Market Lett (2009) 20:245–261
DOI 10.1007/s11002-009-9068-3

The effect of experience on Internet auction bidding dynamics

Xin Wang · Ye Hu

Published online: 4 February 2009

Abstract On the basis of the bidding history of a panel of new eBay bidders, we examine the impact of different types of experiences on bidding behavior evolution. Accounting for unobserved bidder heterogeneity, the results indicate that losing experiences make the bidders' bidding behavior evolve toward the normative predictions of auction theory, in that they submit fewer bids and bid later. Winning experiences, however, do not have such an effect. Moreover, the experience effect pertains to the bidder's entire previous bidding experience regardless of product categories. We also assess the potential bias introduced by using feedback ratings (compared with actual participation) as experience measures.

Keywords Internet auction · Asymmetric experience effects · Bidding behavior

1 Introduction

The invention and expansion of the Internet during the 1990s popularized auctions as successful and powerful pricing tools. Consumers can bid on everything from collectable coins to an automobile on eBay. To help auction bidders minimize their bidding effort, eBay allows bidders to submit their maximum willingness to pay (WTP) at any time during the auction (hidden from other bidders), and then bids on their behalf. Previous auction literature prescribes that because a person's WTP (i.e., final bid) conveys private valuation for the product, the equilibrium bidding outcome should be that a bidder submits only one bid, equal to his or her WTP, near the end of an auction (e.g., Bajari and Hortascu 2003; Ockenfels and Roth 2006; Wilcox

X. Wang (✉)
International Business School, Brandeis University, Waltham, MA 02454, USA
e-mail: xinwang@brandeis.edu

Y. Hu
C.T. Bauer College of Business, University of Houston, Houston, TX 77204, USA
e-mail: yehu@uh.edu

2000). However, empirical observations reveal that, despite the convenience of proxy bidding, many bidders constantly follow the bidding progress and submit multiple incremental bids (Bradlow and Park 2007; Park and Bradlow 2005). Large variation also exists in the submission timing of final bids. Correspondingly, previous research investigates two important bidding behavioral variables: the number of bids submitted (or multiple bidding) and late bidding (e.g., Borle et al. 2006; Ockenfels and Roth 2006; Roth and Ockenfels 2002; Wilcox 2000).

We use unique panel data that track all bidding activities of a group of new eBay bidders over 6 months to determine the effect of various types of experience on bidding behavior dynamics. Following the convention of learning literature (e.g., Darr et al. 1995), we define experience as the actual number of auctions in which a person participates. Therefore, the research question we address considers whether the experience effect (i.e., learning as a result of experience) derives solely from prior experience within the same product category or from the complete bidding history of a bidder. Furthermore, we quantify the asymmetric effects of winning and losing experiences on the dynamics of individual bidding behavior (i.e., number of incremental bids submitted and late bidding). Losing experiences prompt bidders to bid more efficiently than do winning experiences and move bidding strategies toward the theoretical predictions of equilibrium strategies more quickly. Winning experiences, in contrast, do not drive bidders toward the bidding equilibrium predicted by auction theory.

The research contribution of this paper therefore is threefold. First, our study employs a different construct for experience than that used by prior research (i.e., feedback ratings). With the complete bidding history, we can categorize experience by various types, such as in- versus out-of-category and winning versus losing. This construct also facilitates a fuller understanding of the experience effect, compared with the feedback rating, which represents only a subset of the winning experiences. Our analysis shows that the experience effect is not, by and large, product-category specific; rather, prior experiences across product categories contribute to the convergence of bidding behavior toward the theoretically predicted bidding equilibrium. Second, we examine the behavioral aspect of experience and the quantified asymmetric impact of winning and losing experiences on bidding behavior. We find that losing experiences push the bidders' bidding behavior toward the normative predictions of auction theory, in that they submit fewer bids and bid later. Winning experiences, however, can be counterproductive. Third, we compare models using various experience measures and constructs to shed light on the biases that may arise in inferences about the experience effect.

2 Antecedents of online bidding equilibrium

To date, most research on Internet auctions consider how various auction sellers or environmental factors, uncontrolled by the bidder, may influence the outcome of an auction. For example, Melnik and Alm (2002) examine the seller's reputation; Kamins et al. (2004) study reserve prices and minimum bids; Wang et al. (2008) address "buy-it-now" auctions (i.e., allowing the bidder to end an auction prematurely at a fixed price); Nunes and Boatwright (2004) investigate incidental prices (deemed irrelevant to the goods); and Park and Bradlow (2005) develop an integrated model that characterizes within-auction bidding process by modeling bidders' willingness to bid (WTB).

Some previous research have particular relevance for our study. For example, the timing of bids has received significant attention due to its important strategic implications for both private- and common-value auctions.[1] Late bidding represents the best response to incremental bidding and protects private information about product valuation (Bajari and Hortascu 2003; Ockenfels and Roth 2006; Roth and Ockenfels 2002). Roth and Ockenfels (2002) survey eBay bidders in the computers and antiques categories and find that experienced bidders tend to snipe (submit a bid toward the end of the auction) more often than do inexperienced bidders. Several studies consider both bid timing and number of incremental bids empirically. For example, Wilcox (2000) documents that experienced bidders are more likely to snipe and less likely to submit multiple bids than are inexperienced ones. When a common value component marks the auctioned product, this experience effect becomes more pronounced. Similarly, Ockenfels and Roth (2006) report that the bidder's feedback ratings relate negatively to the number of incremental bids submitted, though they do not seem to have statistically significant relationships with late bidding. Borle et al. (2006) analyze the degree of multiple bidding and late bidding using cross-sectional data from 15 eBay product categories and find that experienced bidders refrain from submitting multiple bids but tend to bid at either the beginning or the end of the auction.

Yet prior research almost exclusively uses the bidder's feedback as a proxy measure for experience. Because an eBay customer can act as both a bidder and a seller, received feedback usually does not come solely from bidders. In addition, feedback ratings in general vastly underreport actual experiences, because not all auction transactions receive feedback. In our data set, at the end of the data collection period, the auction buyers had participated on average in 22.88 auctions but received only 3.16 feedback rating points. Moreover, because a losing bidding experience receives *no* feedback, the feedback ratings only (partially) capture winning experiences. In this study, we use eBay bidders' actual participation numbers, obtained from a cross-category panel data set. By examining the bidders' full history of auction participation and taking into account the nature of the experience, we provide more accurate insights into the impact of experience on bidding behavior both qualitatively and quantitatively.

More importantly, studies of the experience effect generally draw from product-category-centric data. For example, Roth and Ockenfels (2002), Park and Bradlow (2005), and Ockenfels and Roth (2006) analyze one or a few preselected product categories. Borle et al. (2006) conduct a larger-scale analysis based on 15 product categories, but their data are cross-sectional in nature and their inferences remain category specific. Because research findings thus far have been limited to a particular product category, the question of whether bidding behavior is attributable

[1] In private-value auctions, bidders' valuations are assumed to be independent. In contrast, a common component affects all bidders' valuations (e.g., Wilson 1977) in common value auctions. Reasons for such a common component include "some prestige value of owning and might be admired by others, or items that may be resold later at an unknown price" (Milgrom and Weber 1982, p. 1095; Wilcox 2000, p. 369).

to within-category experiences or to the entire bidding history has not been resolved. To gauge the effect of experience on bidding behavior, especially its evolution, we require user-centric data and must observe the full participation history of each bidder.

Another key focus of this research pertains to the ability to gauge the effects of different types of experience on the basis of auction outcomes. Consider the bidding sequence of a real bidder in our data set, whom we call Jane, to demonstrate the dynamics of bidding behavior (Fig. 1).

Jane was a new eBay user at the beginning of our observation. She participated in 23 auctions during a 6-month period, of which she won seven (marked as squares in Fig. 1). Early in her bidding history, she submitted multiple incremental bids, sometimes as many as 17 in one auction. Despite her persistent effort, she lost all four of her first auctions. As time went by, she decreased the number of incremental bids she submitted, and she won her fifth auction, for which she submitted only one bid. As she continued to gain experience, the number of bids she submitted seemed to decrease. Overall, the timing of her last bid (dotted line, normalized to [0, 1] with respect to the auction duration, for which the smaller number indicates closer to the end of auctions) also seems to have moved closer to the auction ending time. This example suggests that Jane's bidding behavior was influenced differentially by her winning and losing experiences. Such dynamics cannot be captured accurately by the cross-sectional data employed by previous research (e.g., Borle et al. 2006; Ockenfels and Roth 2006; Roth and Ockenfels 2002; Wilcox 2000). Therefore, to determine how the outcome of the auction experience (winning vs. losing) influences the auction participant's bidding behavior, research requires complete bidding histories to ascertain the nature of the experience.

3 Data description

To provide more accurate assessments of experience effects on bidding behavior, we employ a novel panel data set that consists of the complete bidding history of

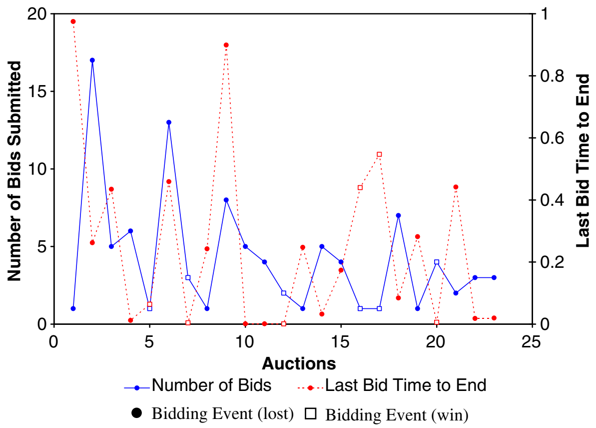

Fig. 1 Bidder Jane's number of bids and last bid time to end

131 new eBay customers (tagged as “new” by eBay at the beginning of the data collection) during a 6-month window from December 2004 to May 2005. In total, we obtain 2,997 auction observations. The data are extracted from eBay’s Web site, which includes publicly available auction information and bidding histories.

The sample eBay customers in our analysis are selected randomly. They bid on a wide variety of products: 23% of the auctions involve apparel and accessories (e.g., coats, hats, pants, ties, sunglasses, jewelry), 42% are for consumer electronics (e.g., TV, VCR, DVD player, camera, camcorder, games); 11% for house wares such as tools and toys; 15% for collectibles such as coins, autographed art, and artworks; and the remaining 9% are products such as gift certificates, vacation packages, and concert tickets.

On average, the bidders in our data set participated in 22.88 auctions (standard deviation=32.40) during the 6-month period and won 26% of the time (mean=5.95). The number of auctions each individual bidder participated in varies widely, from 3 to 244. Because of these variations in the number of observations, the data set is unbalanced. We treat the number of auction participations as exogenous, because it depends largely on demand for a certain product, which can arise randomly over time.

In Table 1, we present the descriptive statistics of our data. Among the bidder–auction observations, an average bidder submits 2.42 incremental bids, and the last bid is submitted 62% of the way into the auction time span. The highest losing bid falls short of the winning price by 33%. Seller feedback achieves a mean of 5,504 and a median of 551. The average number of unique bidders is 6.48 per auction (standard deviation=5.08), and the market value of the products bid on has a median cost of $44 (mean=$198, standard deviation=$851).

One caveat regarding our data set is that a new bidder may have had experience with auctions before, whether at eBay (using a different user identification) or on other Web sites. In this case, the bidder’s behavior could demonstrate a more mature pattern overall and less systematic time-series evolution. In other words, our inference of behavior dynamics would be more conservative.

Table 1 Descriptive statistics of the data

Variables	Mean	Std. deviation	Min	Median	Max
Number of incremental bids	2.42	2.55	1	1	35
Last bid time	0.38	0.36	0	0.26	1
Total experiences	22.88	32.40	3	12	244
Bidder’s feedback ratings	3.16	5.90	0	1	35
Winning experience	5.95	8.96	0	3	61
Losing experience	16.93	24.89	1	8	183
Lose amount	0.33	0.34	0	0.17	1
Number of unique bidders	6.48	5.08	1	6	61
Minimum bid	38.38	356.48	0.01	5	13,276.85
Winning prices	197.88	850.82	0.01	44	16,402
Seller’s feedback ratings	5,504.7	17,004.7	0	551	250,961
Private value	0.56	0.50	0	1	1

4 Experience effect on bidding behavior

4.1 Hypotheses

As we noted, previous studies on bidding experience cannot ascertain if bidder learning accrues only to the product category under study. Our data set contains complete bidding history, including product category information, which enables us to separate in-category experiences from those out of the category and thus address our central research question for the first time. If experiences from the same category are more relevant or more likely to be recalled, within-category experiences should have a greater effect in pushing behavior toward a rational equilibrium. On this point, we offer two hypotheses:

H_{1a} *In-category experience has a greater impact than the out-of-category experience in leading bidding strategies toward equilibrium.*

However, if an experience is an experience, regardless of product category, for each bidder, we likely will observe that both within- and outside-category experiences contribute to change bidding behavior.

H_{1b} *All past experiences in the bidding history of a bidder contribute to bidding behavior evolution, not just experiences associated with the same product category of the current auction.*

Consumer behavior and decisions also may depend on the outcome of an experience. Hoeffler et al. (2006) find in lab experiments that favorable early experiences reduce the extent of search and lead to less developed preferences. Park and Bradlow (2005) empirically study bidders' latent WTB as a function of their total winning and losing experiences and find that the total number of losing experiences decreases bidders' WTB. Although the winning experience effect is negative, it is not statistically significant. Larger bid increments (i.e., difference between WTB and the immediate previous bid) also slow the bidding intensity. Therefore, we hypothesize that different types of past experiences (i.e., winning vs. losing) should affect multiple bidding and late bidding differently.

To understand this point, consider two presumptive cases. First, if a bidder wins an auction, that winning experience likely reinforces the incremental bidding strategy the bidder adopted. In other words, the bidder is more likely to be complacent and maintain current behavior patterns in subsequent auction; in this sense, winning slows the behavioral evolution toward equilibrium bidding strategies (Hoeffler et al. 2006). This claim is consistent with Lant and Montgomery's (1987) finding that, for organizational learning, the proportion of successful R&D projects has a negative effect on the current innovativeness of search. Second, imagine a bidder loses an auction in which she submitted incremental bids; finding her incremental bids unsuccessful, she is more likely to adjust her future bidding strategies. Such adjustments should involve fewer bids and later bidding, moving toward more optimal bidding behavior. Because of the monitoring and cognitive costs involved in bidding, we expect that losing experiences exert a greater impact on the convergence of the bidding behavior than do winning experiences. This hypothesized greater effect of losing experiences appears consistent with findings from organizational learning research (e.g., Herriott et al. 1985) and operations research (e.g., Ocaña and Zemel 1996).

H_2 (asymmetric effects of winning and losing): Losing experiences induce fewer incremental bids and later bidding, whereas winning experiences do not. The magnitude of the effect of a losing experience is greater than that of a winning experience.

In addition to the amount of previous participation, the outcome of the immediate past experience (e.g., win or lose, magnitude of loss) likely affects bidding behavior during the current auction. Bidders may adjust their strategies in subsequent auctions after they learn the winning price of the previous auction. The closer a losing bidder's last bidding amount is to the winning price, the stronger the remorse effect should be, especially when a bidder is opportunistic and submits a bid lower than his or her WTP. For the notebook PC data that Park and Bradlow (2005) study, this effect emerges in the form of two variables: a dummy variable if the bidder has won the previous auction (LWIN) and a continuous variable that measures the amount by which the bidder lost the previous auction (AMTLOST). The former represents a recency effect and the latter a monetary effect of the Recency–Frequency–Monetary Value (RFM) framework. Their research findings suggest that the closer the bidder is to the winning price, the higher the bidder's WTB, which in turn negatively influences the rate for bid speed. Thus, there may exist a short-term impact of a recent win or loss on multiple bidding and/or late bidding, which would move bidding behavior in the direction of predicted bidding equilibrium.

H_3 (short-term remorse effect): The closer the bidder's final bid to the previous winning price, the more likely he or she is to submit fewer and later bids in the current auction.

Furthermore, a bidder's current bidding behavior likely depends somewhat on previous behavior, commonly referred to as the carry-over or inertia effect, which captures the persistence of behavior. We hypothesize that the carry-over effect exists in the evolution of bidding strategies. Specifically,

H_4 The carry-over effect of the previous bidding behavior is positive.

4.2 Model specification

Available information about bidders and auctions in the data set consists of behavioral variables, auction outcome variables, and auction environment variables. For example, to test H_1, we estimate the within-category effect (*InExp*) and outside-category effect (*OutExp*) explicitly, while controlling for the influences of auction-specific factors (e.g., minimum bid, seller feedback) and individual bidder-specific propensities. Formally,

$$\begin{aligned} Y_{it}^{(m)} = \alpha_i^{(m)} &+ \beta_0^{(m)} Y_{it-1}^{(m)} + \beta_1^{(m)} \ln(InExp_{it}+1) + \beta_2^{(m)} \ln(OutExp_{it}+1) \\ &+ \beta_3^{(m)} LoseAmt_{it} + \beta_4^{(m)} \ln(NInd_{it}) + \beta_5^{(m)} \ln(MinBid_{it}) \\ &+ \beta_6^{(m)} \ln(WP_{it}) + \beta_7^{(m)} \ln(SellFB_{it}) + \beta_8^{(m)} Prvt_{it} + \varepsilon_{it}^{(m)} \end{aligned}, \quad (1)$$

where the bracketed superscript $^{(m)}$ denotes the two equations pertaining to the number of incremental bids (m=1) and late bidding (m=2), respectively. The dynamic regression specified in Eq. (1) represents a lagged dependent variable model (LDV), which nests within autoregressive distributed lag models (Beck 1991; Greene 1997). We use $Y_{it}^{(1)}$ to denote the logarithm of the number of incremental bids submitted by bidder i during auction t. We consider the last bid of a bidder as his or her final bid (Borle et al. 2006; Ockenfels and Roth 2006) and measure late bidding as the length of the time interval between the last bid and the auction's ending time, scaled by the auction duration. Thus, late bidding is a continuous variable that falls between 0 and 1, such that a smaller number represents a later bid (Borle et al. 2006). We also apply a log-of-odds-ratio transformation to this variable to normalize it and use $Y_{it}^{(2)}$ to denote the transformed late bidding variable for bidder i's auction t. Both equations may be influenced by unobserved exogenous shocks, so we adopt a seemingly unrelated regression model to capture the potential correlation between ${\varepsilon_{it}}^{(1)}$ and ${\varepsilon_{it}}^{(2)}$. The variance of the error is:

$$var(\varepsilon) = \Sigma \otimes I_T, \quad (2)$$

where $\Sigma = \begin{bmatrix} \sigma_1^2 & g_{12} \\ g_{21} & \sigma_2^2 \end{bmatrix}$, from which we can derive the contemporaneous correlation measure, that is, $\rho_{12} = g_{12}/\sigma_1\sigma_2$.

Following organizational learning literature (see Darr et al. 1995 for an explanation of the learning curve), we use the total number of participation events as a measure of experience. That is, we define experience as the number of actual auctions in which a bidder has participated, whether winning or losing and across categories. For in-category experience (*InExp*), we employ the number of previous auctions in which the bidder has participated prior to the current auction of the same category. The remaining previous experiences then represent the out-of-category (*OutExp*) variable. Hence, the two variables equal total experience before the given auction, namely *TotalExp*=*InExp*+*OutExp*. We log transform both variables to ln(*InExp*+1) and ln(*OutExp*+1) to reflect the marginal decreasing effect of experience.

To test H_2 the asymmetric effect of win–lose effects, we replace *InExp* and *OutExp* in Eq. (1), with *WinExp* and *LoseExp*, respectively. Similarly, we employ cumulative winning (*WinExp*) and losing (*LoseExp*) experiences prior to the current auction as our measure.[2] Our operationalization of the experience variables thus differs from that of Park and Bradlow (2005), who measure winning experience (TWIN) and losing experience (TLOSS) as the total number of auctions won and lost by a given bidder over the entire calibration period and use the first half of their data set to initialize the experience variables. In contrast, in our analysis, *WinExp* and

[2] If an auction did not end with a sale, the tracked bidder is considered to have lost the auction because he or she did not win.

LoseExp are fully dynamic; they change for each and every bidder–auction observation. Because their effects are likely to be concave, we log transform the experience variables.

The variable *LoseAmt* captures how close a bid is to winning in the previous auction, that is, the distance between a bidder's final bid and the winning price.[3] However, because our auction data mainly function across categories, we must normalize this distance according to the winning price of the auction to ensure the comparability of the variable across auctions. The resulting variable falls between 0 and 1, and the smaller *LoseAmt*, the closer the bid is to the winning price. In the case in which the bidder has won the previous auction, *LoseAmt* is 0. Therefore, we use one variable instead of two (e.g., Park and Bradlow 2005) to test the short-term experience effect (H_3), and to ensure its normality, we take the log of the odds ratio of this variable.

To test the carry-over effect (H_4), we include the lag of the dependent variable as an explanatory variable. From a modeling perspective, including the lagged dependent variable in the model enables us to study the process explicitly. We intentionally do not specify any restrictions on parameter β_0 in the estimation to test the stationarity of the process. If the estimation suggests it is between 0 and 1, we consider the process stationary. Results from the Box–Pierce test (cf. Box and Pierce 1970) indicate that one lag is sufficient to remove the serial correlation in the error terms in our data.

Ariely and Simonson (2003) develop a multistage framework of decision dynamics in online auctions that posits that bidders are subject to the influences of auction context such as the number of bidders, number of bids, seller reputation, and starting price. They show experimentally that the bidder's value assessment of the product and bidding behavior shift during the course of the auction; therefore, we control for variables related to auction context, which also constitute an essential part of the experience. In particular, we use the winning price for an auction (*WP*) to control for the market value of the item, which varies greatly across auctions. People tend to behave more carefully and be more involved when purchasing a more expensive item, which also means they likely are more willing to engage in price searches. Note that *WP* essentially equals the transaction price of the product, or the second-highest bidder's value plus an increment specified by eBay. If an auction does not end with a sale, perhaps because the seller specified a high secret reserve (accounting for 4.14% of our data), we use the highest bid observed for that auction, which provides the closest available proxy for market value. We also use the number of unique bidders (*NInd*) in an auction as a proxy for auction competitiveness (e.g., Ockenfels and Roth 2006).[4] A seller's positive feedback ratings (*SellFB*) serve as controls for the seller's reputation and experience, which might influence the bidder's WTB (Park and Bradlow 2005). Using rationale similar to that we provided for the experience variables, we choose to log transform these control variables.

[3] Because the highest valuation of the product is not revealed, due to auction rules, we cannot expect it to influence bidders' behavior in general. We use the winning price instead, because it is observable to bidders (Park and Bradlow 2005).

[4] We do not include the number of bids together with the number of unique bidders, because they are highly correlated (Pearson r=0.768, p=0.000).

Wilcox (2000) finds that the experience effect is more pronounced for auction products with a common value component (e.g., pottery, neckties) than for private-value ones (e.g., drills, staplers). Therefore, we include a dummy variable (*Prvt*) to control for the type of auction products, equal to 0 if the product has an obvious common-value component (e.g., apparel, accessories, collectibles) and 1 otherwise (e.g., consumer electronics, toys, vacation packages).[5] Finally, bidders' propensity to submit incremental bids and bid late may be influenced by idiosyncratic characteristics. A prominent advantage of using panel data such as ours, rather than cross-sectional data, is that we can account for such heterogeneity.

5 Results

We adopt a Bayesian framework for the estimation, which has many advantages over the frequentist approach, particularly for the model we study. The number of observations varies across bidders, such that some participated in only a few auctions, whereas others attended many. The Bayesian method is especially useful for borrowing information from the overall mean when making inferences about those who have participated in only a few auctions.

A Gibbs sampling algorithm obtains samples from the full conditional distributions of the parameters specified in the model. Diffused uninformative priors reflect the minimal subjective information available about the parameter estimates. We obtain a total of 25,000 draws but discard the first 10,000 as the burn-in sample. In addition, our analysis of the variance inflation factor indicates no multicollinearity concerns between the independent variables (Allison 1999).

5.1 Parameter estimates

In Table 2, we report the parameter estimates[6] and goodness of fit (assessed by deviance information criterion, DIC) associated with four models: models 1 and 2 test H_1 and H_2, respectively. Models 3 and 4 represent two benchmark models that use the bidder's feedback ratings and the total number of auction participations, respectively, to measure experience. According to our results, model 2 (win–lose effects) statistically achieves the best fit (DIC=19,984), whereas model 3, which uses feedback, offers the worst fit to the data (DIC=20,050). In addition, model 1 (in- vs. out-of-category) performs worse (DIC=20,020) than do the models that use pooled experience (models 2 and 4) and better only than model 3. These results offer strong support for H_{1b}, which posits that changes in bidding behavior depend on

[5] We caution that such coding is based on a simple heuristic, following the precedent in previous literature and our judgment. Private- and common-value need not necessarily be dichotomous, and an affiliated-value framework would include both paradigms (e.g., Laffont and Vuong 1996). Klemperer (1998) shows that small asymmetries among bidders in common value auctions may lead to auctions with almost common values. We thank an anonymous reviewer for pointing this out.

[6] Because we use Bayesian estimation, the parameter estimates appear in distributional form. We report the means, standard deviations, and 2.5–97.5% confidence intervals (CI) for each parameter, unless otherwise noted. A parameter is statistically significant at 5% if the 2.5–97.5% CI falls completely in the positive or negative domain and does not include 0.

collective previous auction experience, rather than being limited to a single category. We also replicate model 1 without *OutExp* and find worse fit (DIC=20,039).

The difference between the parameter estimates of models 3 and 4 indicates the bias that results from using feedback due to underreporting actual experience. Model 3 suggests that more experienced bidders, as measured by eBay feedback, do *not* submit fewer bids (mean=−0.015, 95% CI [−0.058, 0.031]) but bid later than less experienced ones (mean=−0.369, CI [−0.607, −0.140]). Model 4, however, indicates that cumulative participation experience makes a bidder both submit fewer bids (mean=−0.043, CI [−0.070, −0.158]) *and* bid later (mean=−0.433, CI [−0.577, −0.295]).

Neither of the aggregate measures, feedback or total actual experiences, can help test the hypotheses regarding the effect of different types of experience. Model 1 separates out the category effects, and the result supports H_{1a}: In-category experience has a stronger impact than out-of-category experience (non-significant) in reducing multiple bids, and its effect in inducing late bidding is marginally greater. Although this finding in itself is interesting, it unlikely characterizes how bidders learn from their past experiences, because this model is dominated by those that use cross-category experience data.

In addition to offering the best fit of the data, model 2 provides valuable insights into the asymmetric effects of winning and losing experiences. Specifically, cumulative losing experience (*LoseExp*) reduces the number of bids submitted (mean=−0.054, 90% CI [−0.112, −0.007]) and promotes late bidding behavior (mean=−0.916, CI [−1.168, −0.698]), whereas winning experience (*WinExp*) has no significant influence on the number of bids submitted and hampers late bidding (mean=0.476, CI [0.194, 0.775]). These results confirm that losing experiences push a bidder's behavior toward the equilibrium bidding strategy, whereas winning experiences make the bidder more complacent.

When we compare models 2 and 3, we uncover another downside of using feedback to infer the experience effect. Because a losing experience does not receive any feedback, all feedback comes from winning experiences. Using such feedback therefore overestimates the effect of winning experience on multiple bidding (though it is not significant) and can suggest the incorrect conclusion that winning experiences promotes late bidding, whereas in fact it hampers late bidding (after we control for the nature of the experiences).

The variable *LoseAmt* captures the short-term remorse shock to the bidder, in the sense that the closer a losing bidder's previous final bid is to the winning price, the stronger the remorse effect is, especially when a bidder opportunistically submits a bid lower than his or her WTP. Such an effect would tend to make bidders more likely to submit bids closer to their WTP (e.g., Park and Bradlow 2005) and place the bid later. We find evidence in support of this argument; that is, *LoseAmt* increases the extent of late bidding (mean=0.078, CI [0.041, 0.114]).

Ariely and Simonson (2003) point out that more bids or bidders have two competing effects: They indicate the attractiveness of the product, but they also convey that the chance of getting a bargain is low. Our results support the latter effect, in that the number of individual participants (*NInd*) decreases late bidding, likely because an auction with many bidders enhances bidding competition. Greater competition lowers each bidder's chance of submitting a late bid, because the chance

Table 2 Effect of experience on bidding behavior evolution

	Variables	Model 1 (in- vs. out-of- category)	Model 2 (win vs. lose)	Model 3 (feedback)	Model 4 (total experience)
Number of Bids $Y_{it}^{(1)}$	$Y_{it-1}^{(1)}$	0.035 (0.017) [0.0007, 0.068]	0.034 (0.017) [0.006, 0.063]*	0.038 (0.018) [0.003, 0.073]	0.031 (0.018) [0.002, 0.060]*
	Experience	–	–	–0.015 (0.023) [–0.058, 0.031]	–0.043 (0.014) [–0.070, –0.016]
	In-category experience (InExp)	–0.031 (0.014) [–0.060, –0.004]	–	–	–
	Out-of-category experience (OutExp)	–0.008 (0.014) [–0.036, 0.019]	–	–	–
	Winning experience (WinExp)	–	0.010 (0.030) [–0.044, 0.077]	–	–
	Losing experience (LoseExp)	–	–0.054 (0.028) [–0.112, –0.007]*	–	–
	Loss amount (*LoseAmt*)	–0.002 (0.003) [–0.001, 0.005]	–0.001 (0.003) [–0.008, 0.005]	–0.001 (0.003) [–0.008, 0.005]	–0.002 (0.003) [–0.008, 0.004]
	Number of bidders (*NInd*)	0.044 (0.025) [–0.004, 0.094]	0.041 (0.025) [–0.008, 0.090]	0.043 (0.026) [0.001, 0.084]*	0.040 (0.025) [–0.010, 0.088]
	Minimum bid (*MinBid*)	–0.046 (0.010) [–0.064, –0.028]	–0.047 (0.009) [–0.065, –0.028]	–0.048 (0.009) [–0.067, –0.030]	–0.047 (0.009) [–0.065, –0.029]
	Winning price (*WP*)	0.109 (0.013) [0.086, 0.135]	0.109 (0.013) [0.084, 0.135]	0.110 (0.013) [0.087, 0.136]	0.108 (0.012) [0.085, 0.136]
	Seller feedback (*SellerFB*)	–0.013 (0.006) [–0.024, –0.002]	–0.012 (0.006) [–0.023, –0.004]	–0.014 (0.006) [–0.025, –0.003]	–0.013 (0.006) [–0.024, –0.002]
	Private value (*Prvt*)	–0.002 (0.046) [–0.092, 0.086]	–0.015 (0.043) [–0.091, 0.072]	–0.007 (0.043) [–0.093, 0.078]	–0.016 (0.043) [–0.103, 0.067]

Last Bid Timing $Y_{it}^{(2)}$	$Y_{it-1}^{(2)}$	0.011 (0.011) [–0.011, 0.034]	0.007 (0.011) [–0.015, 0.029]	0.013 (0.011) [–0.010, 0.036]	0.010 (0.012) [–0.012, 0.033]
	Experience	–	–	–0.369 (0.119) [–0.607, –0.140]	–0.433 (0.072) [–0.577, –0.295]
	In-category experience (InExp)	–0.265 (0.070) [–0.403, –0.128]	–	–	–
	Out-of-category experience (OutExp)	–0.262 (0.065) [–0.389, –0.134]	–	–	–
	Winning experience (WinExp)	–	0.476 (0.140) [0.194, 0.755]	–	–
	Losing experience (LoseExp)	–	–0.916 (0.121) [–10.168, –0.698]	–	–
	Loss amount (*LoseAmt*)	0.066 (0.018) [0.030, 0.101]	0.078 (0.019) [0.041, 0.114]	0.071 (0.018) [0.035, 0.106]	0.063 (0.018) [0.027, 0.097]
	Number of bidders (*NInd*)	0.357 (0.122) [0.114, 0.581]	0.347 (0.119) [0.109, 0.563]	0.350 (0.111) [0.119, 0.557]	0.336 (0.110) [0.108, 0.535]
	Minimum bid (*MinBid*)	–0.204 (0.045) [–0.295, –0.119]	–0.200 (0.045) [–0.287, –0.114]	–0.213 (0.042) [–0.294, –0.132]	–0.204 (0.042) [–0.285, –0.123]
	Winning price (*WP*)	0.363 (0.063) [0.242, 0.363]	0.360 (0.060) [0.240, 0.483]	0.378 (0.057) [0.267, 0.491]	0.365 (0.057) [0.256, 0.482]
	Seller feedback (*SellerFB*)	0.017 (0.028) [–0.039, 0.075]	0.034 (0.027) [–0.030, 0.077]	0.015 (0.027) [–0.039, 0.068]	0.025 (0.027) [–0.030, 0.078]
	Private value (*Prvt*)	–0.369 (0.202) [–0.771, 0.031]	–0.331 (0.194) [–0.656, –0.007]*	–0.311 (0.200) [–0.699, 0.100]	–0.367 (0.200) [–0.696, –0.031]*
	σ_1^2	0.411 (0.011) [0.390, 0.433]	0.410 (0.011) [0.389, 0.432]	0.411 (0.011) [0.390, 0.434]	0.410 (0.011) [0.389, 0.433]
	σ_2^2	8.888 (0.240) [8.439, 9.377]	8.801 (0.238) [8.357, 9.288]	8.936 (0.244) [8.469, 9.429]	8.837 (0.241) [8.373, 9.324]
	ρ_{12}	–0.282 (0.017) [–0.316, –0.249]	–0.287 (0.017) [–0.320, –0.254]	–0.277 (0.018) [–0.311, –0.243]	–0.285 (0.018) [–0.319, –0.252]
	DIC	20022	19984	20050	19997

Notes: Standard deviations are in brackets; 95% confidence intervals are in square brackets unless otherwise indicated. *90% confidence interval.

of facing opposing bids that reach higher than his or her WTP increase (Ockenfels and Roth (2006) report a similar result in their analysis of both eBay and Amazon auction data). Though our model does not focus on the bidding process within an auction with regard to how bidders drop out as the auction progresses, the result echoes previous research that does so, which finds that the number of latent bidders decreases as the auction draws closer to the end (Bradlow and Park 2007) and furthermore that the number of bids and bidders significantly increase the final price of the auction (Ariely and Simonson 2003), a sign of heightened competition.

Similarly, a high minimum required bid (*MinBid*) reduces the chance of attracting many bidders (and thus a bidding frenzy) and leads to more rational behavior, fewer incremental bids, and later bidding. The results also indicate that the more involved the purchase is, as measured by the winning price of an item, the more incremental bids we observe. Bidders seem to be more cautious and involved in "finding the right price" when they bid on more expensive items, which leads to more instances of multiple bidding. However, later bidding is less extensive for more expensive items, possibly because bidders fear that their late bid might not be transmitted in time (Roth and Ockenfels 2002). Again, people appear more cautious when bidding on expensive items and less willing to sacrifice the probability of winning to gain a surplus. The seller's positive feedback (*SellerFB*) has a negative effect on the number of bids submitted, probably because of the decreased uncertainty or risk associated with that auctioned item. Unlike Wilcox (2000), however, we find that new bidders in our data set tend to submit their last bids later in private- than in common-value auctions (marginally significant 90% CI [−0.656, −0.007]). Whether such behavior results from their naïveté about auctions requires further (and most likely lab-based, experimental) studies. Finally, the negative significant contemporaneous correlation (ρ) suggests that exogenous shocks affect the number of bids and late bidding in opposite directions.

In summary, our empirical results suggest that in-category and out-of-category experiences exert differential impacts on multiple bidding and late bidding, such that in-category experiences play a bigger role. However, the experience effect in online auctions derives from across all previous experiences (i.e., across categories) rather than category-specific ones. Thus, we find support for both H_{1a} and H_{1b}. Our findings also confirm H_2, which pertains to the asymmetric effects of winning and losing experiences. We find only partial support for H_3 and H_4: The short-term remorse effect is statistically significant only for late bidding, and the carry-over effect is evident only for multiple bidding. Hence, it is important to consider multiple dimensions of bidding behavior as they react differently to experiences.

5.2 Steady state effects

To offer a closer look at how bidding behavior evolves on the basis of parameter estimates, we assess the convergence of bidding behavior through steady-state experience elasticity and a simulation study. In the LDV model specification, the independent variables influence the dependent variable geometrically. Whereas b represents the current (or short-term) impact of the covariates on current Y_t (conditional on Y_{t-1}), the effect of covariates in the previous period (X_{t-1}) on Y_t still exists through Y_{t-1}, which captures the effect of X_{t-1}. Therefore, the steady-state (or long-term) effect of a covariate with parameter β is $\beta/(1-\beta_0)$, where β_0 is the autoregressive effect of Y_{t-1}. Thus, for LDV models, the effect of covariates takes place gradually and geometrically, whereas autoregressive models assume the impact of the independent variables is only immediate (Beck 1991).

In our case, the steady-state elasticity of the winning experience for late bidding is 0.480 (CI [0.195, 0.760]) and not significantly different from 0 for multiple bidding (mean=0.010, CI [−0.045, 0.080]). For losing experiences, the steady-state elasticity for multiple bidding is −0.055 (CI [−0.116, 0.000]), and that for late bidding is −0.922 (CI [−1.172, −0.701]). Therefore, the long-term losing experience is two to five times more effective in leading the bidder toward the predicted bidding strategy equilibrium. In Fig. 2, we plot the convergence path of multiple bidding and late bidding as a result of the accumulation of winning and losing experiences; all other variables remain at their mean values. The diverging effects of the two types of experience are clear, though in reality, the paths would not be as smooth, because bidders both win and lose and therefore are subject to two opposite influences over time.

The estimated fixed-effect intercepts indicate great variation across bidders in terms of their propensity to submit multiple bids and bid late. According to Model 2, the means of the intercept for the multiple and late bidding equations are 0.268 (standard deviation=0.341) and −1.147 (standard deviation=1.973), respectively. The Bayesian information criterion suggests classifying the 131 new bidders into two distinct groups according to their propensity to bid multiple times and late, as we report in Table 3. Group 1 (45%) consists of people who tend to submit fewer incremental bids but submit their last bid early, whereas the members of group 2 (55%) tend to submit more bids and like to bid late. Both indicate the naïveté of these new bidders.

6 Conclusion

We examine how bidding behavior, measured as the number of bids submitted and the extent of late bidding, evolves over time, especially as a result of bidders' experiences. Using bidder-level panel data, we find that losing experiences play more crucial roles in improving bidding strategies than do winning experiences. An old saying, "Good judgment comes from experience; experience comes from bad judgment," depicts the main gist of this finding. In addition, our empirical findings shed new light on the experience effects in online auctions, in that we find behavioral evolutions in online auctions are influenced by the entire previous experience of the bidder, rather than just experience with a particular category. Furthermore, using feedback ratings as a proxy of experience causes bias as a result of both underreporting of experiences and the lack of controls for the nature of the experience. Additional research in this area should study the relationship and dynamics between experience measures and attempt to uncover the latent construct that underlies the various experience measures.[7]

[7] We thank an anonymous reviewer for this suggestion.

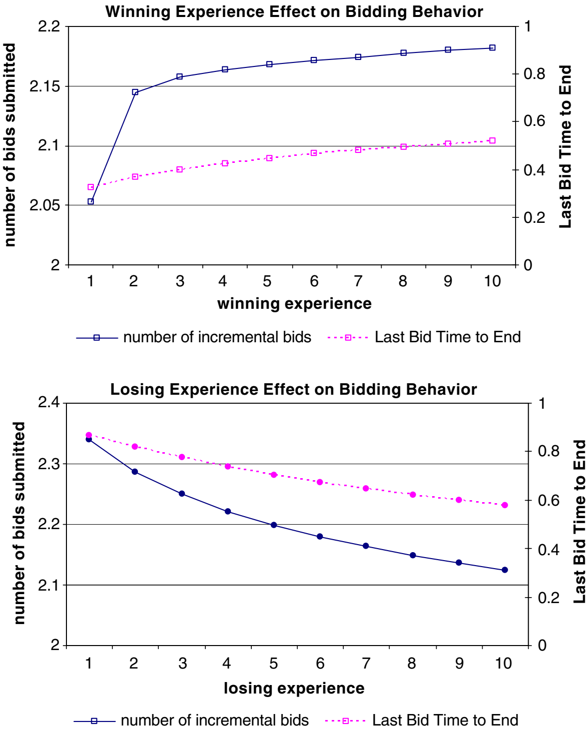

Fig. 2 Asymmetric effects of winning and losing experiences

A better understanding of the dynamics of auction bidders' behavior and experience (outcomes) also would represent an important step toward more accurate assessments of customer satisfaction and customer value in Internet auctions. According to our findings, auctioneers should provide training for newcomers to promote customer satisfaction. For example, eBay's "Learning Center" for newcomers should focus on simulating the actual bidding process and "rehearsing" losing experiences. New bidders unfamiliar with the bidding process could both practice bidding and accumulate necessary experience quickly. They can also become better acquainted with virtual opponents' "tactics," as well as eBay's carefree proxy bidding, before participating in real auctions. Experiences, especially losing ones, gained prior to actual auctions can improve a new bidder's skills quickly and in turn enhance customer value.

Table 3 Bidder heterogeneity in multiple bidding and late bidding propensity

Group	Number of bidders (*N*)	Multiple bidding		Late bidding	
		Mean	Std. deviation	Mean	Std. deviation
1	59 (45%)	−0.009	0.184	−0.674	2.421
2	72 (55%)	0.496	0.262	−1.534	1.415
Combined	131 (100%)	0.268	0.341	−1.147	1.973

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