THE RATIONAL IRRATIONALITY OF AUCTION FEVER: EVIDENCE FROM AMAZON.COM GIFT CARDS, CONSUMER PRODUCTS ON EBAY, AND THE BEHAVIORAL LABORATORY

Abstract

There is a growing body of research in the social sciences on auction fever, an irrational behavior where individuals bid more for an item at auction than it is worth to them. While research in behavioral economics, organizational behavior, and consumer behavior examine different antecedents and mechanisms of auction fever, an understudied area is the impact of financial stakes on the tendency to catch auction fever. The few empirical auction studies that do study financial stakes leave a confusion gap in need of filling. Navigating the limitations in these previous studies and drawing on political economy's rational irrationality theory, we predict that the irrational behavior of auction fever will be less likely to occur as the financial stakes surrounding the item at auction increases. We test this general prediction by triangulating two field studies with an experiment in the behavioral laboratory. We find that people are less likely to catch auction fever when bidding for Amazon.com gift cards, consumer products sold on eBay, and laboratory items as the financial stakes of those items increase. Our findings are also practically significant. Moving from the minimum item value to the maximum reduces the estimated probability of overbidding by 35.4 percentage points for Amazon.com gift cards, 19.4 percentage points for the median consumer product, and a minimum of 67.7 percentage points in laboratory experiments. Theoretical and managerial implications about the burgeoning literature about auction fever and competitive decision making are discussed.

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INTRODUCTION

Auction fever – an irrational behavior where a person bids in an auction more for an item than it is worth to them – is a burgeoning topic in consumer behavior (e.g. Adam, Krämer, Jähnig, Seifert, & Weinhardt, 2011; Adam, Krämer, & Müller, 2015; Heyman, Orhun, & Ariely, 2004; Lee, Kim, & Fairhurst, 2009; Müller et al., 2016), organizational behavior (e.g. Ku, 2008; Ku, Malhotra, & Murnighan, 2005; Malhotra, 2010; Malhotra, Ku, & Murnighan, 2008), and behavioral economics (e.g. Heyman et al., 2004; Jones, 2011; Malmendier & Lee, 2011; McGee, 2013). Its popularity is not surprising given that most of us have experienced, witnessed, or heard about someone getting carried away in an auction and spending more than they intended. Auction fever has different names depending on whether it is studied in management, economics, or marketing: the most common names include bidding fever (e.g. Jones, 2011), the bidder's curse (e.g. Malmendier & Lee, 2011), bidding frenzy (e.g. Häubl & Popkowski-Leszczyc, 2004), and overbidding (e.g. Adam, Krämer, & Weinhardt, 2012).

While scholars in these fields explore different explanations and antecedents for this irrational behavior, an area that has had only a few contributions with mixed conclusions is about the effect of financial stakes on the prevalence of auction fever. The few studies about the impact of financial stakes on auction fever is surprising considering that "price is one of the most important considerations in purchase decisions" (Brown, 1971: 110). Further, the two published empirical studies that do examine the relationship between auction fever and financial stakes come to different conclusions. One study finds no relationship (Malmendier & Lee, 2011) while the other finds a positive one (Malhotra et al., 2008). The disagreement about the auction-fever-financial-stakes relationship is a "confusion gap" to resolve (Sandberg & Alvesson. 2011). Resolving the gap will help inform the academic and the administrator whether financial stakes effects auction fever and what the magnitude of the effect is.

We assess and propose a remedy to the discrepant findings in earlier work about impact of financial stakes on auction fever. Drawing from rational irrationality theory, we predict that the irrational behavior of auction fever becomes less frequent and severe as the costs of overbidding rise. Using a methodological triangulation approach (Denzin, 2009), we find that higher financial stakes has an attenuating effect on the irrationality of auction fever with Amazon.com gift cards (Study 1), 104 consumer products across 12 product categories on eBay (Study 2), and items in a behavioral laboratory experiment (Study 3).

We provide several contributions to the auction fever literature. In Study 1, we find a negative relationship between financial stakes and auction fever using secondary data from Jones' (2011) study about Amazon.com gift cards on eBay. In Study 2 we provide a conceptual extension of Study 1 by using secondary data from Malmendier and Lee's (2011) paper about consumer product auctions on eBay. Study 2's detailed analysis shows – contrary to Malmendier and Lee's (2011) conjecture – a negative relationship between financial stakes and auction fever. Study 3 creates an empirical generalization and extension of Studies 1 and 2 by replicating the two studies' findings and testing several additional hypotheses about the auction-fever-financial-stakes relationship.

THEORETICAL BACKGROUND

A Summary of Auction Fever Research and Some Boundary Conditions

It is important at the outset to distinguish between private value and common value auctions. In a private value auction each bidder forms a valuation of the item at auction. Bidders are typically assumed to know their valuations with certainty. For the most common auction formats (including the English auction, which we describe in detail below) a rational bidder, whose objective in the auction is to maximize pecuniary gains, should never bid above his own private valuation.

In a common value auction the item up for bid is worth the same amount to all bidders, although they may have differing estimates of its value. An example would be an auction for drilling rights to an oil deposit of unknown size. The revenue stream generated by the deposit will be the same regardless of who wins the auction. However, the bidders may disagree on the size of that revenue stream. For example, they may have each conducted their own geological surveys that produced varying estimates of the amount of oil in the deposit. In this case the bidder with the most optimistic estimate will likely bid the highest, and win the auction. However, the fact that the winner's estimate is the most optimistic means that the winner has probably overestimated the revenue stream, and therefore paid more for the drilling rights than they are actually worth. This is the well-known "winner's curse" (Capen, Clapp, & Campbell, 1971; Thaler, 1988).

Some overbidding is to be expected in common value auctions unless all bidders know the item's value with certainty. One example would be bidding on a gift card whose face value was commonly known. To explain overbidding in such an auction one must look for alternatives to the winner's curse.

While there is no dearth on the study of auctions (see Klemperer, 1999, for a review), the spate of auction fever research is, and it can be broken into two bodies. One body of work focuses on the emotions that drive competitive bidding behavior and the contextual features under which the desire to win at any cost is most likely to lead to auction fever (e.g. Adam et al., 2011; Ku, 2008; Ku et al., 2005; Lee et al., 2009; Malhotra, 2010; Malhotra et al., 2008). The second body of work focuses on how cognitive limitations lead to individuals catching auction fever (e.g. Heyman et al., 2004; Jones, 2011; Malmendier & Lee, 2011; McGee, 2013). What these two bodies do have in common is the auction format and their involvement in the financial-stakes-auction-fever debate.

English auctions. The irrational behavior of auction fever is examined in both literatures primarily using an English auction format – the most common type of auction (Haile & Tamer, 2003). The English auction follows an iterative format in which an initial price (or "opening bid") is offered and buyers make higher bids until some closing rule is invoked to bring the auction to an end. The closing rule may be "hard," such as a definite time limit for bidding or "soft," such as a bid being made with no higher bid within a certain time frame. The winner of the auction is the highest bidder (i.e., the last buyer to submit a bid), who pays a price equal to the final bid.

Assuming that the bidder's objective is to maximize his financial wellbeing, the Nash Equilibrium strategy in English auctions is to bid up to one's willingness to pay (WTP) for the item. Dropping out at a lower price ensures a loss when the item might have been won at a favorable price. Bidding above one's WTP risks paying more for the item than it is worth, making losing the auction preferable.

Financial stakes and decision making. Of course, the nature of the task may impact when financial stakes matter and when they do not in decision making. Camerer and Hogarth's (1999) seminal essay on incentives conjectures that incentives are most likely to influence decision making behavior in a positive way when the decisions are simple (e.g. adding two digit numbers) compared to when decisions require complex calculations using such methods as backwards induction. The reason for this relationship is that optimal decision making in complex tasks often requires cognitive skills that an individual does not possess and cannot acquire in the short time horizon given to perform the task. The current paper's task – bidding in English auctions – is simple by Camerer and Hogarth's standards and should be a setting where increasing financial stakes will impact decision-making behavior.

Financial stakes and auction fever. Little empirical consideration has surfaced in the auction fever literature about financial stakes. The two exceptions come respectively from the emotion and cognitive limitation bodies of auction fever scholarship. The first is empirical research conducted by behavioral economists Malmendier and Lee (2011) of a host of eBay auctions for consumer products. Their study takes advantage of eBay's website design, in which an item search returns a list containing both competitive auctions and fixed price "Buy it Now" (BIN) listings. They operationalize overbidding as bidding more for an item than the price of a matching BIN listing.

Malmendier and Lee (2011) compiled a dataset of almost 1,900 auctions of 104 different item types. For each of these auctions they were able to find a set of BIN offers for the same item that were available for at least part of the duration of the auction. They then found the lowest-priced BIN offer for each item and matched this price to every corresponding active auction for the same item. This matching allowed them to determine whether there had been overbidding in an auction.

Malmendier and Lee (2011) claim that they "find no significant relation between price level and overbidding" (p. 766). However, the Malmendier and Lee (2011) paper does not include statistical analysis to establish this claim, though it does provide scatterplots of overbidding frequency against item price in an online appendix. We maintain below, however, that their data do in fact show a negative relationship between price and overbidding.[1]

The second paper is from the organizational behavior literature and goes further. Malhotra, Ku, and Murnighan (2008) report results from laboratory experiments that show that an increase in financial stakes increases the prevalence and extent of auction fever. Malhotra et al. (2008) point to unpublished experiments by Ku (2004) in which participants were given a cash-redeemable endowment of 800 points and instructed to bid for an item worth 356 points. Each auction had two bidders, both of whom were required to pay their bid although only the high bidder won the item. The participants, unbeknownst to them, were matched with computerized opponents and required to submit the first bid. The computerized opponents were programmed to always respond to a participant's bid with a higher bid, so that the human participants never won. Consequently the human bidders always earned an amount equal to the endowment minus their bids. Financial stakes were manipulated by adjusting the exchange rate so that the item value of 356 points equaled 89¢ in the low stakes treatment and $8.90 in the high stakes treatment.

In the low stakes experiments the participants bid on average 14% more than the item value. In the high stakes experiments they bid 54% more. However, it is problematic to conclude from these results that higher stakes encourage auction fever for three reasons. First, the fact that both bidders paid their bid means that the auction format was a dollar auction, not the more common English auction. Shubik (1971) notes that, in a dollar auction, bidding more than the value of the item is not an irrational strategy so long as there are two active bidders. In a dollar auction the price of losing increases at the same rate as the price of winning, but the winner's costs are offset to some extent by the value of the item. Buying a dollar for $1.05 is less costly than losing the auction with a bid of $0.95. In an English auction, where only the winner pays for the bid, there is no financial incentive to bid past the value of the item. Consequently, it is unwarranted to apply the results of the Ku (2004) experiments to auctions in general or English auctions in particular.

The second limitation in the experimental design is the scale of payments. Even if stakes of $8.90 encourage auction fever, it could well be that this effect will not persist as the item value reaches hundreds or thousands of dollars. The current research navigates this limitation by examining items priced from a few dollars to more than a thousand dollars.

Lastly in the Ku (2004) experiments, the exchange-rate manipulation increased the value of the participants' cash endowments *and* the value of the items. Doing so may have led to overbidding differences because of a "house money" effect (Thaler & Johnson, 1990). Participants were bidding with $2 of house money in the low stakes condition and $20 of house money in the high stakes condition.

The contradictory findings about financial stakes in the Malmendier and Lee (2011) and Malhotra et al. (2008) papers create a confusion gap in the auction fever literature that warrants filling. We now turn to the political economy domain, drawing from rational irrationality theory to address the confusion gap.

Why May Financial stakes Curb Auction Fever? Rational Irrationality

Caplan (2000) developed rational irrationality theory as a framework to explain why individuals' beliefs often fail to conform to rational expectations theory. The central insight of the theory is that if agents have preferences over their beliefs they may be willing to sacrifice some amount of wealth to hold beliefs that are irrational. This sacrifice is rational in the sense that agents choose a combination of cognitive biases and wealth that maximizes utility. If the cost of an irrational belief increases, then the optimal combination will contain relatively more wealth and fewer (or less pronounced) cognitive biases. For instance, it is common for Major League Baseball players to engage in rituals and superstitious behaviors. These include refusing to wash uniforms or undergarments during a winning streak, eating a particular meal before each game and going through a warm up routine – such as spitting on one's hands or knocking the dirt off one's shoes – in the batter's box before each pitch. Such behavior is irrational in the sense that it does not objectively enhance their performance, but it is also low-cost because it does not hinder their performance either. Conversely, few if any professional baseball players engage in irrational behaviors when it comes to their diet and conditioning regimens. They do not, for instance, replace batting practice with positive thinking sessions, or treat their injuries with energy healing, as this would be detrimental to their performance on the field.

Rational irrationality theory has been applied primarily to the domain of political economy to explain why voters' economic views systematically deviate from the views of economists (B. Caplan, 2002a, 2002b) and how this influences public policy (B. Caplan, 2001a, 2001b, 2011). However, the core insight of the theory is not bound to any particular area of study. We submit that in auctions the bidders may also be bidding so as to choose the optimal combination of wealth and some non-financial objective, which leads them to engage in a certain amount of overbidding. However, as the tradeoff between wealth and the other objective becomes larger overbidding will attenuate.

More formally, suppose that a bidder's utility function is defined across wealth, denoted as *W*, and some other competing objective, *X*. In the context of an English auction, the bidder can maximize *W* by bidding optimally; that is bidding until the price has reached his WTP for the item. The variable *X* may be any non-pecuniary goal that the bidder wishes to achieve, but we assume that achieving it will, at least probabilistically, require deviating from bidding optimally. For example, the bidder may get utility simply from winning the auction, or from spitefully forcing the winning bidder to pay a high price, or from performing some other task concurrent with the auction. In the first case, the bidder may be forced to overbid if there is another bidder whose WTP is higher. In the second case the bidder may continue bidding after the price has reached his WTP simply to raise the final price that the winner must pay. In the third case the bidder may split his attention between the auction and the alternative task and overbid on accident.

The variable *X* may therefore account for any of the many explanations that have been offered for overbidding, including joy of winning (Morgan, Steiglitz, & Reis, 2003), a quasi-endowment effect (Heyman et al., 2004), escalation of commitment (Ku, 2008), competitive arousal (Ku et al., 2005) and limited attention (Malmendier & Lee, 2011). We do not single out any source of overbidding for scrutiny. Rather, we wish to show that whatever its cause, overbidding will diminish as it comes into greater conflict with achieving wealth. This follows from a straightforward application of indifference curve analysis.

Figure 1 provides a graphical illustration of the analysis that follows. The bidder's utility function implies a family of convex indifference curves, each representing that bidder's willingness to substitute *W* for *X* (or vice versa) at a given level of utility. (See curves U1 and U2 in Figure 1.) Because increasing *X* requires bidding sub-optimally the bidder faces a constraint that imposes an exogenous tradeoff between *W* and *X*. The constraint defines what combinations of *W* and *X* the bidder can actually achieve. Figure 1 displays two hypothetical constraints. The thick solid line represents a situation in which the bidder can trade off one unit of *W* for one unit of *X*. The thick dotted line represents an alternative situation in which the bidder must give up two units of *W* for one unit of *X*.

The bidder will maximize utility by satisfying two conditions. The first condition is that he must choose a (*W*, *X*) combination that lies on the constraint. Choosing a combination off the constraint would needlessly sacrifice some amount of *W* and/or *X*. The second condition is that at the chosen (*W*, *X*) combination it must not be possible to substitute some *W* for *X* to achieve a higher level of utility. These two conditions imply that the optimal (*W*, *X*) combination will be the point on the constraint that is tangent to an indifference curve. Figure 1 demonstrates that, holding a bidder's preferences constant, the constraint determines the degree to which the bidder will pursue wealth versus the competing objective *X*. With the thick solid constraint the bidder does not have to trade off much wealth to achieve a substantial amount of his competing objective. He therefore chooses the combination at point A, which includes a large component of *X*. However, with the thick dotted constraint the bidder must sacrifice twice as much wealth for the same gain in his competing objective. Consequently, he chooses the combination at point B, which is heavily weighted toward *W*.

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HYPOTHESES

What is the Value of the Item?

So long as bidders are budget constrained, there is an opportunity cost associated with winning the auction. Money spent on the item at auction is unavailable to pursue the next best alternative. Additionally, if inexperienced with the item at auction, a bidder faces the risk of finding out the item is not worth the price that was paid (Rothschild, 1979). Consequently, higher item values imply a costlier tradeoff between wealth and the bidder's competing objective. Empirical studies of consumer behavior in retail markets show that higher prices lead customers to greater levels of comparison shopping and information seeking behavior which we would characterize as cautious and rational. The pattern is found in markets for electrical appliances (Newman & Staelin, 1972; Udell, 1966), cars (Kiel & Layton, 1981), groceries (Urbany, Dickson, & Kalapurakal, 1996), and a variety of consumer goods (Laurent & Kapferer, 1985).

Rational irrationality theory predicts that the rationalizing effect of higher prices is not limited to retail markets, but will hold in auctions as well. Thus we would expect bids to be closer to an item's value the higher that value is. This proposed convergence implies two testable hypotheses about the relationship between item value and overbidding. First, we expect bidders to overbid less frequently in auctions for items of higher value than for items of lower value.

Hypothesis 1: There will be a negative relationship between an item's value and the propensity to overbid on the item in an English auction.

Second, because high item values lead to bids that are closer to value, we expect overbids in auctions for high valued items to be of smaller magnitude than overbids in auctions for low valued items. We measure the magnitude of an overbid as the percent by which the bid exceeds the item's value. This is because bidders likely view their bids in the context of anticipated final prices (Tversky & Kahneman, 1981). Overbidding by $1 is likely more salient if the bidder values the item at $5 than if he values it at $1,000. Thus we formulate our second hypothesis.

Hypothesis 2: There will be a negative relationship between an item's value and the percentage of the value by which bidders overbid on the item in an English auction.

What is the Cost of Overbidding?

The final negative relationship between financial stakes and auction fever concerns the cost that overbidding would impose on the bidder in the event that he wins the auction. The cost of overbidding is simply the price paid for the item minus the bidder's private valuation. Because bids must always increase in an English auction the same bidder may have multiple opportunities to overbid on the same item. Initial overbids may not impose substantial costs, and in the heat of the moment a bidder may consider that cost a fair price to pay for victory. But as the bidding pushes the price farther above the bidder's valuation of the item it becomes more costly to continue. If bidders are rationally irrational, most of their overbids will be at prices that are relatively close to their valuations for the item. Thus, we propose our third hypothesis.

Hypothesis 3: There will be a negative relationship between the costliness of overbidding and the propensity to overbid.

OVERVIEW OF THE CURRENT METHODOLOGY

Theory Development through Replication, Generalization, and Extension

To address the confusion gap about the relationship between financial stakes and auction fever, we us *methodological triangulation*, the use of multiple methodologies to study a phenomenon (Denzin, 2009:

301). As suggested by Weick (1979), methodological triangulation resolves Thorngate's (1976) *impostulate of theoretical simplicity* or the idea that social behavior research that uses only one source of data or method must make trade-offs among generalizability, accuracy, and simplicity of theory development. Further, methodological triangulation increases the confidence and validity of our findings by developing theory through replication (Johnson, Onwuegbuzie, & Turner, 2007). We use Tsang and Kwan's (1999) broad conceptualization of replication, using improved methodological practices to re-analyze data along with the traditional idea of duplicating a finding with different variable operationalizations and populations. We do this using *within* methodological triangulation (Denzin, 2009): all datasets are quantitative but two come from secondary sources in previously published papers (i.e. Jones, 2011; Malmendier & Lee, 2011) and one comes from the primary source of the behavioral laboratory.

Table 1 summarizes how we address the confusion gap through replication, and is based on Tsang and Kwan's (1999) taxonomy of theory development. The Tsang-Kwan taxonomy classifies contributions by replication into six quadrants, and these quadrants come from crossing the source of a study's population and its method of analysis. In Tsang and Kwan's (1999) terminology, Study 1 tests Hypotheses 1 and 2 by *re-analyzing data* from Jones' (2011) paper on eBay auctions of Amazon.com gift cards (Quadrant II). In Study 2, we provide a *conceptual extension* of Study 1 by re-analyzing data from Malmendier and Lee's (2011) paper of a wide breadth of consumer product auctions on eBay (Quadrant IV). Study 2 is a conceptual extension because it replicates the tests of Hypotheses 1 and 2 with different dependent and independent variable operationalizations while maintaining the same population as Study 1: consumers on eBay. Study 3 provides a *generalization and extension* of Studies 1 and 2 through a laboratory experiment: it first replicates the tests for Hypotheses 1 and 2 using a population of university students in an artificial auction environment (Quadrant V); and it tests Hypothesis 3, which is not possible in Studies 1 and 2 (Quadrant VI). Figure 2 displays the operationalizations of our key independent and dependent variables.

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Addressing Potential Confounds in the eBay Data

Our first two studies rely on datasets of eBay auctions. In Study 1, we identify overbidding by comparing the auction price to a gift card's face value. In Study 2, we identify overbidding by comparing the auction price to the lowest available BIN price for the same item. Due to certain features of eBay's website and business model it is possible that – in some cases – these definitions of overbidding capture behavior that is consistent with rational bidding strategies.[2] Here we consider three potential confounds in the eBay datasets and address each. The first two are most relevant to Study 1 on gift cards, the third is relevant to Study 2 on consumer products.

First, eBay and a number of financial intermediaries offer discounts on certain purchases. Bidders with such discounts may therefore win a gift card at a price above face value while paying a price less than or equal to face value. This would appear in our dataset as an overbid even though the bidder did not overpay. However, the discounts are not typically dependent on the final auction price, so there is no reason to expect our data to overstate disproportionately overbidding in low value gift cards relative to high value gift cards. In our statistical models, intermediary discounts might positively bias the estimated constant terms, but not bias the estimated relationship between face value and overbidding. Since our hypotheses involve this relationship, but not the baseline level of overbidding, discounting is not a major concern.

Second, eBay offers users a cash back reward – eBay Bucks – that may encourage bidding above an item's value (Boehnke, 2013). Users who sign up for the program receive a voucher equal to 2% of their qualifying purchases for the prior quarter. The voucher is valid for all eBay purchases within 30 days of issue. Bidders may be willing to bid above a gift card's face value if the gain in eBay Bucks exceeds the difference between their bid and face value. But, as with discounting, this should not systematically lead to more overbidding at lower face values than at greater face values. A greater concern is that bidders may bid on gift cards as a way to convert their eBay Bucks into a fungible financial instrument before the voucher's expiration date, and the bidder may be willing to pay a premium for the gift card to do so. Since eBay Bucks are a percentage of previous spending, it is reasonable to expect that there will be more of these bidders for gift cards of low value rather than high value.

Fortunately, eBay Bucks have well defined issue and expiration dates. The quantity of eBay Bucks that a bidder earns is based on qualified purchases in the previous quarter. They are issued 15 days after the start of the quarter and expire 30 days later, on the 45th day of the quarter. The data from Jones (2011) was gathered from September 1 to October 28, 2008, which spans the third and fourth quarter. The eBay Bucks issued for the third quarter had expired by September 1, and in the fourth quarter they were not issued until October 15. This means that overbidding to convert eBay Bucks could have only occurred in the last 13 days of the dataset, and we can control for this in our statistical models.

The third potential confound in the eBay data is related to the reliability of the lowest matching BIN offer as a measure of an item's value. Schneider (Forthcoming) points out that eBay’s search algorithm can return dozens (even hundreds) of results for a given query. The items in the search results may have some degree of heterogeneity, and they will not necessarily prioritize the lowest priced offers. Thus, finding the lowest matching BIN may incur considerable search costs. If a bidder pays more for an item than the lowest matching BIN but less than the lowest matching BIN plus search costs, she cannot be said to have truly overbid, but she will be recorded as having done so in the data. Misidentification of overbidding may be heightened if there is significant uncertainty about an item’s true market value or if the lowest matching BIN offer was made by a seller lacking the knowledge or desiring to price according to the market value; e.g. an inexperienced seller, or one who is trying to sell stolen property.

Ignoring search costs might bias the observed relationship between item value and overbidding because the volume of offerings may be larger for low-value items than high-value items. A lower offering volume would reduce the number BINs to search through, thus reducing transaction costs. However, the Malmendier and Lee (2011) data includes every matching BIN offer, which allows us to calculate the price dispersion of every item, as well as the fraction of the available matching BINs with prices equal to the lowest matching BIN offer. These variables allow us to control for the ease of finding the lowest BIN price.

STUDY 1: AMAZON.COM GIFT CARDS

Method and Sample

We first turn to archival auction data for Amazon.com gift cards on eBay published in Jones' (2011) study on auction fever. Jones (2011) collected data from 506 eBay auctions for Amazon.com gift cards of known face values. Jones' (2011) dataset contains information for each auction on the face value of the gift card, the number of bids placed in the auction, the final price of the gift card, the cost of shipping, and the winner's bidder rating (which is a proxy for bidding experience). Auctions on eBay are a modified English auction with proxy bidding. The provisional price during the auction is always equal to the second highest bid plus one bid increment. Bidders have the option of submitting a bid equal to their maximum WTP and allowing this pricing system to effectively bid for them by proxy. However, they can also submit lower bids and raise them incrementally if they are outbid.

Analysis

The archival data from Jones (2011) to test Hypotheses 1 and 2. We measure item value by the face value of the gift card. Figure 3 is a scatterplot of the frequency of overbidding against the face value of the gift cards for Jones' (2011) data. The data are organized in bins of $10, and marker sizes in Figure 3 reflect the number of observations in the bin. There is a clear negative relationship. Overbidding is frequent for gift cards with face values of $255 or lower, but virtually nonexistent for gift cards of higher face value.

We tested the negative relationship between item value and overbid propensity (Hypothesis 1) using a logistic regression (Model 1) with *Overbidding* as the binary dependent variable: *overbidding* equals 1 if the bidder's bid plus shipping costs exceeded the face value of the gift card. Our primary independent variable was *Item Value* (measured by the card's face value, scaled in dollars). We also included a dummy variable indicating whether or not eBay Bucks were redeemable when the auction closed (1 = yes, 0 = no) and its interaction with Item Value. This allowed us to control for bidders paying a premium to convert their eBay Bucks into gift cards, which are more fungible and have a later expiration date. If the eBay Bucks program encouraged overbidding in general, the dummy variable should be positive. If it specifically encouraged overbidding on gift cards with low face values then the interaction should be negative. We also included the number of bids that occurred in an auction, because we expect this to be positively correlated with competitive arousal (Ku et al., 2005; Malhotra, 2010; Malhotra et al., 2008). Calm, rational bidders can submit bids equal to their valuation of the item and await the outcome of the auction; irrationally excited bidders are more likely to revise their bids upward to win the auction. We included a third variable, the bidder's rating percentile, as a proxy for bidders' experience. A bidder's rating is incremented by one when he receives positive feedback from a seller, and decremented by one when he receives negative feedback. It is possible for a highly experienced bidder with a mix of positive and negative feedback to have a low rating, but it is not possible for an inexperienced bidder to have a high rating. We converted the raw ratings into percentiles because the values of the ratings ranged from 0 to 20,453 with just 477 rated bidders.

We test the negative relationship between item value and the magnitude of overbidding (Hypothesis 2) with a Tobit regression. In Model 2 the dependent variable is the percent by which the winning bid exceeded the gift card's face value. This model uses the same independent variables as Model 1. Using a Tobit regression is more appropriate than an ordinary least squares regression because the independent variable is censored: a bid is only counted as an overbid if it is greater than the value of the gift card.

Results and Discussion

The results of our statistical models are in Table 2. The eBay Bucks program did not affect overbidding in general. In Model 1 the estimated coefficient of the dummy variable is positive as expected, but not statistically significant ($p = 0.725$). In Model 2 the dummy is statistically insignificant ($p = 0.3317$) and its estimated coefficient is negative. However, the interaction of the dummy variable with Item Value is negative and statistically significant in both models ($p = 0.024$ in Model 1, $p = 0.026$ in Model 2). This confirms Boehnke's (2013) conjecture that a substantial number of bidders pay a premium to transfer their eBay Bucks to gift cards before their expiration date.

Testing hypothesis 1. Yet when we control for this source of overbidding, Hypothesis 1 is supported for the Amazon.com gift card auctions. In Model 1 the coefficient of *Item Value* is negative and statistically significant ($p = 0.022$). The marginal effect size is rather small. Setting the continuous variables to their mean values assuming eBay Bucks were not redeemable, our model estimates that a $1 increase in the face value of a gift card decreased the probability of auction fever by 0.1 percentage points. However, the total effect of face value on the propensity to overbid is quite large. If we hold bidder rating percentile and the number of bids constant at their mean values, increasing the face value of the gift card from the minimum observed value to the maximum observed value ($5 to $573.38) reduces the likelihood of overbidding from 46.5% to 16.5%. This is a reduction of 29.9 percentage points or 64.5% relative to the baseline. These effects are independent of a bidder's experience and number of times they bid.

Indeed, Model 1 indicates that more experienced bidders were less likely to bid past face value. The coefficient for bidder rating percentile is -0.156 ($p < 0.001$). With the continuous variables set to their mean values the estimated marginal effect of a 1 percentile increase in bidder rating was to reduce the probability of overbidding by 0.4 percentage points. In contrast, the *Number of Bids* did not have a significant effect on the propensity to overbid.

Testing hypothesis 2. Hypothesis 2 is supported as well. The baseline overbid in Model 2 is 0.022, or 2.2% of face value. The estimated coefficient of *Item Value* is -0.0002 ($p = 0.004$), indicating that a $1 increase in the face value reduces the overbid by 0.02% of the face value. Although this effect may appear to be small, notice that at a face value of $110 the model estimates that bids will be at or below value. Experience reduced the magnitude of overbidding. A one percentile increase in a bidder's rating reduced the estimated amount overbid by 0.11 percentage points of the face value ($p < 0.001$). EBay Bucks had an effect opposite to the one expected. When eBay Bucks were redeemable, the magnitude of the estimated overbid was lower by 4.88 percentage points ($p < 0.001$).

Our analysis of Jones' (2011) archival data on overbidding in eBay gift card auctions provides initial support that rational irrationality applies to auction fever. In these auctions, a negative relationship holds between an item's face value and the probability that a bidder will experience auction fever. This implies that overbidding does not persist as financial stakes increase. We replicate and extend conceptually this finding by examining an archival dataset of overbidding on eBay consumer product auctions.

= = = Insert Table 2 about here = = =

STUDY 2: CONSUMER PRODUCTS ON EBAY

Method and Sample

In Study 2, we analyze Malmendier and Lee's (2011) cross-sectional data on 1,886 eBay auctions conducted in February, April, and May of 2007. The auctions covered a wide variety of item types, price ranges and consumer demographics. Malmendier and Lee (2011) classified the auctions into 104 item types, placing each type into twelve different categories. For each auction in this dataset Malmendier and Lee (2011) were able to find a set of BIN offers for the same item that were available for at least part of the duration of the auction. They then found the lowest-priced BIN offer for each item and matched this price to every corresponding active auction for the same item. This matching allowed them to determine whether there had been overbidding in an auction.

The primary goal of our analysis is to determine whether overbidding is negatively correlated with the value of the auctioned item. We use an item's BIN price as a proxy for its market value. Before conducting our analysis, we made a number of refinements to Malmendier and Lee's (2011) data. We found that two of the original item classifications included products with more than one level of quality. We gave each quality level its own item classification and re-matched the relevant auctions with the appropriate lowest BIN offers. Auctions in the refined dataset are therefore classified into 107 different items. This affected 12 auctions. We also found 14 auctions that had been matched with BIN offers of the wrong item, and re-matched them accordingly. In addition, we dropped three auctions from the dataset because they had no valid matching BIN offer. In two of these auctions the auction description did not match any of the available BIN offers; in the third auction, five units of the item were being sold simultaneously but all of the relevant BIN offers were for a single unit.

Finally, there were six auctions in which the lowest price BIN offer was dramatically below the median. In two of these auctions (for iPod Shuffles) the lowest price BIN offer was $0.49, while the median offer was $72.77. For these two auctions we compared the winning bid to the second lowest BIN price of $58.88. In the remaining four auctions (for Canon digital cameras) the median BIN price was $152.25, while the lowest BIN price was just $0.01. However, for this item type there was no large discontinuity between the lowest and second lowest BIN price. Consequently, we omit them from the analysis. Including these six auctions with their original BIN price matches does not substantially affect the tests of statistical difference, sign or magnitude of our results.

Figure 4 is the frequency of overbidding against the item's lowest matching BIN price. For visual clarity the figure omits four auctions for an item with a BIN price of $3,000. These auctions – in three of which the winning bidder overbid – are included in the statistical analysis below. As with the Amazon.com gift cards there is an apparent negative correlation between item value and the frequency of overbidding.

Statistical Models

Malmendier and Lee's (2011) data allow us to replicate the tests for Hypotheses 1 and 2, that higher item values attenuate the frequency and magnitude of overbidding. It also allows us to test rational irrationality in an additional way: the ease of finding the lowest BIN offer. Maximizing wealth through optimal bidding depends on finding the lowest BIN offer. Therefore, making the lowest BIN offer harder to find limits the amount of wealth to be gained from the auction. This makes it relatively less expensive for the bidder to pursue his competing objective.

For each item there was a set of BIN offers. In some cases, the number of fixed price alternatives was quite large. In the most extreme case, there were over 21,000 BIN offers for Tickle Me Elmo dolls, with 72 unique prices. In other cases there was only a single matching BIN offer. For each item, we calculated the percent of BIN offers with a price equal to the lowest priced BIN offer, which we call *BIN Frequency*. We also calculated the standard deviation of each item's matching BIN prices. This gave us a measure of the price dispersion bidders faced when searching for the lowest BIN offer. The lowest BIN offer should be easier to find with a higher BIN frequency, but harder to find with a higher price dispersion. Thus, rational irrationality predicts a negative relationship between an item's BIN frequency and auction fever, and it also predicts a positive relationship between an item's price dispersion and auction fever.

To test Hypothesis 1, we fit the data to a logistic regression with robust standard errors. The dependent variable in the model is a binary variable where a value of one indicates that the final auction price exceeded the lowest BIN price. We refer to this as Model 3. To test Hypothesis 2, we fit the data to a Tobit regression. The dependent variable in this model – Model 4 – is the percent by which a bid exceeded the lowest matching BIN offer. The dependent variable equals zero for observations where there is no overbid. Both models use the set of control variables described below. Dummy variables are based on categorizations made by Malmendier and Lee (2011).

1. ***Market price.*** We include the natural log of the BIN price of the lowest priced matching offer.
2. ***Ease of finding the lowest priced BIN offer.*** We use the natural log of the BIN frequency and the price dispersion (i.e. the standard deviation of matching BIN prices) as measures of the difficulty bidders would have had in finding the lowest priced BIN offer.
3. ***Demographics.*** Items in the dataset may appeal to consumers based on their age (young, teenagers or adults). Additionally, some of the items (particularly books) appeal to liberal or conservative consumers, while others are non-ideological. We use the adult items and non-ideological items as the baselines and include dummy variables for items that appeal to younger consumers and for items whose appeal is based – at least in part – on political ideology.
4. ***Product category.*** The items in the dataset fall into twelve broad categories. We take consumer electronics as the baseline and include dummy variables for the following product categories: computer hardware, financial software, sports equipment, personal care products, perfume/cologne, games and toys, books, cosmetics, household products, hair products and DVDs. In the twelfth category – automotive products – there were nine auctions, all of which had a final bid price less than the lowest BIN price. Consequently, the Auto dummy would predict failure to overbid perfectly in our logistic regression. We therefore exclude the nine automotive product auctions from the analysis.

Results and Discussion

Replicating the test for hypothesis 1. Table 3 shows our statistical model's results, controlling for shipping costs (Hossain & Morgan, 2006).[3] The estimated effect of the log of the BIN price is negative in our model and statistically significant at the 0.1% level. Hypothesis 1 is supported. Bidders react to higher market prices by overbidding less frequently. The data are therefore consistent with rational irrationality.

The marginal effects of our main independent variables appear rather small, but their total effects across the range of the variables' values are substantial. Table 4 displays the estimated marginal effects of our main independent variables on the probability of overbidding on an item of each product category, holding the continuous variables at their mean value and all demographic dummy variables at zero. A one percent increase in the BIN price reduces the probability of overbidding by 0.05 to 0.08 percentage points, depending on the product category. The range of marginal effects of a one percent increase in the minimum BIN frequency is -0.07 to -0.10 percentage points. Price dispersion has a stronger marginal effect. A one dollar increase in the standard deviation of BIN prices increases the probability of overbidding by 0.25 to 0.4 percentage points.

To estimate the total effects of the main independent variables we calculated the change in probability of overbidding between the minimum and maximum observed BIN price in each product category, holding the minimum BIN frequency and BIN standard deviation at their mean values. We then repeated this process to find the change in probability of overbidding between the minimum and maximum observed values of the BIN frequency and BIN standard deviation. The results are displayed in Table 5.

Across the range of observed values, the main independent variables have a much larger impact on bidding behavior. For consumer electronics, the estimated probability of overbidding falls by 34 percentage points between the minimum and maximum observed BIN prices within that category. For cosmetics – where the lowest BIN prices ranged from \$9.99 to \$10.99 – the probability of overbidding fell by only 0.7 percentage points. The median reduction in the probability of overbidding across observed BIN prices was 19.4 percentage points.

The ease of finding the lowest matching BIN price had an even larger impact on the propensity to overbid. In four of the categories (consumer electronics, computer hardware, financial software and personal care) bidders were more than 50 percentage points more likely to overbid at the minimum observed value of BIN frequency than at the maximum observed value. The median reduction in overbidding probability was 38.8 percentage points.

Price dispersion had the largest marginal effect on the propensity to overbid, but for most categories the observed range of BIN standard deviations was narrow. For most product categories price dispersion had little practical impact. The median change in the probability of overbidding was only 7.6 percentage points. Two exceptions are consumer electronics and personal care. In those categories the estimated probability fell by 69.6 and 50.9 percentage points across the range of observed BIN standard deviations.

Replicating the test for hypothesis 2. The Tobit regression model supports Hypothesis 2. In Model 4 the item's BIN price has a statistically significant negative correlation with the percent by which a bid exceeded the item's value (p = 0.046). Since the model uses the natural log of the BIN price, we interpret the coefficient estimate as the marginal effect of a one-percent increase in the BIN price. A 10% increase in the BIN price reduced the relative overbid by 1.62 percentage points. A 10% increase in the BIN frequency reduced the relative overbid by one-percentage point ($p < 0.001$). In contrast, a \$10 increase in the standard deviation of BIN prices was associated with a 0.5% increase in the relative overbid ($p = 0.005$).

Our analysis of Malmendier and Lee's (2011) data of consumer goods adds further support that auction fever is responsive to incentives. Bidders were less likely to overbid when they were vying for highly valued items that could have a substantial impact on their wealth. However, when it was difficult to bid optimally – because the lowest BIN offer was difficult to find – bidders were more likely to overbid.

Studies 1 and 2 both support Hypothesis 1: overbidding is less frequent for higher valued items. These two studies also support Hypothesis 2: the relative magnitude of overbidding is lower for higher valued items. However, Studies 1 and 2 do not allow us to test Hypothesis 3, that the higher the (expected) cost of overbidding the less likely bidders are to submit a bid. This is because the data for Studies 1 and 2 only provided information on final prices, not bid histories. To test Hypothesis 3 and replicate our support for Hypotheses 1 and 2, we conducted a series of laboratory experiments, which are described in Study 3.

= = = Insert Table 3, Table 4, and Table 5 about here = = =

STUDY 3: LABORATORY EXPERIMENTS

Method

Participants were 94 graduate and undergraduate students from a southwestern university who were paid \$7 for participating in the experiment where they bid for abstract items. Participants could earn additional compensation based on their decisions. The experiment followed the procedures for randomization outlined by Friedman and Sunder (1994). Sessions were scheduled over the course of [NUMBER] days, with each session assigned one of [NUMBER] treatments and balanced by time of day. Because the design required additional sessions of [TREATMENT], [number] more sessions were scheduled. Treatments were assigned to the schedule prior to students arriving to the laboratory. Students were randomly assigned across treatments through a computer software program that randomly selected eligible students from the subject pool for each session and solicited their participation by email. A participant only received solicitation for one session.

In all sessions the participants were escorted into a classroom where they participated in a series of auctions using a software interface on laptop computers. The classroom setting allowed the participants to see one another, but the laptops were arranged so that they could not see one another's screens. Before conducting any auctions, a laboratory monitor explained the rules of the experiment; reading aloud an instructional script that described the auction mechanism, the user interface, and the way in which participants' decisions would be used to determine their earnings.

Design

All of the experimental auctions had the following elements in common:

1. ***English auction format.*** At the start of the auction a low initial price was posted for the item. Each time a participant submitted a bid (by pressing a key on his laptop) the price increased by $1. The participant with the high bid was not eligible to submit a new bid until he was outbid by a competitor. The last participant to submit a bid won the item at the price he had bid.
2. ***Private values.*** Each participant was given a unique private value for the item, representing that participant's maximum willingness-to-pay. The values were drawn randomly without replacement from a pre-determined distribution for each auction. In each auction a random shock was added to the values of the distribution to change the equilibrium price. The lowest value assigned to any bidder was $14. The highest value assigned to any bidder was $55. The difference between the (expected) highest and second highest values was always $10. Each participant's value was displayed only on his own computer screen, and could not be seen by any other participant.
3. ***Salient earnings.*** Each time a subject won an auction he earned an amount equal to his private value minus the price he paid for the item. Participants who lost an auction did not earn any money for that auction, but winning the item for a price greater than one's value resulted in negative earnings. At the end of a session a random sample of the auctions was selected. Selecting a sample of the auctions allowed us to offer higher possible earnings in each auction while keeping the cost of conducting the experiments reasonable. Each participant was paid his earnings for the selected auctions plus a $3 cash endowment. If a participant's earnings from the auctions were negative, that amount was deducted from his cash endowment. The rules governing payment of earnings were explained to the participants in detail before any auctions began. A participant earned on average $15.19 from the auctions in addition to a $7 attendance payment. The range of participant earnings (excluding the attendance payment) was $0 - $59.25.
4. ***Time pressure.*** The auctions used a soft closing rule. When the first bid was submitted a three second timer was initiated. Each time a subsequent bid was submitted the timer was reset to three seconds. The auction continued until the participants allowed the timer to run down to zero without submitting a higher bid.
5. ***Display of public information.*** Every participant was randomly assigned an ID color, which was displayed on their own private screens, as well as on a paper placard in front of their laptops. A screen at the front of the room conveyed information that was public knowledge to all of the participants. This information was 1) the auction timer, 2) the current price of the item, 3) the ID color of the participant who currently had the high bid on the item, and 4) the bid that would be necessary for one of the other participants to submit to take the lead as high bidder.

To assess our findings' robustness we conducted our auctions in a wide range of settings. Prior research suggests that overbidding is more common when items are of uncertain value (McGee, 2013), when there is high rivalry among bidders (Malhotra, 2010) and when observers are present (Ku et al., 2005). We manipulated these three treatment variables in a 2 × 2 design. [4]

The first treatment variable, *value uncertainty*, determined whether the participants received certain or uncertain signals of their private values. In the *certain-value auctions*, the participants' screens displayed their precise private values, so they knew exactly how much they could bid without the risk of losing money. In the *uncertain-value auctions* the screens showed a minimum and maximum value that defined the support of a uniform distribution from which the value would be drawn. The expected value was equal to a corresponding value in the certain value treatment, but the difference between the minimum and maximum value was always $10. Thus, participants faced considerable uncertainty about how high they could bid before they would incur a financial loss if they won the auction. At the conclusion of an uncertain-value auction only the winning participant learned his value.

Regarding the second treatment variable, *rivalry*, Ku et al. (2005) and Malhotra (2010) posit that bidders become more competitive as the auction progresses and the field of bidders narrows to two. In their terminology, rivalry increases as the number of active bidders falls. In other words, the impact of rivalry on auction fever is more likely when two bidders emerge out of a larger group of bidders compared to an auction where there are only two bidders from the start. Our second treatment variable was the number of bidders in the auction: 2 bidders vs. 6 bidders. In the *2-bidder* sessions, eight participants were randomly assigned to four dyads. Each dyad then competed in six auctions. The auctions were organized into one block of three using certain values and one block of three using uncertain values. With each dyad, we reversed the ordering of auction blocks so that if dyad n saw certain values first, then dyad n + 1 saw uncertain values first, and vice versa. In the *6-bidder* sessions, 12 participants were randomly assigned to two hexads. Each hexad competed in eighteen auctions organized in blocks of nine by value type. The ordering of auction blocks was reversed between hexads. Our 2-bidder auctions always had only two active bidders, which should theoretically short-circuit the process of rivalry building up over the course of the auction. Moreover, with only two bidders the bidding proceeded in an orderly back-and-forth format which could generate a sense of predictability or pattern to the auction. In contrast, the 6-bidder auctions could (and often did) begin with a flurry of bids from multiple participants, which made for a comparatively disorderly, emotionally charged bidding environment. In the 2-bidder sessions the participants in the last dyad each rolled a six-sided die. The result of the first (second) roll determined which auction would be selected from each participant's first (second) block for payment. In the 6-bidder sessions the participants in the last hexad each rolled a 10-sided die three times. The first (second) nine rolls determined which auctions would be selected from each participant's first (second) block for payment. This payment method assured the same expected earnings from a given auction across treatments. [5]

Table 6 displays a summary of the experimental design. We conducted six sessions with 2-bidder auctions, and five sessions with 6-bidder auctions. In five of the 2-bidder sessions we conducted 24 auctions; in the remaining session only six participants attended, so we conducted 18 auctions. In three of the 6-bidder sessions we conducted 36 auctions; in the two remaining sessions only six participants attended, which resulted in conducting 18 auctions in each of these sessions. This gives us an initial total of 282 auctions. However, due to a programming error some of our uncertain-value auctions failed to properly record a bidder's range of item values. As a result, we discarded 40 auctions, leaving us with 242 auctions for our analysis.

= = = Insert Table 6 about here = = =

Results and Discussion

Summary statistics. Table 7 displays the summary statistics regarding overbidding in each treatment and overall in our laboratory experiments. Across all treatments, almost a quarter (23.4%) of winning bidders bid beyond their (expected) value for the item at least once, and roughly an eighth (12.4%) of winning bids were overbids. The average overbid exceeded the participant's (expected) value by 29.4%, with a standard deviation of 22.8%.

Overbidding was concentrated in the auctions with uncertain item values, but its frequency did not vary substantially with the number of bidders. The rate of overbidding among winning bids was 19.6% in the 2-bidder uncertain value auctions and 26.7% in the 6-bidder uncertain value auctions. In the certain value auctions only 4.3% of winning bids were overbids with 2 bidders; 5.6% were overbids with 6 bidders. Overbidding did have a somewhat larger magnitude in the 6-bidder auctions, however. On average, overbids exceeded the item's (expected) value by 19.2% and 25.6% in the 2-bidder auctions with certain and uncertain values. In the 6-bidder auctions the average overbid was 36.2% with uncertain values and 40.5% with certain values.

A second replication for testing Hypotheses 1 and 2. Figure 5 plots participants (expected) item values against the frequency of overbidding among winning bidders. As with Jones' (2011) gift card auctions and Malmendier and Lee's (2011) consumer product auctions the bidders in our experiments were least likely to overbid when their induced values were high. Thirteen of the winning bidders had values or less than \$30, and 8 of these (61.5%) overbid. In contrast, 143 of the winning bidders had values greater than \$40, and of these only 5 (3.5%) overbid.

We replicated the test of Hypothesis 1 yet again with a logistic regression. The binary dependent variable was whether the winning bidder had bid past his (expected) item value (1 = yes, 0 = no). Focusing on the winning bidders made these data as comparable to Jones (2011) and Malmendier and Lee (2011) as possible. However, unlike the data from those studies, our experiments allowed us to track the identity of every bidder in every auction. Thus, we included bidder-specific random effects in our model to capture individual idiosyncrasies in bidding behavior. The independent variable of primary interest is the item's (expected) value. We also included three binary variables to capture the main treatment effects and their interaction. Finally, we included the auction number to account for learning effects. We refer to this logistic regression as Model 5.

To replicate our test of Hypothesis 2, we calculated the percent by which overbidding participants bid above their (expected) values and used these data as the dependent variable in a Tobit regression. The independent variables in this model – Model 6 – are the same as those for Model 5. Like in Model 5, we also included bidder-specific random effects to capture the idiosyncratic bidding decisions of our participants. The results of Model 5 and Model 6 are displayed in Table 8.

Model 5 replicates our previous findings that the probability of overbidding is reduced by a higher item value. The estimated effect of the item's value is significantly negatively correlated with overbidding ($p < 0.001$). To illustrate the effect size we assume a winning bidder in his first auction with the average winner's (expected) item value of $42.55. Depending on the treatment condition, a $1 increase in (expected) item value reduces the probability of auction fever by a minimum of 0.3 percentage points (from 1.7% to 1.4% in the 6-bidder certain value auctions) and a maximum of 1.5 percentage points (from 8.5% to 7% in the 6-bidder uncertain value auctions with no observers). In both cases this is a reduction in the probability of overbidding by 17.6% relative to the baseline.

Model 6 estimates that the item's value shows a statistically significant ($p < 0.001$) negative correlation with the magnitude of overbidding. The estimated coefficient implies that a $1 increase in item value reduced the percent by which a bid exceeded the item's value by 0.8 percentage points. Thus our experiments successfully replicate our support of Hypothesis 2.

= = = Insert Table 7 and Table 8 about here = = =

Testing hypothesis 3. To test Hypothesis 3, we used the bid histories of our experiments to construct a binary variable, B_{ijp}, which takes a value of 1 if bidder i submitted a bid in auction j at a price of p and takes a value of 0 if bidder i refrained from submitting a bid at that price. We used a random effects logistic regression with B_{ijp} as the dependent variable. To control for treatment effects, we included three binary variables indicating whether the auction was for items of certain value (1 = yes, 0 = no) and whether the auction involved six bidders (1 = 6 bidders, 0 = 2 bidders), as well as their interaction.

We specified the logistic regression model to test whether participants bid less frequently when doing so could result in losing money, and to test whether bids become even less frequent as the magnitude of the monetary loss increases. For the first test, we constructed a binary variable that took a value of 1 if the participant's bid exceeded the item's value, or its expected value in the case of uncertain auctions, 0 otherwise. We also included interactions of this variable with the treatment variables for item value certainty and 6 bidders. Interactions with the observers treatment variable all proved to be statistically insignificant without affecting the main results of the model, and are excluded.

For the second test, we constructed a continuous variable to measure the magnitude of the financial loss that would occur if the participant won an auction at a given bid. If the bid was no greater than the item's (expected) value this variable took a value of zero. If the bid was above the (expected) value, then the variable was equal to the bid minus the item's (expected) value. As above, we included interactions of this variable with binary variables indicating whether the auction was for items of certain value and whether the auction involved six bidders.

Over ninety-five percent (95.6%) of bidders (44 of 46) in the 2-bidder certain-value auctions never bid more than \$2 above their induced values. However, two bidders bid at least \$7 above their values in two of their certain-value auctions. We cannot observe the behavior of the 95.6% of bidders in cases where bidding would have cost them \$7, because their auctions ended before such losses were possible. Consequently, when using the entire dataset our model inflates the probability of overbidding in 2-bidder certain-value auctions when the cost is high. We therefore exclude all data from the two bidders who overbid by high amounts, as well as the two bidders with whom they were competing.

The marginal effect estimates of logistic regressions are complicated to interpret, particularly when there are a large number of interacting variables (Hoetker, 2007). To offer an intuitive interpretation we display the results of our models in two separate tables. Table 9 contains probability estimates generated by the models. Each row in the table contains the results for a particular permutation of the treatment variables. The three right-hand columns display the estimated probability of submitting a bid when it could result in no monetary loss, a \$1 loss and a \$5 loss. Table 10 displays estimated marginal effects from the logistic regressions. We refer to these estimates to determine the level of confidence we can have that the patterns of probabilities in Table 9 are not due to chance.

There are three main patterns in the probability estimates in Table 9 that are consistent with Hypothesis 3. First, in the 2-bidder auctions, bidding was always less frequent when it could result in a monetary loss. When item values were uncertain in the 2-bidder auctions, moving from no monetary loss to a \$1 loss reduces the estimated probability of submitting a bid by 11.8 percentage points, from 98.0% to 86.2%. Increasing the monetary loss to \$5 reduces the estimated probability by another 10.3 percentage points to 75.9%. When item values were certain, the effect of monetary losses was even more dramatic. The estimated probability of submitting a bid is 98.0% with no monetary loss, but falls to 18.8% with just a \$1 loss. A \$5 loss reduces the estimated probability of bidding to 0.3%. In the logistic regression estimates in Table 10, the main effect of a bid exceeding an item's expected value is negative and statistically significant (p < 0.001) while its interaction with value certainty marginally significant (p = 0.086). Moreover, magnitude of the expected monetary loss has a negative, statistically significant effect on the probability of bidding (p = 0.023). Therefore, we have high confidence that higher costs of overbidding reduced auction fever in the 2-bidder auctions.

The second pattern consistent with Hypothesis 3 is that in the 6-bidder uncertain-value auctions the probability of bidding declines as the losses increase. Table 9 shows that the estimated probability of bidding in these auctions increases from 22.8% with no monetary loss to 26.3% when a bid would result in a \$1 loss, but this is not statistically significant. The relevant variables in the logistic regression are the main effect of a bid exceeding its expected item value, the main effect of the expected monetary loss, and the interaction of these variables with six bidders. The sum of these effects is positive, but a Wald test cannot reject the null hypothesis that the sum of the coefficients is zero (p = 0.166).

As noted above, the main effect of the monetary loss from winning is negative and statistically significant in the bidding model. Its interaction effect with having six bidders in the auction is small and statistically insignificant (p = 0.983). Thus the greater expected losses from winning discourage bidding in the 6-bidder uncertain-value auctions. The estimated probability of submitting a bid decreased to 15.4% when expected monetary loss was \$5.

The final pattern consistent with Hypothesis 3 is that expected monetary losses monotonically reduce the propensity to bid in 6-bidder certain-value auctions. As in the 2-bidder certain-value auctions, most of the reduction in bidding occurred as soon as the bid would result in a loss. The effect of going from no monetary losses to a \$1 loss was a reduction in the probability of bidding from 26.3% to 7.9%. Increasing the monetary loss to \$5 further reduced the probability by an additional 1.1 percentage points. This pattern is statistically significant. The relevant logistic regression variables are the two-way interaction of the bid exceeding expected value with certain item values and the three-way interaction of exceeding expected value, certain item values and six bidders. The sum of these interactions is negative and statistically significant (Wald test, $p < 0.001$).Overall the pattern of results in our logistic regression models supports Hypothesis 3. There were two bidders who were willing to risk fairly high losses to win the auction. The remaining 96 bidders exhibited rational irrationality with regard to auction fever.

In summary, the current study's experiments replicated and extended the key finding in the previous studies on gift cards and consumer products. The propensity to catch auction fever and its magnitude declines as financial stakes increase. We also find a negative relationship between the costliness of overbidding and the propensity to overbid.

= = = Insert Table 9 and Table 10 about here = = =

GENERAL DISCUSSION AND CONCLUSION

We used methodological triangulation to fill a confusion gap about the relationship between financial stakes and auction fever. Whether it was Amazon.com gift cards (Study 1), a host of consumer products on eBay (Study 2), or abstract items in a behavioral laboratory (Study 3), we found that people were less likely to fall victim to auction fever and its magnitude declined as financial stakes increased. Further, our behavioral laboratory experiments gave us the control to test for a negative relationship between the costliness of overbidding and the propensity to overbid, which was supported. These findings push our thinking about auction fever and competitive decision making in several ways.

First, we fill a confusion gap in the auction fever literature. The late philosopher Justus Buchler (2013) envisioned science as a method by which "the ultimate conclusion of every man [about a phenomenon] shall be the same" (p. 18). The current research was motivated by observing that the evidence about the relationship between auction fever and financial stakes was not the same. Some scholars state that financial stakes make little difference on auction fever (Malmendier & Lee, 2011) and others claim that increasing them make matters worse (Malhotra et al., 2008). Through re-analyses of data, conceptual extension, and generalization, we found that there are limits to auction fever. Whereas previous auction-fever scholarship focuses on the psychology of winning at any cost (Ku et al., 2005; Malhotra, 2010), we show how the cost of winning affects bidding behavior. Our studies suggest that the theory of auction fever carries the most impact when studying competitive environments with low financial stakes. This does not make auction fever a phenomenon to dismiss in organizational behavior, behavioral economics, or consumer behavior research. Rather, auction fever is a phenomenon that scholars may find of great value when studying the thousands of organizations auctioning off large quantities of low-priced items every day.

The second contribution is practical, adding size to the science of auction fever. Our second contribution is complementarity to auction fever scholarship. Across behavioral economics, organization behavior, consumer behavior research, the burgeoning literature on auction fever focuses primarily on whether auction fever exists and whether various factors (including financial stakes) impact auction fevers prevalence. The focus on whether an effect exists is essential for scholars generating knowledge and useful for managers generating profits. But economic historians Ziliak and McCloskey (2008) remind us that the knowledge that an effect exists is only as useful as knowing how large that effect is. As their examination of the historical use of the ideas of statistical and practical significance asserts (McCloskey & Ziliak, 1996), scholars who only know whether an effect exists – and not also how much the effect matters – risks unintentionally giving people a bait and switch. While there was variance across our studies as to the impact financial stakes had on auction fever, the boundaries of the impact are significant. When auctioning Amazon.com gift cards, moving from the minimum item value to the maximum reduced the estimated probability of overbidding by 23.9 percentage points (Study 1). When auctioning off items on eBay, moving from the minimum item value to the maximum item value reduced auction fever by 19.4 percentage points for the median consumer product (Study 2). Finally, there was a 67.7 percentage difference in overbidding between the maximum and minimum values of our items in our laboratory experiments (Study 3).

Addressing a 30-year old question. Our third contribution is broader and derives from our use of datasets with incentives spanning from cents to the thousands of dollars. Thirty-years ago, Thaler (1986) asked general question about competitive decision making: “Do people tend to make better decisions when the stakes are high?" In our setting, "better decisions" translate to an auction winner not falling victim to auction fever. Thaler's (1986) tentative conclusion was that there is little evidence in the affirmative. However, the "evidence" cited in the Thaler (1986) paper shares a characteristic with other papers taking the same position (e.g. Malhotra et al., 2008). The shared characteristic is that the range of incentives in these competitive decisions under investigation is small ($2 to $40) relative to the current research's range: 99¢ to $3,000. Competitive decisions in the real world often involve considerably larger ranges of stakes. The current paper therefore challenges this assumption that stakes are irrelevant by using a range that is more realistic – at least when it comes to English auctions. This contingency of the English auction context is necessary. Camerer and Hogarth's (1999) often-cited review reminds us that incentives help people make better decisions when the task is cognitively simple compared to complex: such as deciding whether or not to bid at auction versus calculating the answer to a multivariate calculus problem. Thus, our answer to Thaler's (1986) question is "it depends" rather than "no." Should we push stakes into the hundreds and thousands of dollars, irrationality has its boundaries – at least in the widespread English auction.

Often we hear stories of people getting carried away and overbidding in English auctions. We find evidence that, while some people do get carried away, the tendency to catch auction fever is reduced as the financial stakes surrounding the item increase. Indeed, auction fever is an irrational behavior that comes at a price, but it seems that the price is a powerful predictor of whether people get carried away.

ENDNOTE

[1] Counter to the Malmendier and Lee's (2011) paper's claim, the plot of the relationship between financial stakes and auction fever found in Panel A of their online appendix presents a negative trend.

[2] We thank the editor for bringing this possibility about eBay's platform and auction system to our attention.

[3] A factor that could impact bidding behavior on eBay is shipping cost neglect. Hossain and Morgan (2006) find that bidders in eBay auctions tend to ignore or steeply discount shipping costs as part of the price of an item, focusing instead on the bid price. Shipping costs are not shown in eBay's search lists, and on bidding pages they are listed separately in smaller font than the bid price. If bidders focus on the bidding price of the item, then including shipping costs would add unnecessary noise to the data. We tested for shipping cost neglect in Malmendier and Lee's data by analyzing the effect of changes in shipping costs on final bid prices. Bidders who take full account of shipping costs will respond to a $1 increase in shipping costs with a $1 reduction in their maximum bid. Consequently, regressing bid prices against shipping costs should generate a $\hat{\beta}$ of -1. Because the dataset contains 107 distinct item types of varying prices and shipping costs, we scaled the data to allow us to test the relationship between shipping costs and final bids across all items simultaneously. For each item type we calculated the average final bid and average shipping cost. We then subtracted these averages from the observed final bid and shipping cost in each auction, and divided these de-meaned observations by the average final bid. Regressing the scaled bid prices against the scaled

shipping costs we estimate a relationship of -0.495 (s.e. = 0.126, $p < 0.001$). The reported standard error is robust to heteroscedasticity, which is present in the data. In our sample a \$1 increase in shipping costs reduced the final bid price by only about 50 cents. The 95% confidence interval for this estimate is ± 0.246, which excludes -1 by a comfortable margin. Moreover, very little of the variance in bid prices can be explained by variance in shipping costs: the model $R^2 = 0.0522$. We conclude that there was substantial shipping cost neglect among the bidders in this sample, and we therefore focus on bid prices in our statistical analysis.

[4] When conducting the auctions we included a third treatment variable, the presence or absence of observers. Ku, et al. (2005) report more overbidding in a live auction – where there is an audience to the bidding – than in online auctions. In half of our experiments the participants who were waiting for their turn to bid sat in the room with the active bidders and watched them compete. In the other half the participants waiting to bid were kept in a separate room. We found no significant main or interaction effect of these observers. Consequently, we pooled the data across this treatment variable and exclude it from our statistical models for simpler interpretation of the results.

[5] Conventional auction theory holds that in an English auction the bidder with the highest value ($v1$) will win the item at a price equal to the second highest value ($v2$), resulting in a surplus of $\Delta = v1 - v2$. A participant's expected earnings in a given auction was equal to the product of the probability that he was assigned the highest value (p_h), the probability that that auction was selected for payment on a given roll (p_s), the number of rolls (R) and Δ. Consequently, for the 2-bidder auctions the expected earnings were $1/2 \times 1/3 \times 1 \times \Delta = \Delta/6$, and for the 6-bidder auctions it was $1/6 \times 1/9 \times 9 \times \Delta = \Delta/6$.

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Table 1. The current paper fills a confusion gap about the relationship between financial stakes and auction fever through theory development by replication.

	Same Measurement and Analysis	**Different Measurement and/or Analysis**
Same Data Set	*Checking of analysis* is not applicable in the current paper. I	The current Studies 1 and 2 *re-analyze data* from the ML&J papers. II
Same Population	*Exact replication* is not applicable in the current paper. III	The current Study 2 is a *conceptual extension* of our Study 1. IV
Different Population	The current Study 3 is an *empirical generalization* of our Study 1. V	The current Study 3 is a *generalization and extension* of our Study 2. VI

Note: The table and italicized terms are adapted from Tsang and Kwan (1999: 766). ML&J denotes the Malmendier and Lee (2011) and Jones (2011) papers.

Table 2. In Study 1, there is a negative relationship between an individual's willingness-to-pay and the likelihood and magnitude of auction fever using Jones' (2011) Amazon.com gift card auctions on eBay.

	Model 1		Model 2	
	Propensity to overbid		Percent bid above face value	
Variable	Coefficient	Standard Error	Coefficient	Standard Error
Constant	0.3701	0.2625	0.0169	0.0143
Item Value (Face value of gift card)	**-0.0026****	**0.0011**	**-0.0002*****	**0.0001**
eBay Bucks Redeemable	0.1233	0.3506	-0.0172	0.0172
eBay Bucks Redeemable x Item Value	-0.0139**	0.0062	-0.0008**	0.0004
Bidder Rating Percentile	-0.0150***	0.0034	-0.0011***	0.0002
Number of Bids	0.0324	0.0223	0.0030**	0.0012
Observations	477		477	
* $p < .10$, ** $p < .05$, *** $p < .01$				

Note: Key relationships are **bolded**. Model 1 is a logistic regression with bidding beyond a gift card's face value as the dependent variable. Model 2 is a Tobit regression with the percent by which an overbid exceeded the card's face value as the dependent variable.

Table 3. In Study 2, there is a negative relationship between an individual's willingness-to-pay and the likelihood and magnitude of auction fever using Malmendier and Lee's (2011) consumer product auctions on eBay.

	Model 3		Model 4	
	Propensity to overbid		Percent bid above face value	
Variable	Coefficient	Standard Error	Coefficient	Standard Error
Constant	-0.705	0.436	0.111	0.104
Natural log of the BIN Price	**-0.317*****	**0.086**	**-0.162*****	**0.025**
Natural log of the BIN Frequency	**-0.422*****	**0.046**	**-0.100*****	**0.009**
Standard Deviation of BIN Prices	**0.016*****	**0.004**	**0.005*****	**0.001**
Male	0.208	0.197	0.120***	0.412
Female	-0.140	0.260	0.026	0.053
Young	-2.738***	1.061	-0.559***	0.165
Teen	-0.722	1.052	-0.078	0.159
Liberal	-1.063**	0.501	-0.369***	0.091
Conservative	-1.141**	0.484	-0.356***	0.095
Computer Hardware	-0.044	0.235	-0.016	0.045
Financial Software	0.761***	0.272	0.072	0.057
Sports Equipment	0.930***	0.324	0.628***	0.106
Personal Care Products	-0.238	0.206	-0.113***	0.042
Perfume & Cologne	-0.165	0.340	-0.141*	0.072
Games & Toys	1.329	1.032	0.159	0.154
Books	0.999***	0.287	0.179***	0.065
Cosmetics	0.525	0.561	-0.096	0.109
Household Products	-0.460	0.465	-0.080	0.096
DVD	0.876***	0.312	0.064	0.056
Observations	1,870		1,870	
Pseudo R^2	0.1360		N/A	
* $p < .10$, ** $p < .05$, *** $p < .01$				

Note: Key relationships are **bolded**. Model 3 is a logistic regression with bidding beyond an item's lowest matching BIN price as the dependent variable. Model 4 is a Tobit regression with the percent by which an overbid exceeded the item's lowest matching BIN price as the dependent variable.

Table 4. In Study 2, there is a negative effect of absolute price and percentage increase of an item on the probability of overbidding on that item – even across a host of consumer products auctioned on eBay.

Product Category	BIN Price	BIN Frequency	BIN Standard Deviation
Consumer Electronics	-0.06	-0.09	0.33
Computer Hardware	-0.05	-0.07	0.26
Financial Software	-0.08	-0.10	0.40
Sports Equipment	-0.08	-0.10	0.39
Personal Care	-0.06	-0.07	0.29
Perfume & Cologne	-0.07	-0.10	0.38
Games & Toys	-0.05	-0.07	0.28
Books	-0.07	-0.09	0.34
Cosmetics	-0.08	-0.10	0.40
Home Products	-0.05	-0.07	0.25
DVDs	-0.07	-0.10	0.38

Note: A $1 increase in the BIN price reduced the probability of overbidding by 0.05 to 0.08 percentage points. A one-percentage point increase in the BIN frequency reduced the probability of overbidding by 0.07 to 0.1 percentage points. A $1 increase in the standard deviation of available BIN prices increased the probability of overbidding by 0.25 to 0.39 percentage points.

Table 5. Study 2 – Change, in percentage points, in estimated probability of overbidding between the minimum and maximum values of the main independent variables.

Product Category	BIN Price	BIN Frequency	BIN Standard Deviation
Consumer Electronics	-34.0	-62.6	69.6
Computer Hardware	-23.8	-63.1	28.6
Financial Software	-23.8	-56.9	12.7
Sports Equipment	-27.4	-41.0	7.6
Personal Care	-19.9	-63.8	50.9
Perfume & Cologne	-3.3	-29.7	2.1
Games & Toys	-10.5	-32.6	13.6
Books	-6.3	-38.8	1.1
Cosmetics	-0.7	-8.0	0.2
Home Products	-19.4	-28.4	6.7
DVDs	-5.1	-33.3	2.4

Note: Between the minimum and maximum BIN price the median reduction in the probability of overbidding was 19.9 percentage points. Between the minimum and maximum BIN frequency the median reduction in the probability of overbidding was 38.8 percentage points. Between the minimum and maximum standard deviation of available BIN prices the median increase in the probability of overbidding was 7.6 percentage points.

Table 6. Study 3's experimental design of the English auction

Session	Bidders per Group	No. of Groups	Auctions per Group	Uncertain Value Auctions Discarded	Total Auctions
1	2	4	6	4	20
2	2	4	6	4	20
3	2	4	6	5	19
4	2	4	6	0	24
5	2	3	6	0	18
6	2	4	6	0	24
7	6	2	18	18	18
8	6	2	18	0	36
9	6	1	18	9	9
10	6	1	18	0	18
11	6	2	18	0	36
Total	--	31	--	40	242

Table 7. In Study 3, overbidding occurred most frequently when item values were uncertain. Overbids were of greatest magnitude when there were 6 bidders rather than 2 bidders.

Treatment Condition	Percent of bidders who bid above value[a] at least once	Percent of bids that were above value	Mean percent by which overbids exceeded item value (Standard Deviation)
2 bidders, uncertain item values	21.7%	19.6%	19.2% (13.1%)
2 bidders, certain item values	4.3%	4.3%	25.6% (7.5%)
6 bidders, uncertain certain item values	19.6%	26.7%	36.2% (27.6%)
6 bidders, certain item values	8.7%	5.6%	40.5% (30.0%)
Overall	23.4%	12.4%	29.4% (22.8%)

a. For the auctions with uncertain values, expected value is used.

Table 8. In Study 3, the frequency and magnitude of auction fever declines as the item's value increased in the behavioral laboratory.

	Model 5 Propensity to overbid		Model 6 Percent bid above (expected) value	
Variable	Coefficient	Standard Error	Coefficient	Standard Error
Constant	6.225***	1.586	0.371***	0.045
Six bidders in the auction	0.015	0.724	0.049**	0.024
Item values were certain	-1.665*	0.788	-0.022	0.020
Six bidders × Item values certain	-0.007	1.060	-0.032	0.028
Auction number	0.058	0.068	0.000	0.002
Item value	**-0.204*** **	**0.043**	**-0.008*** **	**0.001**
Observations	242		242	
Wald χ^2	29.52		80.88	
Log likelihood	-62.66		194.47	

* p < .10, ** p < .05, *** p < .01

Note: Key relationships **bolded**. Model 5 is a random-effects logistic regression with bidding beyond an item's induced (expected) value as the dependent variable. Model 6 is a random-effects Tobit regression with the percent by which an overbid exceeded the item's induced (expected) value as the dependent variable.

Table 9. In Study 3, there is a negative relationship between the probability of submitting a bid and the monetary loss from winning.

Treatment Condition	No Monetary Loss	$1 Loss	$5 Loss
Two bidders, uncertain item values	98.0%	86.2%	75.9%
Two bidders, certain item values	98.0%	18.8%	0.3%
Six bidders, uncertain item values	22.8%	26.3%	15.4%
Six bidders, certain item values	26.3%	7.9%	6.8%

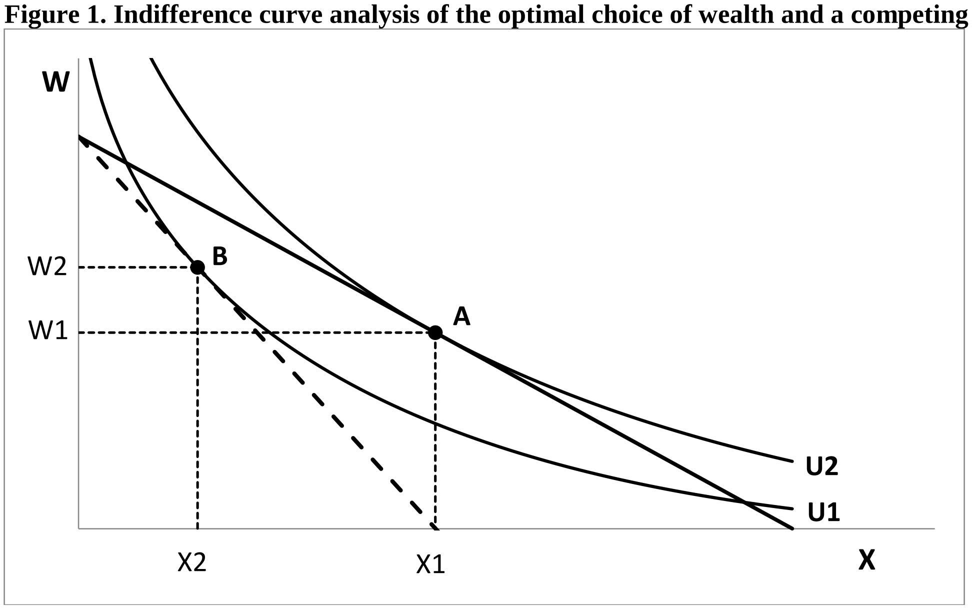
Table 10. In Study 3, the propensity to submit a bid is negatively affected by whether the current bid would exceed the expected value of the item and the expected monetary loss of winning the item.

Independent Variable	Coefficient (Standard Error)
Constant	3.872*** (0.217)
Item values were certain	0.041 (0.271)
Six bidders in the auction	-5.091*** (0.240)
Six bidders × Item values certain	0.145 (0.281)
Bid would exceed expected item value	**-1.871*** (0.516)**
Bid would exceed expected item value × Item values certain	-2.454* (1.420)
Bid would exceed expected item value × Six bidders	2.229*** (0.5537)
Bid would exceed expected item value × Six bidders × Item values certain	0.717 (1.433)
Expected monetary loss from winning at the current bid	**-0.171** (0.075)**
Expected monetary loss × Item values certain	-0.877 (0.837)
Expected monetary loss × Six bidders	0.002 (0.078)
Expected monetary loss × Six bidders × Item values certain	1.006 (0.838)
Observations	17,353
Wald χ^2	1,387.65
Log likelihood	-7,308.59

* $p < .10$, ** $p < .05$, *** $p < .01$

Note: Key relationships **bolded.** The above analysis is a random-effects logistic regression model.

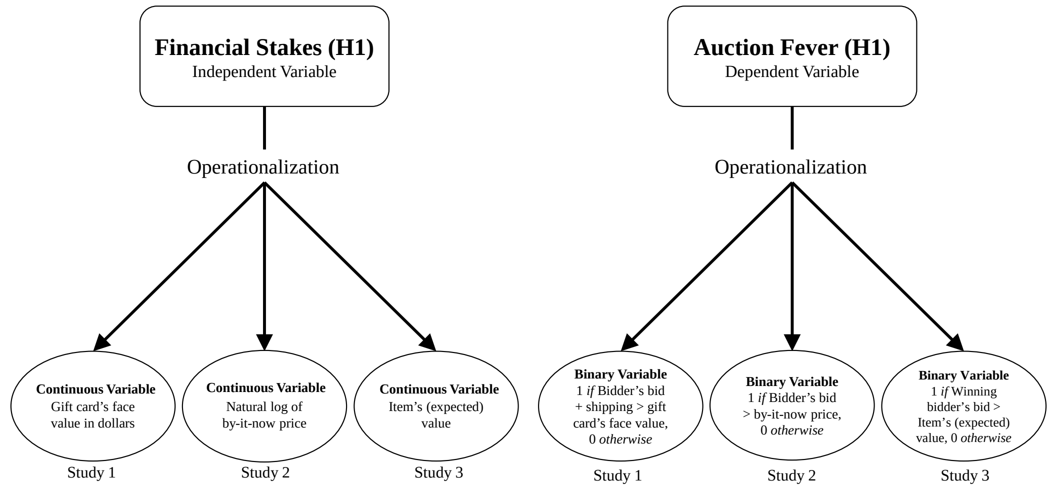
Figure 1. Indifference curve analysis of the optimal choice of wealth and a competing objective.



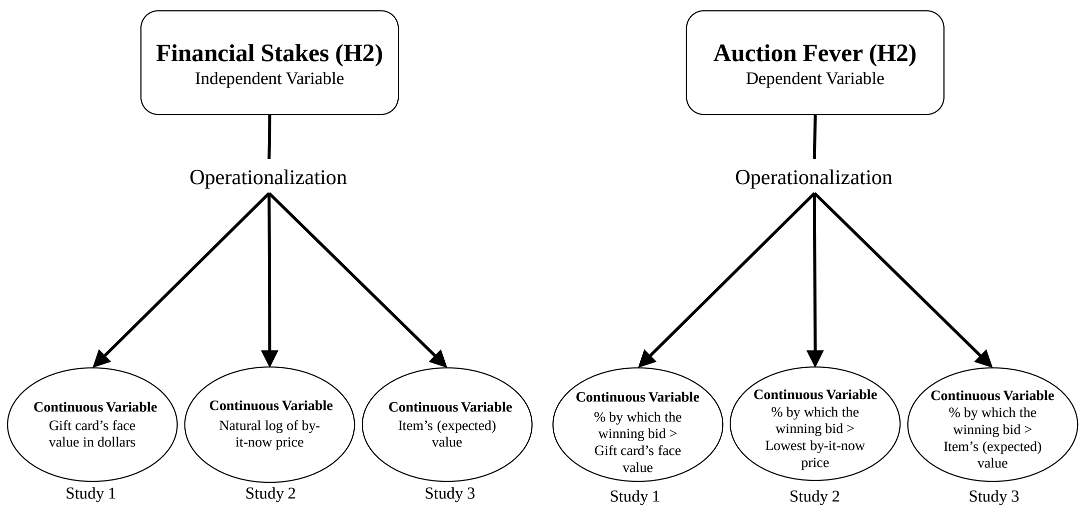
Note: When the tradeoff of wealth for the competing objective is less favorable, the optimal choice is more heavily weighted toward wealth (point B versus point A).

Figure 2. The constructs financial stakes and auction fever were operationalized in multiple ways in our studies.

Panel A. Hypothesis 1



Panel B. Hypothesis 2



Panel C. Hypothesis 3

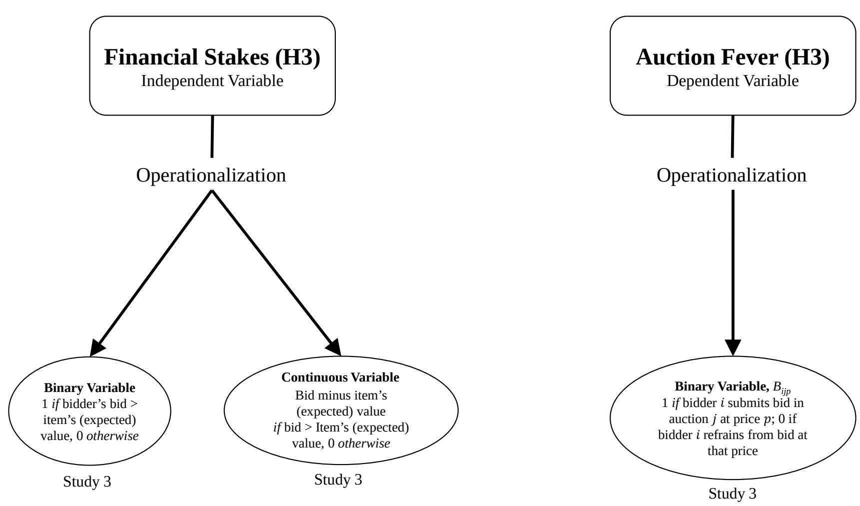
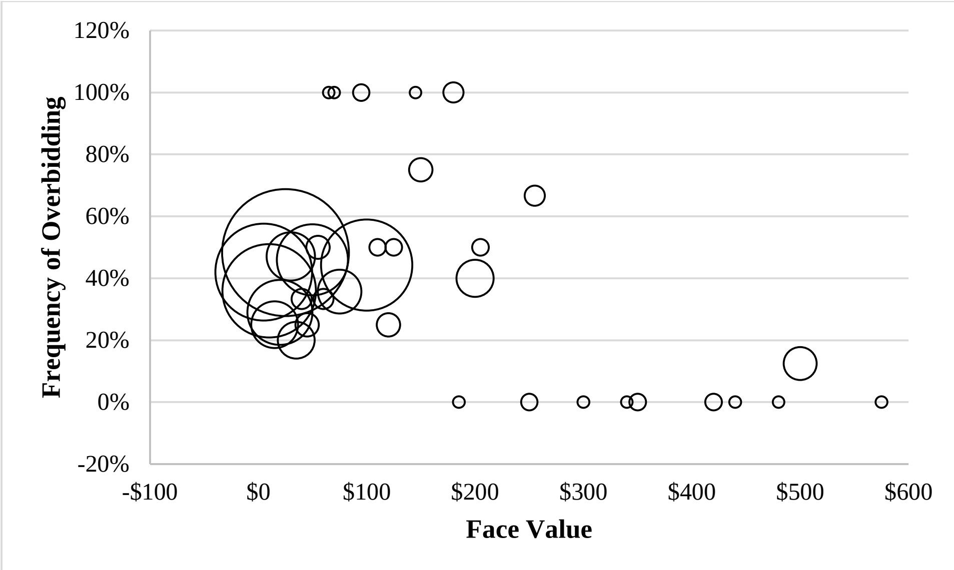
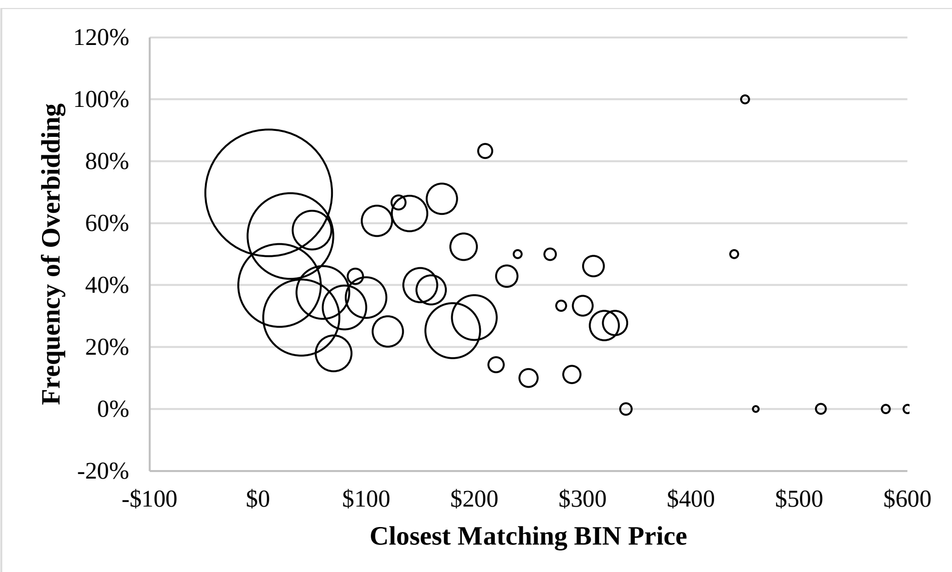


Figure 3. In Study 1, the negative relationship between the face value of Amazon.com gift cards and the frequency of auction fever in Jones' (2011) eBay auctions.



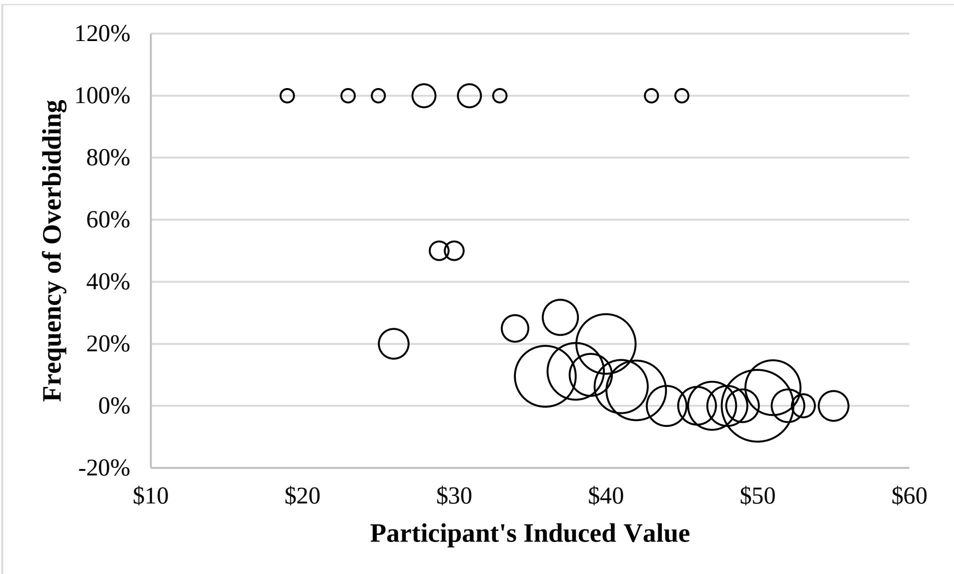
Note: Marker size indicates the number of observations.

Figure 4: In Study 2, the negative relationship between the value of consumer product and the frequency of auction fever in Malmendier and Lee's (2011) eBay auctions.



Note: Marker size indicates the number of observations.

Figure 5: In Study 3, the negative relationship between the participant's (expected) induced value and the frequency of auction fever in our laboratory experiments.



Note: Marker size indicates the number of observations.