.341
Competitor Expertise*Auction Outcome *time	6	270	15.720	2.620	0.015	0.015
REG	1	270	1.620	1.620	0.204	0.204
SAT	1	270	0.080	0.080	0.777	0.777
EXC	1	270	15.410	15.410	<.001	<.001
AGE	1	270	5.080	5.080	0.024	0.024
GENDER	2	270	4.330	2.160	0.115	0.115

Notes: Model estimation relied on maximum likelihood within SAS PROC GLIMMIX, and several alternative models were analyzed using distributions appropriate for continuous data. For parsimony the same covariates were retained from the previous analysis. The preferred distribution was selected by identifying the Generalized Chi-Square/DF closest to 1, and ultimately the retained distribution was generalized gamma ($\frac{\chi^2}{d.f.} = 4.90$). Examination of the coefficients show that higher levels of Excitement (EXC) produced higher post-auction WTP. Furthermore, an increase in age predicted lower post-auction WTP.

Table of Means (∆WTP)

Outcome	Overall	Product	Process	Hybrid	Amateur
Win at $50	--	--	--	--	--
Lose at $50	-0.93 (0.97)	0.26 (2.55)	-4.45 (1.72)	0.07 (1.49)	0.42 (1.74)
Lose at < $44	0.67 (0.76)	3.31 (1.22)	2.04 (1.34)	-0.31 (2.21)	-2.38 (1.10)
Lose at $44-49	-0.48 (0.48)	0.36 (0.94)	0.20 (0.95)	-2.11 (0.98)	-0.38 (0.98)
Lose $44-50	-0.50 (0.43)	0.35 (0.88)	-0.78 (0.84)	-1.29 (0.78)	-0.04 (0.81)

Notes: Sample sizes by outcome: Win at $50 (n = 134), Lose at $50 (n = 132), Lose below $44 (n = 99), Lose between $44-49 (n = 219), Lose $44-50 (n = 351). Total number of participants, n = 598 (14 dropped due to a glitch resulting in lack of assignment to focal conditions).

Appendix O., Valuation Measures and Covariates Across Studies

Chapter 3, Study 2 Valuation Measures
WTA: Given that you won the auction what are you willing to accept (in dollars) if someone wanted to buy the product from you? [Slider Scale with whole numbers from $40-90]
WTP: You did not win the product in the auction. However, what are you willing to bid in order to win it? [Slider Scale with whole numbers from $40-90]
WTPDIR: How much are you willing to pay the auctioneer to buy the product directly without bidding in the auction? [Slider Scale with whole numbers from $40-90]

Chapter 3, Study 3 Valuation Measures
WTA: Given that you won the auction for the bottle of wine, what is the smallest amount you are willing to accept (in dollars) if someone wanted to buy the product from you? [Free entry numeric field allowing decimals to two places, range $25-75.00]
WTP: Given that you did not win the auction for the bottle of wine, what is the highest amount you would have been willing to bid in order to win it? [Free entry numeric field allowing decimals to two places, range $25-75.00]
WTPDIR: What is the highest you would have been willing to pay for this bottle of wine if you could have bought it directly from the auctioneer (e.g., in a "buy-it-now" auction)? [Free entry numeric field allowing decimals to two places, range $25-75.00]

Chapter 4, Study 1 Valuation Measures
WTA: Given that you won the auction, what is the smallest amount you are willing to accept (in dollars) if someone wanted to buy the bottle of wine from you? [Free entry numeric field allowing decimals to two places, range $25-75.00]
WTP: Given that you did not win the auction, what is the highest amount you would have been willing to bid if you did not have a budget constraint? [Free entry numeric field allowing decimals to two places, range $25-75.00]
WTPDIR: If you could have bought the bottle of wine directly from the auctioneer (e.g., there was a "buy-it-now" option), what is the highest amount you would have been willing to pay assuming you had no budget constraint? [Free entry numeric field allowing decimals to two places, range $25-75.00]

Chapter 5, Study 2 Valuation Measures
WTA: Given that you won the auction, what is the smallest amount you are willing to accept (in dollars) if someone wanted to buy the bottle of wine from you? [Free entry numeric field allowing decimals to two places, range $25-75.00]
WTP: Given that you did not win the auction, what is the highest amount you would have been willing to bid if you did not have a budget constraint? [Free entry numeric field allowing decimals to two places, range $25-75.00]
WTPDIR: If you could have bought the bottle of wine directly from the auctioneer (e.g., there was a "buy-it-now" option), what is the highest amount you would have been willing to pay assuming you had no budget constraint? [Free entry numeric field allowing decimals to two places, range $25-75.00]

Behavioral Measures

Excitement

Chapter 3, Study 2: $\boldsymbol{r_{Time\,1} = 0.90, r_{Time\,2} = 0.92}$

1. I found this auction exciting. [Likert Scale, Disagree to Agree, 1-7]
2. I found this auction fun. [Likert Scale, Disagree to Agree, 1-7]

Chapter 3, Study 3: $\boldsymbol{r_{Time\,1} = 0.85, r_{Time\,2} = 0.89}$

1. This auction was exciting. [Likert Scale, Disagree to Agree, 1-7]
2. This auction was fun. [Likert Scale, Disagree to Agree, 1-7]

Chapter 4, Study 1: $\boldsymbol{r_{Time\,1} = 0.84, r_{Time\,2} = 0.90}$

1. This auction was exciting. [Likert Scale, Disagree to Agree, 1-7]
2. This auction was fun. [Likert Scale, Disagree to Agree, 1-7]

Chapter 4, Study 2: $\boldsymbol{r_{Time\,1} = 0.85, r_{Time\,2} = 0.91}$.

1. This auction was exciting. [Likert Scale, Disagree to Agree, 1-7]
2. This auction was fun. [Likert Scale, Disagree to Agree, 1-7]

Regret

Chapter 3, Study 2: $\boldsymbol{r_{Time\,1} = 0.48, r_{Time\,2} = 0.50}$

1. I was overly cautious in my bidding in this auction. [Likert Scale, Disagree to Agree, 1-7]
2. I wish I had bid differently. [Likert Scale, Disagree to Agree, 1-7]

Chapter 3, Study 3: $\boldsymbol{r_{Time\,1} = 0.54, r_{Time\,2} = 0.44}$

1. I was too cautious in my bidding in this auction. [Likert Scale, Disagree to Agree, 1-7]
2. I wish I had bid differently. [Likert Scale, Disagree to Agree, 1-7]

Chapter 4, Study 1: $\boldsymbol{\alpha_{Time\,1} = 0.88, \alpha_{Time\,2} = 0.92}$

1. I could have made a better bidding decision. [Likert Scale, Disagree to Agree, 1-7]
2. I wish I had thought more about how I bid. [Likert Scale, Disagree to Agree, 1-7]
3. I wish I had bid differently. [Likert Scale, Disagree to Agree, 1-7]

Chapter 4, Study 2: $\boldsymbol{\alpha_{Time\,1} = 0.87, \alpha_{Time\,2} = 0.89}$

1. I could have made a better bidding decision. [Likert Scale, Disagree to Agree, 1-7]
2. I wish I had thought more about how I bid. [Likert Scale, Disagree to Agree, 1-7]
3. I wish I had bid differently. [Likert Scale, Disagree to Agree, 1-7]

Satisfaction

Chapter 3, Study 2: $r_{Time\ 1} = 0.53, r_{Time\ 2} = 0.68$

1. I am satisfied with how I bid in the auction. [Likert Scale, Disagree to Agree, 1-7]
2. I am satisfied with the final outcome of the auction. [Likert Scale, Disagree to Agree, 1-7]

Chapter 3, Study 3: $r_{Time\ 1} = 0.55, r_{Time\ 2} = 0.67$

1. I am satisfied with how I bid in the auction. [Likert Scale, Disagree to Agree, 1-7]
2. I am satisfied with the final outcome of the auction. [Likert Scale, Disagree to Agree, 1-7]

Chapter 4, Study 1: $\alpha_{Time\ 1} = 0.88, \alpha_{Time\ 2} = 0.90$

1. I am satisfied with how I bid in the auction. [Likert Scale, Disagree to Agree, 1-7]
2. I am pleased with the auction outcome. [Likert Scale, Disagree to Agree, 1-7]
3. I am satisfied with the final outcome of the auction. [Likert Scale, Disagree to Agree, 1-7]

Chapter 4, Study 2: $\alpha_{Time\ 1} = 0.91, \alpha_{Time\ 2} = 0.94$

1. I am satisfied with how I bid in the auction. [Likert Scale, Disagree to Agree, 1-7]
2. I am pleased with the auction outcome. [Likert Scale, Disagree to Agree, 1-7]
3. I am satisfied with the final outcome of the auction. [Likert Scale, Disagree to Agree, 1-7]

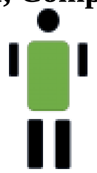
Appendix P., Study Set 2, Study 1 Instructions
Instructions (Please read carefully)

Thank you for agreeing to participate in this task which involves a simulated auction. The product for auction is wine. You will read instructions describing the auction task, participate in a demo auction, select a product to bid on, and then participate in a live auction. You will then answer a series of questions based on your experience.

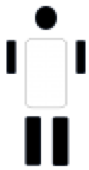
You will receive a base compensation of twenty-five cents ($0.25). In addition to this you may also earn a substantial performance bonus based on how well you bid against your competitors.

In this auction the highest bidder wins and pays a price one price level lower than what they bid, and bidding progresses in increments of $1.00. For example, a bidder who wins the auction at $100.00 would pay a price of $99.00.

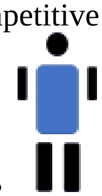
Appendix Q., Study Set 2, Study 1, Competitor Expert Descriptions



Expertise: Wine-Auction Experts
Key Descriptors:
- Wear GREEN shirts
- Are experts in discerning wine quality
- Are experts in competitive bidding strategies



Expertise: Amateurs
Key Descriptors:
- Wear WHITE shirts
- Are NOT experts in discerning wine quality
- Are NOT experts in competitive bidding strategies



Expertise: Wine Experts
Key Descriptors:
- Wear BLUE shirts
- Are experts in discerning wine quality
- Are NOT experts in competitive bidding strategies

Expertise: Auction Experts
Key Descriptors:
- Wear GOLD shirts
- Are NOT experts in discerning wine quality
- Are experts in competitive bidding strategies

Notes: Note that in Study Set 2 the expertise types have been relabeled: Wine-Auction Experts are Hybrid Experts, Wine Experts are Product Experts, and Auction Experts are Process Experts. Also, Study Set 2, Study 1 featured Self-Expert Hybrid Experts, Product Experts, Process Experts, and Amateurs and Competitor Expert Hybrid Experts and Amateurs. Study 2 featured Self-Expert Hybrid Experts and Amateurs and Competitor Expert Hybrid Experts and Amateurs.

Appendix R., Study Set 2, Studies 1-2, Key Auction Parameters and Task Earnings

	Study 1	**Study 2**
Key Auction Values		
Budget Amount	$50.00	$50.00
Starting Bid	$42.00	$42.00
Bid Increment	$1.00	NA
Announced Product Market Value	$55.00	$55.00
Winning Bid Level	$50.00	Variable between $42.00 - $50.00
Amount Paid by Winners	$49.00	Same value as above
Resulting Task Earnings		
Task Base Pay	$0.25	$2.17
Conversion Rate - Residual Budget	$0.005	$0.005
Conversion Rate - Product	$0.01	$0.01
Residual Budget Earnings (Win/Loss)	$0.01 / $0.25	Variable / $0.25
Product Earnings (Win/Loss)	$0.55 / $0.00	$0.55 / $0.00
Total Earnings (Win/Loss)	$0.81 / $0.50	Variable / $2.42

Notes: Conversion rates per game dollar. Total earnings = Task Base Pay + Residual Budget Earnings + Product Earnings.

Appendix S., Study Set 2, Study 1, Illustrative Example for Auction Incentive Structure

Payout Structure
In this auction your budget will be $50.00.
Your total performance bonus will depend on whether or not you win the auction, how carefully you bid and manage your budget, as well as the product's assessed market value which may be higher or lower than what you bid for it. Remember, that in these auctions if you win by bidding say $X, you will actually pay $X - 1 (i.e., one dollar less than what you bid).

Your payoff will be determined as follows:
Base pay ($0.25) +
Budget Savings bonus: (Budget savings * 0.005) +
Product Value bonus if you win: (Product's Market Value * 0.01)

Please review the following example scenarios for payoff calculations:
Example 1:
Assume your budget is $50.00
Say you bid $48 and WIN. You pay $47.
Your budget saving is $3
Your Budget Savings bonus is $3 * .005 = $0.02
A. **If the appraised market value for the product turns out to be $57** ($10 more than what you paid), your Product Value bonus is $57 * .01= $0.57
Your TOTAL PAYOUT is: $0.25 + $0.02 + $0.57 = $0.84
B. **If the appraised market value for the product turns out to be $47** (same as what you paid) your Product Value bonus is $47 * .01 = $0.47
Your TOTAL PAYOUT is: $0.25 + $0.02 + $0.47 = $0.74
C. **If the appraised market value for the product turns out to be $37** ($10 less than what you paid) your Product Value bonus is $37 * .01 = $0.37
Your TOTAL PAYOUT is: $0.25 + $0.02 + $0.37 = $0.64

Example 2:
Assume your budget is $50.00
Say you LOST because you were outbid. You pay nothing because you lost.
Your budget saving is $50
Your Budget Savings bonus is $50 * .05 = $0.25

The product's market value does not matter to you because you did not win the product.
Hence, your Product Value bonus is $0
Your TOTAL PAYOUT is: $0.25 + $0.25 = $0.50
Make sure you understand the payout structure as this will significantly impact your HIT payout. Take some time if you need to review these.

Do you need more time to review the payout structure?

Appendix T., Study Set 2, Studies 1-2, Self-Expertise Manipulation "Tips"
Please review the following statements carefully:

Auction Tips
1. Most people who bid in auctions focus on obtaining the product at the best price possible. However, really savvy bidders attend closely to what their competition is doing.
2. In many auctions bidders have a limited amount of time to place a bid. Many bidders like to bid early in the allotted time. However, more experienced bidders wait so that they can learn about their competition without revealing their own intentions.
3. Many bidders think that a lot of people bidding for the same product is a good sign. However, research shows that savvy bidders are happiest when there are fewer competitors since this yields results that are more advantageous for buyers than for sellers.

User Experience Tips
1. Internet auctions require participants to monitor screens for extended periods of time. Eye fatigue is a real thing and can lead to poor choices. Some people focus on selecting internet auction sites based on functionality. However, one should take into account both functionality and visual appeal.
2. It is important that the user experience include the ability to seek out new and different information on demand. Internet auction sites should make needed information more accessible.
3. Internet auction sites should be easy to navigate and inform bidders regarding the site's features. This makes it easier to bid and track their competition.

Appendix U., Study Set 2, Studies 1-2, Assessed Self-Expertise Manipulation "Test"

[Note: Correct answers in bold]

1. What flavor would result in the best Merlots?
   - Grass
   - Flowers
   - **Fruit**
   - Vanilla
   - Butter
2. Pinot Noirs flavor is best typified by hints of:
   - **Mushroom**
   - Wood shavings
   - Lemon zest
   - Earth
   - Strawberry
3. The region best suited to growing Cabernet Sauvignon is:
   - Lombardy
   - Umpqua Valley
   - Loire Valley
   - **Napa Valley**
   - Simi Valley
4. Pinot Noir flavors are generally more:
   - Fragrant
   - **Subtle**
   - Fruity
   - Dry
   - Sweet
5. An example of a good Merlot might be:
   - Strong notes of rosewood with undertones of lemon
   - Buttery notes of grass with undertones of wood shavings
   - Creamy blends of oak and coffee
   - **Strong notes of raspberry with undertones of oak**
   - Smooth blends of pencil shavings with undertones of raspberry
6. Experienced bidders attend carefully to:
   - The auctioneer's body language
   - Product appraisals
   - Reviews
   - **Your competitors' actions**
   - The auction house's staff's body language

7. Experienced bidders place their bids:
    - Immediately
    - **After waiting for some time**
    - Based on the appraisal value
    - Right before the competition
    - Early and often
8. Experienced bidders tend to focus on:
    - The price range of the products
    - The product types sold
    - **The number of bidders**
    - The appraisers used
    - The return policy
9. Experienced bidders know it is to their advantage when:
    - There are more bidders competing
    - There is a reserve price
    - **There are fewer bidders competing**
    - The bid level rises slowly
    - The bid level rises quickly
10. Experienced bidders tend to:
    - **Not reveal their own intentions**
    - Submit low initial bid levels
    - Look for low reserve prices
    - Look for more product choices
    - Focus on the website's attractiveness

Appendix V., Study Set 2, Study 1, Assessed Self-Expertise Manipulation Test Results

Results:

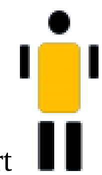
Based on your performance relative to other competitors:

You qualify as having relatively GREATER experience related to AUCTIONS.

You qualify as having relatively LESS experience related to WINE.

You are an Auction Expert.

During the auction your avatar will wear a GOLD shirt (below).

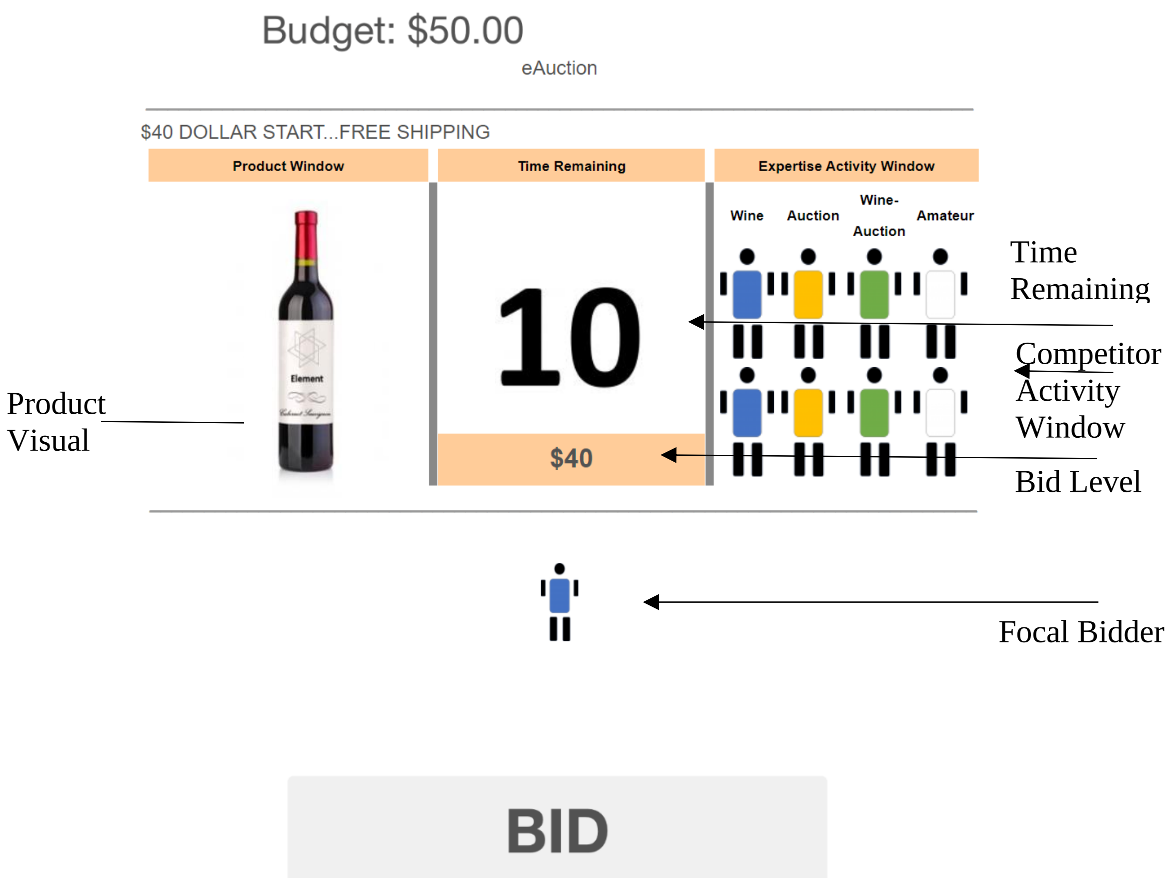
- I acknowledge I am an Auction Expert 

Notes: The above text shows the false feedback provided to participants classifying them into various their assigned Assessed Self-Expertise conditions. Similar feedback was used to classify participants into the other three categories (Amateurs, Product Experts, and Hybrid Experts)

Appendix W., Study Set 2., Study 1, Product Selection and Bidding User Interface
Panel 1: Illustrative Product Selection Interface

Please select the wine you wish to bid on.
You will then proceed to the next screen, acknowledge your choice, and start bidding.
You have a $50.00 budget with which to bid.
Bidding will begin at $42.00.

Panel 2: Illustrative Bidding User Interface



Appendix X., Study Set 2, Study 1, Schedule of Participant Exposure to Focal Conditions and Bidding Round

Round	Bid Level	Amateur Competitors	Hybrid Expert Competitors
0	$42	A H	A H
		A H	A H
1	$43	A H	A H
		A H	A H
2	$44	A	H
		A	H
3	$45	A	H
4	$46	A	H
5	$47	A	H
6	$48	A	H
7	$49	A	H
8a	$50	A	H
8b	$50		

Notes: Please read the Amateur Competitors column as follows.

1. In round 0 (bid level $42), all participants begin the auction competing against two Amateurs (A) and two Hybrid Experts (WA).
2. In round 2 (bid level $44), two Amateurs remain, and participants are fully exposed to their assigned Amateur condition.
3. In round 8 (bid level $50), for bidders assigned to win (8b) the final Amateur competitor drops out. The winning focal bidder pays $49 for the product.
4. In round 8 (bid level $50), for bidders assigned to lose the final Amateur competitor remains in the auction until the focal bidder's budget ($50) runs out (8a).

The dropout sequence for Hybrid Expert Competitors are interpreted similarly as above.

Appendix Y., Study Set 2, Study 1, Manipulation Checks

	Assessed Self-Expertise Manipulation Check Questions: I am a(n) …			
Assessed Self-Expertise	**Amateur**	**Wine Expert**	**Auction Expert**	**Wine-Auction Expert**
Amateur	6.60 (1.25)	1.30 (1.04)	1.29 (0.96)	1.25 (0.91)
Product Expert	2.32 (2.13)	5.67 (2.16)	1.31 (1.03)	1.36 (1.16)
Process Expert	2.91 (2.31)	1.53 (1.24)	5.23 (2.20)	1.67 (1.47)
Hybrid Expert	2.10 (2.05)	3.08 (2.58)	2.59 (2.35)	5.43 (2.31)

Notes: All comparisons of interest < 0.001.

	Competitor Expertise Manipulation Check Questions: My final opponent was a(n) …	
Assessed Self-Expertise	**Amateur**	**Wine-Auction Expert**
Amateur	6.19 (1.62)	2.06 (1.91)
Hybrid Expert	1.79 (1.57)	5.80 (1.91)

Notes: All comparisons of interest < 0.001.

Appendix Z., Study Set 2, Study 1, Number of Assignments Based on Actual Outcome

	Auction Outcome				
	Win ($50)	**Lose ($50)**	**Lose ($44-$49)**	**Lose (< 44.00)**	**Total**
CE: Hybrid					
SE: Amateur	16	22	22	18	**78**
SE: Process Expert	13	25	22	9	**69**
SE: Product Expert	23	20	20	10	**73**
SE: Hybrid Expert	22	10	31	9	**72**
CE: Amateur					
SE: Amateur	16	7	36	12	**71**
SE: Process Expert	22	19	21	13	**75**
SE: Product Expert	9	18	33	13	**73**
SE: Hybrid Expert	13	11	34	15	**73**
Total	**134**	**132**	**219**	**99**	**584**

Appendix AA., Study Set 2, Study 1, Number of Participants Staying/Quitting

Panel 1: Competitor Expertise

	Assigned to Win or Lose at $50				
	Total	**Stay #**	**Stay %**	**Quit #**	**Quit %**
Amateur	292	115	39.04%	177	60.96%
Hybrid Expert	292	151	51.71%	141	48.29%

$X^2(1) = 8.95, p = 0.003$

Panel 2: Self-Expertise

	Assigned to Win or Lose at $50				
	Total	**Stay #**	**Stay %**	**Quit #**	**Quit %**
Amateur	149	61	40.94%	88	59.06%
Process Expert	144	79	54.86%	65	45.14%
Hybrid Expert	145	56	38.62%	89	61.38%
Product Expert	146	70	47.95%	76	52.05%

$X^2(3) = 9.46, p = 0.02$

Panel 3: Self-Expertise * Competitor Expertise

		Assigned to Win or Lose at $50				
Self-Expertise	**Competitor Expertise**	**Total**	**Stay #**	**Stay %**	**Quit #**	**Quit %**
Amateur	Amateur	71	23	32.39%	48	67.61%
	Hybrid Expert	78	38	48.72%	40	51.28%
Process Expert	Amateur	75	41	54.67%	34	45.33%
	Hybrid Expert	69	38	55.07%	31	44.93%
Hybrid Expert	Amateur	73	24	32.88%	49	67.12%
	Hybrid Expert	72	32	44.44%	40	55.56%
Product Expert	Amateur	73	27	36.99%	46	63.01%
	Hybrid Expert	73	43	58.90%	30	41.10%

$X^2(7) = 22.48, p = 0.002$

Appendix AB., Study Set 2, Study 1, Censored Regression Results

Panel 1: Study Set 2, Study 1 (WTPDIR1): Censored Regression Results

Effect (Type III)	**Df**	**Wald χ^2**	**Pr > χ^2**
SExpertise	3	1.772	0.621
Cexpertise	1	4.480	0.034
SExperti*Cexpertise	3	0.541	0.910
AuctionOutcome	3	18.616	0.000
SExperti*AuctionOutcome	9	10.539	0.309
Cexpertis*AuctionOutcome	3	0.394	0.942
SExpe*Cexper*AuctionOutcome	9	4.386	0.884
REG1	1	1.306	0.253
SAT1	1	0.481	0.488
EXC1	1	13.905	0.000
AGE	1	1.025	0.311
GENDER	1	3.596	0.058
INCOME	1	1.341	0.247

Notes: Model estimation relied on maximum likelihood within SAS PROC LIFEREG, and several alternative Tobit models were analyzed using distributions appropriate for continuous data. Subsequent model selection relied on likelihood ratio tests using -2LL values to determine best distributional fit, and a comparison of AIC values was used to determine final covariate selection. Ultimately, generalized gamma was the retained distribution (-2LL = 4216.727) along with the above covariates (Satisfaction, Regret, Excitement, Age, and Gender; AIC = 4296.727). Note that for all analyses means are provided as unlogged transformations of the exponentiated Tobit model (i.e., provided valuations are in dollars). Estimation of the coefficients showed that higher levels of excitement (EXC1) increased WTPDIR1. Furthermore, males tended to post higher post-auction WTPDIR1 than females.

Panel 2: Table of Means – Self-Expertise (WTPDIR1)

Outcome	Amateur	Product	Process	Hybrid
Win at $50	48.89 (2.15)	48.52 (2.32)	48.42 (2.06)	46.16 (2.13)
Lose at $50	50.07 (2.64)	56.18 (2.03)	51.95 (1.81)	55.16 (2.74)
Lose at $44-49	50.91 (1.58)	47.49 (1.70)	49.34 (1.87)	48.56 (1.52)
Lose at <$44	44.47 (2.15)	49.30 (2.40)	45.87 (2.58)	46.73 (2.58)
Lose at $44-50	50.28 (1.36)	50.93 (1.39)	50.39 (1.36)	50.03 (1.42)

Notes: Sample sizes: Win at $50 (n = 134), Lose at $50 (n = 132), Lose below $44 (n = 99), Lose between $44-49 (n = 219), Lose $44-50 (n = 351). Total number of participants, n = 584.

Panel 3: Table of Means – Competitor Expertise (WTPDIR1)

Outcome	Amateur	Hybrid
Win at $50	47.12 (1.66)	48.87 (1.54)
Lose at $50	52.07 (1.89)	54.61 (1.61)
Lose at $44-49	48.36 (1.20)	49.79 (1.29)
Lose at <$44	45.09 (1.69)	48.10 (1.84)
Lose at $44-50	49.53 (1.07)	51.28 (1.07)

Notes: Sample sizes: Win at $50 (n = 134), Lose at $50 (n = 132), Lose below $44 (n = 99), Lose between $44-49 (n = 219), Lose $44-50 (n = 351). Total number of participants, n = 584.

Panel 4: Table of Means – Self-Expertise * Competitor Expertise (WTPDIR1)

	Amateur	
Outcome	**Amateur**	**Hybrid**
Win at $50	47.52 (2.92)	50.26 (2.94)
Lose at $50	49.62 (4.34)	50.51 (2.73)
Lose at $44-49	50.43 (1.93)	51.39 (2.44)
Lose at <$44	43.87 (3.31)	45.07 (2.70)
Lose at $44-50	50.04 (1.81)	50.51 (1.89)

	Product Expert	
Outcome	**Amateur**	**Hybrid**
Win at $50	48.07 (3.83)	48.97 (2.45)
Lose at $50	56.05 (2.84)	56.30 (2.67)
Lose at $44-49	46.54 (2.10)	48.44 (2.57)
Lose at <$44	47.90 (3.13)	50.71 (3.60)
Lose at $44-50	49.67 (1.78)	52.18 (1.93)

	Process Expert	
Outcome	**Amateur**	**Hybrid**
Win at $50	48.88 (2.49)	47.97 (3.18)
Lose at $50	51.02 (2.67)	52.88 (2.33)
Lose at $44-49	47.09 (2.58)	51.49 (2.52)
Lose at <$44	43.55 (3.35)	48.20 (3.80)
Lose at $44-50	48.71 (1.92)	52.06 (1.77)

	Hybrid Expert	
Outcome	**Amateur**	**Hybrid**
Win at $50	44.01 (3.19)	48.30 (2.61)
Lose at $50	51.59 (3.80)	58.73 (3.70)
Lose at $44-49	49.40 (2.04)	47.72 (2.11)
Lose at <$44	45.05 (3.03)	48.42 (3.97)
Lose at $44-50	49.69 (1.89)	50.35 (1.89)

Notes: Sample sizes: Win at $50 (n = 134), Lose at $50 (n = 132), Lose below $44 (n = 99), Lose between $44-49 (n = 219), Lose $44-50 (n = 351). Total number of participants, n = 584.

Panel 5: Table of Means – Auction Outcome (WTPDIR1)

Outcome	Overall
Win at $50	48.00 (1.23)
Lose at $50	53.34 (1.38)
Lose at $44-49	49.07 (0.96)
Lose at <$44	46.59 (1.31)
Lose at $44-50	50.40 (0.87)

Notes: Those who bid $50.00 and won posted significantly lower WTPDIR values than those who lost after bidding to $50.00 and running out of budget (p = 0.001). Sample sizes: Win at $50 (n = 134), Lose at $50 (n = 132), Lose below $44 (n = 99), Lose between $44-49 (n = 219), Lose $44-50 (n = 351). Total number of participants, n = 584.

Panel 6: Study Set 2, Study 1 (WTA1): Censored Regression Results

Effect (Type III)	Df	Wald χ^2	Pr > χ^2
SExpertise	3	5.3727	0.1465
Cexpertise	1	1.1055	0.2931
SExperti*Cexpertise	3	5.8219	0.1206
REG1	1	1.7949	0.1803
SAT1	1	0.0348	0.8521
EXC1	1	0.0171	0.8958
AGE	1	0.025	0.8743
GENDER	1	0.1606	0.6886
INCOME	1	2.5672	0.1091

Notes: Model estimation relied on maximum likelihood within SAS PROC LIFEREG, and several alternative Tobit models were analyzed using distributions appropriate for continuous data. Subsequent model selection relied on likelihood ratio tests using -2LL values to determine best distributional fit, and a comparison of AIC values was used to determine final covariate selection. Ultimately, generalized gamma was the retained distribution (-2LL = 950.306) along with the above covariates (Satisfaction, Regret, Excitement, Age, and Gender; AIC = 982.306). Note that means are provided as unlogged transformations of the exponentiated Tobit model (i.e., provided valuations are in dollars).

Panel 7: Table of Means – Self-Expertise (WTA1)

Outcome	Amateur	Product	Process	Hybrid
Win at $50	52.36 (4.03)	58.96 (4.87)	57.46 (3.12)	58.67 (3.59)

Panel 8: Table of Means – Competitor Expertise (WTA1)

Outcome	Amateur	Hybrid
Win at $50	58.04 (3.54)	55.68 (3.54)

Panel 9: Table of Means – Self-Expertise * Competitor Expertise (WTA1)

	Amateur	
Outcome	**Amateur**	**Hybrid**
Win at $50	50.37 (5.28)	54.36 (3.92)

	Product	
Outcome	**Amateur**	**Hybrid**
Win at $50	63.72 (5.34)	54.21 (5.73)

	Process	
Outcome	**Amateur**	**Hybrid**
Win at $50	56.09 (3.37)	58.83 (4.21)

	Hybrid	
Outcome	**Amateur**	**Hybrid**
Win at $50	62.00 (4.48)	55.34 (3.90)

Panel 10: Study Set 2, Study 1 (WTP1): Censored Regression Results

Effect (Type III)	Df	Wald χ^2	Pr > χ^2
SExpertise	3	2.541	0.468
Cexpertise	1	5.276	0.022
SExperti*Cexpertise	3	1.740	0.628
AuctionOutcome	2	68.196	<.001
SExperti*AuctionOutcome	6	12.805	0.046
Cexpertis* AuctionOutcome	2	0.025	0.988
SExpe*Cexper* AuctionOutcome	6	10.377	0.110
REG1	1	4.296	0.038
SAT1	1	1.653	0.199
EXC1	1	5.360	0.021
AGE	1	0.391	0.532
GENDER	1	1.040	0.308
INCOME	1	0.503	0.478

Notes: Model estimation relied on maximum likelihood within SAS PROC LIFEREG, and several alternative Tobit models were analyzed using distributions appropriate for continuous data. Subsequent model selection relied on likelihood ratio tests using -2LL values to determine best distributional fit, and a comparison of AIC values was used to determine final covariate selection. Ultimately, generalized gamma was the retained distribution (-2LL = 3131.841) along with the above covariates (Satisfaction, Regret, Excitement, Age, and Gender; AIC = 3195.847). Estimation of the coefficients showed that higher levels of excitement (EXC1) and regret (REG1) increased WTPDIR1.

Panel 11: Table of Means – Self-Expertise (WTP1)

Outcome	Amateur	Product	Process	Hybrid
Lose at $50	53.74 (2.01)	60.47 (1.52)	55.59 (1.41)	55.46 (2.10)
Lose at $44-49	52.82 (1.26)	50.63 (1.30)	54.16 (1.52)	51.46 (1.20)
Lose at <$44	45.69 (1.69)	45.72 (1.90)	46.53 (1.99)	45.04 (1.97)
Lose at $44-50	50.05 (1.07)	54.46 (1.07)	54.75 (1.12)	52.41 (1.13)

Panel 12: Table of Means – Competitor Expertise (WTP1)

Outcome	Amateur	Hybrid
Lose at $50	55.25 (1.43)	57.38 (1.18)
Lose at $44-49	51.27 (0.97)	53.27 (1.00)
Lose at <$44	44.57 (1.30)	46.92 (1.43)
Lose at $44-50	52.71 (0.87)	54.62 (0.81)

Panel 13: Table of Means – Self-Expertise * Competitor Expertise (WTP1)

	Amateur	
Outcome	**Amateur**	**Hybrid**
Lose at $50	52.39 (3.41)	55.09 (1.99)
Lose at $44-49	52.05 (1.53)	53.59 (1.93)
Lose at <$44	45.40 (2.61)	45.98 (2.12)
Lose at $44-50	51.96 (1.46)	54.15 (1.47)

	Product	
Outcome	**Amateur**	**Hybrid**
Lose at $50	60.99 (2.22)	59.96 (2.01)
Lose at $44-49	48.18 (1.63)	53.08 (1.99)
Lose at <$44	45.33 (2.47)	46.12 (2.86)
Lose at $44-50	52.49 (1.46)	56.43 (1.48)

	Process	
Outcome	**Amateur**	**Hybrid**
Lose at $50	57.00 (2.07)	54.17 (1.85)
Lose at $44-49	53.01 (2.08)	55.31 (2.00)
Lose at <$44	44.56 (2.61)	48.49 (2.97)
Lose at $44-50	54.84 (1.55)	54.66 (1.45)

	Hybrid	
Outcome	**Amateur**	**Hybrid**
Lose at $50	50.63 (2.92)	60.29 (2.88)
Lose at $44-49	51.84 (1.62)	51.08 (1.66)
Lose at <$44	42.99 (2.33)	47.09 (3.09)
Lose at $44-50	51.55 (1.52)	53.26 (1.52)

Panel 14: Table of Means – Auction Outcome (WTP1)

Outcome	Overall
Win at $50	--
Lose at $50	52.27 (0.76)
Lose at $44-49	45.75 (1.01)
Lose at <$44	56.32 (0.99)
Lose at $44-50	53.67 (0.68)

Appendix AC., Study Set 2, Study 1, Difference-in-Differences Analysis

Panel 1: Study Set 2, Study 1 (ΔWTPDIR): Difference-in-Differences Results

Effect (Type III)	Num Df	Den Df	Wald χ^2	F Value	Pr > χ^2	Pr > F
SExpertise	3	549	2.420	0.810	0.489	0.489
Cexpertise	1	549	4.120	4.120	0.042	0.042
SExpertise*Cexpertise	3	549	2.970	0.990	0.397	0.397
AuctionOutcome	3	549	22.730	7.580	<.001	<.001
SExpertise* AuctionOutcome	9	549	11.710	1.300	0.230	0.230
Cexpertise* AuctionOutcome	3	549	0.140	0.050	0.987	0.987
SExpertise*Cexpertise* AuctionOutcome	9	549	6.580	0.730	0.680	0.680
Time	1	549	0.000	0.000	0.964	0.964
SExpertise*Time	3	549	5.060	1.690	0.168	0.168
Cexpertise*Time	1	549	2.830	2.830	0.093	0.093
SExpertise*Cexpertise*Time	3	549	7.240	2.410	0.065	0.065
AuctionOutcome *Time	3	549	1.500	0.500	0.682	0.682
SExpertise* AuctionOutcome *Time	9	549	4.370	0.490	0.886	0.886
Cexpertise* AuctionOutcome *Time	3	549	6.260	2.090	0.100	0.100
SExpertise*Cexpertise* AuctionOut*Time	9	549	13.990	1.550	0.123	0.123
REG	1	549	6.020	6.020	0.014	0.014
SAT	1	549	0.300	0.300	0.582	0.582
EXC	1	549	10.520	10.520	0.001	0.001
AGE	1	549	0.840	0.840	0.360	0.360
GENDER	2	549	5.730	2.870	0.057	0.057
INCOME	2	549	2.740	1.370	0.254	0.254

Notes: Model estimation relied on maximum likelihood within SAS PROC GLIMMIX, and several alternative models were analyzed using distributions appropriate for continuous data. For parsimony the same covariates were retained from the Tobit analysis. The preferred distribution was selected by identifying the Generalized Chi-Square/DF closest to 1, and ultimately the retained distribution was generalized gamma ($\frac{\chi^2}{d.f.} = 3.61$). Estimation of the coefficients showed that higher levels of excitement (EXC1) and regret (REG1) increased WTPDIR1. Furthermore, males tended to post higher post-auction WTPDIR1 than females.

Panel 2: Table of Means – Self-Expertise (ΔWTPDIR)

Outcome	Amateur	Product	Process	Hybrid
Win at $50	0.14 (0.59)	-0.04 (0.68)	-0.38 (0.65)	-0.79 (0.54)
Lose at $50	-0.07 (0.77)	0.60 (0.66)	-0.56 (0.58)	0.17 (0.83)
Lose at $44-49	1.12 (0.51)	0.27 (0.47)	-0.07 (0.50)	-0.48 (0.43)
Lose at <$44	0.97 (0.62)	-0.44 (0.77)	-0.44 (0.69)	0.10 (0.69)
Lose at $44-50	0.70 (0.39)	0.38 (0.38)	-0.32 (0.38)	-0.28 (0.37)

Notes: Sample sizes: Win at $50 (n = 134), Lose at $50 (n = 132), Lose below $44 (n = 99), Lose between $44-49 (n = 219), Lose $44-50 (n = 351). Total number of participants, n = 584

Panel 3: Table of Means – Competitor Expertise (ΔWTPDIR)

Outcome	Amateur	Hybrid
Win at $50	-0.37 (0.45)	-0.15 (0.41)
Lose at $50	0.34 (0.53)	-0.27 (0.48)
Lose at $44-49	0.17 (0.31)	0.25 (0.37)
Lose at <$44	0.95 (0.45)	-0.87 (0.52)
Lose at $44-50	0.26 (0.26)	-0.02 (0.28)

Notes: Sample sizes: Win at $50 (n = 134), Lose at $50 (n = 132), Lose below $44 (n = 99), Lose between $44-49 (n = 219), Lose $44-50 (n = 351). Total number of participants, n = 584.

Panel 4: Table of Means – Self-Expertise * Competitor Expertise (∆WTPDIR)

Outcome	Amateur: Amateur	Amateur: Hybrid
Win at $50	0.23 (0.84)	0.05 (0.81)
Lose at $50	0.16 (1.39)	-0.30 (0.69)
Lose at $44-49	1.45 (0.63)	0.79 (0.81)
Lose at <$44	4.16 (0.98)	-2.23 (0.75)
Lose at $44-50	1.23 (0.57)	0.17 (0.53)

Outcome	Product: Amateur	Product: Hybrid
Win at $50	0.21 (1.12)	-0.28 (0.75)
Lose at $50	0.80 (0.98)	0.38 (0.87)
Lose at $44-49	0.38 (0.55)	0.17 (0.76)
Lose at <$44	-0.08 (1.00)	-0.80 (1.16)
Lose at $44-50	0.48 (0.48)	0.27 (0.58)

Outcome	Process: Amateur	Process: Hybrid
Win at $50	-1.23 (0.77)	0.48 (1.04)
Lose at $50	0.03 (0.87)	-1.16 (0.76)
Lose at $44-49	-0.11 (0.67)	-0.03 (0.74)
Lose at <$44	-0.16 (0.81)	-0.71 (1.11)
Lose at $44-50	-0.07 (0.53)	-0.57 (0.53)

Outcome	Hybrid: Amateur	Hybrid: Hybrid
Win at $50	-0.72 (0.84)	-0.86 (0.68)
Lose at $50	0.34 (0.92)	-0.01 (1.39)
Lose at $44-49	-1.02 (0.59)	0.07 (0.61)
Lose at <$44	-0.10 (0.81)	0.31 (1.11)
Lose at $44-50	-0.61 (0.50)	0.06 (0.56)

Notes: Sample sizes: Win at $50 (n = 134), Lose at $50 (n = 132), Lose below $44 (n = 99), Lose between $44-49 (n = 219), Lose $44-50 (n = 351). Total number of participants, n = 584.

Panel 5: Table of Means – Overall (ΔWTPDIR)

Outcome	Overall
Win at $50	0.26 (0.31)
Lose at $50	0.03 (0.36)
Lose at $44-49	0.21 (0.24)
Lose at <$44	0.05 (0.35)
Lose at $44-50	0.12 (0.19)

Notes: Sample sizes: Win at $50 (n = 134), Lose at $50 (n = 132), Lose below $44 (n = 99), Lose between $44-49 (n = 219), Lose $44-50 (n = 351). Total number of participants, n = 584.

Panel 6: Study Set 2, Study 1 (ΔWTA): Difference-in-Differences Results

Effect (Type III)	Num Df	Den Df	Wald χ^2	F Value	Pr > χ^2	Pr > F
SExpertise	3	123	7.570	2.520	0.056	0.056
Cexpertise	1	123	0.570	0.570	0.450	0.450
SExpertise*Cexpertise	3	123	10.290	3.430	0.016	0.016
Time	1	123	5.830	5.830	0.016	0.016
SExpertise*Time	3	123	1.870	0.620	0.601	0.601
Cexpertise*Time	1	123	0.000	0.000	0.978	0.978
SExpertise*Cexpertise*Tim	3	123	3.970	1.320	0.264	0.264
REG	1	123	0.990	0.990	0.319	0.319
SAT	1	123	0.080	0.080	0.775	0.775
EXC	1	123	0.480	0.480	0.489	0.489
AGE	1	123	0.010	0.010	0.920	0.920
GENDER	1	123	2.400	2.400	0.122	0.122
INCOME	2	123	5.040	2.520	0.080	0.080

Notes: Model estimation relied on maximum likelihood within SAS PROC GLIMMIX, and several alternative models were analyzed using distributions appropriate for continuous data. For parsimony the same covariates were retained from the Tobit analysis. The preferred distribution was selected by identifying the Generalized Chi-Square/DF closest to 1, and ultimately the retained distribution was generalized gamma ($\frac{\chi^2}{d.f.} = 2.63$).

Panel 7: Table of Means – Self-Expertise (ΔWTA)

Outcome	Amateur	Product	Process	Hybrid
Win at $50	-3.01 (1.16)	-0.31 (1.64)	-1.54 (1.36)	-1.76 (1.37)

Notes: Sample sizes: Win at $50 (n = 134), Lose at $50 (n = 132), Lose below $44 (n = 99), Lose between $44-49 (n = 219), Lose $44-50 (n = 351). Total number of participants, n = 584.

Panel 8: Table of Means – Competitor Expertise (ΔWTA)

Outcome	Amateur	Hybrid
Win at $50	-1.67 (1.06)	-1.64 (0.86)

Notes: Sample sizes: Win at $50 (n = 134), Lose at $50 (n = 132), Lose below $44 (n = 99), Lose between $44-49 (n = 219), Lose $44-50 (n = 351). Total number of participants, n = 584.

Panel 9: Table of Means – Self-Expertise * Competitor Expertise (∆WTA)

	Amateur	
Outcome	**Amateur**	**Hybrid**
Win at $50	-4.62 (1.50)	-1.41 (1.74)

	Product	
Outcome	**Amateur**	**Hybrid**
Win at $50	0.08 (2.89)	-0.69 (1.46)

	Process	
Outcome	**Amateur**	**Hybrid**
Win at $50	-2.22 (1.57)	0.85 (2.21)

	Hybrid	
Outcome	**Amateur**	**Hybrid**
Win at $50	0.06 (2.29)	-3.59 (1.50)

Notes: Sample sizes: Win at $50 (n = 134), Lose at $50 (n = 132), Lose below $44 (n = 99), Lose between $44-49 (n = 219), Lose $44-50 (n = 351). Total number of participants, n = 584.

Panel 10: Study Set 2, Study 1 (ΔWTP): Difference-in-Differences Results

Effect (Type III)	Num Df	Den Df	Wald χ^2	F Value	Pr > χ^2	Pr > F
SExpertise	3	423	3.06	1.02	0.383	0.384
Cexpertise	1	423	3.97	3.97	0.047	0.047
SExpertise*Cexpertise	3	423	1.39	0.46	0.708	0.708
AuctionOutcome	2	423	50.98	25.49	<.001	<.001
SExpertise* AuctionOutcome	6	423	13.6	2.27	0.035	0.037
Cexpertise* AuctionOutcome	2	423	0.24	0.12	0.889	0.889
SExpertise*Cexpertise* AuctionOutcome	6	423	6.63	1.11	0.356	0.358
Time	1	423	10.95	10.95	0.001	0.001
SExpertise*Time	3	423	2.57	0.86	0.463	0.463
Cexpertise*Time	1	423	1.87	1.87	0.171	0.172
SExpertise*Cexpertise*Time	3	423	2.24	0.75	0.524	0.525
AuctionOutcome *Time	2	423	9.52	4.76	0.009	0.009
SExpertise* AuctionOutcome *Time	6	423	2.79	0.47	0.834	0.834
Cexpertise* AuctionOutcome *Time	2	423	1.37	0.68	0.505	0.505
SExpertise*Cexpertise*AuctionOut*Time	6	423	4.94	0.82	0.551	0.552
REG	1	423	3.12	3.12	0.077	0.078
SAT	1	423	2.18	2.18	0.140	0.141
EXC	1	423	15	15	0.000	0.000
AGE	1	423	0.29	0.29	0.588	0.588
GENDER	1	423	1.73	1.73	0.189	0.189
INCOME	2	423	2.97	1.48	0.227	0.228

Notes: Model estimation relied on maximum likelihood within SAS PROC GLIMMIX, and several alternative models were analyzed using distributions appropriate for continuous data. For parsimony the same covariates were retained from the Tobit analysis. The preferred distribution was selected by identifying the Generalized Chi-Square/DF closest to 1, and ultimately the retained distribution was generalized gamma ($\frac{\chi^2}{d.f.} = 11.58$). Estimation of the coefficients showed that higher levels of excitement (EXC1) increased WTPDIR1.

Panel 11: Table of Means – Self-Expertise (ΔWTP)

Outcome	Amateur	Product	Process	Hybrid
Lose at $50	-3.52 (1.76)	-0.86 (1.54)	-3.56 (1.29)	-0.82 (1.81)
Lose at $44-49	-2.23 (1.09)	-2.74 (1.09)	-2.63 (1.18)	-1.48 (0.98)
Lose at <$44	0.48 (1.34)	1.58 (1.53)	-0.38 (1.55)	-0.01 (1.44)
Lose at $44-50	-2.62 (0.86)	-1.78 (0.88)	-3.07 (0.87)	-1.34 (0.85)

Notes: Sample sizes: Win at $50 (n = 134), Lose at $50 (n = 132), Lose below $44 (n = 99), Lose between $44-49 (n = 219), Lose $44-50 (n = 351). Total number of participants, n = 584.

Panel 12: Table of Means – Competitor Expertise (ΔWTP)

Outcome	Amateur	Hybrid
Lose at $50	-2.27 (1.20)	-2.10 (1.08)
Lose at $44-49	-1.22 (0.70)	-3.32 (0.83)
Lose at <$44	1.12 (0.96)	0.29 (1.12)
Lose at $44-50	-1.54 (0.59)	-2.87 (0.63)

Notes: Sample sizes: Win at $50 (n = 134), Lose at $50 (n = 132), Lose below $44 (n = 99), Lose between $44-49 (n = 219), Lose $44-50 (n = 351). Total number of participants, n = 584.

Panel 13: Table of Means – Self-Expertise * Competitor Expertise (∆WTP)

	Amateur	
Outcome	**Amateur**	**Hybrid**
Lose at $50	-2.43 (3.09)	-4.60 (1.70)
Lose at $44-49	-0.82 (1.33)	-3.65 (1.73)
Lose at <$44	1.91 (2.09)	-0.94 (1.68)
Lose at $44-50	-1.11 (1.23)	-4.12 (1.22)

	Product	
Outcome	**Amateur**	**Hybrid**
Lose at $50	-1.30 (2.22)	-0.44 (2.13)
Lose at $44-49	0.23 (1.24)	-5.69 (1.78)
Lose at <$44	1.63 (2.01)	1.51 (2.32)
Lose at $44-50	-0.18 (1.09)	-3.38 (1.38)

	Process	
Outcome	**Amateur**	**Hybrid**
Lose at $50	-4.99 (2.00)	-2.12 (1.63)
Lose at $44-49	-3.56 (1.64)	-1.70 (1.72)
Lose at <$44	1.06 (1.85)	-1.84 (2.50)
Lose at $44-50	-4.22 (1.27)	-1.92 (1.19)

	Hybrid	
Outcome	**Amateur**	**Hybrid**
Lose at $50	-0.39 (2.13)	-1.27 (2.94)
Lose at $44-49	-0.72 (1.36)	-2.26 (1.40)
Lose at <$44	-0.10 (1.67)	0.07 (2.36)
Lose at $44-50	-0.63 (1.15)	-2.05 (1.27)

Notes: Sample sizes: Win at $50 (n = 134), Lose at $50 (n = 132), Lose below $44 (n = 99), Lose between $44-49 (n = 219), Lose $44-50 (n = 351). Total number of participants, n = 584.

Panel 14: Table of Means – Auction Outcome (∆WTP)

Outcome	Overall
Win at $50	--
Lose at $50	-2.19 (0.81)
Lose at $44-49	-2.27 (0.54)
Lose at <$44	0.42 (0.74)
Lose at $44-50	-2.20 (0.43)

Notes: Sample sizes: Win at $50 (n = 134), Lose at $50 (n = 132), Lose below $44 (n = 99), Lose between $44-49 (n = 219), Lose $44-50 (n = 351). Total number of participants, n = 584.

Appendix AD., Description of Competitor Expertise Types (Study 2)

Competitive Expertise
In this study you will encounter competitors with different levels of expertise.

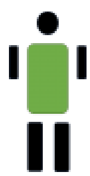
Competitive bidders may be:
- Hybrid Experts
- Amateurs

On the next page, please review the descriptions carefully and answer the questions below each description.

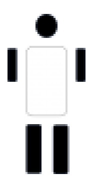
When you are satisfied you understand the differences between competing bidder types, click --> to continue.

Please review the below competitor types and descriptions.

On the following pages you will be asked to answer questions related to each competitor's capabilities.

Expertise: Hybrid Experts 

Key Descriptors:
- Wear GREEN shirts
- Are experts in discerning wine quality
- Are experts in competitive bidding strategies

Expertise: Amateurs 

Key Descriptors:
- Wear WHITE shirts
- Are NOT experts in discerning wine quality
- Are NOT experts in competitive bidding strategies

Appendix AE., Study Set 2, Study 2, Illustrative Example for Auction Incentive Structure

Payout Structure
In this auction your budget will be $50.00.

Your total performance bonus will depend on whether or not you win the auction, how carefully you bid and manage your budget, as well as the product's assessed market value which may be higher or lower than what you bid for it.

Your payoff will be determined as follows:

Base pay ($2.17) +
Budget Savings bonus: (Budget savings * 0.005) +
Product Value bonus if you win: (Product's Market Value * 0.01)

Please review the following example scenarios for payoff calculations:

Example 1:
Assume your budget is $50.00
Say you bid $46 and WIN. You pay $46.
Your budget saving is $4
Your Budget Savings bonus is $4*.005 = $0.02

A. If the appraised market value for the product turns out to be $56 ($10 more than what you paid), your Product Value bonus is $56*.01 = $0.56
Your TOTAL PAYOUT is: $2.17 + $0.02 + $0.56 = $2.75
B. If the appraised market value for the product turns out to be $46 (same as what you paid) your Product Value bonus is $46*.01 = $0.46
Your TOTAL PAYOUT is: $2.17 + $0.02 + $0.46 = $2.65
C. If the appraised market value for the product turns out to be $36 ($10 less than what you paid) your Product Value bonus is $36*.01 = $0.36
Your TOTAL PAYOUT is: $2.17 + $0.02 + $0.36 = $2.55

Example 2:
Assume your budget is $50.00
Say you LOST because you were outbid. You pay nothing because you lost.
Your budget saving is $50
Your Budget Savings bonus is $50*.05 = $0.25

The product's market value does not matter to you because you did not win the product.
Hence, your Product Value bonus is $0
Your TOTAL PAYOUT is: $2.17 + $0.25 = $2.42

Make sure you understand the payout structure as this will significantly impact your HIT payout.

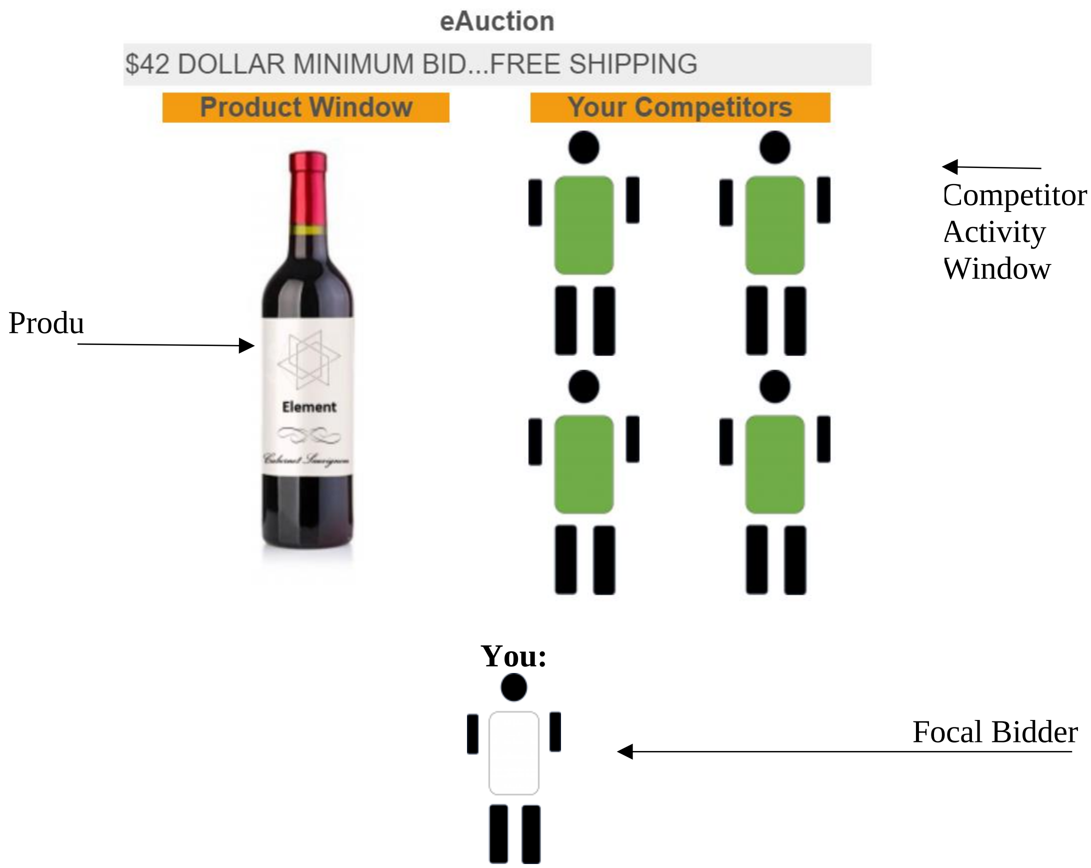
Take some time if you need to review these.

Do you need more time to review the payout structure?

Appendix AF., Study Set 2, Study 2, Product Selection and Bidding User Interface
Panel 1: Illustrative Product Selection Interface

Please select the wine you wish to bid on.
You will then proceed to the next screen, acknowledge your choice, and start bidding.
You have a $50.00 budget with which to bid.
Bidding will begin at $42.00.

Panel 2: Illustrative Bidding User Interface



Budget: $50.00

Starting Bid: $42.00

Please enter a bid value. When finished click the BID button below.
$ ____

Appendix AG., Study Set 2, Study 2, Number of Participants According to Study Conditions and Auction Outcome

	Winners	Losers	Total
CE: Amateur			
SE: Amateur	53	55	**108**
SE: Hybrid Expert	54	53	**107**
CE: Hybrid			
SE: Amateur	52	49	**101**
SE: Hybrid Expert	55	54	**109**
Total	**214**	**211**	**425**

Appendix AH., Study Set 2, Study 2, Bidding Results:

Panel 1: Study Set 2, Study 2 (Bid Level): Censored Regression Results

Effect (Type III)	Df	Wald χ^2	Pr > χ^2
SExpertise	1	5.870	0.015
CExpertise	1	8.457	0.004
SExperti*CExpertise	1	0.793	0.373

Notes: Model estimation relied on maximum likelihood within SAS PROC LIFEREG, and several alternative Tobit models were analyzed using distributions appropriate for continuous data. Subsequent model selection relied on likelihood ratio tests using -2LL values to determine best distributional fit, and a comparison of AIC values was used to determine final covariate selection. Ultimately, generalized gamma was the retained distribution (-2LL = 1818.173) along with the above covariates (AIC = 1830.173).

Panel 2: Table of Means (Self-Expertise)

Expertise	Mean
Amateur	43.84 (0.28)
Hybrid Expert	44.51 (0.27)

Panel 3: Table of Means (Competitor Expertise)

Expertise	Mean
Amateur	43.79 (0.27)
Hybrid Expert	44.57 (0.29)

Panel 4: Table of Means (Self-Expertise * Competitor Expertise)

Amateur

Amateur	Hybrid
43.57 (0.33)	44.11 (0.35)

Hybrid

Amateur	Hybrid
44.00 (0.32)	45.02 (0.34)

Appendix AI., Study Set 2, Study 2, Censored Regression Results

Panel 1: Study Set 2, Study 2 (WTPDIR1): Censored Regression Results

Effect (Type III)	**Df**	**Wald χ^2**	**Pr > χ^2**
SExpertise	1	3.138	0.077
CExpertise	1	0.124	0.725
SExpertise*CExpertise	1	3.995	0.046
AuctionOutcome	1	51.873	<.001
SExperti*AuctionOut	1	1.034	0.309
CExpertis*AuctionOut	1	0.216	0.642
SExpe*CExper*Auctio	1	3.501	0.061
REG1	1	5.684	0.017
SAT1	1	10.799	0.001
EXC1	1	29.737	<.001
GENDER	2	0.047	0.977
INCOME	2	5.678	0.059
AGE	1	12.634	0.000

Notes: Model estimation relied on maximum likelihood within SAS PROC LIFEREG, and several alternative Tobit models were analyzed using distributions appropriate for continuous data. Subsequent model selection relied on likelihood ratio tests using -2LL values to determine best distributional fit, and a comparison of AIC values was used to determine final covariate selection. Ultimately, generalized gamma was the retained distribution (-2LL = 2972.197) along with the above covariates (Satisfaction, Regret, Excitement, Age, and Gender; AIC = 3008.197). Examination of the coefficients show that higher levels of regret (REG1) and satisfaction (SAT1) produced loser post-auction WTPDIR1 whereas higher levels of excitement (EXC1) produced higher post-auction WTPDIR1. Furthermore, higher income was associated with lower post-auction WTPDIR1, and an increase in age resulted in decreased WTPDIR1.

Panel 2: Table of Means: Self-Expertise * Auction Outcome (WTPDIR1)

Outcome	Amateur	Hybrid
Win	47.80 (2.12)	45.63 (2.12)
Lose	55.32 (2.15)	55.16 (2.11)

Panel 3: Table of Means: Competitor Expertise * Auction Outcome (WTPDIR1)

Outcome	Amateur	Hybrid
Win	46.70 (2.10)	46.73 (2.13)
Lose	55.46 (2.10)	55.02 (2.14)

Panel 4: Table of Means: Self-Expertise * Competitor Expertise * Auction Outcome (WTPDIR1)

	Amateur	
Outcome	**Amateur**	**Hybrid**
Win	47.84 (2.34)	47.77 (2.29)
Lose	56.80 (2.36)	53.83 (2.37)

	Hybrid	
Outcome	**Amateur**	**Hybrid**
Win	45.57 (2.25)	45.70 (2.35)
Lose	54.12 (2.29)	56.21 (2.32)

Panel 5: Study Set 2, Study 2, WTA1 Censored Regression Result

Effect (Type III)	Df	Wald χ^2	Pr > χ^2
SExpertise	1	2.984	0.084
CExpertise	1	0.813	0.367
SExperti*CExpertise	1	1.608	0.205
REG1	1	0.173	0.677
SAT1	1	0.108	0.742
EXC1	1	2.478	0.116
GENDER	2	1.206	0.547
INCOME	2	6.731	0.035
AGE	1	6.365	0.012

Notes: Model estimation relied on maximum likelihood within SAS PROC LIFEREG, and several alternative Tobit models were analyzed using distributions appropriate for continuous data. Subsequent model selection relied on likelihood ratio tests using -2LL values to determine best distributional fit, and a comparison of AIC values was used to determine final covariate selection. Ultimately, generalized gamma was the retained distribution (-2LL = 1513.332) along with the above covariates (Satisfaction, Regret, Excitement, Age, and Gender; AIC = 1588.456). Examination of the coefficients show that loser levels of income were associated with increased post-auction WTA1, and an increase in age resulted in decreased WTA1.

Panel 6: Table of Means: Self-Expertise * Auction Outcome (WTA1)

Outcome	Amateur	Hybrid
Win	50.30 (2.96)	52.48 (3.04)
Lose	--	--

Panel 7: Table of Means: Competitor Expertise * Auction Outcome (WTA1)

Outcome	Amateur	Hybrid
Win	50.94 (2.98)	51.84 (3.02)
Lose	--	--

Panel 8: Table of Means: Self-Expertise * Competitor Expertise * Auction Outcome (WTA1)

	Amateur	
Outcome	**Amateur**	**Hybrid**
Win	50.49 (3.22)	50.11 (3.08)
Lose	--	--

	Hybrid	
Outcome	**Amateur**	**Hybrid**
Win	51.38 (3.11)	53.58 (3.35)
Lose	--	--

Panel 9: Study Set 2, Study 2, WTP1 Censored Regression Results

Effect (Type III)	**Df**	**Wald χ^2**	**Pr > χ^2**
SExpertise	1	0.730	0.393
CExpertise	1	0.527	0.468
SExperti*CExpertise	1	0.481	0.488
REG1	1	2.821	0.093
SAT1	1	7.510	0.006
EXC1	1	7.245	0.007
GENDER	2	0.120	0.942
INCOME	2	2.450	0.294
AGE	1	7.968	0.005

Notes: Model estimation relied on maximum likelihood within SAS PROC LIFEREG, and several alternative Tobit models were analyzed using distributions appropriate for continuous data. Subsequent model selection relied on likelihood ratio tests using -2LL values to determine best distributional fit, and a comparison of AIC values was used to determine final covariate selection. Ultimately, generalized gamma was the retained distribution (-2LL = 1492.985) along with the above covariates (Satisfaction, Regret, Excitement, Age, and Gender; AIC = 1520.985). Examination of the coefficients show that higher levels of satisfaction (SAT1) produced lower post-auction WTP1 whereas higher levels of excitement (EXC1) produced higher post-auction WTP1. Furthermore, and an increase in age resulted in decreased WTP1.

Panel 10: Table of Means – Self-Expertise * Auction Outcome (WTP1)

Outcome	Amateur	Hybrid
Win	--	--
Lose	57.15 (3.72)	55.83 (3.71)

Panel 11: Table of Means – Competitor Expertise * Auction Outcome (WTP1)

Outcome	Amateur	Hybrid
Win	--	--
Lose	55.96 (3.64)	57.03 (3.77)

Panel 12: Table of Means – SExpertise * CExpertise * AOutcome (WTP1)

	Amateur	
Outcome	**Amateur**	**Hybrid**
Win	--	--
Lose	57.14 (3.77)	57.17 (3.97)

	Hybrid	
Outcome	**Amateur**	**Hybrid**
Win	--	--
Lose	54.77 (3.82)	56.89 (3.88)

Appendix AJ, Study Set 2, Study 2, Differences-in-Differences Analysis
Panel 1: Study Set 2, Study 2 (ΔWTPDIR1): Censored Regression Results

Effect (Type III)	Num Df	Den Df	χ^2	F-Value	Pr > χ^2	Pr > F
CExpertise	1	413	0	0	0.956	0.956
SExpertise	1	413	0	0	0.986	0.986
CExpertise*SExpertise	1	413	0.02	0.02	0.885	0.885
AuctionOutcome	1	413	63.29	63.29	<.001	<.001
CExpertise*AuctionOutcome	1	413	0.04	0.04	0.849	0.849
SExpertise*AuctionOutcome	1	413	1.63	1.63	0.201	0.202
CExpertise*SExpertise* AuctionOutcome	1	413	0.12	0.12	0.726	0.726
time	1	413	2.5	2.5	0.114	0.115
CExpertise*time	1	413	1.6	1.6	0.207	0.207
SExpertise*time	1	413	0.08	0.08	0.778	0.778
CExpertise*SExpertise*time	1	413	0.29	0.29	0.591	0.591
AuctionOutcome*time	1	413	0.09	0.09	0.770	0.770
CExpertise*AuctionOutcome*time	1	413	0.14	0.14	0.713	0.713
SExpertise*AuctionOutcome*time	1	413	0.84	0.84	0.360	0.361
CExpertise*SExpertise* AuctionOutcome*time	1	413	0.73	0.73	0.393	0.394
REG	1	413	5.37	5.37	0.021	0.021
SAT	1	413	0.25	0.25	0.616	0.616
EXC	1	413	29.66	29.66	<.001	<.001
GENDER	2	413	1.74	0.87	0.419	0.420
AGE	1	413	5.62	5.62	0.018	0.018
INCOME	2	413	1.89	0.94	0.389	0.390

Notes: Model estimation relied on maximum likelihood within SAS PROC GLIMMIX, and several alternative models were analyzed using distributions appropriate for continuous data. For parsimony the same covariates were retained from the Tobit analysis. The preferred distribution was selected by identifying the Generalized Chi-Square/DF closest to 1, and ultimately the retained distribution was generalized gamma ($\frac{\chi^2}{d.f.} = 2.70$). Examination of the coefficients revealed higher levels of regret (REG) produced a positive change in WTPDIR whereas higher levels of age (AGE) produced a negative change in WTPDIR.

Panel 2: Table of Means – Self-Expertise * Auction Outcome (ΔWTPDIR1)

Outcome	Amateur	Hybrid
Win	-0.11 (0.32)	-0.52 (0.31)
Lose	-0.32 (0.35)	-0.11 (0.37)

Panel 3: Table of Means – Competitor Expertise * Auction Outcome (ΔWTPDIR1)

Outcome	Amateur	Hybrid
Win	-0.59 (0.31)	-0.04 (0.31)
Lose	0.37 (0.36)	-0.07 (0.36)

Panel 4: Table of Means – SExpertise * CExpertise * Auction Outcome (ΔWTPDIR1)

	Amateur	
Outcome	**Amateur**	**Hybrid**
Win	-0.34 (0.45)	-0.85 (0.44)
Lose	-0.71 (0.48)	-0.03 (0.54)

	Hybrid	
Outcome	**Amateur**	**Hybrid**
Win	-0.85 (0.44)	-0.19 (0.43)
Lose	-0.06 (0.51)	-0.19 (0.51)

Panel 5: Study Set 2, Study 2, ΔWTA Differences-in-Differences

Effect (Type III)	Num Df	Den Df	χ^2	F-Value	Pr > χ^2	Pr > F
SExpertise	1	413	3.740	3.740	0.053	0.053
CExpertise	1	413	0.100	0.100	0.753	0.753
SExpertise*CExpertise	1	413	1.010	1.010	0.315	0.315
time	1	413	4.720	4.720	0.030	0.030
SExpertise*time	1	413	0.170	0.170	0.683	0.683
CExpertise*time	1	413	3.010	3.010	0.083	0.083
SExpertise*CExpertise*time	1	413	0.330	0.330	0.565	0.565
REG	1	413	0.880	0.880	0.347	0.347
SAT	1	413	0.420	0.420	0.519	0.519
EXC	1	413	1.030	1.030	0.309	0.309
GENDER	2	413	0.260	0.130	0.876	0.876
AGE	1	413	2.570	2.570	0.109	0.109
INCOME	2	413	3.510	1.750	0.173	0.173

Notes: Model estimation relied on maximum likelihood within SAS PROC GLIMMIX, and several alternative models were analyzed using distributions appropriate for continuous data. For parsimony the same covariates were retained from the Tobit analysis. The preferred distribution was selected by identifying the Generalized Chi-Square/DF closest to 1, and ultimately the retained distribution was generalized gamma ($\frac{\chi^2}{d.f.} = 3.66$).

Panel 6: Table of Means – Self-Expertise * Auction Outcome (∆WTA)

Outcome	Amateur	Hybrid
Win	-0.81 (0.63)	-1.19 (0.67)
Lose	--	--

Panel 7: Table of Means – Competitor Expertise * Auction Outcome (∆WTA)

Outcome	Amateur	Hybrid
Win	-0.20 (0.66)	-1.80 (0.65)
Lose	--	--

Panel 8: Table of Means – SAExpertise * CExpertise * AOutcome (∆WTA)

	Amateur	
Outcome	**Amateur**	**Hybrid**
Win	-0.28 (0.90)	-0.13 (0.95)
Lose	--	--

	Hybrid	
Outcome	**Amateur**	**Hybrid**
Win	-1.35 (0.89)	-2.25 (0.94)
Lose	--	--

Panel 9: Study Set 2, Study 2, △WTP Differences-in-Differences

Effect (Type III)	Num Df	Den Df	χ^2	F-Value	Pr > χ^2	Pr > F
SExpertise	1	413	0.350	0.350	0.556	0.556
CExpertise	1	413	0.710	0.710	0.401	0.401
SExpertise*CExpertise	1	413	0.010	0.010	0.921	0.921
time	1	413	0.910	0.910	0.341	0.341
SExpertise*time	1	413	0.340	0.340	0.558	0.558
CExpertise*time	1	413	1.420	1.420	0.234	0.234
SExpertise*CExpertise*time	1	413	0.510	0.510	0.473	0.473
REG	1	413	0.650	0.650	0.421	0.421
SAT	1	413	1.860	1.860	0.172	0.172
EXC	1	413	8.570	8.570	0.003	0.003
GENDER	2	413	0.510	0.260	0.773	0.773
AGE	1	413	8.030	8.030	0.005	0.005
INCOME	2	413	3.770	1.880	0.152	0.152

Notes: Model estimation relied on maximum likelihood within SAS PROC GLIMMIX, and several alternative models were analyzed using distributions appropriate for continuous data. For parsimony the same covariates were retained from the Tobit analysis. The preferred distribution was selected by identifying the Generalized Chi-Square/DF closest to 1, and ultimately the retained distribution was generalized gamma ($\frac{\chi^2}{d.f.} = 3.08$). Examination of the coefficients revealed higher levels of excitement (EXC) produced a positive change in WTP whereas higher levels of age (AGE) produced a negative change in WTPDIR.

Panel 10: Table of Means – Self-Expertise * Auction Outcome (△WTP)

Outcome	Amateur	Hybrid
Win	--	--
Lose	-0.65 (0.60)	-0.15 (0.59)

Panel 11: Table of Means – Competitor Expertise * Auction Outcome (△WTP)

Outcome	Amateur	Hybrid
Win	--	--
Lose	-0.90 (0.60)	0.10 (0.59)

Panel 12: Table of Means – SExpertise * CExpertise * AOutcome (∆WTP)

	Amateur	
Outcome	**Amateur**	**Hybrid**
Win	--	--
Lose	-1.45 (0.83)	-0.36 (0.87)

	Hybrid	
Outcome	**Amateur**	**Hybrid**
Win	--	--
Lose	0.16 (0.87)	0.05 (0.81)