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Do Auction Parameters Affect Buyer Surplus in E-Auctions for Procurement?

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Although the initial euphoria about Internet-enabled reverse auctions has given way to a cautious but widespread use of reverse auctions in business-to-business (B2B) procurement, there is a limited understanding of the effect of auction design parameters on buyer surplus. In this paper, we study the effect of bidding competition, information asymmetry, reserve price, bid decrement, auction duration, and bidder type on buyer surplus. We collected field data on more than 700 online procurement auctions conducted by a leading auctioneer and involving procurement items worth millions of dollars. Consistent with the predictions of auction theory, the results indicate that bidding competition, reserve price, and information sharing affect buyer surplus. Unlike previous findings in the consumer-to-consumer context, we find that bid decrement and auction duration have no effect in B2B procurement auctions. Our results suggest that use of the rank-bidding format increases buyer surplus when incumbent suppliers participate in the auction. We discuss the theoretical and managerial implications of these findings for future research and for optimal design of online procurement auctions.

Key words: business value of information technology; supply chain management; buyer surplus; reverse auctions; internet-enabled procurement auctions

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1. Introduction

Information technology (IT) in general, and the Internet in particular, have fueled the widespread adoption of auctions in business-to-consumer (B2C), consumer-to-consumer (C2C), and business-to-business (B2B) environments (Bapna, Goes, and Gupta 2000; Bichler et al. 2002; Elmaghraby 2004; Van Heck and Vervest 1998). Although the tremendous popularity and familiarity of Web sites such as eBay and priceline.com has sparked significant research activity related to B2C and C2C auctions (Ba and Pavlou 2002; Bapna, Goes, and Gupta 2001; Bapna, Goes, and Gupta 2003a; Kauffman and Wood 2006), B2B auctions involving much larger portions of the economy and having implications for firm performance have remained understudied (Jap 2003). Internet B2B transactions were valued at $90 billion in 1999, more than five times the value of Internet B2C transactions (Lucking-Reiley 2001). According to one estimate, by 2007, a quarter of U.S. B2B e-commerce will involve the use of auctions (Rosenthal 2003).

Despite the economic significance of online B2B auctions, there are few empirical studies of B2B auctions because of the limited availability of proprietary data needed for such research (Choudhury, Hartzel, and Konsynski 1998). Researchers have used laboratory experiments to test auction theory and generate insights for the B2B environment (Bichler 2000; Brosig and Reiss 2003; Katok and Roth 2004; Koppius and Van Heck 2002). The laboratory experiments are attractive because they allow for randomization and enable researchers to control the auction environment (Roth 1988). However, the realism of the laboratory setting continues to be an issue, because most college students who are used in experimental studies are unfamiliar with the type or complexity of goods and services being auctioned (Rothkopf and Harstad 1994). Furthermore, it is difficult to generalize insights from the observed behavior of these laboratory bidders to participants in real-life procurement auctions, because real-world auctions are significantly more complex for at least two reasons. First, real-world procurement auctions involve significantly larger stakes for participants, such as the gain or loss of business worth millions of dollars. In contrast, participants in laboratory experiments have much less to lose or gain (Harrison 1989; Hendricks and Paarsch 1995; Milgrom 2004; Milgrom and Weber 1982). Second, real-world auctions require much more rapid decision making to integrate more diverse and complex information made available by the auctioneer as the auction proceeds, by competitive reactions of other bidders, and by the information on bidders' own private costs (Jap 2002; Milgrom 2004). Thus, there is a need for field studies to complement the insights of laboratory auctions to generalize findings and to learn how "real economic agents" behave in electronic markets (Bapna, Gupta, and Jones 2006).

In this paper, we study the effect of auction design parameters on cost savings realized by buyers using reverse auctions. In particular, our research addresses the following research question: What is the effect of bidding competition, information asymmetry, reserve prices, bid decrement, and auction duration on buyer surplus? We performed an empirical study of more than 700 auctions conducted by a leading online auctioneer in the automotive industry and involving millions of dollars' worth of procurement items. The study comprised a literature review, development of the conceptual model, and interviews with senior supply chain management executives from a leading online auctioneer and an automotive firm to include relevant contextual details in the econometric models. To the best of our knowledge, this is the first study to use such a large-scale, real-world data set on Internet-enabled procurement auctions to test the predictions of auction theory.

This study is important from both the academic and the managerial perspectives. From an academic perspective, this study contributes to the growing literature in the supply chain management area that has "become the dominant theme in the operations management research" (Kouvelis, Chambers, and Wang 2006, p. 449). Our work is also related to the supply chain and information systems literature that studies the implications of IT for electronic integration, organizational capabilities, and firm performance (Bardhan, Whitaker, and Mithas 2006; Brynjolfsson and Hitt 1998; Mithas, Krishnan, and Fornell 2005; Mukhopadhyay and Kekre 2002; Prahalad, Krishnan, and Mithas 2002; Rai, Patnayakuni, and Seth 2006; Sambamurthy, Bharadwaj, and Grover 2003; Whitaker, Mithas, and Krishnan 2007). We approach the IT-enabled reverse auctions from a business value perspective (Barua, Kriebel, and Mukhopadhyay 1995; Kauffman and Kriebel 1988; Lucas 1993) and test some predictions of auction theory while identifying areas in which empirical regularities in the B2B domain do not conform to the predictions of the traditional analytical models or findings reported in the B2C domain. Our empirical results suggest that reverse auctions help buyers realize savings in procurement costs, and they provide implications to develop more realistic analytical models of procurement auctions. By studying the effect of reverse auctions that facilitate both identification and selection of vendors, we extend previous work that studies the use and effect of IT applications and IT-enabled electronic market mechanisms in supply chain relationships (Bakos and Brynjolfsson 1993; Bensaou 1997; Choudhury, Hartzel, and Konsynski 1998; Clemons, Reddi, and Row 1993; Johnson and Whang 2002; Mithas, Jones, and Mitchell 2006c; Snir and Hitt 2003; Subramani 2004; Wang and Archer 2004). From a managerial perspective, our findings shed light on the optimal auction format parameters to maximize buyer surplus in Internet-enabled B2B reverse auctions. Auctioneers and buyers can use our findings to design and conduct more effective procurement auctions.

The paper continues as follows. Section 2 reviews the background literature and develops the hypotheses. Sections 3 and 4 discuss the methodology and present the results. Section 5 provides a discussion and concluding remarks.

2. Background and Hypotheses

This section reviews the salient features of the data-generating auction mechanism we used in the context of relevant auction theory. We discuss how auction theory is being tested in electronic markets, and then we develop research hypotheses.

2.1. Reverse Auction Mechanism in Procurement

An auction is a market institution with an explicit set of rules that determine resource allocation and prices to match a buyer with a supplier to achieve a market-clearing price. The auction rules affect bidding strategies and incentives and, thus, transaction efficiency. The English auction, by far the most common type of auction, is an oral, outcry, ascending auction in which progressively higher bids are solicited until only a single bidder remains. At equilibrium, the bidder who values the item the most will retain the object at a price equal to the second-highest valuation; therefore, the English auction is efficient (Milgrom 1989). Because of the open nature of the auction, bidders can observe the behavior of other bidders, process this information, and dynamically modify their reservation prices under the common value (CV) model. The dominant bidding strategy is to bid until the price reaches the buyer's willingness to pay, normally a small increment below the bidder's true valuation.

Reverse auctions are similar to the English auction, except with descending bids. With this bidding direction, the bids get lower as the auction continues. Reverse auctions allow buyers to announce purchasing requirements and select suppliers from among the lowest bidders (Anandalingam, Day, and Raghavan 2005; Mithas, Jones, and Mitchell 2006c). Reverse auctions are increasingly used in procurement in which a buyer is trying to get the lowest price and several bidders are competing for the buyer's business. The buyer initiates the auction, usually by issuing a request for quote (RFQ), and acts as the bid taker. The seller is the bid maker, posting bids that indicate the amount for which he or she is willing to sell the goods or services.

The auction mechanisms we used in this paper have certain characteristics that have been widely adopted in the B2B arena. We describe some key features of the mechanisms relevant to this research (see Anderson and Frohlich 2001 for details). After a buyer, such as a tier-1 automotive firm, has engaged an auctioneer or a market maker, the first step involves preparation of the RFQ. Typically, an RFQ includes a detailed specification of the products or services to be auctioned, proposed contract terms, and an initial list of potential suppliers the auctioneer proposes to invite to the auction event. The participants are based on the auctioneer's database of qualified suppliers, characteristics of the goods and services to be auctioned, buyer specifications, and any other relevant buyer requirements. Next, the buyer reviews the auctioneer's list of proposed supplier invitees. Although a larger number of potential bidders would likely make a more competitive market and increase buyer surplus, buyers typically prune the list proposed by the auctioneer because they have a better understanding of the capabilities and limitations of many of these suppliers, depending on their unique needs. In some cases, the buyer may also add suppliers to the list. At this point, the buyer must also decide whether to invite the incumbent supplier to the auction. After the auctioneer receives approval from the buyer, the auctioneer invites all the "potential bidders" to participate in the reverse auction. Potential bidders receive the detailed product and service specification and are encouraged to submit a bid in advance of the actual event. This bid is referred to as a "saved bid" and is solicited so that the auctioneer can assess the viability of the market.

After the viability of the market has been established, the auctioneer and buyer discuss the format of the auction. Choice of the auction format involves setting the auction parameters, such as the existence and level of a reserve price, bid decrement, auction starting time, auction duration, and information revelation during the auction. Reserve price is normally determined as a percentage of the historical price the buyer was paying before the auction. Typically, the auctioneer selects the following information revelation policies: rank format or starting-gate format. In rank format, bidders (suppliers) see only their position with respect to other bidders at any point in time. Bidders do not see either the bid amounts or the distance between their bids and other bids. The bid history and bid graph are not displayed. Only the lead bidder knows that he or she possesses the lowest bid. Rank format is typically used when the buyer is concerned with market-price confidentiality. The starting-gate format hides all bidding action information from a bidder until after the bidder submits his or her first bid. This prevents bidders from simply watching the bidding action without submitting bids and discourages them from waiting to bid until the last minute. Before the actual auction event, the auctioneer conducts separate training sessions for buyer and supplier representatives to make them familiar with the auction process, that is, how to submit bids, track auction progress, and contact the auctioneer if there are any problems during the auction, such as poor auction display and lost Internet connectivity.

The actual auction event is preceded by extensive preparations, and the auctioneer ensures that all auction participants are available during the auction time frame to submit their bids electronically. Typically, both buyer and supplier representatives are in telephone contact during the auction to resolve any issues quickly and to postpone or extend the auction duration as necessary. Bidders are expected to submit a bid for the current asking price if it is not below their valuation of the auction lot, a typical strategy characterized as the "pedestrian" approach (Rothkopf and Harstad 1994). All bids submitted by bidders have a time stamp, and only the bids that conform to auction rules are considered valid. Invalid bids typically arise if a bidder submits a bid that is higher than the current bid in a reverse auction. Sometimes bids become invalid because of the lag in electronic transmission. Because bidders can see the auction progress in real time, they immediately receive a notification if their bid is invalid, which allows them to place their next bid.

The auction terminates at the predetermined closing time unless there is last-minute bidding activity. Most auctions have a soft closing, which means that the auction duration is automatically extended by a few minutes after the last bid to allow other bidders to respond. Unlike the multi-unit settings described by Bapna et al. (2002) that may have discriminatory pricing structures, we treat our setting as single-unit and nondiscriminatory in terms of its pricing structure because in most cases, the buyer is expected to award the contract to the lowest bidder.

There are two commonly assumed models for how bidders in an auction place value on objects: the independent private value (IPV) model and the CV model. If bidders know with certainty the value they place on an item, the auction is said to use the IPV model. Individual valuations have a common distribution but are statistically independent of the other bidders' valuations. In contrast, a CV object is assumed to have a single value, but information regarding this value varies among bidders (Milgrom 1989). Because of the statistical dependence inherent in the CV model, bidders tend to infer information from other bids, leading to a positive correlation among bidder valuations (Milgrom and Weber 1982). The CV model relies on the assumption that there is a liquid market for the item being sold and that the item has an economic value based on the profits generated by or the salvage value of the item. Common value is typically invoked in B2C or C2C auctions in which the objects being sold have some price in the open market. Because B2B auctions do not involve any resale of business among bidders and the profits of bidders depend on their unique cost structures, we follow Vakrat and Seidmann (2000), and assume that such auctions meet the IPV assumption. The payoff function involves decisions surrounding the financial transfer of a product, such as the award mechanism or the rule used to determine the winning bid, the final price and recipient, the presence or absence of a reservation price, and other participation costs (Engelbrecht-Wiggans 1980). In the case of reverse auctions, the payoff function may award the object to the lowest bidder if the bid is lower than the reserve price set by the buyer (Jap 2003).[1]

2.2. Prior Literature on Electronic Auctions

The introduction of auctions on the Internet has sparked tremendous interest in auctions as a selling mechanism and as an area of academic research. Bapna Goes, and Gupta (2001) classify online auctions into the B2C, C2C, and B2B categories. Electronic auctions have lowered entry barriers for all auction participants, including auctioneers, buyers, and suppliers. For example, in the B2C context, eBay provides a forum in which any seller can submit items for sale and reap the benefits of worldwide exposure. Online auctions also provide several benefits to buyers and suppliers in the B2B context. For example, traditional auctions are typically held at a physical location, are conducted by an auctioneer, and last a few minutes. However, this involves a great deal of expense to establish a site, employ an auctioneer, and gather potential bidders. In contrast, electronic procurement auctions can be conducted anytime and anywhere by means of multimedia and database facilities to describe the complexity of the items (Klein and O'Keefe 1998; Lucking-Reiley 2000). The Internet also provides access to a global pool of bidders with the potential for more aggressive bidding resulting from increased participation. Electronic auctions can also use computing power to establish more complex trading rules, such as combinatorial and multi-attribute auctions (Jones and Koehler 2002; Parkes and Kalagnanam 2005).

Much of the classic auction theory is being reevaluated in light of this new medium. Among early work, on the basis of a field study of 100 online auctions, Beam and Segev (1998) provide an overview of practices, trends, and recommended criteria for "good" auctions in the B2C context. The relatively inexpensive nature of items involved in many B2C auctions (e.g., baseball cards, coins) and the ease of replicating such auctions in experimental settings have helped the empirical testing of auction theory predictions in the B2C context (Bajari and Hortacsu 2004; Bolton, Katok, and Ockenfels 2004; Lucking-Reiley 1999). Such empirical examinations have led to the detection of empirical regularities that run counter to classical auction theory and the search for better models to explain these regularities (Bajari and Hortacsu 2004). On the basis of their empirical investigation of multi-item progressive electronic auctions in the B2C context, Bapna, Goes, and Gupta (2000) suggest that the assumptions underlying classical auction theory do not hold in electronic auctions. They found heterogeneity among bidders, characterized by different bidding motivations (e.g., the entertainment value of participation), and other rational and irrational bidding strategies. In another study, Lucking-Reiley (1999) suggests that the revenue equivalence theorem does not hold for online auctions.

Although much of the empirical work on auctions has been done in the B2C context, as noted previously, B2B auctions involve significantly more business activity and dollars than B2C auctions (Lucking-Reiley 2001). Because of a wide variety of products and services involved in B2B transactions, B2B auctions are significantly more complex. According to one estimate, there are more than 160 million possible combinations of bidding formats, display formats, and other auction design parameters in B2B auctions (Anderson and Frohlich 2001). For these auctions to lead to desired outcomes, the auctioneer must choose the optimal bidding format. It is important for buyers and auctioneers to understand the features of the auction format and the rules that maximize buyer surplus.

[1] Although all supplier bids are legally binding, most buyers using reverse auctions retain the right to award the contract on criteria other than price.

From a theoretical perspective, B2B auctions pose an opportunity to develop more realistic auction theory models that consider the variety and sophistication of newer bidding formats and auction rules in industrial settings.

Early work on B2B electronic markets involved the use of detailed case studies. For example, Gebauer and Buxman (2000) studied an Internet-based procurement system in a university setting in which the initiating buyer organization uses a private exchange to interact with a small and fixed set of suppliers to award contracts using an RFQ-based bidding process. Choudhury, Hartzel, and Konsynski (1998) found that electronic markets had a statistically insignificant impact on prices in the aircraft industry, particularly for parts for which quality was important. However, it is difficult to generalize findings from this study to electronic markets using reverse auctions, because this study involved an electronic market to identify potential trading partners rather than a market to select a specific partner and execute a trade. More recently, Mithas, Jones, and Mitchell (2006c) studied the effect of asset specificity, noncontractibility, and product specialization on the buyer decision to use reverse auctions. Although their study provides further evidence for the importance of supplier investments in the noncontractible elements of exchange relationships to affect buyer loyalty, which has implications for firm performance (Fornell et al. 2006), they do not study how auction parameters affect buyer surplus.

Unlike B2C auctions in which the plentiful availability of auction data in the public domain has attracted significant research activity, the lack of available proprietary data has seriously hindered research on the effect of auction parameters in the B2B domain. The difficulties involved in B2B auctions research have not gone unnoticed. As Pinker, Seidmann, and Vakrat (2003) note: "There is a need for the academic community to forge stronger ties with the leaders in the B2B online auction market. Only by gaining access to the proprietary data of these market makers will we be able to address issues that truly have significance to business decision makers, and develop tools that improve the way online auctions are used" (p. 1481). Jap (2003) conducted one of the first exploratory studies on the effect of auction parameters in B2B reverse auctions, using data from six reverse auctions with 105 lots across six product categories. She provides some specific suggestions for B2B auction research and observes the following: "[M]ore work is needed on the circumstances that create cost savings. What role do the numbers of bidders, the size of purchase contract play in motivating how suppliers bid in various types of online reverse auctions? Further research should consider these questions across many more auctions" (pp. 105–106).

Our work complements that of Jap (2003) by considering the effect of bidding competition, bid decrement, reserve price, auction duration, and information transparency on buyer surplus.

2.3. Hypotheses

2.3.1. Bidding Competition. Bidding competition refers to the number of bidders and the number of bids in an auction. In addition to the individual impact of these variables on auction effectiveness, there is a correlation between the number of bidders and the number of bids. In forward auctions, seller revenue rises with the number of bidders and aggressive bidding (McAfee and McMillan 1987). On the basis of their analytical work, Holt (1980) and Harris and Raviv (1981) show that increasing the number of bidders increases seller revenue and buyer surplus (i.e., it reduces the difference between the winning bid and the marginal bid). The reason for an increase in seller revenue is that as the number of bidders increases, the second-highest valuation also increases (Das and Sundaram 1997). In addition, McAfee and McMillan (1987) suggest that higher variance in the distribution of valuations (another indicator of bidding competition) increases seller revenue.

In the case of procurement auctions and contract bidding, several studies of traditional auctions report that greater competition lowers price. For example, Gaver and Zimmerman (1977) report a reduction in prices as the number of bidders increases in contract bidding. In their study, bids declined by 2% for every unit increase in the number of bidders. Brannman, Klein, and Weiss (1984) find a significant effect of the number of bidders on price in government auctions. Along similar lines, Yuseph (1976) reports price differences that average 50% between sole-source and competitive-bidding contracts for identical items in military procurement. Consistent with previous findings, we expect that greater bidding competition in Internet-enabled procurement auctions is associated with greater buyer surplus. Thus:

H1a: *The higher the numbers of bidders participating in a reverse auction, the greater is the buyer surplus.*

H1b: *The higher the numbers of bids in a reverse auction, the greater is the buyer surplus.*

2.3.2. Bid Decrement. Previous research has noted that bid increment can have a significant influence on auction outcomes. In the context of B2C Yankee auctions (also known as multi-item progressive electronic auctions), Bapna, Goes, and Gupta (2001) find that bid increment has a significant influence on the number of active participants and auctioneer revenues. Indeed, bid increment is the most important auction attribute in their analysis. They also find that the valuation of the marginal bidder influences auction revenues and that the bid increment affects the types of bidders who participate in auctions. Extending Bapna, Goes, and Gupta's (2001) findings in B2C forward auctions to the context of B2B reverse auctions, we posit that buyer surplus will be greater if buyers stipulate a higher bid decrement.

H2: *Higher bid decrement is positively associated with buyer surplus.*

2.3.3. Reserve Price. As noted in Section 2.1, the setting of a reserve price can involve two sequential decisions. The first decision is whether to set a reserve price. If a buyer decides to do so, the second decision involves the level of reserve with respect to the historical price he or she paid before using a reverse auction.

Auction theory makes several predictions about the effect of reserve prices on selling prices in forward auctions. The work of Vickrey (1961) and Riley and Samuelson (1981), assuming independent private values and an exogenous number of bidders, suggests that setting a reserve price increases seller revenues in forward auctions. However, in their models, the effect of a reserve price diminishes significantly as the number of bidders increases. In contrast, in models in which the number of bidders is endogenously determined, Engelbrecht-Wiggans (1987) shows that setting a lower reserve price in forward auctions may lead to higher expected revenues if a lower reserve price increases the number of bidders participating in an auction.

Informal evidence on the infrequent use of reserve prices indicates a discrepancy between theoretical predictions and actual practice (Cassady 1967; McAfee and McMillan 1987). However, Milgrom (1986) argues that the observed practice may not conflict with theory if sellers lack the ability to precommit to their selling policy in the context of forward auctions. In field-based experiments using C2C auctions of trading cards, Reiley (2005) finds that an increase in reserve prices is associated with a decrease in the probability of selling the goods, but higher revenues if the goods are sold. In the context of online reverse auctions, we expect that setting a reserve price has a positive influence on buyer surplus. Furthermore, we posit that setting a reserve price close to historical prices (i.e., a relatively low reserve price) may enhance bidding activity and generate larger buyer surplus. Thus:

H3a: *Setting a reserve price is positively associated with buyer surplus.*

H3b: *Setting a lower reserve price with respect to historical price is associated with greater buyer surplus.*

2.3.4. Auction Duration. Auction duration plays an important role in Internet auctions because auction duration may affect the participation levels of bidders, the number of bids, and buyer surplus. Higher auction duration also increases the costs of conducting a global auction and providing support services to multiple sites across different time zones. Even when bidders are preselected and the auction duration will not induce more bidders to join, a longer auction may allow preselected bidders to become more familiar with the bidding process and allow greater participation from those bidders. At our research site, managers and auctioneer representatives believe that unfamiliarity may be acting as a deterrent to auction participation because despite incurring the cost of the preselection process and indicating their willingness to participate in an auction, some bidders did not place a single bid in actual auctions.

Lucking-Reiley (1999) provides evidence for longer auction duration leading to higher prices for sellers in forward coin auctions on eBay. This may result from attracting a greater number of bidders to participate when the duration is longer (Pinker, Seidmann, Vakrat 2003). From this discussion and drawing on the results in C2C auctions, we hypothesize the following:

H4: *Auction duration is positively associated with buyer surplus.*

2.3.5. Information Transparency. Information revelation during an auction can have a significant influence on auction outcomes. As Jap (2003) mentions: "Future research might consider whether online reverse auction formats that reveal less information, perhaps only the lowest market bid or a rank ordering of the bids, would produce different effects (p. 105)." Schrader, Schrader, and Eller (2004) also suggest that reverse auctions have introduced information asymmetries in favor of the buyer, thus producing cost savings.

Auction theory also suggests that uncertainty of the number of participants can be exploited in first price auctions under the IPV assumption. Milgrom and Weber (1982) provide examples of the choices a seller can make to share information in forward auctions, such as concealing all information, adding noise to the data, reporting rough summary statistics, reporting only the most favorable information, and reporting complete information. In their general model, sharing complete information appears to maximize the expected price a seller can obtain in forward auctions using the first price, second price, and English auction formats. In addition, if suppliers are risk averse, auctions with sealed bids submitted simultaneously are likely to have a lower expected price than the price in sequential auctions in which bidders reveal their bids as they sequentially withdraw (Holt 1980). McAfee and McMillan's (1987) analytical work shows that if the number of bidders is unknown and bidders have constant or decreasing absolute risk aversion, concealing the number of bidders enhances seller revenue in forward auctions. In a section titled "A Machiavellian Advice to a Monopolist," McAfee and McMillan note: "You should, if possible, keep secret from each bidder how many other bidders he is competing with" (p. 734). Extending these arguments to reverse auctions, we posit the following:

H5: *Information transparency about auction parameters is negatively associated with buyer surplus.*

We control for other variables that are likely to influence the relationship between auction parameters and auction effectiveness: potential bidders, saved bids, presence of incumbent, and lot size. Following the work of Hansen (1985), we control for the number of potential bidders in the auction. We also control for the number of saved bids that are posted before the auction and that serve both as a proxy for the bid interest and as a control for the unobserved characteristics of the goods and services being auctioned. We control for the presence of the incumbent in the auction because incumbents have better knowledge of the cost structure of the goods and services and may be in the best position to lower their price to variable costs, which may affect the auction dynamics. Finally, we control for lot size because it may influence bidder behavior and buyer surplus.

3. Research Design and Methodology

3.1. Sample and Data Collection

We collected archival data on procurement auctions from a leading firm in the U.S. automotive industry. Our research site began experimenting with Internet-enabled online reverse auctions in April 2000 to achieve the twin objectives of supplier consolidation and cost reduction. Initial experience with four pilot auctions met these objectives and led to expanded use of reverse auctions. Reverse auctions also provided additional benefits that our research site did not initially expect or consider important, such as reducing the cycle time to negotiate and award contracts. The continued use of reverse auctions has helped our research site achieve cycle-time reduction for advanced projects in supplier negotiations. Note that switching to reverse auctions required a significant strategic shift in the firm's supply chain management practices, because in the automotive industry, replacing a supplier even for a commodity such as fasteners may require revalidation and regulatory testing.

3.2. Variables

We collected detailed data on more than 700 auction lots from our research site for all auctions conducted during the period 2001 to 2003.

The dependent variable in this study is buyer surplus, which we operationalized by calculating the price of the lowest winning bid as a percentage of the historical price (BIDVHIST). A lower value of BIDVHIST denotes a larger difference between historical price and the lowest winning bid (as a percentage of the historical price) and thus indicates greater buyer surplus.

We measured bidding competition using the number of valid bids and the number of bidders. The variable NUMVALIDBID measures the total number of valid bids received in an auction. A valid bid is one that followed auction rules such as minimum bid decrement. The variable NUMBIDDERS measures the actual number of bidders who participated in the auction for the lot. The variable LNLOTHIST measures the historical value of lots being auctioned in dollars. We took the log of the dollar value to reduce the skewness of this variable. We measured the presence and value of the reserve price in auctions using two variables. RESERVEYN is a binary variable that indicates whether a reserve price was set in the auction (1 = reserve price set, 0 = reserve price not set). If a reserve price was set, RESVHIST measures the reserve value of the lot as a percentage of the historical price of the item being auctioned. INCUM is a binary variable that indicates whether the incumbent supplier participates in the auction (1 = incumbent participates, 0 = incumbent does not participate). Use of this variable enables us to account for an observed source of bidder heterogeneity based on bidders' current incumbency status (Jap 2003). AUCDURMTS measures actual auction duration in minutes. BIDDECR measures the minimum bid decrement in dollar terms allowed under auction rules for that lot.

Our research site used rank-bidding and starting-gate-bidding formats to provide different degrees of information transparency to the bidders. We use the variation on these formats to study their effects on buyer surplus. In the rank-bidding (RANK) format, bidders see only their own ranks among the other bidders. In the starting-gate-bidding (STRTGATE) format, a bidder receives no information about the bidding action until after submitting his or her first bid. We also collected data on the number of bidders invited (NUMINVITEDBIDDERS) and the number of bids received (NUMSAVEDBIDS) before the actual auction. The auctioneer used these data to establish the viability of the auction. Table 1 provides a summary and brief definition of all the variables used in this study.

Tables 2 and 3 report the descriptive statistics and the correlations between constructs. Table 2 shows that the buyer uses reverse auctions for goods and services ranging in value from $5,712 to approximately $52 million. The buyer invited an average of 20

Table 1 Variable Definition

Variable	Description
BIDVHIST	Lowest bid as a percentage of historical price
NUMBIDDERS	Number of actual bidders in a lot
NUMVALIDBIDS	Number of valid bids in a lot
LNLOTHIST	Natural log of historical price
RESERVEYN	Reserve price set or not (1 = Yes, 0 = No)
RESVHIST	Reserve price as a percentage of historical price
RANK	Bidding format in which bidders (suppliers) see only their own ranks among the other bidders. Bidders do not see the bid amounts or their bids' distance from the other bids. The bid history and bid graph are not displayed. Only the lead bidder knows the lowest bid. Rank-only bidding is typically used when the buyer is concerned with market-price confidentiality
STRTGATE	Bidding format in which a bidder receives no information about the bidding action until after submitting his or her first bid. This prevents bidders from watching the bidding action without submitting bids and discourages them from waiting until the last minute to bid
AUCDURMTS	Auction duration in minutes
BIDDECRE	Bid decrement in dollars
INCUM	Presence of incumbent in a lot (1 = Yes, 0 = No)
RANK × INCUM	Interaction term involving rank bidding and incumbent in a lot

Source: Auction vendor documentation and field interviews.

bidders to participate in each auction and, in general, requested bidders to indicate their interest by submitting a bid before the auction to ascertain the auction viability up front. On average, four bids were received before each auction. The lowest bid at the conclusion of each auction averaged approximately 85% of the historical price. An average of six bidders participated in each auction, and each lot attracted an average of 23 bids during the auction. Approximately 80% of the auctions were conducted with a reserve price. On average, buyers set the reserve price at 91% of the historical price. Buyers used the starting-gate mechanism in 96% of the auctions and rank bidding in 73% of the auctions. Approximately 36% of auctions had incumbents as a bidder. Of the 770 auctions analyzed, the incumbent participated in 277 and was the lowest bidder in only 10 of the auctions. On average, the incumbent's final bid was 17% higher than the lowest bid as a percentage of the historical price and was the 12th lowest at the end of the auction. The raw difference in cost savings offered by current and new suppliers in our study appears to be significantly higher than Jap's (2003) finding of less than one percentage point difference in cost savings offered by new suppliers compared with current suppliers.

Table 2 Descriptive Statistics

Variable	*n*	Mean	Std. Dev.
BIDVHIST	770	85.46	13.05
NUMBIDDERS	770	6.17	4.53
NUMVALIDBIDS	770	25.00	28.13
LNLOTHIST	770	13.09	1.60
RESERVEYN	770	0.79	0.40
RESVHIST	496	90.65	10.89
RANK	770	0.72	0.45
STRTGATE	770	0.95	0.21
AUCDURMTS	770	92.47	46.82
BIDDECRE	770	0.49	0.27
INCUMBENT	770	0.36	0.48
NUMINVITEDBIDDERS	770	19.77	11.49
NUMSAVEDBIDS	712	3.99	3.30

3.3. Empirical Models and Econometric Issues

We use a linear model estimation approach to relate auction design parameters to buyer surplus. Table 4 shows the results of the estimation of our empirical models. Column (1) of Table 4 shows a model with a binary measure of reserve price (RESERVEYN), and column (2) shows a model with reserve price as a percentage of historical price (RESVHIST). As Table 4 shows, the explanatory power of our models is reasonable, as reflected by the overall R-square values. For both models in Table 4, we performed several diagnostic checks to ascertain the stability of our results. We tested for multicollinearity by computing the variance inflation factors. The highest variance inflation factor in our models was lower than five, indicating that multicollinearity was not a serious concern in our analysis. We also calculated Hat values to check for leverage and studentized residuals to detect outlying cases. Our analysis of measures of influence (DFbetas and Cook's distance) did not suggest the presence of influential observations in our sample (Belsley, Kuh, and Welsch 1980).

4. Results

Hypothesis 1 predicted a positive association between bidding competition (number of bids and number of

Table 3 **Pairwise Correlations among Variables**

		1	2	3	4	5	6	7	8	9	10	11
1	BIDVHIST	1.00										
2	NUMBIDDERS	−0.22	1.00									
3	NUMVALIDBIDS	−0.46	0.46	1.00								
4	LNLOTHIST	−0.12	−0.01	0.32	1.00							
5	RESERVEYN	0.04	−0.15	−0.08	−0.03	1.00						
6	RESVHIST	0.27	0.17	−0.19	−0.34		1.00					
7	RANK	0.08	0.13	−0.28	−0.32	0.20	0.51	1.00				
8	STRTGATE	−0.11	−0.15	−0.26	−0.35	0.14	0.17	0.36	1.00			
9	AUCDURMTS	−0.10	0.00	0.16	0.10	0.05	−0.04	0.01	0.07	1.00		
10	BIDDECRE	0.08	0.06	−0.25	−0.81	−0.01	0.19	0.16	0.15	−0.14	1.00	
11	INCUM	0.03	0.01	0.09	0.28	0.19	0.11	0.03	−0.10	0.17	−0.30	1.00

Note: All correlations greater than 0.08 are significant at $p < 0.05$.

bidders) and buyer surplus. We find that greater buyer surplus is associated with the total number of bids in the auction. Each extra bid increases the buyer surplus by 0.255% ($\alpha_{22} = -0.255$, $p < 0.01$) of the historical price. When we control for the number of bids, we find no evidence for an effect of number of bidders on buyer surplus (α_{11} and α_{21} are statistically insignificant).

Hypothesis 2 predicted a positive association between bid decrement and buyer surplus. However, we did not find any effect of bid decrement on buyer surplus ($\alpha_{28} = -1.233$, $p = 0.703$). This result is in sharp contrast to findings in the B2C domain. For example, in B2C auctions, Bapna, Goes, and Gupta (2001) found that bid increment has a significant influence on the number of active participants and auctioneer revenues. Bid increment was one of the most important auction attributes in their analysis.

Hypothesis 3a predicted that setting a reserve price would increase buyer surplus. We cannot reject this hypothesis, because we do not find any significant difference in buyer surplus across auctions with or without reserve price ($\alpha_{13} = 0.617$, $p = 0.561$). Hypothesis 3b predicted that setting a reserve price relatively lower than the historical price would increase buyer surplus. This hypothesis is supported ($\alpha_{23} = 0.307$, p

Table 4 **Parameter Estimates for Effect of Auction Format on Buyer Surplus**[a]

		(1) BIDVHIST		(2) BIDVHIST		(3) BIDVHIST		(4) BIDVHIST
NUMBIDDERS	α_{11}	−0.083	α_{21}	0.088	β_{11}	−0.131	β_{21}	0.086
		(0.450)		(0.553)		(0.229)		(0.562)
NUMVALIDBIDS	α_{12}	−0.228***	α_{22}	−0.255***	β_{12}	−0.223***	β_{22}	−0.255***
		(0.000)		(0.000)		(0.000)		(0.000)
RESERVEYN	α_{13}	0.617			β_{13}	0.834		
		(0.561)				(0.425)		
RESVHIST			α_{23}	0.307***			β_{23}	0.290***
				(0.000)				(0.000)
RANK	α_{14}	0.227	α_{24}	−2.298*	β_{14}	3.804***	β_{24}	−0.438
		(0.835)		(0.092)		(0.003)		(0.794)
STRT	α_{15}	−16.668***	α_{25}	−17.231***	β_{15}	−14.267***	β_{25}	−16.082***
		(0.000)		(0.000)		(0.000)		(0.000)
INCUM	α_{16}	1.615*	α_{26}	−0.532	β_{16}	8.542***	β_{26}	2.763
		(0.078)		(0.629)		(0.000)		(0.182)
AUCDURMTS	α_{17}	−0.004	α_{27}	−0.012	β_{17}	0.002	β_{27}	−0.011
		(0.631)		(0.271)		(0.804)		(0.337)
BIDDECRE	α_{18}	−5.123*	α_{28}	−1.233	β_{18}	−4.838*	β_{28}	−0.921
		(0.053)		(0.703)		(0.064)		(0.776)
LNLOTHIST	α_{19}	−1.242**	α_{29}	0.252	β_{19}	−0.867*	β_{29}	0.477
		(0.010)		(0.693)		(0.072)		(0.461)
RANK × INCUM					β_{191}	−10.034***	β_{291}	−4.632*
						(0.000)		(0.061)
Observations		770		496		770		496
R-squared		0.275		0.338		0.299		0.343

Note: p values are in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.
[a] All ordinary least squares models include an intercept term.

< 0.01) because reducing the reserve price relative to the historical price decreases the lowest bid and thus, increases buyer surplus. This finding is similar to that of Reiley (2005) in the C2C context, in which he found that setting higher reserve prices in forward auctions led to increased revenue. Given that the optimal auction design in an IPV model with risk-neutral bidders depends on setting an optimal reserve price (Bichler and Kalagnanam 2006; Wolfstetter 1996), buyers can use this finding to set reserve prices for procurement auctions. Hypothesis 4 predicted a positive association between auction duration and buyer surplus. We did not find any effect of auction duration on buyer surplus ($\alpha_{27} = -0.012$, $p < 0.271$).

Hypothesis 5 predicted that sharing less information with bidders would increase buyer surplus. We find that buyer surplus is higher when suppliers are given access to information on auction progress and to other suppliers' bidding behavior only when they have submitted at least one bid below the reserve price ($\alpha_{25} = -17.231$, $p < 0.01$). We also find that use of the rank-bidding format has a marginal effect on buyer surplus because the coefficient of rank bidding is only moderately statistically significant ($\alpha_{23} = -2.298$, $p = 0.092$). Recall that rank bidding hides competitors' bids and supplies the individual bidder with only the relative position or rank of his or her bid compared with other bids. We discuss this issue further as part of our additional analyses.

An analysis of the effect of control variables provides additional insights. We expected that the presence of the incumbent in the auction would lead to greater buyer surplus because we expected the current supplier to aggressively compete and lower his or her price to variable cost as necessary to maintain existing business, according to the predictions of microeconomic theory. Incumbent suppliers also hold an advantage over the buyer because replacing a supplier in the automotive industry may require the buyer to undertake costly revalidation and regulatory tests. Our results were not consistent with that expectation, because the coefficient of INCUM is not statistically significant ($\alpha_{26} = -0.532$, $p = 0.629$). This result may be because new suppliers may have cost advantages due to their access to cheaper labor or economies of scale in their other businesses and therefore are able to offer similar prices as those offered by the incumbent. It is also possible that new suppliers do not have any advantages and simply lowballed their bids to get incremental business (Jap 2003). Similarly, we did not find a statistically significant effect of lot size on buyer surplus ($\alpha_{29} = 0.252$, $p = 0.693$). Because lot size indicates a potential for economies of scale and higher profits, we would expect lot size to have a positive effect on buyer surplus if suppliers are likely to lowball their bids to get the business. However, nonsignificance of the effect of lot size implies that suppliers may not have behaved opportunistically in the B2B procurement auctions in our sample.

One advantage of working with real-world auctions is the ability to study regularities that are difficult to model analytically or anticipate up front because of a lack of knowledge on how players behave in actual auctions. Because auction theory does not predict how player characteristics (e.g., incumbent vs. nonincumbent) might interact with an auction format (e.g., information revelation) and what their effects might be on buyer surplus, we used cross-tabulations and interaction terms in our econometric specifications to study such patterns in our data.

Table 5 shows a four-way tabulation of mean value of buyer surplus (BIDVHIST) along with the number of observations used to calculate the mean buyer surplus. We tabulate the mean buyer surplus by starting-gate-bidding format, rank-bidding format, presence of incumbent, and setting of reserve price. Figure 1 uses box plots to convey this information visually. We observe from Table 5 and Figure 1 that under starting-gate bidding, the presence of an incumbent decreases buyer surplus in the no-rank-bidding condition. However, the presence of an incumbent has the opposite effect in the rank condition. This suggests the potential of an interaction effect between presence of incumbent and rank bidding.

We present the results of our econometric analysis for this interaction effect in columns (3) and (4) of Table 4. For brevity, we interpret column (4) only. The key finding is captured by the statistically significant coefficient of the interaction term RANK $\times$ INCUM ($\beta_{291} = -4.632$, $p = 0.061$). In substantive terms, this finding implies that the rank-bidding format increases buyer surplus when the incumbent is present in the auction.

The intuition for the interaction effect between rank bidding and incumbent presence is as follows: Because there is less information available to the bidders under the rank-bidding format (bidders only see their rank rather than the monetary value of other bids), they bid aggressively to stay ahead in the rankings. The presence of the incumbent in such auctions exacerbates this situation because the incumbent already knows his or her costs and can theoretically bid until the market reaches variable cost, as predicted by microeconomic theory. Thus, we believe that auctions with the rank-bidding format and an incumbent have greater competition and, thus, greater buyer surplus. This finding has theoretical significance because this result is not anticipated or explained by the classical auction theory, which does not consider such complex interaction effects arising from the interplay between information revelation policy (i.e., rank bidding) and bidder heterogeneity (i.e., incumbent vs. new suppli-

Table 5 Effect of Auction Format on Buyer Surplus

		Reserve and Presence of Incumbent					
		No Reserve		Reserve		Total	
		No incumbent	Incumbent	No incumbent	Incumbent	No incumbent	Incumbent
No Starting-Gate Bidding Format							
No Rank							
Bidding	BIDVHIST	86.77	91.44	87.97	98.25	87.52	94.68
	n	6	11	10	10	16	21
Rank							
Bidding	BIDVHIST	—	—	—	—	—	—
	n	—	—	—	—	—	—
		No incumbent	Incumbent	No incumbent	Incumbent	No incumbent	Incumbent
Starting-Gate Bidding Format							
No Rank							
Bidding	BIDVHIST	78.27	99.01	79.79	86.99	79.26	89.53
	n	45	11	83	41	128	52
Rank							
Bidding	BIDVHIST	85.31	78.72	87.69	84.48	87.16	84.28
	n	78	7	271	197	349	204

ers). This finding also has practical significance for buyers and auctioneers in the design of online auctions for procurement activities.

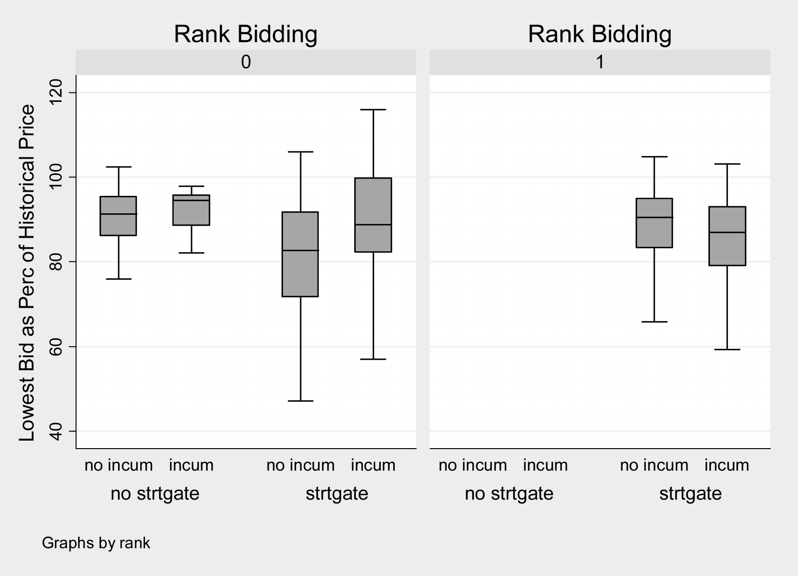
5. Discussion

The goal of this study was to shed light on the emerging phenomenon of Internet-enabled procurement auctions in the B2B context from a business value perspective by studying the relationship between auction design parameters and realized buyer surplus. We use a data set of more than 700 procurement auctions conducted by a leading auctioneer and involving millions of dollars' worth of high value items. We next discuss our findings, and then we discuss implications and opportunities for future research.

5.1. Findings

The results of this study provide insights into the effects of certain key auction parameters on buyer cost savings in electronic auction environments. We observe some parallels between our findings and those of B2C studies on auctions. For example, the findings

Figure 1 Box Plots on the Effect of Auction Format Parameters on Lowest Bid as a Percentage of Historical Price.



showing the effect of the number of bids, reserve price, and information revelation policies on buyer surplus are consistent with those reported in B2C auctions. More specifically, we find that bidding competition in terms of the number of bids and information revelation policy affects buyer surplus. We also find that information revelation policies become increasingly important if incumbent suppliers participate in the auction. Although, on average, the presence or absence of reserve price did not appear to make a difference, an analysis of auctions with reserve price only reveals that setting reserve price lower than the historical price is positively associated with buyer surplus.

We find that the number of bidders has no effect on buyer surplus. In contrast, Gaver and Zimmerman (1977) report an increase of 2% in buyer surplus for every additional bidder. Although Internet auctions may systematically differ from traditional auctions in the effect of the number of bidders, an alternative explanation for this result may be that traditional auctions do not allow the same bidder to submit multiple bids in an auction, and therefore the effect attributed to the number of bids in our study was attributed to the coefficient of number of bidders in Gaver and Zimmerman's (1977) study. We tested this explanation by omitting the number of bids variable from our models, and the revised models showed a statistically significant coefficient of the number of bidders at conventional significance levels. There is a need for future research to replicate these findings further to explore the validity of alternative explanations.

In contrast to previous research in the B2C and C2C contexts that finds a significant effect of bid increment and auction duration on auction outcomes, we did not find an effect of bid decrement and auction duration on buyer surplus in the B2B context. One explanation for the statistical nonsignificance of bid decrement in procurement auctions may be the relatively small amount of variation in bid decrement across auctions in our sample. Another explanation may be that buyers in procurement auctions may be far off from optimal bid decrement levels (Bapna, Goes, and Gupta 2003b). Further research is needed to investigate this issue more systematically by collecting data from other procurement auctions. Taking the finding of nonsignificance of bid decrement at face value implies that all electronic auctions may not behave in the same way in terms of the effect of auction design parameters on auction outcomes, and there may be systematic differences between B2B and B2C auctions.

Our study found no relationship between auction duration and buyer surplus in B2B auctions. This result is in contrast to the findings of Lucking-Reiley (1999) in the C2C context, which show that longer auction duration leads to higher prices for sellers in forward coin auctions on eBay. We offer two explanations for the differences between the B2B and the C2C contexts. One explanation for the nonsignificant effect of auction duration on buyer surplus in the B2B context is that the number of potential bidders in the B2B context is fixed (because B2B bidders are preselected and approved to participate in the auction). This is unlike the B2C context in which auction duration can intensify the bidding competition because of the arrival of new bidders. Another explanation is that the relatively short duration of procurement auctions and the recurring participation of bidders in those auctions make it easy for buyers to plan better for these auctions, which in turn makes buyer surplus relatively insensitive to auction duration. There is a need for replication of these studies in the B2B and B2C context to investigate whether these differences are systematic and whether the explanations based on restricted entry of new bidders and/or short durations of B2B auctions are valid.

5.2. Implications and Future Research

Our results have significant implications for research and practice. From a research perspective, our study provides an example of how empirical testing of the game theory-based predictions of auction theory using rich data on B2B procurement auctions is likely to lead to the refinement of existing theories and better modeling. Although we found some similarities in empirical findings across the B2B and B2C contexts, we note that some of the empirical regularities observed in the B2C context do not extend to the B2B context. For example, we find that bid decrement and auction duration have no effect on buyer surplus in the B2B context. Our results suggest that information revelation policies in an auction (e.g., use of the rank-bidding format) interact with player characteristics (e.g., presence of the incumbent in the auction), and these may jointly affect buyer surplus. These results suggest the need to develop theoretical models that consider such interaction effects, thus enriching auction theory through the development of more realistic models. This will require analytical work that explicitly considers the empirical regularities of bidder behavior in real online auctions (Bapna et al. 2004). The work of Arora et al. (2005) and Greenwald, Kannan, and Krishnan (2005) makes a valuable start in that direction. Likewise, our results point to the need to explain the differences between predictions of the classical auction theory and the empirical results across the B2B, B2C, and C2C contexts.

Another research implication of this study from a business value perspective is the finding that deployment of IT-enabled reverse auctions can provide significant savings to buyers in terms of procurement costs for improved firm performance. Thus, IT interventions are beneficial when they are undertaken not only in the customer-facing business processes (Mithas, Krishnan, and Fornell 2005), but also in the supplier-facing business processes. In other words, IT systems can help firms to become ambidextrous and manage both customers and suppliers to achieve revenue growth and cost reduction simultaneously (Mithas, Bardhan, and Goh 2006b; Rust, Moorman, and Dickson 2002). Although our study focuses only on cost benefits (measured by buyer surplus), there is a need to investigate how better coordination in the supply chain can also help firms improve their revenues by avoiding stockouts, improving customer satisfaction, and reducing cycle time for the development of new products and services (Dutta, Lee, and Whang 2007).

From a managerial perspective, our study implies that managers must recognize the importance of auction parameters as a determinant of savings through procurement auctions. By analyzing the data on reverse auctions systematically, managers can recalibrate the auction parameters in the light of their experience to devise better and more effective auction designs. This becomes even more important as firms more broadly incorporate reverse auctions into their supply chain strategies (Chatterjee and Watson 2005; Jap 2003; Mithas, Jones, and Mitchell 2006c; Wang and Archer 2004). In addition, although auctioneers conducting reverse auctions have amassed a wealth of data, it is not clear if the richness of that data has been adequately exploited to refine the design and conduct of auctions. Our field interviews suggest that buyers did not always know the rationale for the choice of auction parameters or how that might have affected cost savings from auctions. This study provides a template for auctioneers to conduct or facilitate such research toward the better understanding and design of procurement auctions, leading to even greater adoption of these auctions.

Finally, as IT applications and IT-enabled mechanisms such as reverse auctions become increasingly ubiquitous in supply chains (Johnson and Whang 2002; Swaminathan and Tayur 2003), supply chain professionals must acquire necessary IT and change management skills that can be used across functional and organizational boundaries. This is because successful use of IT interventions requires significant changes in business processes and incentive structures (Bresnahan, Brynjolfsson, and Hitt 2002; Clark and Hammond 1997; Dutta, Lee, and Whang 2007). By treating IT deployment as part of a bigger strategic initiative and organization change, firms will be able to take full advantage of IT's potential and "grow revenue while reducing expenses" (Dischinger et al. 2006, p. 66).

Although our research provides useful insights into the differences between B2B and B2C auctions, further research could suggest optimal auction formats for lower search costs, greater buyer surplus, and efficient price discovery. We suggest several directions for future research. First, our study is based on data collected from one firm from the automotive industry in the United States. These findings could be replicated at other auction sites for different firms, industries, and national contexts to validate the robustness of our empirical findings and to achieve generalizability. Such studies would enhance the understanding of the situational and contextual factors that may be relevant in explaining bidder behavior and auction effectiveness. From a methodological perspective, it would be useful to employ a potential outcomes-based propensity score approach in line with recent work that shows applicability of this method in information systems and e-commerce literature (e.g., Mithas, Almirall, and Krishnan 2006a; Mithas, Krishnan, and Fornell 2005; Rubin and Waterman 2006). This would help researchers assess the extent to which our findings have a causal interpretation and are robust to the selection on unobservables.

Second, in this study we focused on the critical auction design parameters and did not consider visual design parameters that may affect auction effectiveness. There is a need for research to understand the effect of visual parameters in online auctions and how they affect bidder behavior. Understanding these visual parameters will help auctioneers design more intuitive interfaces that may spur better bidder participation in the bidding activity. Third, although our research generates insights based on a snapshot view of the bid tally at the end of the auctions, such an analysis could be enriched by the study of the dynamics and evolution of auctions preserving the temporal dimension. Recent work focusing on bidding dynamics opens up a promising line of enquiry for such research (Koppius et al. 2006).

Finally, future research should develop typologies of bidder heterogeneity in the B2B context similar to those that Bapna et al. (2004) developed in the B2C context. Differences in bidder heterogeneity across the B2B and other contexts may account for some of the differences between our findings and those reported in the B2C and C2C contexts. There is also a need to test the efficacy of the estimators proposed in previous research based on the buyer's risk statement for a winning bid (Bichler and Kalagnanam 2006), to set reserve price using field data and to determine the effect of deviations from the optimal reservation prices suggested by these estimators for the observed buyer surplus.

In conclusion, in this paper we study the effect of bidding competition, information asymmetry, reserve price, bid decrement, auction duration, and bidder type on buyer surplus from a business value perspective. We collected field data on online procurement auctions conducted by a leading auctioneer. Consistent with the predictions of auction theory, our results indicate that bidding competition, reserve price, and information sharing affect buyer surplus. Unlike previous findings in the C2C context, we find that bid decrement and auction duration have no effect in B2B procurement auctions. Our results suggest that the use of the rank-bidding format increases buyer surplus when incumbent suppliers participate in the auction. These findings have implications for the development of more realistic models of procurement auctions and for the design of more effective procurement auctions. Further empirical research on procurement auctions using field data will help firms design more effective auctions and integrate the use of reverse auctions into their procurement strategies and activities for improved firm performance.

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