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Internet Auction Features as Quality Signals

Internet auction companies have developed innovative tools that enable sellers to reveal more information about their credibility and product quality to avoid the "lemons" problem. On the basis of signaling and auction theories, the authors propose a typology of Internet auction quality and credibility indicators, adopt and modify Park and Bradlow's (2005) model, and use eBay as an example to examine empirically how different types of indicators help alleviate uncertainty. This empirical evidence demonstrates how Internet auction features affect consumer participation and bidding decisions, what modifies the credibility of quality indicators, and how different buyers react to indicators. The signaling-based hypotheses provide coherent explanations of consumers' bidding behavior. As the first empirical study to evaluate the signaling role of comprehensive Internet auction institutional features in mitigating the adverse selection problem, this research provides evidence to clarify the economic foundation behind innovative Internet auction designs.

Keywords: information asymmetry, lemons problem, winner's curse, signaling, consumer bidding strategies, Internet auction, e-commerce, eBay

Internet auctions are characterized by the separation of buyers from sellers (Lucking-Reiley 1999). Typically, Internet auction companies act as auctioneers and do not assign responsibility for items listed on their Web sites; the sellers describe, list, and ship the product and specify payment methods. Because shipment usually occurs after the payment has been received (Lucking-Reiley 2000), it is impossible for bidders to inspect the goods before bidding, and buyers bear significant risks for items not delivered or those significantly misrepresented by sellers. The impersonal transactions of Internet auctions introduce severe information asymmetry regarding both product quality and seller credibility. Thus, compared with customers' decision-making task in bricks-and-mortar retail stores, online auction consumers must make decisions under more severe uncertainty (Cheema et al. 2005; Dewally and Ederington 2006).

Without enough information to distinguish good from bad products (i.e., uncertainty about product quality) and reputable from disreputable sellers (i.e., uncertainty about seller credibility), buyers may choose not to participate in an auction. This dual uncertainty contributes to a "lemons" market, in which the potential of purchasing poor-quality products from a disreputable seller drives buyers away from the market. As a result, adverse selection could eventually drive good-quality items from the auction market and cause lemons problems (Akerlof 1970).

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As Huston and Spencer (2002), Bajari and Hortacsu (2004), and Kazumori and McMillan (2005) note, the lemons problem stems from impersonal transactions and information asymmetry and may be the greatest obstacle to the rapid growth of Internet auction marketplaces. Despite their soaring popularity, Internet auctions remain far from mainstream e-commerce outlets. According to Forrester Research (Johnson and Hult 2008), only one-third of North American households with Internet connections made an auction purchase in 2004. Many consumers voice concerns about trust and safety issues associated with Internet transactions (Pinker, Seidmann, and Vakrat 2001), fueled by reports of product misrepresentation, delivery failures, fee stacking, black-market goods, and so forth.[1] In 2006, the Internet Crime Complaint Center (IC3 [a partnership between the Federal Bureau of Investigation and National White Collar Crime Center]) received approximately 207,492 Internet fraud complaints, with total losses from these complaints exceeding $198.44 million, and Internet auction fraud was the top complain on the list (IC3 2006).

Therefore, to attract more users to an auction site or a particular auction, Internet auction companies and sellers must address an important question: What is the best auction design to mitigate uncertainty and attract more bidders? Since the emergence of the Internet, Internet auction companies have continued to develop innovative institutional features that enable sellers to reveal more information about their credibility and product quality to potential buyers. For example, in 2001, sellers were given the option to post multiple pictures to eBay, for a fee, to provide more visual

[1]Buyer-related fraudulent activities, such as nonpayment, triangulation, multiple bidding, and shield bidding, also exist; however, we study how sellers' quality indicators help mitigate buyers' concerns and affect bidding decisions. We leave the study of how to improve auction designs to overcome buyers' fraudulent problems to further research.

ISSN: 0022-2429 (print), 1547-7185 (electronic)

information about their listed products. Sellers are also allowed to specify a minimum bid (i.e., the smallest amount that can be bid for a specific auction) or a reserve price, which remains hidden from bidders but must be exceeded before the seller is required to sell. In 2002, eBay instituted the buy-it-now (BIN) option, which further allowed sellers to specify the exact price at which they were willing to sell their products immediately. Acquired by eBay in 2002, PayPal offers eBay buyers coverage of up to $2,000 for claims of nondelivery or significant misrepresentation. Thus, sellers can adopt a third-party payment system to reduce the risks associated with the transaction. Most Internet auction companies offer a feedback system that enables both sellers and buyers to rate each other according to their performance. The cumulative rating points are displayed next to the participant's name, along with all previous comments from other users.

As an important format for electronic commerce, the rapid development of Internet auctions demands additional research to understand how such innovative auction features affect consumer participation and bidding decisions and the implications for solving the lemons problem. As Chakravarti and colleagues (2002) and Herschlag and Zwick (2002) assert, research should investigate how the design of Internet auction mechanisms or institutional features influence bidding behavior and price and revenue outcomes.

Existing auction research in marketing and economics literature centers on modeling bidders' specific behaviors, such as late bids (Ockenfels and Roth 2006; Roth and Ockenfels 2002), sale prices (Ariely and Simonson 2003; Bajari and Hortacsu 2003; Dholakia 2005), reactions to minimum bids (Borle, Boatwright, and Kadane 2005; Kamins, Drèze, and Folks 2004; Lucking-Reiley 1999), willingness to pay (Bradlow and Park 2007; Nunes and Boatwright 2004; Park and Bradlow 2005), reactions to the BIN option (Budish and Takeyama 2001; Wang, Montgomery, and Srinivasan 2004), and bidder heterogeneity in bidding strategies (Sinha and Greenleaf 2000; Wilcox 2000).[2] To the best of our knowledge, little research has empirically investigated how innovative auction features affect bidders' decisions when they suffer from information asymmetry or has evaluated whether current Internet auction designs help alleviate the lemons problem.

In this article, we recognize the dual information asymmetry and separate all observed Internet auction features into potential direct product quality indicators, indirect product quality indicators, and seller credibility indicators. We draw from signaling theory (Akerlof 1970; Milgrom and Roberts 1982; Spence 1973) to develop a typology of most currently observed Internet auction features and examine their potential signaling roles. On the basis of signaling and auction theory (Bajari and Hortacsu 2004; Milgrom and Weber 1982; Rothkopf 1969; Wilson 1969), we hypothesize that different auction features affect bidders' interdependent decisions, such as whether to participate, who bids, when to bid, and how much to bid. Using field data collected from eBay auctions, we test the hypotheses by applying a modification of Park and Bradlow's (2005) model, implemented in a hierarchical Bayesian framework, to describe consumers' dynamic bidding behavior in the form of latent competition within auctions (Ariely and Simonson 2003; Bajari and Hortacsu 2004).[3]

Our empirical results show that quality indicators that directly reveal information on product quality and seller credibility (e.g., multiple picture postings, money-back guarantee, seller's cumulative rating, third-party payment method) encourage bidders not only to participate but also to shade bids. The opposite is true for indirect quality indicators (e.g., minimum starting bid, hidden reserve price, the BIN option), which discourage participation but increase bidding amount. We further demonstrate that the simultaneous use of quality indicators and seller credibility indicators (e.g., seller's rating, third-party payment) strengthens the effects of quality indicators. More experienced consumers tend to make better inferences about the roles of both credibility and quality indicators. On the basis of these estimation results, we run a simulation to examine how bidding decisions may change when the auction features appear more frequently. Overall, the signaling-based hypotheses are consistent with both the estimation and the simulation results and provide coherent explanations of consumers' bidding behavior.

Although previous studies have documented quality signaling as a solution for information asymmetry (e.g., Anderson and Simester 2001; Balachander and Srinivasan 1994; Chu 1992; Desai 2000; Desai and Srinivasan 1995; Kalra and Li 2008; Kirmani and Rao 2000; Moorthy and Srinivasan 1995; Soberman 2003; Spence 1973; Srinivasan 1991; Wernerfelt 1988), we find no empirical tests of general signaling theory in an Internet auction setting (cf. Dewally and Ederington 2006). Therefore, our research attempts to fill this gap by recognizing dual information uncertainties and investigating whether the current design of Internet auctions helps increase trust among buyers and sellers and alleviate the lemons problem. In doing so, we also shed light on the evaluation of auction designs.

Research Hypotheses

In this section, we first classify commonly observed auction features into possible direct quality indicators, indirect quality indicators, and seller credibility indicators. We then proceed to determine whether each classification qualifies as a signaling tool, and we predict how each might affect bidders' decisions, such as whether to bid, how much to bid, and when to bid.

Classification of Auction Features

In the first column of Table 1, we list the major auction features that many online auction houses adopt. The adoption of multiple picture postings enables the seller to reveal directly more visual information about the product. Speci-

[2]For a comprehensive review of Internet auctions, see Bajari and Hortacsu (2004) and Baker and Song (2007).

[3]When we collected our data in 2001, features such as product or seller certification were not yet available. Thus, our empirical analysis is applied to a subset of the indicators that we discuss in the "Research Hypotheses" section.

TABLE 1
Typology of Internet Auction Features

	Classification of Quality Indicators		Qualification as Signaling Device			Expected Effects on Bidding Behavior		
			Signaling Cost		Single-Crossing Property			
Auction Features	Uncertainty	Type of Indicator	Upfront	Future		Entry	Time	Amount
Possible Direct Quality Indicators								
Picture postings	Product quality	Direct	Yes	No	Yes	+	–	–
Money-back guarantee			No	Yes	Yes	+	–	–
Certification of product			Yes	No	Yes	+	–	–
Product description			No	No	No	N.A.[a]	N.A.	N.A.
Possible Indirect Quality Indicators								
Minimum bid	Product quality	Indirect	Yes	Yes	Yes	–	–	+
Hidden reserve price			Yes	Yes	Yes	–	–	+
BIN option			Yes	Yes	Yes	–	–	+
Possible Seller Credibility Indicators								
Seller's rating	Seller credibility	Direct	No	Yes	Yes	+	–	–
Third-party payment			No	Yes	Yes	+	–	–
Certification of seller			Yes	No	Yes	+	–	–
Credit card payment			No	No	No	N.A.	N.A.	N.A.
Escrow service			No	No	No	N.A.	N.A.	N.A.

[a]Predictions are not applicable to these auction features because they are not eligible to serve as quality indicators.

fying a money-back guarantee reveals information about the seller's confidence in the product quality. Certification of the auction item (e.g., professional appraisal of baseball cards) demonstrates its true quality level. Sellers may also disclose the condition or quality level of their auctioned items in the product description. These four auction features directly reveal information about the quality of the auctioned products. Thus, we label them as potential "direct quality indicators."

The minimum starting bid specifies the lowest bidding amount, and the hidden reserve price places a lower bound on the final sale price. The BIN option spells out the price at which the seller is willing to sell the auctioned item and to end the auction immediately (Budish and Takeyama 2001). Therefore, these three features may reveal information about product quality as forms of price signals (Milgrom and Roberts 1982; Moorthy and Srinivasan 1995). Furthermore, they reveal the values imposed by the seller and thus indirectly provide information about the product quality. We label these three auction features as potential "indirect quality indicators."

The seller's feedback rating, third-party payment, and certification of seller (i.e., by an independent trade association) reveal information about the credibility of the seller and may increase the buyer's trust. Adopting credit card payment methods and online escrow services may also increase the buyer's trust in both the seller and the transaction because buyers receive some fraud protection from the credit card issuers or the escrow service providers.[4] Therefore, these auction features could potentially reveal direct information on a seller's credibility and thus are all potential direct indicators. We label these as "seller credibility indicators."

Although these auction features contain information about product quality or seller credibility, they do not necessarily function as signaling devices. As Spence (1973) and Kirmani and Rao (2000) note, two conditions must be met before features represent signaling devices. First, it should be costly for the seller to adopt the signaling device; in the terminology of signaling literature, the device must induce signaling costs. Second, the signaling costs must satisfy the single-crossing property that such costs are higher for "bad" sellers than for "good" sellers so that a separating equilibrium occurs. In such equilibrium, consumers correctly infer the seller's true type on the basis of the different signaling strategies adopted.

Next, we borrow the signaling theory that Spence (1973) proposes in the labor market context to examine whether each of these indicators satisfies the two conditions, and we rely on both signaling and auction theories to motivate and provide an analogy for the hypotheses, in which we predict how each of the indicators will affect consumer participation and other bidding decisions. In the remainder of Table 1, we summarize the qualification status and predicted direction of each indicator's influence on whether, when, or how much to bid.

Direct Quality Indicators

The signaling costs of posting additional pictures equal the fixed fees the seller pays up front, as well as the sunk costs of any associated photography and/or scanning equipment (Dewally and Ederington 2006). For example, eBay charges a nonrefundable fee of $.15 for each additional picture after the first picture posting. Because multiple picture postings require nonrefundable costs, regardless of a sale, low-quality sellers are less likely to incur that cost, especially because multiple pictures may just reveal the true (poor) quality of the product. Thus, it is more costly for low-quality sellers to adopt this tool (Desai 2000; Kalra and Li 2008; Moorthy and Srinivasan 1995), and consumers can rely on this indicator to separate high-quality from low-quality products.

Sellers can specify a money-back guarantee in the product description section. Because it is usually not enforced by most Internet auction companies, sellers do not need to pay any fee for their verbal promise. However, this option incurs some future cost because of the existence of the IC3, which handles disputes between sellers and buyers (Lutz 1989). That is, the signaling cost results from the potential future refund (Moorthy and Srinivasan 1995). Because low-quality products have higher return rates, it is more expensive for sellers with low-quality products to adopt money-back guarantees.

Certifying auctioned items can also require significant seller costs. For example, Dewally and Ederington (2006) note that it typically costs the seller $20–$55 to have a comic book certified by Comics Guaranty, and according to Jin and Kato (2006), professional grading of baseball cards costs $6–$20 per card when performed by the Professional Sports Authenticator or Beckett Grading Service. These certification costs represent nonrefundable, upfront signaling costs. Both studies show that the certification of auctioned items satisfies the single-crossing property because a low-quality product is less likely to earn a high rating.

Sellers may disclose quality-related information (e.g., a condition that excludes a money-back guarantee) about the auctioned item in the product description. However, this information disclosure is "cheap talk" and does not incur any cost to the seller (Baker and Song 2007; Jin and Kato 2006). Therefore, it does not qualify as a signaling device.

In summary, multiple picture postings, money-back guarantees, and product certification not only incur signaling costs but also satisfy the single-crossing property, which qualifies them to serve as signaling devices. Next, we discuss how these tools can affect bidding decisions.

Whether to bid. Intuitively, posting multiple pictures, offering money-back guarantees, and certifying products should offer bidders more information about the product and signal its quality. With more information, consumers should be more likely to participate in the auction (Gilkeson

[4]Companies offering genuine escrow services provide a form of secure payment mechanisms that enable buyers to escrow payments until they have inspected, approved, and accepted the delivered merchandise. Online escrow services protect the interests of buyers against fraud and the risk of nonperformance. They usually are paid for by the buyers and appear in high-value transactions. As a relatively new feature, eBay recommends using escrow guarantees provided by Escrow.com for merchandise worth $500 or more.

and Reynolds 2003; Ottaway, Bruneau, and Evans 2003). Therefore, we expect that direct quality indicators encourage consumers to participate in auctions.

How much and when to bid. Knowing how the quality indicators affect bidders' bidding amount (how much to bid in each bidding occasion) and bidding time (when to submit each bid) during the course of an auction is also important. Unlike private-value auctions, in which the bidder knows the value of the item with certainty and his or her valuation is independent of other bidders' valuations (Vickrey 1961), a bidder's valuations of a product can depend on the preferences of others in an Internet auction (Milgrom and Weber 1982). As Bajari and Hortacsu (2003) and Milgrom and Weber (1982) indicate, when bidders are uncertain about their own evaluations of a product, auctioned items may have an affiliated value that can be affected by other bidders. Recent empirical work (Dholakia and Soltysinski 2001; Gilkeson and Reynolds 2003) supports the view that the affiliated-value model is the most descriptive type of Internet auctions. When buyers decide how much to bid for a product, they are likely to rely on the bidding behavior of other bidders to form their willingness-to-pay amount. For example, speculative investors who buy for future resale are likely to adjust their bidding amount according to the observed bidding prices submitted by other bidders. Early bids transmit information about the item's value to competitive bidders and may drive up the final winning price. In turn, too many bidders or too frequent early bids may create the winner's curse, such that the winner of the auction overbids or pays a higher price than the true value of the item (Thaler 1988).

Bidders are rational (Bajari and Hortacsu 2003; Ockenfels and Roth 2006), such that when they expect more bidders to be attracted by the use of quality indicators, they realize the increase of the affiliated value of the product and the potential winner's curse. Several studies of Internet auctions (i.e., Bajari and Hortacsu 2003; Jin and Kato 2006; Yin 2006) show that when they anticipate more bidders, rational bidders strategically shade their bids by reducing the amount they submit on each bidding occasion. Specifically, Bajari and Hortacsu (2003) show that buyers of collectable coins bid 10% less than their own private signals to compensate for the winner's curse. Adding another bidder reduces those equilibrium bids by 3.2%. Similarly, Yin (2006) finds that the bidding strategy in the common value second-price auction model responds negatively to an increase in the variance of the bidder's private valuation. Therefore, we expect that consumers reduce their bidding amount during the course of the bidding process when they observe the use of direct quality indicators.

Auction theory further indicates that in auctions with common value, it is in the bidders' best interests to bid as infrequently and/or as late as possible (Bajari and Hortacsu 2003; Ockenfels and Roth 2006). This is because more frequent or earlier bids increase the common value of other bidders or the chances of a bidding war. However, the use of direct quality indicators reduces information asymmetry, which may make consumers less likely to depend on other bidders' bidding information and encourage them to bid their maximum value earlier in affiliated-value auctions. Furthermore, according to Rasmusen (2001), late bidding occurs because bidders suffer uncertainty about their valuation for an item and want to economize the costs of acquiring information. In contrast, with more complete information about a product, bidders bid earlier. Therefore, we predict that the use of direct quality indicators encourages early bidding.

H_1: Direct quality indicators (e.g., multiple picture postings, money-back guarantees, product certification) encourage bid participation, decrease bidders' bidding amount, and encourage bidders to bid early.

Indirect Quality Indicators

Indirect quality indicators, such as minimum starting bid, hidden reserve price, and BIN price, may experience two types of signaling costs. The first type entails the publicly visible, nonrefundable fees the seller pays that are independent of the sale of the auctioned item. For example, eBay charges nonlinearly increasing insertion fees to the seller according to the amount of the minimum starting bid, with a maximum of $4.80 (i.e., $.30 to set the starting bid between $.01 and $.99, $.35 for starting bids between $1.00 and $9.99, and so on). In addition, eBay charges a reserve fee of either $.50 or $1.00 for the use of a hidden reserve price, which may be refunded if the item sells at a price higher than the reserve price. The use of the BIN price on eBay costs the seller a fixed amount of $.05.

The second type of signaling costs includes the potential loss of revenue when minimum starting bids and hidden reserve prices screen out consumers with low willingness to pay. Wang, Montgomery, and Srinivasan (2004) demonstrate that the BIN option may lower the chances of winning a bid and discourages bidders, especially those who are willing to bear participation costs. As Bajari and Hortacsu (2003, 2004) show, having fewer participating bidders lowers the revenues. Katkar and Reiley (2006) support this claim by noting that a high secret reserve price deters bidding and reduces both the likelihood of sale and the final bid amount.

The sum of the two types of signaling costs is greater for low-quality sellers, which normally have lower marginal costs (Desai 2000; Kalra and Li 2008; Moorthy and Srinivasan 1995). Although the nonrefundable fees may be the same to both high-quality and low-quality sellers, the potential revenue loss will be higher for the low-quality seller because of the lower marginal costs. That is, for each unit loss incurred by the high-quality seller that adopts these indicators, the low-quality seller must incur more than one unit of loss to mimic it (Moorthy and Srinivasan 1995). In this sense, the signaling role of such quality indicators is similar to that of traditional price signals, such that higher prices result in a loss of revenue for the high-quality seller that the low-quality seller must incur more of if it wants to mimic the high-quality seller (Milgrom and Roberts 1982; Moorthy and Srinivasan 1995). Therefore, the three possible indicators satisfy the single-crossing property and qualify as quality signaling devices.

Whether to bid. The use of minimum bids and hidden reserve prices should discourage consumers' participation by placing lower and higher bounds on their valuations, respectively (Budish and Takeyama 2001). Consumers with low valuations are screened from an auction with a lower bound, and the transaction will not occur if the upper bound is not met. Furthermore, as Wang, Montgomery, and Srinivasan (2003) and Bajari and Hortaçsu (2003) argue, significant participation costs play important roles in bidders' decisions to participate in Internet auctions. Because the reserve price is unknown to the bidders, they face higher participation costs and run the risk that sellers will withdraw the product, making their bidding efforts obsolete.

Impatient sellers adopt the BIN option to avoid both the transactional and the monetary costs of the bidding process (Wang, Montgomery, and Srinivasan 2004). The BIN option mixes dynamic pricing with fixed pricing and tempts buyers to accept the fixed price without going through the bidding process. Thus, it lowers the chance of winning a bid and discourages bidders, especially those who are willing to bear participation costs. Therefore, in general, we predict that indirect quality indicators discourage auction participation.

How much and when to bid. In contrast to H_1, when consumers observe the use of indirect quality indicators and thus expect fewer participating bidders, they increase the bid amount with less concern about the potential winner's curse. By revealing sellers' valuation of the product, indirect quality indicators help consumers form more accurate valuations (Bajari and Hortacsu 2004; Baker and Song 2007). With less uncertainty, bidders can be more deterministic about how much to bid and do not need to revise their bidding prices by observing competitive bids (Ariely and Simonson 2003). With more complete information about a product, bidders bid earlier (Rasmusen 2001). Therefore, we expect that indirect quality indicators encourage them to bid early.

> H_2: Indirect quality indicators (e.g., minimum bid, hidden reserve price, the BIN option) discourage bid participation, increase bidders' bidding amount, and encourage early bidding.

Seller Credibility Indicators

Long-term performance evaluations, such as feedback ratings, motivate sellers to be consistently truthful in their representations of product information and delivery (McDonald and Slawson 2002). A seller must devote time and effort to monitor and build up a reputation and to receive strong positive feedback from buyers after each transaction. Again, the signaling costs are related to the future revenue at stake. A poor reputation resulting from inconsistent signals results in lower future sales (Dholakia 2005; Dholakia and Soltysinski 2001; Gilkeson and Reynolds 2003; Houser and Wooders 2006; Lucking-Reiley 2000; Melnik and Alm 2002). In addition, because a low-credibility seller must incur more costs to attain the same reputation, the signaling costs are greater, so this feature satisfies the single-crossing property, and the seller's rating qualifies as a signaling device. Ariely and Simonson (2003) argue that a seller's investment in feedback ratings is similar to that of brand reputation.

Third-party payment methods (i.e., PayPal) offer secure online payments. After an auction is completed, the winning bidder contacts the seller to pay for the auctioned item through Paypal, on which both the seller and the buyer open accounts (which is free). The seller ships the item to the buyer, and a signaling cost of the transaction fees is charged to the seller to receive payment from the buyer. For example, PayPal charges 2.9% of the transferred funds plus $.30 per transaction to the seller to receive payments from buyers in the United States when the seller's monthly sales fall between $0 and $3,000. Again, this signaling cost is a future cost that is applied at the end of the auction; it will be higher for a low-quality seller because it invokes a greater probability of disputes and being held accountable than for the high-quality seller. Therefore, a third-party payment method qualifies as a signaling device.

Similar to the signaling role of product certification, seller certification by an independent third party, such as a trade association, creates costs for the seller. These signaling costs are higher for low-credibility sellers because the chance of obtaining a high ranking is lower than it would be for high-credibility sellers. Therefore, seller certification provides another signaling device.

In contrast, the adoption of credit card payment and/or online escrow services do not qualify as signaling tools, because these approaches do not cost the seller anything. Thus, no signaling cost exists, though both methods could provide some protection to the buyer.

Whether, how much, and when to bid. In Internet auctions, the seller's credibility is related to the delivery of the product and the accuracy of the product description. For reasons similar to those we pose regarding direct quality indicators, we posit that seller credibility indicators encourage consumers to participate and bid early. However, because the use of such indicators may result in more bidders, it also may decrease bidders' willingness to bid (WTB) (Bajari and Hortacsu 2003; Jin and Kato 2006; Yin 2006).

> H_3: Seller credibility indicators (e.g., seller rating points, third-party payment, seller certification) encourage bid participation, decrease bidders' bidding amount, and encourage bidders to bid early.

Although sellers can adopt Internet auction features to signal product quality, bidders can question the credibility of these indicators. Sellers are motivated to send false indicators if the (short- and long-term) cost of sending such signals is lower than the price premium (Jin and Kato 2006). The cumulative rating system developed by eBay reveals the degree of consistency between the sellers' signals and the quality and delivery of all the products they have sold (McDonald and Slawson 2002). Thus, buyers can rely on the historical performance of the sellers to make inferences about the credibility of their indicators. Higher seller ratings imply higher consistency between sellers' signals and the true quality of their products. All else being equal, the signals sent by sellers with higher ratings can be deemed to be truer than those from sellers with lower ratings. Similarly, the use of third-party payment methods and seller certification may increase consumers' trust because their payment is secure and the seller must pay a transaction fee to receive the funds from the buyer, whereas a PayPal account is free for the buyer (Gilkeson and Reynolds 2003). In addition, PayPal offers eBay buyers coverage of up to $2,000 for claims of nondelivery or significant misrepresentation. All PayPal transactions also are covered by 100% protection against unauthorized payments from the buyer's account. Therefore, seller credibility indicators, such as seller rating points, third-party payment, and seller certification, should amplify the effect of quality indicators (both direct and indirect) on consumer bidding behavior. More specifically, the simultaneous use of seller credibility and product quality indicators amplifies the signaling effect.

> H_4: Seller credibility indicators (e.g., seller rating points, third-party payment, seller certification) amplify the effects of quality indicators.

Thus, seller credibility indicators play dual roles: They provide verifiable information about the seller's credibility or reputation, and they may lend credibility to other product quality–related auction features. Note that we are not interested in the intraindicator-type amplification because, as Kirmani and Rao (2000) show, if one signal has already revealed the true quality, another signal of the same type is unnecessary.

Impact of Bidder Experience

Empirical analysis reveals that when an Internet auction starts, some bidders lack knowledge about the auction format, and the impact of bidders' experience on their decisions is significant in Internet auctions. For example, Wilcox (2000) shows that more experienced bidders bid later than less experienced bidders. Experimental studies also demonstrate that inexperienced bidders tend to overbid and suffer from the winner's curse (Bajari and Hortacsu 2004; Kagel and Roth 1995; Wilcox 2000). For example, online chat rooms often feature experienced bidders reminding other bidders to pay attention to feedback. Bidders with more experience may understand the auction mechanism and signaling roles of indicators better than less experienced bidders. New to Internet auctions, inexperienced bidders are still learning about the design of the bidding system and the economic functions of indicators. Therefore, we expect that the impact of quality and credibility indicators on bidding decisions will be greater for more experienced bidders.

> H_5: The effects of indicators in H_1–H_4 are stronger for experienced bidders.

Model

To test our hypotheses, we adopt and modify Park and Bradlow's (2005) model, which entails a general integrated statistical framework that captures consumers' dynamic bidding behavior within auctions using a multistage process. The integrated model of bidding behavior includes four key components: (1) whether consumers participate in an auction; (2) if so, who bids or becomes the actual observed bidder at a particular bidding occasion; (3) when the bid takes place; and (4) how much the consumer bids during the entire sequence of bids in the auction. The key latent construct that integrates all four modules is consumers' WTB at each bidding occasion. Thus, the framework incorporates consumers' endogenous entry and competition among potential bidders, including those not directly observed in the auction. We account for consumer heterogeneity with a hierarchical Bayesian framework. In summary, the integrated modeling framework enables us to examine how different quality/credibility indicators affect bidders' WTB and their bidding decisions.

A Consumer's WTB

A consumer's WTB is a time-varying stochastic valuation that can be updated for a particular item over the course of the auction and can change from one bidding occasion to another because the consumer's affiliated valuation of the auctioned item may vary according to the actions of other bidders (Ariely and Simonson 2003). Intuitively, a consumer's WTB should be determined by perceived seller credibility and product quality, as well as the auction and bidder characteristics (Bradlow and Park 2007; Chan, Kadiyali, and Park 2007). Let WTB^r_{ijm} represent bidder i's WTB for auction j in product category m at the rth round of bidding. More formally, we model consumer's WTB^r_{ijm} as follows:

$$\text{(1)} \quad WTB^r_{ijm} = \beta_{im0} + \mathbf{C}_{ijm} + \mathbf{Q}_{ijm} + \boldsymbol{\beta}'_{i1}\mathbf{X}^r_{jm} + \phi_j + \eta^r_{ijm}.$$

Thus, $\mathbf{C}_{ijm}$ and $\mathbf{Q}_{ijm}$ are consumers' perceptions of seller credibility and product quality, respectively, which are unobservable. However, without directly observing the product or seller, bidders can assess the seller's credibility and the product's quality using cues (auction features) on the site. On the auction site, consumers can observe public information published by the seller, including the seller's rating points ($SRATING_{jm}$), third-party payment ($THIRDPAY_{jm}$), multiple picture postings ($PICTURE_{jm}$), money-back guarantees ($MONEY_{jm}$), minimum bids ($MBID_{jm}$), reservation prices ($RESERVE_{jm}$), and BIN options ($BUYITNOW_{jm}$). (Note that we collected our empirical data in 2001, and at that time, the use of product or seller certification was not yet available.) Therefore, we assume that consumers form perceptions about seller credibility and product quality according to the following equations:

$$\text{(2)} \quad \mathbf{C}_{ijm} = \phi_{i1}SRATING_{jm} + \phi_{i2}THIRDPAY_{jm}, \text{ and}$$

$$\begin{aligned}\text{(3)} \quad \mathbf{Q}_{ijm} = {} & \phi_{i3}PICTURE_{jm} + \phi_{i4}MONEY_{jm} + \phi_{i5}MBID_{jm} \\ & + \phi_{i6}RESERVE_{jm} + \phi_{i7}BUYITNOW_{jm} \\ & + \phi_{i8}SRATING_{jm} \times PICTURE_{jm} \\ & + \phi_{i9}SRATING_{jm} \times MONEY_{jm} \\ & + \phi_{i10}SRATING_{jm} \times MBID_{jm} \\ & + \phi_{i11}SRATING_{jm} \times RESERVE_{jm} \\ & + \phi_{i12}SRATING_{jm} \times BUYITNOW_{jm}\end{aligned}$$

$$+ \phi_{i13}\text{THIRDPAY}_{jm} \times \text{PICTURE}_{jm}$$
$$+ \phi_{i14}\text{THIRDPAY}_{jm} \times \text{MONEY}_{jm}$$
$$+ \phi_{i15}\text{THIRDPAY}_{jm} \times \text{MBID}_{jm}$$
$$+ \phi_{i16}\text{THIRDPAY}_{jm} \times \text{RESERVE}_{jm}$$
$$+ \phi_{i17}\text{THIRDPAY}_{jm} \times \text{BUYITNOW}_{jm}.$$

As we discussed previously, sellers' cumulative rating points and use of third-party payments may convey information about seller credibility and relate directly to product delivery. We include multiple picture postings, money-back guarantee, minimum bid, reservation price, and BIN option in the perceived quality component because they may signal product quality under information asymmetry. Recall our discussion that sellers' rating points and third-party payment not only are credibility indicators themselves but also determine the effectiveness of the other quality indicators. We include the interaction terms of seller rating points and third-party payment with the other quality indicators to capture whether the seller credibility indicators amplify the effectiveness of the product quality indicators.[5] We also examine the correlation of the independent variables in Equations 2 and 3 and find that the correlations are low (i.e., the highest is equal to .45). Therefore, multicollearity is not a concern for our model.

The quality/credibility indicators we investigate usually are set at the beginning of the bidding process, before the bidder's participation or bidding decisions are revealed, and do not change across bidding occasions. To account for the time-varying factors that affect WTB during the course of the bidding, we follow Park and Bradlow (2005) and include bid-specific characteristics at any particular bidding occasion. The term $\mathbf{X}^r_{jm}$ is a vector of covariates for the rth bid-specific and auction-specific characteristics in auction j in product category m, including the following exogenous variables: (1) length of auction duration (BIDDAY_{jm}); (2) whether the rth bid occurs on a weekend (WEEKEND^r_{jm}); (3) the time remaining until the end of the auction (REMAIN^r_{jm}); (4) the number of bids submitted before the rth bid (NUMBID^r_{jm}); (5) the bid rate, defined as (r – 1) divided by the total elapsed time (BIDRATE^r_{jm}); and (6) the rate of bid increments, determined as the incremental bid amount in the previous round divided by its elapsed time (AMTRATE^r_{jm}). These variables affect the bidder's WTB or the bidding amount as control variables (Baker and Song 2007; Park and Bradlow 2005). The inclusion of NUMBID^r_{jm} enables us to test whether bidders vary their bidding decisions according to the bidding behavior of other bidders or the existence of affiliated value in Internet auction. The error term φ_j captures unobserved auction-specific characteristics that affect WTB, which we assume are independently and identically distributed across bidders, $\varphi_j \sim N(0, \sigma^2_\varphi)$, and η^r_{ijm} captures the unobserved variation affecting WTB and varying with bidder, auction, and product with the i.i.d. distribution $\eta^r_{ijm} \sim N(0, \sigma^2_\eta)$.

In Equation 1, β_{im0} represents consumer i's intrinsic WTB for product category m, after we control for the idiosyncratic differences across product categories. The 17×1 parameter vector $\Phi_i = (\phi_{i1}, \phi_{i2}, \ldots, \phi_{i17})'$ captures the impacts of various indicators on bidders' WTB. Specifically, ϕ_{i1-2} measure the effectiveness of the credibility indicators with regard to WTB, ϕ_{i3-7} measure the main effects of the quality indicators on WTB, and ϕ_{i8-17} indicate the effects of sellers' reputation and third-party payment on the credibility of each quality indicator. The term β_{i1} is a 6×1 vector of parameters that measures the effects of the control variables on WTB.

Park and Bradlow (2005) use the latent construct of WTB as the core of their proposed model of online bidding behavior that determines the consumer's bid speed, which in turn governs the decisions about whether to bid, who bids, when to bid, and how much to bid. Specifically, bid speed, d^r_{ijm}, of potential bidder i at bid occasion r in auction j in product category m follows an exponential distribution. Ariely and Simonson (2003) show that consumers' value assessment and decision dynamics differ in the entry stage compared with during the auction. Therefore, we allow the consumer's WTB to have a different impact on the bid speed in different decision stages, as well as on the consumer's decisions about whether to bid, who bids, and when to bid (i.e., d^r_{ijmk}, where k = 1, 2, or 3, representing decisions whether to bid, who bids, and when to bid, respectively). Formally,

$$(4) \qquad d^r_{ijmk} \sim \lambda^r_{ijmk} \times \exp[-\lambda^r_{ijmk} \times (t^r_{ijm} - t^{r-1}_{jm})],$$

where

$$(5) \qquad \log(\lambda^r_{ijmk}) = \alpha_{k0} + \alpha_{k1}(\text{WTB}^r_{ijm} - \text{BID}^{r-1}_{jm}) + \varepsilon^r_{ijmk},$$
$$\varepsilon^r_{ijmk} \sim N(0, \sigma^2_\varepsilon).$$

In this equation, t^r_{ijm} is potential bidder i's bidding time at bid occasion r in auction j in product category m, as we explain subsequently. Let t^{r-1}_{jm} and BID^{r-1}_{jm} denote the observed bidding time and observed bidding amount in the previous bid occasion (r – 1) in auction j in product category m, respectively. The mean of the bidding speed equals $E(d^r_{ijmk}) = 1/\lambda^r_{ijmk}$, given the exponential distributional assumption. Intuitively, Equations 4 and 5 note that bidder i's bidding speed at bid occasion r for item j in product category m is determined by the bidding surplus for item j (i.e., $\text{WTB}^r_{ijm} - \text{BID}^{r-1}_{jm}$) because the bidder's WTB must be greater than the observed bidding amount in the previous round if the bidder is to participate in the current bid. In turn, α_{k0} and α_{k1} measure the bidder's intrinsic rate of bidding speed and the impact of the bidding surplus on the bidding speed, respectively. If α_{k1} is negative, higher bidding surplus increases bidding speed—that is, given $E(d^r_{ijmk}) = 1/\lambda^r_{ijmk}$.

The expectation of bidding speed is the inverse of λ^r_{ijmk}, which is determined by the bidding surplus (i.e., WTB^r_{ijm} –

[5]We include the interaction term between SRATING_{jm} (or THIRDPAY_{jm}) and other quality indicators to test H_4. We also tried some other interaction terms, such as $\text{PICTURE}_{jm} \times \text{MONEY}_{jm}$; however, many of them were not significant. Therefore, we do not include them in the proposed model.

BID_{jm}^{r-1}). Therefore, the impacts of quality or credibility indicators on the bidder's bidding speed can be captured by the reverse sign of $\alpha_{k1} \times \Phi_i$ for k = 1, 2, and 3, where vector Φ_i refers to the impact of quality/credibility indicators on WTB as in Equations 2 and 3. Intuitively, bidding speed captures the bidder's urgency. By incorporating the bidder's perceptions of seller credibility and product quality, we can investigate the potential effects of these indicators on bidding behavior (Bradlow and Park 2007; Chan, Kadiyali, and Park 2007; Park and Bradlow 2005).

Whether an Auction Receives a Bid

Many listed auctions result in no participation, so we assume that whether an auction receives a bid depends on whether the lowest bidding time (i.e., $\min[t_{ijm}^1]$) of all potential bidders at the first potential bid lies within the auction duration. We use $I_{jm}^{r=1}$ to represent the number of potential bidders for item j in product category m during round 1 and T_{jm} to denote the length of auction j in product category m. In other words, the probability that auction j ends with no bidders equals the probability that the lowest bidding time ($\min[t_{ijm}^1]$) for all $i \in I_{jm}^{r=1}$ exceeds the auction duration T_{jm}. The minimum of a set of exponentials is exponentially distributed with the rate equal to the sum of the rates, so the probability that auction j in product category m receives no bids over its whole T_{jm} duration is

$$(6) \qquad \mathrm{pr}\left[\min(t_{ijm}^1) > T_{jm}\right] = \exp\left[-\left(\sum_{i=1}^{I_{jm}^{r=1}} \lambda_{ijm}^1\right) \times T_{jm}\right].$$

The probability that auction j attracts at least one bidder (i.e., $WBID_{jm} = 1$) is

$$(7) \qquad \mathrm{prob}(WBID_{jm} = 1) = 1 - \mathrm{pr}\left[\min(t_{ijm}^1) > T_{jm}\right]$$

$$= 1 - \exp\left[-\left(\sum_{i=1}^{I_{jm}^{r=1}} \lambda_{ijm}^1\right) \times T_{jm}\right].$$

That is, the entry probability for consumer i in auction j is related positively to the consumer's bid rate λ_{ijm}^1 from Equation 7, and we can test the impacts of credibility or quality indicators on a consumer's entry decisions with the sign of $\alpha_{11} \times \Phi_i$.

Who Bids

Next, we model whose bids we observe during round r out of the I_{jm}^r latent bidders in auction j. According to Equations 4 and 5, the consumer's bidding speed follows an exponential distribution with the rate determined by his or her WTB. Therefore, at each bidding occasion r, intuitively consumers are engaging in an exponential race that matches rates related to their WTB, and the person with the shortest time wins as the actual bidder at the rth bid. Of the I_{jm}^r latent bidders at bid r in auction j in product category m, the bidder becomes the person with the shortest bidding time within the time interval $[t_{jm}^{r-1}, T_{jm}]$ with a probability of

$$(8) \qquad \mathrm{pr}\left[\min(t_{ijm}^r) = t_{jm}^r | t_{jm}^{r-1} < \min(t_{ijm}^r) \le T_{jm},\ \forall i \in I_{jm}^r\right]$$

$$= \frac{\lambda_{ijm}^r}{\sum_{\substack{i=1 \\ i \ne i^{r-1}}}^{I_{jm}^r} \lambda_{ijm}^r}.$$

A person cannot bid twice in a row or outbid him- or herself in Internet auctions; therefore, we remove the rate of bid speed by the previous bidder from the denominator in Equation 8. In addition, in the bid speed race, the observed bidder at bid r must be in the race by definition, so his or her WTB must be truncated below the outstanding bid. Note that the inequality in Equation 8 enables the bidders to bid before or right on the ending time of an auction. The bid probability for consumer i in auction j in product category m at bid r is related positively to the consumer's bid rate λ_{ijm}^r. Therefore, we can test the impacts of credibility or quality indicators on a consumer's competitive entry or participation decisions at bid r according to the sign of $\alpha_{21} \times \Phi_i$.

When to Bid

At each bidding occasion r, the bidder as the winner of the aforementioned exponential race has the shortest bidding time. Therefore, conditional on who has submitted a bid, the bidding time at bid r is the minimum order statistic of the bid speeds of the I_{jm}^r latent bidders. The probability of observing t_{jm}^r is given by

$$(9) \qquad \mathrm{pr}\left[\min(t_{ijm}^r) - t_{jm}^{r-1} = \Delta t_{jm}^r | t_{jm}^{r-1} < \min(t_{ijm}^r) = t_{jm}^r \le T_{jm}, \forall i \in I_{jm}^r\right]$$

$$= \frac{\sum_{\substack{i=1 \\ i \ne i^{r-1}}}^{I_{jm}^r} \lambda_{ijm}^r \times \exp\left(-\sum_{\substack{i=1 \\ i \ne i^{r-1}}}^{I_{jm}^r} \lambda_{ijm}^r \times \Delta t_{jm}^r\right)}{1 - \exp\left[\sum_{\substack{i=1 \\ i \ne i^{r-1}}}^{I_{jm}^r} \lambda_{ijm}^r \times (T_{jm} - t_{jm}^{r-1})\right]}.$$

Because the bidding time of bidder i at bid r is the minimum order statistic of the bid speeds among the I_{jm}^r latent bidders, conditional on who has bid, the when-to-bid probability is related negatively to the consumer's bid rate λ_{ijm}^r from Equation 9. Therefore, the impacts of the credibility or quality indicators on a consumer's bidding time decisions at bid r are related negatively to the sign of $\alpha_{31} \times \Phi_i$.

How Much to Bid

Let AMT_{ijm}^r represent the latent bidding amount at bid r for auction item j in product category m. Thus, the latent bidding amount should be determined by WTB before this moment, following a normal distribution with mean WTB_{ijm}^r and variance σ_ξ^2:

$$(10) \qquad AMT_{ijm}^r = WTB_{ijm}^r + \xi_{ijm}^r,\ \ \xi_{ijm}^r \sim N(0, \sigma_\xi^2).$$

Let b^r_{jm} denote the observed bid amount at the rth bid in auction j in product category m. When an auction offers a BIN option with a prespecified price BIN_{jm}, the bidding process terminates if some bidders exercise the option. In other words, when the bidding amount AMT^r_{ijm} is greater than the BIN asking price BIN_{jm}, bidder i can either end the auction by bidding BIN_{jm} or continue it by bidding less than BIN_{jm}. To determine whether BIN_{jm} is exercised in auction j when AMT^r_{ijm} is greater than BIN_{jm}, we denote p^r_{ijm} as the probability of bidding BIN_{jm} and model it in a logit framework:

$$(11) \qquad p^r_{ijm} = \frac{\exp\left[\delta_0 + \delta_1(WTB^r_{ijm} - b^{r-1}_{jm})\right]}{1+\exp\left[\delta_0 + \delta_1(WTB^r_{ijm} - b^{r-1}_{jm})\right]},$$

where δ_0 and δ_1 are coefficients to be estimated. The impacts of credibility or quality indicators on the consumer's decisions to bid the BIN and end the auction are related positively to the sign of $\delta_1 \times \Phi_i$.

Note that p^r_{ijm} is a conditional probability of bidding BIN_{jm}, given that AMT^r_{ijm} is greater than BIN_{jm}. If the opposite is true (i.e., $AMT^r_{ijm} < BIN_{jm}$), in an auction with BIN_{jm} price, bidder i's bid amount is truncated by BIN_{jm}. Finally, in auctions without a BIN price, bidder i can choose any level of bid amount based on his or her WTB.

Taking all these cases into account, we model the bidder's bid amount as follows:

$$(12) \quad pr(AMT^r_{ijm} = b^r_{jm}) = \begin{cases} \text{I.} \ \left[pr(AMT^r_{ijm} \geq BIN_{jm})\right] \times (p^r_{ijm}) \\ \text{II.} \ \left[pr(AMT^r_{ijm} \geq BIN_{jm})\right] \times (1 - p^r_{ijm}) \\ \quad \times \left[\phi\left(b^r_{jm}, b^{r-1}_{jm}, BIN_{jm} | WTB^r_{ijm}, \sigma^2_\xi\right)\right] \\ \text{III.} \ \left[pr(AMT^r_{ijm} < BIN_{jm})\right] \\ \quad \times \left[\phi\left(b^r_{jm}, b^{r-1}_{jm}, BIN_{jm} | WTB^r_{ijm}, \sigma^2_\xi\right)\right] \\ \text{IV.} \ \left[\phi\left(b^r_{jm}, b^{r-1}_{jm} | WTB^r_{ijm}, \sigma^2_\xi\right)\right] \end{cases},$$

where $\phi(b^r_{jm}, b^{r-1}_{jm}, BIN_{jm}|WTB^r_{ijm}, \sigma^2_\xi)$ is the normal density with mean WTB^r_{ijm} and variance σ^2_ξ, truncated at b^{r-1}_j from below and BIN_{jm} from above, and $\phi(b^r_{jm}, b^{r-1}_{jm}|WTB^r_{ijm}, \sigma^2_\xi)$ is the truncated normal density with mean WTB^r_{ijm} and variance σ^2_ξ, truncated below by b^{r-1}_{jm}. Note that there are four cases in Equation 12: Cases I and II represent bids when AMT^r_{ijm} is greater than BIN_{jm}, Case III refers to a bid when AMT^r_{ijm} is lower than BIN_{jm}, and Case IV deals with a bidder's decision about how much to bid in auctions without a BIN price. Moreover, Φ_i directly measures the impact of quality or credibility indicators on the consumer's bidding amount, given Equation 10.

In summary, the mechanism of how various quality/credibility indicators affect consumers' bidding decisions proceeds as follows: First, the indicators directly determine the consumer's WTB at each bidding occasion according to Φ_i in Equations 1–3. Second, the consumer's WTB affects his or her bidding speed through α_{k1} (where k = 1, 2, or 3) in Equations 4 and 5. Third, consumers engage in bidding speed races in which their bidding speeds determine decisions of whether to bid, who bids, and when to bid. Therefore, we measure the impacts of the indicators on these three bidding decisions by the product of α_{k1} and Φ_i for k = 1, 2, or 3, respectively. Finally, conditional on who bids, the bidder's WTB determines his or her bidding amount at each bidding occasion because the consumer's bidding amount is mean centered on his or her WTB, as in Equation 10. The impact of the indicators on bidding amount is also directly measured by Φ_i.

Unobserved Heterogeneity and Estimation

Wilcox (2000) demonstrates that experienced bidders are more likely to bid later than inexperienced ones. To account for this heterogeneity (Allenby and Rossi 1999; Gönül and Srinivasan 1996), we write the coefficients in Equation 1 as functions of the participating bidders' experiences. Let $\boldsymbol{\pi}_i = (\Phi_i, \beta_i)'$. Thus:

$$(13) \qquad \boldsymbol{\pi}_i = \boldsymbol{\gamma}_0 + \boldsymbol{\gamma}_1 BEXPER_i + \boldsymbol{\mu}_i, \quad \boldsymbol{\mu}_i \sim N(0, \sigma^2_\mu).$$

With the coefficient $\boldsymbol{\gamma}_1$, we study how bidders' experiences modify the effect of credibility or quality indicators on bidding decisions. The hierarchical structure we use to account for consumer heterogeneity differs from that of Park and Bradlow (2005), who specify consumer unobserved heterogeneity only in the intercept of the WTB function for simplicity.

We directly model the latent competition among a varying number of potential bidders (I^r_{jm}) over the course of an auction. To calculate I^r_{jm}, we use the number of potential bidders who have positive surplus (i.e., $WTB^r_{ijm} > b^{r-1}_{jm}$) out of the maximal number of potential bidders (I_{jm}) for auction j in product category m. We discuss how we approximate I_{jm} in the "Data Description" section. To estimate the model, we also introduce a hierarchical Bayesian approach that accounts for unobserved heterogeneity (Allenby and Rossi 1999). We then apply the Markov chain Monte Carlo method (Gibbs sampler) and data augmentation with Bayesian Inference Using Gibbs Sampling (WinBUGS) software to estimate the model parameters. We run two independent chains with 25,000 Markov chain Monte Carlo iterations each and discard the first 20,000 iterations as a "burn-in" period to ensure convergence. The last 5000 iterations from both chains combine to calculate the estimates. We conduct standard eyeball scanning and Gelman and Rubin's (1992) F-statistic diagnostic to test the convergence of the chains (for detailed information about the log-likelihood functions and estimation method, see Park and Bradlow 2005).

To summarize, our model is an adaptation of Park and Bradlow's (2005) integrated modeling framework that captures consumers' dynamic bidding behavior (whether to bid, who bids, when to bid, and how much to bid) within auctions. However, we made the following adaptations: First, we explicitly model consumers' perceptions of unobserved seller credibility and product quality (i.e., $\mathbf{C}_{ijm}$ and $\mathbf{Q}_{ijm}$), whereas these are not the focus of Park and Bradlow's model. Second, we model consumers' WTB across product categories, whereas Park and Bradlow's model focuses on auctions within one product category. Third, we make the model more flexible by allowing the consumer's WTB to have different impacts on the bid speed in different decision stages. In other words, we let the bid speed to be decision stage specific (d_{ijmk}, where k = 1, 2, or 3, representing decisions of whether to bid, who bids, and when to bid, respectively). Accordingly, we allow bid speed to have different effects on the consumer's decisions of whether to bid, who bids, and when to bid. Finally, we allow bidder preference heterogeneity to be explained by bidder experience (Equation 13) using a hierarchical Bayesian framework. This is different from Park and Bradlow's model, which takes into account heterogeneity only in the constant term.

Empirical Applications

Data Description

We collect data from two areas—paintings and silver plates—of eBay's super antiques category. We chose these areas because as representatives of the super antique category, their values may be determined by future resale prices. Therefore, we speculate that asymmetric information and the affiliated-value elements may be greater for these product categories, which is important in studies of adverse selection issues (Bajari and Hortacsu 2004).

Our data contain 1324 auctions listed on eBay by 806 randomly selected participating bidders from April 15, 2001, to May 6, 2001. We randomly selected 75% of our sample for estimation and used the remaining 25% to form a holdout sample. In Table 2, we report the definitions of all the variables we used and their sample statistics. There were seven quality indicators adopted by eBay during our observation period. The frequencies of the adoption of quality indicators are 72%, 16%, 72%, 24%, and 9%, respectively, for multiple picture postings, money-back guarantee, third-party payment, hidden reserve price, and the BIN option. The mean of the minimum starting bid prices is $92.7, and the mean and standard deviation of the sellers' cumulative rating points are 458.02 and 796.86, respectively. (We also tried the sellers' percentage of positive rating points in the estimation. The results remain similar.) The average number of days specified by the bidder is 7.35 days.

The average bidding time is 28.48 hours since the start of the auction. The average bidding amount, which reflects a bidder's observed bid amount, is $72.03, and 42% of the submitted bids occurred on weekends. We follow the work of Wilcox (2000) and measure bidder experience by the bidder's cumulative feedback points, which approximate the total number of auctions. The mean and standard deviation of bidders' experience are 104.9 and 203.9, respectively.

Of the 1324 auctions, almost half result in no bids at all (i.e., 49%). The average number of unique bidders for each auction is 1.06, ranging from 0 to 9. The average number of bids is 2.65. The mean of the BIN option price is $10.50, with a minimum of $0 and a maximum of $1,399. The average values of remaining time to the end of the auction (REMAIN), number of bids submitted before the rth bid (NUMBID), bid rate (BIDRATE), and the rate of bid increments (AMTRATE) are 95.05, 2.65, .04, and .44, respectively. Finally, because we use two product categories in the data, we mean-center the category-specific variables by product category.

TABLE 2
Definitions of Variables

	Seller's Options	M	(SD)
SRATING	Seller's cumulative rating point	458.02	(796.86)
THIRDPAY	Whether third-party payment is specified (1) or not (0)	.72	(.45)
PICTURE	Whether there are two or more pictures of the item (1) or not (0)	.72	(.13)
MONEY	Whether money-back guarantees are specified in the auction (1) or not (0)	.16	(.37)
MBID	Amount of minimum starting bid specified by the seller	92.70	(1026.64)
RESERVE	Whether the seller uses the hidden reserve price (1) or not (0)	.24	(.43)
BUYITNOW	Whether the seller uses the BIN option (1) or not (0)	.09	(.28)
BIDDAY	Number of days of an auction	7.35	(1.99)
	Bidder's Decisions/Characteristics		
BIDTIME	Bidder's bidding time in hours since the start of the auction	28.48	(71.15)
AMT	Bidder's bidding amount	72.03	(202.86)
WEEKEND	Whether a bid is placed on a weekend (1) or not (0)	.42	(.49)
BEXPER	Bidder's bidding experience (calculated from cumulative rating point)	104.87	(203.88)
	Other Auction- or Bid-Specific Variables		
WBID	Whether there is any bidder participating in the auction (1) or not (0)	.51	(.50)
NBIDDER	Number of unique bidders in an auction	1.06	(1.55)
BIN	The amount of BIN price	10.50	(68.72)
REMAIN	The remaining time to the end of the auction for a particular bid	95.05	(157.65)
NUMBID	The number of bids submitted before a particular bid	2.65	(3.82)
BIDRATE	The bid rate defined as (r – 1) divided by the total elapsed time	.04	(.09)
AMTRATE	The rate of bid increments as incremental bid amount at previous round divided by its elapsed time	.44	(5.54)

We observe the number of people who view a particular auction and use it to approximate the total number of potential bidders I_{jm} for auction j in product category m. We gather this information with an automatic counter option that is free and is set by sellers; this was employed in 87% of the auctions in our data. For auctions without such information, we impute the value using the mode of the variable (approximately 72). This variable offers a good proxy of I_{jm} because the automatic counter uses each Internet user's cookie address to identify unique bidders; thus, we have additional information to measure the latent competition among dynamically changing potential bidders during the course of an auction, compared with Park and Bradlow's (2005) windowing procedure, which lacks this proxy information.

Results

To evaluate the fit of our model, we estimate two benchmark models. The first model considers only observed bidders and assumes that bidders are homogeneous, similar to our proposed model but without consideration of competition among latent bidders or bidder heterogeneity. The second model is similar to Park and Bradlow's (2005) and incorporates competition among latent bidders but ignores bidder preference heterogeneity, except in the intercept.

In Table 3, we report the log of posterior marginal density (Kass and Raferty 1995); the hit rate for the whether-to-bid model; and the mean absolute errors (MAEs) for the number of unique bidders in each auction, for when to bid, and for how much to bid using both the estimation and the holdout samples. We also compute the Bayes factors (Kass and Raferty 1995) to assess model fit. The results strongly favor our proposed model over the two benchmark models by odds of 329.9 and 199.6, respectively. In addition, the proposed model performs better than the two benchmark models on all other dimensions for both the estimation sample and the holdout sample, which indicates the importance of recognizing latent bidder competition with endogenous entry and bidder preference heterogeneity.

Impact of direct quality indicators: H_1. In Table 4, we report the estimation results for the three models, focusing on Model 3, or our proposed model. As we expected, α_{k1} (k = 1, 2, 3) are all estimated to be negative, which suggests that higher bidding surplus increases bidding speed because of the greater urgency for bidders with high surplus (Park and Bradlow 2005). The coefficient of PICTURE is significant and negative ($\phi_{i3} < 0$) because multiple pictures reveal more information about product quality and help bidders differentiate high- from low-quality products. This reduction in incomplete information leads consumers to be more willing to participate, which results in more auction participants (i.e., $\alpha_{11} \times \phi_{i3} > 0$, and $\alpha_{21} \times \phi_{i3} > 0$). However, $\phi_{i3} < 0$ suggests that this direct indicator reduces consumers' bidding amount because rational bidders expect more participants and strategically shade their bidding amount to counter the winner's curse. In addition, $\alpha_{31} \times \phi_{i3} > 0$ suggests that as consumers' bid rates increase, they tend to bid early; because the quality indicators provide more information about product quality, bidders are less likely to rely on competitive bids to determine value, and therefore bidders do not need to update their bids constantly.

Money-back guarantees (MONEY) have a significant and negative effect on consumers' WTB and bidding amount (i.e., $\phi_{i4} < 0$). They reduce incomplete information, so consumers become more likely to participate in the auction ($\alpha_{11} \times \phi_{i4} > 0$, and $\alpha_{21} \times \phi_{i4} > 0$) and bid early ($\alpha_{31} \times \phi_{i4} > 0$). To counter the winner's curse, consumers strategically shade their bids ($\phi_{i4} < 0$). Therefore, for both multiple picture postings and money-back guarantees, we find support for H_1.

Impact of indirect quality indicators: H_2. In contrast to the direct quality indicators, the indirect quality indicators (RESERVE and BUYITNOW) increase WTB and bidding amount ($\phi_{i6} > 0$ and $\phi_{i7} > 0$), making consumers less likely to participate (given $\alpha_{k1} \times \phi_{i6-7} < 0$ for k = 1, 2). Indirect quality indicators discourage general participation because RESERVE and BUYITNOW eliminate buyers with low willingness to pay and high participation costs. Because fewer bidders participate, consumers become less concerned about the winner's curse and experience increased WTB and bidding amounts ($\phi_{i6} > 0$ and $\phi_{i7} > 0$). Thus, for hidden reserve prices and BIN options, the empirical results support H_2. However, consumers tend to bid later after

TABLE 3
Comparison of Competing Models

Sample	Criterion	Homogeneous Model with Observed Bidders Only	Park and Bradlow (2005) Model with Latent Bidders	Proposed Model
Estimation sample[a]	Log-marginal density	–868,900.0	–868,700.4	–868,570.1
	Hit rate for whether to bid model	.899	.908	.923
	MAE for number of unique bidders	3.309	2.028	1.490
	MAE for when to bid model	11.500	4.392	2.549
	MAE for how much to bid model	4.566	3.059	1.944
Holdout sample[b]	Hit rate for whether to bid model	.790	.815	.836
	MAE for number of unique bidders	3.772	3.081	2.390
	MAE for when to bid model	13.021	5.078	3.234
	MAE for how much to bid model	5.872	3.531	1.925

[a]Number of auctions = 993, and number of observations = 2772.
[b]Number of auctions = 331, and number of observations = 863.

TABLE 4
Estimation Results

Variable Types	Covariates (Coefficients)	Homogeneous Model with Observed Bidders Only		Park and Bradlow (2005) Model with Latent Bidders		Proposed Model	
Intercept	INTERCEPT – Silver plate (β_{i10})	.070	(.167)	–.036	(.022)	1.997[a]	(.162)
	INTERCEPT – Painting (β_{i20})	2.564[a]	(.541)	.911[a]	(.102)	2.151[a]	(.234)
Seller's credibility indicators	SRATING (ϕ_{i1})	.240	(.638)	–1.238[a]	(.336)	–.324[a]	(.019)
	THIRDPAY (ϕ_{i2})	2.081[a]	(.729)	–6.369[a]	(.399)	–.367[a]	(.014)
Direct quality indicators	PICTURE (ϕ_{i3})	1.001	(.623)	–4.924[a]	(.357)	–.405[a]	(.010)
	MONEY (ϕ_{i4})	.031	(1.066)	.245	(.658)	–.055[a]	(.014)
Indirect quality indicators	MBID (ϕ_{i5})	.265	(.152)	–.151[a]	(.041)	.021	(.028)
	RESERVE (ϕ_{i6})	–.637	(.614)	–.729[a]	(.349)	.036[a]	(.022)
	BUYITNOW (ϕ_{i7})	2.334	(1.693)	–1.562[a]	(.761)	.197[a]	(.019)
Interactions between credibility indicator and quality indicator	SRATING × PICTURE (ϕ_{i8})	.225	(.293)	–.142	(.264)	–.146[a]	(.011)
	SRATING × MONEY (ϕ_{i9})	–.370	(.325)	.473	(.261)	–.125[a]	(.010)
	SRATING × MBID (ϕ_{i10})	–.599	(3.414)	–3.818[a]	(1.359)	–.100[a]	(.054)
	SRATING × RESERVE (ϕ_{i11})	.288	(.500)	.035	(.435)	–.009	(.064)
	SRATING × BUYITNOW (ϕ_{i12})	2.365	(2.031)	1.147	(.780)	–.205	(.121)
	THIRDPAY × PICTURE (ϕ_{i13})	–1.619[a]	(.757)	5.222[a]	(.452)	.382[a]	(.010)
	THIRDPAY × MONEY (ϕ_{i14})	–.542	(1.217)	–.385	(.812)	–.097[a]	(.048)
	THIRDPAY × MBID (ϕ_{i15})	–4.197	(3.753)	5.233[a]	(2.161)	–.455[a]	(.055)
	THIRDPAY × RESERVE (ϕ_{i16})	–1.273	(.822)	1.774[a]	(.516)	–.001	(.014)
	THIRDPAY × BUYITNOW (ϕ_{i17})	–.811	(1.685)	.794	(.751)	–.119[a]	(.062)
Other control variables	BIDDAY (β_{i1})	.208[a]	(.076)	–.291[a]	(.045)	.002	(.002)
	WEEKEND (β_{i2})	–2.151[a]	(.461)	.535[a]	(.267)	.122[a]	(.017)
	REMAIN (β_{i3})	–.014	(.025)	–.001	(.010)	–.016[a]	(.003)
	NUMBID (β_{i4})	–.156[a]	(.032)	.015	(.012)	.022[a]	(.003)
	BIDRATE (β_{i5})	–.892	(1.047)	.448	(.426)	.147[a]	(.027)
	AMTRATE (β_{i6})	.013	(.018)	.002	(.004)	–.033[a]	(.007)
Bid speed	α_{10}	.478[a]	(.130)	–.301[a]	(.059)	–.629[a]	(.041)
	α_{11}	–.946[a]	(.040)	–.310[a]	(.067)	–.686[a]	(.082)
	α_{20}	.255	(.134)	–.014	(.022)	.100[a]	(.040)
	α_{21}	.263[a]	(.144)	.119[a]	(.025)	–.019[a]	(.002)
	α_{30}	.233[a]	(.103)	–.269[a]	(.075)	–.613[a]	(.071)
	α_{31}	–.843[a]	(.057)	–.288[a]	(.069)	–.674[a]	(.053)
Bid BIN price	δ_0	9.976	(6.982)	5.100	(8.385)	11.480[a]	(5.111)
	δ_1	7.361	(6.878)	9.066	(6.420)	1.796	(9.295)

[a]Zero lies outside the 95% posterior probability interval.

observing the use of these two indicators, conditional on being a bidder ($\alpha_{31} \times \phi_{i6-7} < 0$), perhaps because they believe that the chance of winning such an auction is low and thus wait to bid (Budish and Takeyama 2001; Katkar and Reiley 2006).

The minimum starting bid (MBID) has an insignificant impact on consumers' bidding amount, entry, and bidding time, though its coefficient is positive ($\phi_{i5} > 0$), consistent with Standifird's (2001) findings. This result may be due to the usual low values of minimum starting bids set by sellers (e.g., a median of $15 with a minimum of $.01 in our sample), which thus may not become constraints for bidders. Therefore, we find partial support for H_2.

Impact of credibility indicators: H_3. Credibility indicators should encourage bid participation, decrease bidders' bidding amount, and encourage bidders to bid early. In Table 4, we show the support we find for H_3. The seller's feedback rating (SRATING) and the use of third-party payment methods help high-credibility sellers distinguish themselves from low-credibility sellers by revealing their true credibility. Consumers are more confident about participating in the auctions of sellers that use third-party payment systems and thus become more likely to participate in the auction ($\alpha_{k1} \times \phi_{i1-2} > 0$ for k = 1, 2). However, from the consumers' point of view, this willingness increases the expected number of participating bidders, so they shade their WTB ($\phi_{i1-2} < 0$). The coefficient for bid surplus in Equation 5 is negative ($\alpha_{31} < 0$), so $\alpha_{31} \times \phi_{i1-2} >$ 0, which indicates that as consumers' bid rate increases, they become more likely to bid early, assuming that they bid. This finding is consistent with previous results in auction literature (Ba and Pavlou 2002; Brinkman and Siefert 2001; Dewan and Hsu 2001; Houser and Wooders 2006; Livingston 2005). The reduction of quality uncertainty makes consumers less likely to depend on other bidders' bidding information. Because they do not need to observe competitive bids to determine value, bidders do not need to update their bids constantly, in support of H_3.

Interaction between credibility indicators and quality indicators: H_4. The coefficients of the interaction terms between SRATING or THIRDPAY and most of the quality indicators are significant with expected signs, which implies that sellers' cumulative rating points or third-party payment amplify the effects of quality indicators on bidders' decisions about entry, bidding time, and bidding amount. Higher accumulative ratings and the use of third-party payment imply greater consistency between the sellers' signals and the true quality of their products. Therefore, higher ratings or third-party payment methods make sellers' indicators more credible and amplify the effect of quality indicators. After observing the use of both credibility and quality indicators, rational consumers become more likely to participate in the auction ($\alpha_{k1} \times \phi_{i8-17} > 0$ for k = 1, 2), to shade their bids ($\phi_{i8-17} < 0$), and to bid early ($\alpha_{31} \times \phi_{i8-17} > 0$). The only exception is the interaction between THIRDPAY and PICTURE, which is significant and positive, perhaps because these signals are significantly different, such that the former is default contingent and the latter is default independent (Kirmani and Rao 2000). Overall, we find support for H_4.

Impact of bidder heterogeneity on the effects of credibility indicators and quality indicators: H_5. As we show in Table 5, the effect of the indicators differs across bidders' experiences. Most heterogeneity coefficients are significant; that is, the impacts of credibility or quality indicators on consumers' bidding decisions are stronger for bidders with more experience. If we use multiple picture postings as an example, we note that the negative effect of BEXPER on the picture posting coefficient indicates that posting multiple pictures encourages auction participation and bid shading, and the effect is greater for experienced bidders, who make better inferences about quality indicators and are less likely to suffer from the winner's curse, in support of previous research (Bajari and Hortacsu 2004; Kagel and Roth 1995; Wilcox 2000). Similarly, the negative effect of BEXPER on the seller's cumulative rating points (SRATING) coefficient indicates that this credibility indicator is more effective for experienced bidders, encouraging them to shade their bidding amount. Therefore, in general, we find support for H_5. However, the enhancing impact of the bidder's experience does not differ according to the two types of indicators (direct versus indirect). Experienced bidders understand the auction mechanism and signaling roles of indicators better than less experienced bidders, which enables them to make better use of the information delivered by the indicators, which in turn increases their impact. This logic holds for both direct and indirect indicators.

Other auction context variables. The effects of other auction context variables on bidders' WTB include the intercept for the painting category, which is greater than that for the silver plate category, as we show in Table 4, perhaps because the value of auctioned items in the latter category is normally lower. The duration of an auction (BIDDAY) does not have a significant impact on WTB, bidding time, or bidding amount, in support of previous research (Dholakia and Soltysinski 2001; Gilkeson and Reynolds 2003). If a bid occurs over a weekend (WEEKEND), consumers are more likely to increase their WTB, perhaps because they have more free time on weekends and, therefore, lower psychological bidding costs. When more time remains before the end of the auction (REMAIN), WTB tends to be lower. However, the higher the number of bids

TABLE 5
Estimation Results for Heterogeneity Equation

Covariates	Intercept	BEXPER
INTERCEPT – Silver plate	2.211[a] (.180)	–1.857[a] (.252)
INTERCEPT – Painting	2.198[a] (.269)	–.206[a] (.039)
SRATING	–.014 (.023)	–3.125[a] (.042)
THIRDPAY	–.311[a] (.009)	–.513[a] (.064)
PICTURE	–.351[a] (.010)	–.500[a] (.032)
MONEY	–.092[a] (.017)	.346[a] (.188)
MBID	.121[a] (.021)	–.933[a] (.176)
RESERVE	–.105[a] (.014)	1.296[a] (.135)
BUYITNOW	.010 (.031)	1.731[a] (.231)
SRATING × PICTURE	–.030[a] (.011)	–1.071[a] (.032)
SRATING × MONEY	–.011 (.020)	–1.060[a] (.129)
SRATING × MBID	–.518[a] (.055)	3.861[a] (.117)
SRATING × RESERVE	–.034 (.024)	.237 (.567)
SRATING × BUYITNOW	.129[a] (.062)	–3.086[a] (1.355)
THIRDPAY × PICTURE	.293[a] (.011)	.824[a] (.044)
THIRDPAY × MONEY	.175[a] (.022)	–2.516[a] (.321)
THIRDPAY × MBID	–.488[a] (.059)	.304[a] (.093)
THIRDPAY × RESERVE	–.035 (.023)	.316[a] (.124)
THIRDPAY × BUYITNOW	.060 (.046)	–1.651[a] (.300)
BIDDAY	.008[a] (.003)	–.055[a] (.014)
WEEKEND	.070[a] (.016)	.490[a] (.062)
REMAIN	–.013[a] (.004)	–.028[a] (.014)
NUMBID	.024[a] (.004)	–.021 (.018)
BIDRATE	–.249[a] (.031)	3.653[a] (.105)
AMTRATE	–.020[a] (.010)	–.121 (.086)

[a]Zero lies outside the 95% posterior probability interval.

submitted before each bid (NUMBID) or the higher the bid rate (BIDRATE), the higher is bidders' WTB. This supports our argument that the affiliated value in these auctions emerges because consumers' valuation is affected by competition. When the rate of bid increments (AMTRATE) increases, bidders become more cautious and strategically shade their bids to avoid the winner's curse, consistent with Park and Bradlow (2005).

Because the coefficient of surplus δ_1 for how much to bid in Equation 11 is insignificant, consumers' valuations relative to the BIN price do not have a significant impact on whether to exercise the BIN option. Because indirect quality indicators drive up consumers' WTB, sellers with high feedback rating points can increase their final bidding prices and profit margins. Finally, both the variance of the unobserved auction-specific coefficient φ_j (i.e., $\sigma^2_\varphi = .135$, SD = .030) and the variance of the preference heterogeneity σ^2_φ (1.494, SD = .124) are significant, which indicates their significant impacts.

Comparison with benchmark models. When we compare the results from our proposed model with those of the benchmark models, we find that the coefficient estimates are sensitive to the inclusion of latent competition among potential bidders and bidder preference heterogeneity. For example, in Table 4, the homogeneous model with observed bidders only (first benchmark model), which is similar to most models in existing empirical research, shows that the three indirect indicators have no significant impact on WTB or bidding amount. The second benchmark model takes into account the role of latent bidders and their unobserved bidding competition, and the impacts of these indicators become significantly negative. This finding demonstrates the importance of modeling latent bidder competition. Furthermore, when we incorporate bidders' preference heterogeneity into the second benchmark model, the impacts of the indicators become significantly positive, consistent with the findings in choice literature that the failure to account for consumers' unobserved preference heterogeneity leads to inconsistent and biased estimates (Allenby and Rossi 1999; Gönül and Srinivasan 1996). Overall, we find support for all five hypotheses. The proposed signaling-based hypotheses are consistent with the estimation results and provide coherent explanations of consumers' bidding behavior.

Simulations. To demonstrate the implications of the signaling effect of eBay's features on consumers' bidding behavior more intuitively, we conduct a series of policy simulations based on estimates from the proposed model. As we show in Table 6, we change the frequency of the use of each indicator and simulate the probability of auction participation, average number of latent bidders, mean interbidding time since last bid, average final bid price (i.e., last observed bidding amount in an auction[6]), and average bidding experience of the participating bidders to determine how these various indicators might affect consumers' bidding decisions.

When we increase the percentage of auctions with multiple picture postings and money-back guarantees by 10% separately, participation probabilities increase by 1.04% and .84%, respectively. If we increase the frequency of the use of the two indicators by 20%, it encourages auction participation even more (1.13% and 1.41%). These increases also attract 3.53% and 1.34% more latent bidders to a particular bid on average, respectively. Therefore, multiple pictures and money-back guarantees are effective in attracting more potential bidders because they reduce the bidders' quality uncertainty and encourage participation. Thus, direct quality indicators help alleviate the lemons problem.

[6]The last observed bidding amount is the second-highest bidder's maximum bid because the winning bidder's maximum bid is unobservable. At eBay, the bidder with the highest maximum bid wins the item and pays a price equal to the second-highest bidder's maximum bid plus the bid increment.

TABLE 6
Simulation Results

Indicators	Value or Change	Probability of Participation	Average Number of Unique Latent Bidders	Interbidding Time Since Last Bid	Average Final Bid Price	Experience of Participating Bidders
Current values		.512	26.60	.799	139.31	129.22
Picture postings	10% increase	+1.04%	+3.53%	–4.78%	–2.15%	+1.91%
	20% increase	+1.13%	+13.76%	–.34%	–3.10%	+2.93%
Money-back guarantee	10% increase	+.84%	+1.34%	–.65%	–1.21%	+.36%
	20% increase	+1.41%	+.06%	–.29%	–1.35%	+1.39%
BIN	10% increase	–.82%	–3.31%	+2.77%	+1.62%	+.39%
	20% increase	–1.07%	–3.29%	+.44%	+1.48%	+1.36%
Hidden reserve	10% increase	–1.13%	–1.58%	+1.80%	+3.10%	+.44%
	20% increase	–.57%	–2.61%	+.46%	+2.29%	+1.47%
Minimum starting bid	10% increase	–.41%	–.04%	+1.28%	+.10%	+.25%
	20% increase	–.56%	–1.69%	+1.83%	+.40%	+.75%
Seller's feedback rating	10% increase	+.29%	+11.10%	–2.01%	–.55%	+3.09%
	20% increase	+.37%	+12.63%	–3.13%	–.25%	+4.43%
Third-party payment	10% increase	+1.17%	+10.43%	–2.02%	–.63%	+2.30%
	20% increase	+1.54%	+13.03%	–4.17%	–.13%	+3.54%

Increasing the percentage of auctions with multiple picture postings and money-back guarantees by 10% separately also reduces the bidder's interbidding time since the last bid (in hours) by 4.78% and .65%, respectively. Consumers shade their final bid price by 2.15% and 1.21%, respectively, because they observe the significant increase in the number of latent bidders and shade their bids to correct for the potential winner's curse. That is, the use of quality indicators encourages early bidding but decreases the final bid price. However, bid shading is not very dramatic for the products we study; the average observed final bid price is $148.15 across all auctions. We do not attempt to make any conclusions about whether bidders shade the bids enough, because we cannot observe the true values of the auctioned items. Further research should examine the impacts of quality indicators on the degree of the winner's curse by collecting true value information about items (Bajari and Hortacsu 2003). The increasing use of multiple picture postings and money-back guarantees also attracts more experienced bidders by 1.91% and .36%, respectively, which suggests that more experienced bidders tend to understand the indicators better and make better use of such information.

In contrast, a 10% greater frequency of auctions with BIN options, hidden reserve prices, or minimum starting bids reduces participation probability by .82%, 1.13%, and .41%, respectively. In addition, they significantly decrease the number of latent bidders by 3.31%, 1.58%, and .04% and encourage late bidding with the delay of 2.77%, 1.80%, and 1.28%, respectively. Thus, using indirect quality indicators may worsen the lemons problem because placing either lower or upper bounds on valuations discourages bidder entry. However, having fewer latent bidders causes the final bid price to increase by 1.62%, 3.10%, and .10%, respectively. Similar to the direct indicators, these indicators attract more experienced bidders at levels of .39%, .44%, and .25%, respectively. Therefore, when considering such quality indicators, sellers should balance the lower auction participation rates against the higher final bid price. Although indirect quality indicators discourage participation, they may not significantly worsen the lemons problem, because they discriminate in discouraging inexperienced bidders who may be less serious about purchasing. Thus, the use of such indicators may benefit sellers with high-quality products.

The simulation results finally show that the use of credibility indicators significantly increases bidders' auction entry probability and encourages early bidding and bid shading. As we show in Table 6, when we increase a seller's feedback rating or the percentage of auctions designed with third-party payment by 10%, the probability of participation increases by .29% and 1.17%; the average number of latent bidders jumps by a significant 11.10% and 10.43%; interbidding time decreases by 2.01% and 2.02%; the final bid price decreases by .55% and .63%; and the average bidder experience increases by 3.09% and 2.30%, respectively. Again, bid shading is not dramatic for the products in this study, so credibility indicators significantly mitigate the lemons problem. Credibility indicators can improve consumers' trust in both auction sellers and the auctioned items.

Conclusion, Managerial Implications, and Further Research

Many consumers reject Internet auctions because of the physical separation of buyers from sellers. Since the emergence of the Internet, auction companies have attempted to find the most efficient design for their auction mechanisms. The rapid expansion of Internet auctions to consumer-to-consumer and business-to-consumer markets for an increasing number of consumer products and services also demands research into how Internet auction designs affect bidding behavior. We systematically evaluate the effect of auction features (i.e., sellers' cumulative ratings, third-party payment, picture postings, money-back guarantees, minimum bidding price, hidden reserve price, and BIN option) on consumer bidding behaviors, and we provide implications for how these features can help solve the lemons problem.

We acknowledge dual information asymmetry in Internet auctions and therefore develop a typology of Internet auction indicators of seller credibility and product quality that consists of hypotheses about how these indicators may help alleviate the lemons problem. We adopt an appropriate modification of Park and Bradlow's (2005) model to test empirically how these quality indicators affect bidders' decisions about whether to bid, who bids, when to bid, and how much to bid. By accounting for the latent competition among potential bidders, consumer heterogeneity, and the interdependence of bidding decisions, this proposed model simultaneously evaluates the signaling roles of interdependent bidding decisions and accounts for consumer heterogeneity. Specifically, we (1) examine whether Internet auction features serve as effective credibility or quality indicators, (2) analyze factors that affect the reliability and credibility of the indicators, (3) study how different types of indicators affect bidding behavior and their implications for the lemons problem, and (4) investigate how the signaling effect differs across bidders with different experience.

Reputable sellers with high-quality products can use eBay's features to signal their credibility and the products' true quality in each auction and to enhance their reputation and thus distinguish themselves from disreputable sellers or sellers of low-quality items. As a result, bidders benefit from reduced uncertainty about both the sellers' credibility and the quality of their items, which directly affects bidding behavior and WTB. Consistent with common intuition, credibility or direct quality indicators encourage bidders to participate and prompt bid shading in response to concerns about the winner's curse; the opposite is true for indirect quality indicators. However, the bid shading resulting from direct indicators is not very dramatic. Moreover, the simultaneous use of credibility and quality indicators strengthens the effects of quality indicators. More experienced consumers make better inferences about the roles of both credibility and quality indicators. These results are even more evident in the simulation results. We find that the proposed signaling-based hypotheses are consistent with the estimation results and provide coherent explanations of consumers' bidding behavior.

Our study has important managerial implications for Internet auctions sites and sellers, which can use these findings to improve auction site designs and to provide more credibility and quality indicators to improve site use and traffic. Reputable online sellers of high-quality products should combine various credibility and quality indicators to reveal their true credibility and quality, to encourage auction participation, and to enjoy higher closing prices. Thus, we empirically establish the role of Internet auction features as quality or credibility indicators.

This research is subject to several limitations that provide avenues for further research. First, because our intent was to focus on how quality signals help solve the lemons problem, we modeled four interdependent bidding decisions—whether to bid, who bids, when to bid, and how much to bid—based on the assumption of affiliated-value auctions. Additional research might consider private-value auctions and compare them with affiliated-value auctions to better understand the role of the Internet auction indicators. Second, it would be worthwhile to study the dynamics of bidding behavior across multiple auctions over time (e.g., Zeithammer 2006, 2007). For example, how do forward-looking bidders revise their bidding strategies when they observe multiple listing of similar items at the same time? More structural models might enable bidders to update their formation of affiliated value in a Bayesian manner, on the basis of periodically observed decisions of other bidders within and across auctions. Third, we focused on consumer bidding behavior and treated the sellers' decisions as exogenous, but experienced sellers might be strategic in adopting credibility or quality indicators. Therefore, it would be worthwhile to incorporate the strategic behavior of sellers to draw implications about the best strategy to maximize sellers' profits as part of the customer relationship management efforts. The modeling approach that Bajari and Hortacsu (2003) use seems promising in this venue. Finally, we provide empirical evidence about how Internet auction features signal product quality and seller credibility and how these features affect consumers' bidding behavior. Analytical models can be developed to examine the rationale behind these strategies and to compare different indicators in terms of signaling costs.

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