Managing Online Auctions: Current Business and Research Issues

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The Internet's computational power and flexibility have made auctions a widespread and integral part of both consumer and business markets. Though online auctions are a multibillion dollar annual activity, with a growing variety of sophisticated trading mechanisms, scientific research on them is at an early stage. This paper analyzes the current state of management science research on online auctions. It develops a broad research agenda for issues such as the behavior of online auction participants, the optimal design of online auctions, the integration of auctions into the ongoing operation of firms, and the use of the data generated by online auctions to inform future trading mechanisms. These research areas will draw from applied and theoretical work spanning management science, economics, and information systems.

(*Auctions; Internet*)

1. Introduction

Electronic markets based on the Internet—in particular, online auctions—have become popular venues for conducting business transactions (*The Economist* 1999, ModernMaterialsHandling.com 2001, *Purchasing* 2001, O'Brien 2001a, Grenier 2001). In fact, it can be argued that the auction-based electronic markets best represent the changes to business inherent in e-commerce. Consumer-to-consumer (C2C) auctions exemplify the democratization of the Internet: Anyone with an Internet connection can become a merchant, and self-regulating trust mechanisms like buyer and seller rating systems allow transactions between geographically separated strangers. Business-to-consumer (B2C) auctions rapidly develop new sales channels via the Internet and extend the reach of the firm to previously inaccessible markets. Finally, business-to-business (B2B) marketplaces show the changes to both business processes and industry organization that a disruptive technology like the Internet brings. These new B2B marketplaces create opportunities for firms to reinvent core procurement processes and by reducing transaction and search costs (Smith et al. 2000) also blur the boundaries between firms and change the structure of alliances that existed in the past. The economic impact of these auctions is rapidly growing. For instance, United Technologies has been using FreeMarkets to conduct auctions among its suppliers. The company expects to save between 6%–8% on the low end and 20%–30% on the high end. This translates into expected auction savings of about $1.2 billion in 2002 (Treaster 2001).

Although auctions have long been studied in the economics and management literature (Cassady 1967; Stark and Rothkopf 1979; Milgrom and Weber 1982; McAfee and McMillan 1987; Klemperer 1999,

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2000), there remain many unanswered questions of relevance to online auctions. This is not because the previous research has been flawed, but rather because of the enormous change in the opportunities for the use of auctions. Online auctions have greatly increased the variety of goods and services that can be bought and sold using auction mechanisms, have expanded the ways in which auctions can be conducted, and have created altogether new uses for auctions. As a result, managers face decisions regarding the use of auctions that are far more complex than those considered in the past.

In this paper, we seek to map out the major questions about online auctions that we believe could be addressed by the management science research community so that managers can make more informed decisions about their use. Although the advent of online auctions has created many challenges, the computerization of auctions has, in many ways, made it easier to study auctions as well. As a result, there has been recent research activity devoted to analyzing data from real auctions and building theoretical models of their design and use. It is not our aim to present a review of the literature on auction theory, nor is it our intention to suggest solutions to any particular problems related to online auctions. Instead, this paper provides a structured, critical evaluation of the current state of management science research on online auctions, presents some new empirical research results, and develops a broad research agenda for the many open issues. We hope to identify opportunities for detailed quantitative analysis by management scientists in this area and spur valuable research activity, as Geoffrion and Krishnan (2001) have done more broadly for e-commerce. We believe that further work is needed in the following four broad areas related to online auctions:

(1) Empirical and theoretical research to better understand the behavior of participants in online auctions and the degree to which existing theory is still applicable.

(2) Research on the optimal design of online auctions that takes into account elements not previously relevant. These include endogenous entry, competing auctions and alternative selling mechanisms, the diversity of participants, and more complex options for auction rules.

(3) Research on the integration of auctions into the ongoing operations of firms.

(4) Research on how to learn from the vast amount of data generated by online auctions.

In this paper, we consider each of these areas in turn and discuss them in detail. In §2, we present an overview of how the Internet has changed the role and function of auctions in commerce. We also present the results of the most recent empirical studies of online auction activity. In §3, we take a tactical view of the issues faced by a firm using this channel and consider the optimal design of an isolated online auction. We identify several auction design parameters, discuss the business issues surrounding each, report on the relevant research results, and identify open research questions. In §4, we take a more strategic view of the online auction as an integral part of a firm's business operations. This integration means that auctions occur repeatedly and, therefore, cannot be viewed in isolation. We identify the specific concerns of the B2C and B2B markets, report on the relevant research results, and identify open research questions. Finally, we discuss the issue of trust and reputation in online auctions, which is important whenever repeated transactions occur. Throughout this paper, we identify opportunities for learning from auction data. We conclude in §5.

2. The Impact of Internet Technology on Auctions

In this section, we characterize the ways in which Internet technologies have changed the conduct of auctions. The primary effect of the Internet has been to expand the opportunities for the use of auctions. We describe these opportunities and explain the factors that lead to them. We then give an overview of the current state of online research activity by surveying the empirical studies of this phenomenon that have appeared in the literature.

2.1. Why Auctions?

Most business transactions are conducted via one of three mechanisms: (1) a posted price, (2) a negotiation process, or (3) an auction. Casual observation suggests that distinct categories of goods are involved in each of these mechanisms. Surprisingly, there has been relatively little research on why some goods are sold using one mechanism rather than another. Based on our observation that many goods that have been previously sold only at a posted price are now being sold using online auctions, we believe that the Internet has expanded the space of goods for which auctions are appropriate. We therefore focus our attention on what drives the choice between posted price and auction mechanisms. Most consumers are familiar with the posted-price mechanism and assume that it is the most prevalent, but in terms of dollar volume, it probably is not. The larger the scale of the transaction in terms of cost and complexity, the more likely the transaction will be conducted via a negotiation process between the buyer and the seller, or via an auction. The two most important determinants of which mechanism is most appropriate are the sensitivity to transaction costs and uncertainty about the correct price for the good or service.

Economists seem to agree that price discrimination is a reason for using auctions. Bulow and Roberts (1989) strongly make this connection by linking the question of optimal auction design with heterogeneous bidders to third-degree price discrimination. Auctions can be used to elicit a bidder's actual reservation value for a good and then to link the price paid to this reservation value. Consequently, one way to determine whether a good should be sold using an auction is to ask whether there is much to be gained through price discrimination for that good. If demand for the good is relatively inelastic, there is more to be gained from price discrimination than if demand is elastic. This fits with the intuition of Wang (1993) that the greater the dispersion around the mean of reservation prices, the greater the benefit of auctions relative to posted prices. Yet, other factors also appear to be involved in determining when auctions are used.

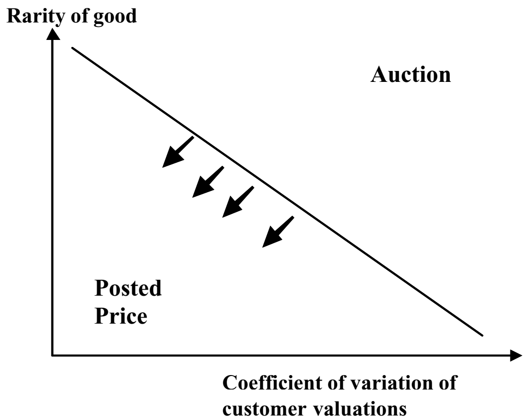
Lu and McAfee (1996) state that "the goods sold through either bargaining or auction institutions have similar properties: they are unique, expensive, and with uncertain equilibrium prices" (p. 229). Wang (1993) rejects the role of mean valuations in determining whether an auction is superior to a posted-price, taking a position consistent with Milgrom (1987), who states that "the only clear common denominator for the kinds of objects that are sold at auction is the need to establish individual prices for each item sold" (p. 2). In Wang's (1993) model, however, the cost of conducting an auction is borne by the seller, and the holding costs, per unit time, faced by a seller are smaller for the auctioneer than for the posted-price seller.[1] As it is commonly agreed that traditional auctions impose greater transaction costs on all the participants than the posted-price mechanism, the magnitude of these costs relative to the value of the sold item influences the choice of a selling mechanism.

De Vany (1987) provides a more detailed model of the transaction costs faced by both the seller and the buyer in his comparison of auction and posted-price selling institutions. Besides the holding costs borne by the seller and inspection costs borne by buyers, he models the opportunity costs of the buyers due to the time spent participating in an auction. De Vany (1987) concludes that the degree of price dispersion and the relative values of buyer opportunity costs and the item being sold determine whether the seller prefers an auction. Harris and Raviv (1981a) show an important connection between the choice of selling mechanism and the relative levels of demand and capacity. In their model of a monopolist whose choice of selling mechanism is endogenous selling to N potential buyers with unit demand, they find that when demand exceeds capacity, auctions may be optimal. When capacity exceeds demand, a single price scheme is optimal. Their results fit with the observation that rare items are often auctioned because with rare items, the demand exceeds the seller's capacity.

We attempt to graphically capture some of these ideas in Figure 1, in which we display how we think the product space tends to be split between products for which auctions are and are not appropriate. For larger dispersions in the customer reservation values for the good relative to the mean valuation, auctions are more appropriate. For rare goods, auctions are also more appropriate. Although we believe that the mean value of the good has some influence on the choice of selling mechanism, it is difficult to separate

[1] The motivation for this cost structure is that the auctioneer only needs to store the good, while the posted-price seller must display it.

Figure 1 The Effect of Online Auctions on the Product Space Partition Between Posted-Price and Auction Sales



Note. Arrows indicate the impact of the reduction in the cost of conducting auctions online and the increased accessibility caused by the Internet.

this effect from the price dispersion and rarity effects. In the next section, we describe how the use of online auctions has expanded the product space for which auctions are appropriate.

For completeness, we also note that an auction can be used as an initial stage of what ultimately results in a negotiation or as a stand-alone mechanism for price discovery. For example, when a house is sold, the potential buyers in effect bid for the right to enter into negotiations with the seller. Auctions have an important benefit over negotiations. By following a strict protocol, auctions have a transparency that gives participants confidence that they are being treated fairly. When two parties negotiate, there may be a question about how the seller selected with whom to negotiate. By conducting an initial filtering through competitive bidding in a public auction, it is possible both to eliminate much doubt about fairness and to encourage participation. The issues of fairness and trust are also important in online auctions, and we return to them later in this paper.

2.2. Expanded Capabilities

In their overviews of the online auction phenomenon, Klein and O'Keefe (1999) and Klein (1997) propose that the Internet has had the following effects on auctions:

- Reduced transaction costs for both buyers and sellers,
- Accessibility to more participants, both bidders and sellers,
- Easier description of complex products,
- The ability to conduct complex auctions.

To these, we add the following:

- Easier collection of data about auctions and
- The possibility for participants to join at any time.

Reduced Transaction Costs. Because the transaction costs of auctions have been reduced, mass-market goods that seemed to be best sold using posted prices are now sold over the Internet through B2C auctions. We now see the sale, via auction, of common consumer electronics, music CDs, computer peripherals, videos, and so on. The arrows in Figure 1 depict the impact of the continuous reduction in auction transaction costs brought about by the Internet. Firms selling products with less uncertainty about their value, and firms selling products of lower value, now find auctions more viable than before. The Internet allows sellers and bidders to track progress in real time and to search for products at a relatively low cost using software tools such as BidXS.com (www.bidxs.com), AuctionPatrol.com (www.auctionpatrol.com), and BidSpotter.com (www.bidspotter.com). The success of C2C auction sites like eBay and the low value of many of the items sold there demonstrate that the transaction costs of Internet auctions are low for both buyers and sellers.

Accessibility. Another way in which the Internet is expanding the space of auctionable goods is by making participation easier, increasing the pool of potential bidders. With a bigger pool of bidders, online auctions seem to make items in some sense "rarer." As a result, we see quite mundane mass-produced items being auctioned online. Additionally, online auctions, which draw on the entire Internet community, make it easier to establish new markets in which multiple sellers transact with multiple buyers for the same goods. We thus see a growth in the use of e-trading markets for securities and the creation of specialized vertical market exchanges such as Covisint for the automotive industry.[2] A key success

[2] In the first half of 2001, Covisint (www.covisint.com) booked $33 billion worth of transactions using both its electronic catalog

factor for such exchanges is establishing sufficient transaction volume and participation levels, i.e., market liquidity. Firms and consumers are more likely to participate and interact in a market that has clearly defined rules and protocols. Because the Internet is drawing on a broad spectrum of participants, the participants in e-markets are less likely to be familiar with each other than participants in traditional markets, so the formalism of a public auction takes on greater importance.

Managing Complexity. Computerization and the use of the Internet also make more complex auctions possible. By broadcasting real-time computations, the Internet makes it possible to conduct *multiunit* auctions easily. Online auction software accepts bids from a large number of bidders, sorts out the bids, and dynamically allocates the goods among the bidders according to predefined priority rules (e.g., price, bid quantity, and time of first arrival to the website), and instantaneously posts results on the Web. No human auctioneer could perform these complex tasks for multiunit auctions in real time.

The computational power of online auctions also allows the auction of complex bundles of goods and services that would otherwise be sold individually or through negotiations. Auctions in which bidders are interested in different, possibly overlapping, bundles of goods require new mechanisms for determining prices and allocating goods to bidders. The design of these so-called combinatorial auctions has attracted much interest in the academic community (see DeVries and Vohra 2001, Rothkopf et al. 1998). Finally, computational advances are improving the multimedia capabilities of the Internet, improving the ability to describe more complex products and further expanding the scope of products that can be auctioned.

Information Gathering. Computerization also makes it much easier to collect data on auctions and participants. By examining auction data, it is possible to learn how different consumers value a particular product and, therefore, how to price it. In reverse auction settings, a seller's costs and indications of product demand can be ascertained. Furthermore, information on the behavior of participants in an auction can be used to design better future auctions, and in and of itself may have commercial value.

Time Element. Bidders in online auctions are not required to be collocated, so online auctions can be longer than traditional auctions. Bidders can easily join the auction at any time by visiting the correct website. Online auction designers must pay attention to how decisions they make influence the participation behavior of consumers over time. These concerns are unique to online auctions.

To summarize, the use of online auctions has blurred the traditional distinctions between situations in which auctions are appropriate and those in which they are not. The multiplicity of auctions provides consumers with an alternative purchasing channel previously unavailable to them. Firms have more opportunities to use auctions and, therefore, must integrate this choice into their general decision making regarding the choice of channels used to purchase and sell goods and services. Firms also have many more choices in the actual implementation of the auctions. The reduced cost of running online auctions makes it more practical to use auctions as a mechanism for learning about the market. In §§3 and 4, we discuss how the wider range of products auctioned, the continuous arrival of bidders over time, and the ability to collect auction data combine to define new research problems for management scientists.

2.3. Overview of Online Auction Activity

The earliest Internet auctions appeared in 1993, with auctions based on Internet news groups (Lucking-Reiley 2000). In 1995, the first Internet auction websites opened, with OnSale (www.onsale.com) and eBay (www.ebay.com) starting operations. (For more information on OnSale, see Moon 1999.) Today, there are hundreds, if not thousands, of websites dedicated to online auctions. An incredible variety of goods and services is auctioned on the Internet: collectibles like stamps and coins, computers, cars,

and auction services. One thousand users participated in 420 auctions during this period (InformationWeek.com, retrieved July 18, 2001).

Figure 2 Classification of Online Auction Types

		BUYERS: ONE	BUYERS: MANY
SELLERS	ONE	1. Bilateral negotiations EDI/XML	2. Web-based sales auctions C2C and B2C
SELLERS	MANY	3. Web-based (Reverse) procurement auctions C2B and B2B	4. Web-based exchanges

and even locomotives and machine tools can all be found on auction sites. Following Van Heck and Vervest (1998), it is useful to characterize e-markets by the number of buyers and sellers and whether the participants are consumers or businesses (see Figure 2). Auctions are found when a single seller is selling to multiple buyers, or when multiple sellers are selling to single or multiple buyers, so we focus our attention on quadrants 2–4 of Figure 2. Quadrant 2 shows single seller to multiple buyer auctions. The two types of auctions in this category are B2C and C2C,[3] of which OnSale and eBay, respectively, are examples. Quadrant 3 covers many sellers and a single buyer. These auctions are known as reverse auctions or procurement auctions. There are many examples of firms using procurement auctions in which sellers compete for a contract in the B2B market; Sorcity (www.sorcity.com) is an example of a third party that specializes in hosting such auctions. In the reverse B2C auctions (C2B auctions), firms vie to make a sale to a particular consumer, e.g., Priceline.com. Regarding quadrant 4 of Figure 2, there are also several B2B exchanges in which forward and reverse auctions, negotiations, and electronic catalog sales are all conducted between buyers and sellers for specific industries. Examples include Covisint for the auto industry, Exostar (www.exostar.com) in the aerospace industry, e-Steel (www.exchange.e-steel.com) for the steel industry, and Chemconnect (www.chemconnect.com) for the chemical industry. Industry-independent third parties, like FreeMarkets (www.freemarkets.com) are also developing these vertical B2B exchanges. It is likely that in a few years, these various B2B exchanges will dwarf the consumer-oriented auctions (Kafka et al. 2000). We are not aware of any active true double online auctions beyond the financial and commodity markets.

Most research on online auctions has focused on the forms that have existed the longest, B2C and C2C. This is because researchers are also consumers and, therefore, have greater access to these auction forms than to B2B auctions. We, too, focus on the consumer-oriented auctions, but we also try to determine what lessons about these auctions can be applied in the B2B arena and identify areas for future research.

Several studies presenting overviews of the C2C and B2C online auction phenomenon have appeared because the debut of online auctions in 1995. Because online auctions are relatively new, these efforts serve as a useful starting point. Beam and Segev (1998) analyze 100 B2C and C2C online auctions selected using a variety of search engines, while Lucking-Reiley (2000) analyzes 142 B2C and C2C auctions selected in a similar fashion. Both studies find that the types of auction mechanisms used on the Internet are actually limited and traditional: the English, Vickrey, Dutch, and first-price sealed-bid auctions are virtually the only mechanisms used, and the English auction is, by far, the most common.[4] New rules, however, are evolving for the auction of multiple units.[5] Lucking-Reiley (2000) finds that auctioneer fees are much lower on the Internet than in traditional auctions, supporting

[3] Categorizing any auction site as purely C2C is unrealistic because many small-scale businesses are using eBay, for example, on a regular basis. For our purposes, we refer to sites that have a significant C2C component as C2C.

[4] English auction: ascending bid auction in which bids are open to all to see. The winner is the highest bidder and the price is the highest bid. Example: eBay.com. First-price sealed bid: bidders make a single secret bid. The winner is the highest bidder and the price is the highest bid. Example: The Chicago Wine Company (TCWC.com). Second-price sealed bid (Vickrey): the same as first-price sealed bid, but the price is the highest losing bid. Example: rare, but it is an option on some sites, such as iauction.com. Dutch: the seller steadily lowers the price across time. The winner is the first bidder to pay the current price. Example: www.pefa.com.

[5] In the case of online multiunit auctions, some use the term "Yankee auction" to refer to an open bid ascending auction in which bidders pick a quantity and price, the units are allocated to the highest bidder, and each bidder pays his bid price. Some also mistakenly call these "Dutch auctions."

the view that the Internet has made auctioning more accessible. He also raises several issues that suggest that the rarified assumptions of classical auction theory are insufficient to address the behavior of online auctions. These include phenomena such as last-minute bidding activity, commonly known as "sniping;" the less than universal use of proxy bidding agents; and jump bidding (see Easley and Tenorio 1999 for an analysis of jump bidding in an Internet auction). These phenomena present some challenges to auction theorists. Additionally, new features such as "buy now" prices have never been addressed by the literature. An exception is a recent paper by Budish and Takeyama (2001), who analyze a limited model of the buy-now price in online auctions.

Beam and Segev (1998) identify several defining characteristics of the business model behind an online auction. In their framework, a business model can be characterized by how significant a part of the business the auction is, the ownership of inventory, and whether the auction is B2C or C2C. The auctioned product's characteristics also help define the business model. Beam and Segev (1998) further classify auction businesses by the breadth of merchandise offered, whether the goods are information or physical, and whether they are new or old/used. The descriptive statistics in their survey are limited, however, as they are based on the frequency of the phenomena in their sample, rather than on sales volume.

Turban (1997) gives many good examples of consumer-oriented online auctions and online procurement auctions, which he terms "online bidding." In the realm of online contract bidding, he finds that both sides save much time and money by electronically doing things. A wider pool of solicitations reduces costs and increases quality for the buyer. For bidders, there is improved access to contracts that might not have been available for smaller, less-known companies. Yet, we are not aware of any systematic research that has proven that the pool of awardees has really changed for contracts tendered online, or that buyers enjoy significant economic benefits as a result.

Bapna et al. (2000, 2001) focus on multiunit B2C auctions, characterizing bidders in these auctions as being one of three types, depending on how they time their bids and how often they bid. This suggests that there is an opportunity to develop richer models of bidders that involve more than valuation heterogeneity, which can be empirically tested using online auction data. Additional overviews of the online auction phenomenon appear in Herschlag and Zwick (2000) and Chui and Zwick (1999).

There is a consensus among all these studies on several important points. Many B2C and C2C auction Internet sites are thriving. Despite the diversity of products being sold using Internet auctions, there is little diversity in the auction mechanisms used. The Internet has changed the conduct of auctions, and a number of unique issues about online auctions need to be investigated. In the next section, we investigate how some of the unique features of online auctions lead to new design decisions for auctioneers.

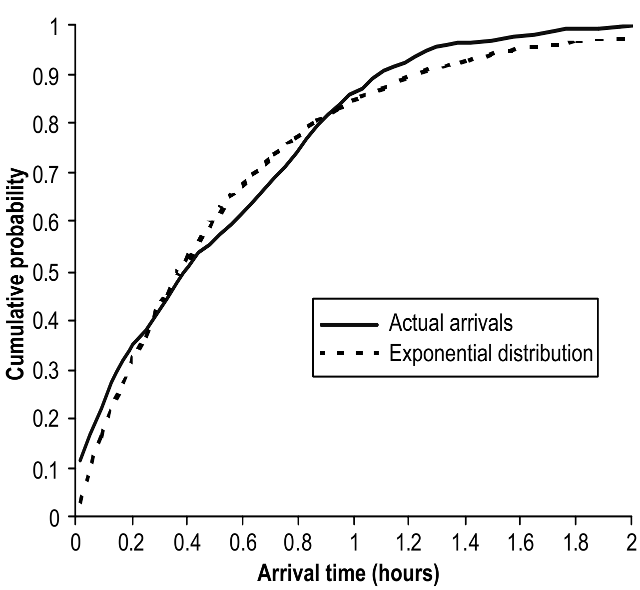
3. The Optimal Design of an Isolated Auction

In this section, we consider the tactical issue of designing an isolated online auction. We critically review the efforts that have been made to understand and model the major design questions for isolated Internet auctions and identify some of the many open questions. The traditional literature on auctions has considered them in isolation and analyzed their behavior based on a number of assumptions that do not typically apply to Internet auctions. Excellent surveys of the classical economic theory of auctions appear in McAfee and McMillan (1987), Milgrom and Weber (1982), Milgrom (1989, 2000), and Klemperer (1999, 2000). Rothkopf and Harstad (1994) point out the numerous limitations of the traditional game-theoretic approaches to auction design. They note that assumptions of bidder symmetry, common knowledge of private valuation distributions, the isolation of auctions, fixed numbers of bidders, and rigid adherence to rules result in a theory of auctions that has limited usefulness in practice. They assert that there is much room for research that improves the models of competitive bidding. We believe that within the context of online auctions, the standard assumptions are even more dubious.

Given the wider pool of participants made possible by the Internet, asymmetries among the bidders will likely occur. In particular, experts and novices will participate in the same auctions. Experts may have specialized knowledge about the valuation of the product for sale or about the bidding process itself. The diversity of the participants will similarly weaken the assumption of common knowledge. On the Internet, multiple auctions for the same product commonly occur simultaneously, and auctions for the same product or types of products repeat over time. These recurrences refute the assumption of isolated auctions.

One of the fundamental differences between traditional auctions and online auctions is that in online auctions, bidders can arrive at any point after the start of the auction. For example, in Figure 3, we show the cumulative fraction of arrivals of new bidders participating in flash (one hour) auctions on SurplusAuction.com and compare it to a cumulative distribution function for an exponential distribution with the same mean (Vakrat and Seidmann 2000). The data is aggregated across 105 different auctions and represents the timing of the first bids of 2,150 different participants. We note that the arrival pattern well

Figure 3 CDF of New Bidder Arrival Times Vs. an Exponential CDF with the Same Mean (0.53 Hours) in One-Hour Online Auctions



matches an exponential distribution. We also see that some bids arrived after the one-hour mark because, even though the auction was scheduled for one hour, it closed only when 10 minutes had passed without bidding activity. Roth and Ockenfels (2002) analyze the timing of the last bids by participants in online auctions. They find that there is a surge in bids close to the end of auctions with strict deadlines. When the auction end is not strict, but is based on a "going, going, gone" rule, in which the auction continues as long as there is recent bidding activity, there is less last-minute bidding.

Given the above observations and that the number of bidders and the way in which they participate determine the auction closing prices, it is important to understand the arrival process of bidders to an online auction. To structure our discussion of the design of single online auctions, in this section we formulate a general mathematical model of the seller's decision problem from the perspective of a forward auction, built upon a model of the bidder arrival process.

We define λ_t as the arrival rate per unit time to an auction t time units after its start. In general, the actual number of arrivals in any time interval $[t, t+\Delta t]$ is a random variable. If we take the perspective of the potential bidder, we can see that λ_t is a function of T, the duration of the auction; and t, the time elapsed because the time remaining in an auction determines the amount of time the bidder must wait to find out if she actually succeeded in purchasing an item through the auction. λ_t is also a function of n_t, the number of bidders currently participating; and k, the lot size offered because larger numbers of bidders relative to the lot size indicate greater potential competition and may deter a consumer from joining the auction. λ_t is also a function of $\hat{b}_t$, the vector of current bids, because the current bids will filter out all potential consumers with lower valuations of the goods. Finally, λ_t is clearly also a function of $\mathbf{R}$, the auction rules. By auction rules, we mean the rules that govern how the closing prices are determined, how the goods are allocated at the end of the auction, whether bids are open or sealed, whether there is a reserve price, what the initial bid and minimum bid increments are, what information is revealed and to whom, how items are allocated, and how the end of the auction is determined.

The state variables for the auction at time t are n_t and $\hat{b}_t$, and these are random variables. If there are k items auctioned, then, at the end of the auction, there is a final price vector $\hat{p} = (p_1, \ldots, p_k)$. This vector is a function of n_T and $\hat{b}_T$, the final values of the state variables, and the auction rules **R**. The seller's problem is

$$\operatorname*{Max}_{R,\,T,\,K} \sum_{i=1}^{k} p_i(n_T, \hat{b}_T). \tag{1}$$

The evolution of the state vector $\hat{b}_t$ over time is a complex process. For the case of a single-unit auction, Bertsimas et al. (2001) have developed efficient algorithms for determining optimal bidding behavior for an individual participant in an online auction. They formulate the problem faced by an individual bidder as an optimal control problem in which the behavior of the rest of the bidders is viewed as an aggregate random process. Segev et al. (2001) approximate an auction of a single item as a two-dimensional Markov chain on the price and the number of bidders. They employ this model to estimate the final price vector for an auction using historical data on arrival rates and bid levels. Although their estimation procedure is sensitive to the accuracy of the inputs, their analysis illustrates the benefit of using the data from previous auctions for design purposes. These results underscore a unique feature of online auctions: They create an excellent environment for collecting actual demand information about and (individuals') reservation prices for numerous products.

From the perspective of the firm, however, the details of the evolution of the bid vector, $\hat{b}_t$, are not as important as the number of bidders participating in the auction and their valuations. All things being equal, the seller prefers more bidders to fewer and high-valuation bidders to low-valuation bidders.

Traditionally, analysis of auction design has focused on the auction mechanism itself. In a seminal paper, Harris and Raviv (1981b) compare discriminating mechanisms, in which winners pay according to their own bids, and competitive mechanisms, in which all winners pay the same price, for multiunit auctions for different bidder risk attitudes. They show that when bidders are risk neutral, both mechanisms result in the same revenues for the seller while discriminating auctions dominate when bidders are risk averse. Meyerson (1981) considers the optimal design of a single auction when bidders have independent private values. Meyerson shows that a revenue equivalence exists between any mechanism for which "the object always goes to the bidder with the highest value estimate" and "every bidder would expect zero utility if his valuation estimate were at its lowest possible value"[6] (p. 66). In these approaches to auction design, an auction is fully characterized by how bidder valuations are revealed and how the actual goods are allocated. The allocation criteria in these analyses are only based on the bid values of the participants. In contrast, during online auctions, the timing of the bid and the quantity requested in multiunit auctions are commonly used in conjunction with price to decide on allocations.

Online auctions require the broader consideration for designing auctions expressed in Equation (1). To "solve" Equation (1), a seller needs to understand the relationships between the design parameters T, R, and K and the closing price vector in online auctions. In the next subsections, we discuss the current research on these relationships.

3.1. Auction Rules

The rules set R for an online auction involves defining two subsets of rules we refer to as the *mechanism* and the *bid constraints*. The mechanism defines the bidding procedure, i.e., how the bids are compared, whether the bids are ascending as in an English auction or the price is descending as in a Dutch auction, and whether the bids are open or closed. The mechanism also determines how the closing price is set and how the goods are allocated to winners. The mechanism likewise determines when the auction is completed, i.e., the stopping rule for new bids. Bid constraints control the type of bids that are accepted. An auction may have minimum allowable bids, secret reserve prices, and restrictions on the allowable bid increments. To evaluate R, one must understand how

[6] Vickrey's (1961) revenue equivalence results turn out to be a special case of Meyerson's (1981) more general approach.

it affects the participation of bidders via the function $\lambda_t(T, t, n_t, k, \hat{b}_t, R)$ and how the rules influence the trajectory of the bid vector $\hat{b}_t$. We expect that the auction mechanism will affect the participation level in the auction and therefore, indirectly, the bid vector $\hat{b}_t$. On the other hand, we expect bid constraints to have a direct impact on the trajectory of bids and influence bidder behavior.

3.1.1. Auction Mechanism Choice. The impact of the rules on participation is determined by a complex set of factors. The English, first-price sealed bid, second-price sealed bid, and Dutch auctions are the most common traditional auction mechanisms for single-unit auctions, and the most heavily studied in the academic literature, with the English auction being by far the most prevalent. Yet, as Milgrom (1989) notes, these mechanisms are popular not because they are "optimal" in the sense that they maximize the expected revenue of the seller, but rather because they work well according to several criteria. A well-designed auction must be robust with respect to assumptions about bidders' behavior, be efficient in its allocations, have low transaction costs, and be resistant to fraud.

Currently the English auction is the dominant mechanism on the Internet. This is not surprising, because using a mechanism that people find familiar and intuitive reduces transaction costs.[7] Furthermore, according to Milgrom (1989), one of the disadvantages of the English auction is its open cry multiround nature. In a traditional auction, this requires the physical presence of the bidders, adding costs to participation. With the Internet, this cost is greatly diminished, making the English auction even more attractive. Some believe that the English auction is susceptible to various forms of cheating. We discuss the issue of fraud in §4.4.

The question remains whether, on the Internet, in practice, the English auction performs as it should. The ability of online auction sites like eBay to attract millions of satisfied customers is strong evidence that there is no problem with the auction mechanism being used. Lucking-Reiley (1999) conducts experiments with Internet auctions of collectible trading cards, comparing the revenue generation of Dutch auctions with that of first-price auctions, and comparing English auctions with second-price auctions. His goal was to assess whether the theoretical revenue equivalence, regardless of risk attitudes, between English and second-price auctions holds.[8] He finds little difference between the two mechanisms, which suggests that theoretical predictions of the performance of English auctions on the Internet are reliable. On the other hand, he finds that Dutch auctions had closing prices on average 30% higher than first-price auctions. He speculates that two possible reasons for this violation of the theory are the effect of endogenous entry on the Dutch auction and the fact that the Dutch auctions were much longer and bidders might have been impatient to complete their purchase. Endogenous entry and the impact of delay on bidder behavior are both issues that are unique to online auctions. We discuss these further in the following sections.

Much of the research on auctions has focused on forward auctions, in which a single seller auctions goods to many buyers. On the Internet, there are many examples of reverse auctions in which a single buyer takes bids from multiple sellers. In the consumer market, these typically take the form of a "name-your-price" system.[9] Buyers describe the service or product they want and the price they wish to pay. These "want ads" are routed to participating sellers or posted on the website. The leading example is Priceline.com, which conducts C2B auctions primarily for travel services (airline tickets, hotels, and car rentals), but also for long-distance telephone service, new cars, and home financing. In some cases, the buyer is committed to purchase at the stated price; in others he is not. At Priceline.com, for example, the buyer names a price for the product or service she requires (e.g., an airline ticket), and then

[7] It is conceivable that the field of optimal auction design based on complex game-theoretic results will one day find its best expression through the use of software agents in Internet auctions, as noted by Rosenschein and Zlotkin (1994).

[8] There is an assumption here that private values hold.

[9] In fact, we do not believe that there exist any true C2B reverse auctions. We refer to them as reverse auctions simply to be consistent with the common practice, but a more accurate term would be "name-your-price mechanisms."

Priceline.com finds a taker for that price.[10] The buyer is committed to purchasing at that price. In the C2B environment, there is considerable ignorance on the part of the consumer about what a reasonable price is from the seller's perspective and, in fact, little guidance is provided to the consumer regarding appropriate pricing. Originally, Priceline.com instituted a seven-day update delay and 24-hour commitment on bids to place a significant cost on trying to collect this information. Hann and Terwiesch (2001) have studied the bidder behavior on a German name-your-price service that allows bidders to update their bids after only a few minutes. They find that bidders do not bid frequently with small increments, as one would expect, but rather bid only a few times (typically less than four) with significant bid increments. They explain this behavior as demonstrating that there is a significant participation cost to the consumers in these online negotiation settings. Their results suggest that more research is needed to determine the optimal rules for these name-your-price markets.

In the B2B setting, many auctions are, in fact, reverse auctions for procurement or the management of requests for quotations (RFQs) with competitive bidding. In theory, these auctions should function like standard forward auctions, except that the price is moving in the opposite direction. In practice, however, it is not only the price that determines the winner. In forward auctions, participants have agreed to conduct business with the seller by virtue of bidding in the auction. Any skepticism they have about the quality of the seller's goods is reflected in their bids. With reverse auctions, unless strict restrictions have been placed on participants, the buyer will have preferences among sellers and may not want to buy from the lowest bidder. Also, although RFQs and competitive bidding for contracts are not new phenomena in the B2B environment, their implementation on the Internet forces firms to make concrete decisions about starting bid levels and reservation prices that they might not have formally considered before.

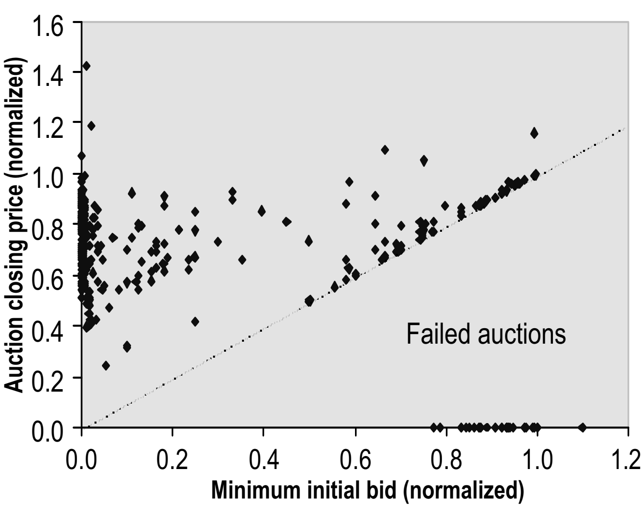
[10] Although Priceline.com is the most well-known C2B site, there are other models being used as well. Request-a-Quote at Lycos.com and myGeek.com serve as lead generators for participating sellers. Consumers give a description of what they would like to purchase, and it is electronically distributed to relevant merchants. These merchants respond with e-mails, giving quotes to the consumer who is not obligated to commit to any transactions.

One of the auction design decisions faced by the firm is choosing between forward auction and reverse auction mechanisms. For example, when does an airline conduct forward auctions for tickets and when does it participate in a name-your-price channel like Priceline.com? Similarly, when should a firm selling a chemical product conduct a forward auction, and when should it look to participate in a procurement auction run by a buyer of such chemicals on FreeMarkets.com? It is also unclear how a firm should decide how much inventory to allocate to serving buyers in C2B auctions, what price limits to place on the bids it accepts, and how often to conduct an auction in a way that maintains market liquidity. It is possible that results from the literature on revenue management (McGill and van Ryzin 1999) can be used to shed light on these questions.

3.1.2. Bid Constraints. In online auctions, several parameters are commonly used to influence bidding. Minimum bids constrain participants to bid above a certain level. Reserve prices are lower bounds placed by sellers on closing prices. If the bidding ends before the reserve price has been reached, the seller has the right to withdraw the offered goods and not make the sale. If the reserve price is posted, then it is equivalent to a minimum bid. If the reserve price is kept secret, sometimes the bidders are notified when the bid has exceeded the reservation price. In a small number of online auctions, the existence of a reservation price is only revealed after the bidding has been completed. A "buy-now" price is set by the seller and is a form of maximum bid. Before any bids have been placed, the first consumer who offers to pay the "buy-now" price, gets the item at that price. The buyer who opts for the buy-now price is guaranteed to "win" the auction at a preset price without the delay of the bidding process. The seller who sets this price benefits by receiving a relatively high price without the risk of the auction ending at a significantly lower price. On the other hand, if the price is set too low, the seller risks undercutting the bidding. A seller sometimes can also set a minimum bid increment, which places a lower bound on new bids, at any time during the auction. There has been no research that quantifies the trade-offs between the levels for "buy-now" prices, minimum initial bids, and reservation prices.

We have seen, in our empirical analysis of bidder arrivals, that if the number of bidders is insufficient, the resulting auction price may be quite low. To protect against such a price collapse, the seller may set a minimum initial bid. This approach is also not risk free, as we show below. Vakrat (2000) analyzes 350 auctions conducted on SurplusAuction.com for items that were simultaneously available on retail sites. In Figure 4, we plot the auction price (normalized to the posted retail price) versus the minimum bid price (also normalized to the posted retail price). The posted prices serve as a benchmark. Each dot in this chart represents an auction. Dots on the diagonal represent auctions in which the product was sold at the minimal initial bid. Dots on the horizontal axis indicate failed auctions, in which nothing was sold, while dots above the diagonal indicate instances when items were sold for prices above the minimal initial bid. Dots at or above one on the vertical axis represent auction closing prices that met or exceeded the posted price at online retail sites. In Figure 4, we see that when there is no minimum bid, items are auctioned at significant discounts over the posted price. As the minimum bid increases, a greater proportion of the auctions result in closing prices that are at the minimum bid level and the seller is protected from giving the product away at a low price. On the other hand, as the minimum bid level increases, we also see that there is an increasing number of auctions with no bids. In such cases, the seller has incurred the cost of setting up the auction and of holding the inventory for the duration of the auction, but has received no revenue.

Figure 4 **The Impact of Minimum Initial Bids on Auction Closing Price**



Bajari and Hortacsu (2000) develop an econometric model of endogenous entry in single-unit eBay coin auctions and show that bidders require a minimum expected profit to join an auction, and find that the minimum bid price strongly affects participation. Their analysis is based on the idea that the winner's profit is dependent on the number of other bidders who participate and on the auction rules in terms of reserve prices and minimum bid levels. Lucking-Reiley et al. (1999) find that minimum bids increase the price but also decrease the probability of a sale.

A secret reserve price can be used in conjunction with a minimum bid level. Bajari and Hortacsu (2000) and Kaiser and Kaiser (1999) recommend that sellers who use a secret reserve price use a low minimum bid. The idea here is that the low minimum bid attracts more bidders, and the secret reserve price serves as insurance against low closing prices. Bapna et al. (2001) also claim that bidding increments play an important role in English auction outcomes. They argue that setting a high bid increment has two effects. First, it raises bids, because the lowest winning bid must be higher than the valuation of the bidder with the next highest valuation by the amount of the bid increment. Second, it reduces participation and overall bidding activity, because it effectively raises the minimum required bid at every point. Reduced participation can reduce the revenue, so these two effects are at odds. It is not clear how important this trade-off is. This is another example of a hypothesis that could be thoroughly examined using the data from online auctions.

All of the studies of the effect of these various parameters on auction results have been somewhat limited. Some have been limited to particular categories of products, such as coins in Bajari and Hortacsu (2000) and Lucking-Reiley et al. (1999), and all have only examined consumer-oriented auctions

(B2C or C2C). Systematic study of these topics could yield a mapping of products to the most appropriate bid constraints. Such a mapping would guide designers of online auctions in practice.

3.2. Auction Duration

Time plays an important role in Internet auctions. In contrast to most traditional open outcry auctions, which last minutes, Internet auctions can last days or weeks. Because bidders are not required to be present and can bid from practically anywhere and at any time, it is practical to conduct auctions over longer stretches of time. This does not mean that the duration of the auction is inconsequential. The duration of an online auction has a significant purpose: it determines the number of bidders, thus, potentially affecting the financial outcome.

Traditional auctions start with a fixed number of bidders, often requiring a screening process. Once the auction begins, no new bidders may join. On the Internet, an auction begins with an announcement describing the product, the rules, and the end time, with the hope that enough bidders will be attracted to generate a high selling price. If the auction is too short and few bidders participate, it is more likely that the final price will be low. Lucking-Reiley et al. (1999) find evidence in coin auctions on eBay that longer auctions lead to higher prices. Yet, there are also costs to increasing an auction's length.

In the case of products with a rapid depreciation like consumer electronics and computer equipment, long auctions can reduce the value of the product and reduce the seller's revenue. If the seller maintains an inventory, additional holding costs may accrue over time. The buyer also has costs associated with length of the auction. If we consider a person deciding between buying a product in an online auction and buying the same or a similar product via a posted-price mechanism, we can see several trade-offs at work. Typically, the buyer is choosing to participate in the auction because it is the only venue in which she can find the product she wants or because it will be cheaper than conventional channels. When the buyer is choosing an auction to save money, she is trading off cost and the extra effort involved in participating in the auction, the risk of fraud, and the delay in receiving the product. The longer the auction lasts, the greater the delay for the buyer, and the greater the probability the buyer will be outbid. Both of these factors can be viewed as reducing the bidders' reservation prices or increasing the discount they expect from the auction.

For illustration, consider the following simple model of a single-unit English auction in which bidders have independent private values drawn from a uniform distribution $[v_l, v_h]$ and the auctioneer's reservation price is 0. We draw on the revenue and strategic equivalence between the English auction and the Vickrey auction (Vickrey 1961) to justify the assumption that all bidders bid truthfully and that the auction's closing price, p_a, is determined by the second-highest valuation. Assuming a fixed number, n, of bidders, it can be shown (using the order statistics of the uniform distribution) that the expected closing price of the auction is

$$E[p_a] = v_l + (v_h - v_l)(n-1)/(n+1).$$

In a single-unit auction, this is the revenue to the firm. If the cost to the bidders per unit time of delay from participating in the auction is w, then, in an auction of duration T, bidders will shade their bids by wT. The expected closing price becomes the following:

$$E[p_a] = \begin{cases} v_l + (v_h - v_l)\dfrac{(n-1)}{(n+1)} - wT \\ \qquad \text{when } wT \le v_l, \\ (v_h - wT)\dfrac{(n-1)}{(n+1)} \\ \qquad \text{when } wT > v_l. \end{cases} \tag{2}$$

Equation (2) has a number of interesting features. First, the auction's closing price increases with the spread of the valuation distribution, $(v_h - v_l)$. Second, because $(n-1)/(n+1)$ is increasing in n, the closing price is increasing in the number of bidders, so greater participation leads to higher revenue. Third, because of delay costs, the expected price decreases with auction duration T. This analysis is limited by the assumption of a fixed number of bidders. As discussed above, the longer the auction, the greater the number of participants, so n is an increasing function of T, and the effect of duration on revenue is more complex. Because $(n-1)/(n+1)$ converges to 1 for large n, if the arrival of bidders per unit time is high (i.e., the website has a lot of traffic), the effect of duration on the number of bidders is less important than its effect on the bid levels. On the other hand, when website traffic is low, lengthening the auction somewhat may help boost the closing price.

Selecting the duration, T, of an online auction has another subtle effect: it creates a bidding deadline, because bidders want to know when they can expect the auction to end. This deadline influences the bidding process. There are two common approaches to handling the deadline in online auctions. One approach, used on eBay, for example, is to have a rigid deadline; no bids are accepted past that time. The second approach is of the "going, going, gone" variety; the auction will continue past the original deadline as long as there has been recent bidding activity, where "recent" typically means within five or ten minutes. The rigid deadline has given rise to the sniping phenomenon, in which bidders place bids in the final moments (minutes or seconds) of an auction so that other bidders will not have time to outbid them.

In theory, it would be optimal for a bidder in a private value auction to bid her reservation value and enter it into a proxy-bidding agent provided by the auction site and for the winner to be the highest bidder, paying a price equal to the second-highest bid. In practice, late bidding and last-minute bidding are common in online auctions, suggesting that people do not behave as the theory predicts. Bapna et al. (2000) call these bidders "Opportunists," and find that they account for the winners in approximately 20% of the auctions observed. This phenomenon can be explained in various ways as a product of some violation of the basic assumptions of the auction model. Bajari and Hortacsu (2000) see it as evidence of common values. Some attribute it to naive behavior of inexperienced bidders (Wilcox 2000). In an elegant analysis, Roth and Ockenfels (2002) prove that last-minute bidding is consistent with bidder rationality and private values. They show that the rigid deadline and the probability of not being able to enter a countering bid late in an auction[11] can cause the late bidding behavior. They provide empirical evidence in a comparison of late bidding behavior in Amazon and eBay auctions to support their thesis. This example shows that the Internet implementation of an auction mechanism may not be isomorphic to its physical world counterpart, so designers of online auctions must not assume that the theoretical predictions carry over unchanged.

3.3. Multiunit Auctions and Lot Size

The Internet makes it easy to conduct auctions for multiple units of the same product in the same lot, and these can be found on all the major online auction sites. In the literature, multiunit auctions have been analyzed in two ways. Most authors assume that each bidder only has demand for one item (Harris and Raviv 1981a, Bapna et al. 2001). In these situations, generalizations of the standard single-unit English auction or second-price sealed bid auction are quite workable. The most common mechanism for online multiunit auctions is often referred to as the "Yankee auction." In a Yankee auction, one or more identical items are simultaneously auctioned. Bidders specify a price and the quantity of items they wish to purchase. Bids are typically ranked by price first and then by quantity. Winning bidders pay their bid price. When bidders only have demand for a single item, the Yankee auction is the multi-item generalization of the single-item English auction discussed above. The second-price sealed-bid model can also be extended to multiunit auctions with single-unit demand, in which k units ($k \geq 1$) are offered in a single auction (Vickrey 1961), in what is called a sealed bid $(k+1)$-*price* auction. In this auction, the uniform price is set by the bid on the $k+1$th unit (because there are only k units on sale, it is not a winning bid). The dominant strategy is to fully reveal one's private information (i.e., one's reservation price). As in the single-unit auction, the Vickrey (1961) mechanism is truth revealing because the winning bidders do not determine the price they pay. At the same time, revealing the true value guarantees a nonnegative consumer surplus. Harris and Raviv (1981b) show that when

[11] The inability to respond to a late bid in an auction may be due to a number of factors. Communications congestion, late updating of the bid history so that the participant does not know the latest bid, or other interruptions that interfere with the precise placement of the bid are examples.

bidders have independent private values and are risk neutral, the expected revenue from the Yankee auction is equivalent to that of the sealed bid $(k+1)$-price auction.

When bidders may have multiunit demand, the situation is more complex. Ausubel and Cramton (1996) demonstrate that the results described above for multiunit auctions do not carry over to the multiunit demand setting. They describe a phenomenon known as demand reduction.[12] Lucking-Reiley (2000) also points out that this is an area in which developments in auction theory may improve the design of online auctions through the use of more sophisticated mechanisms that prevent demand reduction (Ausubel 1997, Ausubel and Cramton 1996). Mechanisms to avoid demand reduction problems are complex, and it is unlikely that they will gain acceptance in the near future, but as the process of bidding becomes increasingly automated, it will be possible to implement more complex auction mechanisms to address this problem.

Regardless of the auction mechanism chosen, sellers in a multiunit auction can choose how many units to auction. All things being equal, increasing the supply in the market by auctioning more units will decrease the price. Lot size is, therefore, also an important auction design parameter. We illustrate this point by considering the following simple model of price determination in a multiunit $(k+1)$-price sealed-bid auction. We assume that a seller is deciding how many items k to auction when n bidders have independent private values uniformly distributed on $[v_l, v_h]$ and each bidder has demand for only one item. If the lot size does not exceed the number of bidders,[13] the expected closing price can be found, using the order statistics of the uniform distribution (Vakrat 2000) to be the following:[14]

$$E[p_a] = v_l + (v_h - v_l)\frac{(n-k)}{(n+1)}. \tag{3}$$

[12] Demand reduction occurs when, because of the mechanism used in a multiunit auction, a bidder with demand for $k_1 > 1$ items finds it optimal to bid on only $k_2 < k_1$ items.

[13] If the lot size exceeds the number of bidders, the seller gives away all the items at the minimum bid level.

[14] The expected price is determined by finding the $k+1$ order statistic of a uniform distribution.

We observe in Equation (3) that price is a decreasing function of lot size, and that the effect of lot size on the price is determined by the spread in the customer's valuations, i.e., $(v_h - v_l)$. This suggests that when determining the optimal lot size, the firm needs to know the variance of the customers' valuation distribution. Pinker et al. (2000) take advantage of these relationships to develop a framework for using information from one auction to learn about the customers' valuation distribution and to improve lot-sizing decisions in consecutive auctions.

The leading Israeli online auction site Olsale (www.olsale.co.il) uses an innovative approach to manage the risk involved in setting lot sizes that may be too big. At the beginning of a typical Olsale auction, a single unit is offered, and then, as bidding progresses and some of the demand for the product is revealed, additional units may be added to the ongoing auction as a function of the current bidding price, turning it into a multiunit auction. This approach has no counterpart in the conventional auction world. There is considerable room for additional research in this area. On the empirical side, it would be interesting to investigate the impact of lot size on bid traffic, and in the case of the Olsale model, to analyze the optimal way to increase the lot size during an auction and its effect on bid traffic. On the supply side, one could examine how production decisions could be integrated with the use of an auction sales channel, and in the case of the Olsale model, to develop strategies for producing (or buying) units for an ongoing auction.

4. Integrating Auctions into a Firm's Business Model

In the previous section, we discussed the design of isolated auctions. Online auctions, however, are rarely isolated events, for several reasons. First, most auctions on the Internet are for common goods for which there will be future auctions or similar auctions simultaneously occurring. Second, given concerns about fraud, both buyers and sellers are concerned with establishing reputations. Third, businesses that use auctions as a channel for selling their products are integrating the auctions into the regular operations of their firms.

We now consider the problem of auction design and implementation from the perspective of a seller who is interested in repeatedly selling products via auctions. We can view this seller as a business that uses auctions as part of an overall business strategy that may include alternative sales channels. This description would apply to private individuals who use auctions to supplement their income as well as to a firm that uses auctions to eliminate excess inventory or to discriminate on price.

There are several ways a firm may use auctions to sell its products to consumers. These approaches are all related to the choice between auctions and posted price.[15] Wang (1993) constructs a simple model comparing a firm's profits from auctions and posted prices, showing that there is a positive relationship between the preference for auctions and the dispersion of customer valuations around the mean. This suggests that if the firm is selling relatively rare or unusual products, then it may be better off selling primarily via an auction. Many firms use auctions to dispose of excess inventory, for example, uBid (www.ubid.com) provides this service for companies like Sony and Hewlett Packard (see Saloner 2000). This is consistent with Wang's (1993) thesis, because it is harder to anticipate the value consumers have for older products. Some may value them essentially as new, while others expect a steep discount. In this business model, a firm's primary selling channel is posted price, and auctions are used in a secondary capacity for older inventory. Yet, this is not the only situation in which auctions are beneficial. A firm can benefit from simultaneously operating online auctions and posted price. Firms may also use auctions as a marketing tool. For example, SharperImage.com conducts many single-item auctions at any one time of products that are available on its retail site. These auctions can be viewed as loss leaders to generate traffic to their main website. A few auctions of hard-to-get popular products like the latest Palm Pilot or exotic vacation travel packages can also be used to attract traffic to a website. Finally, auctions can be used for the purpose of price discrimination.

[15] An exception is provided by the example of Aucnet, an online used car auction site for Japanese used car dealers. This is an example of dual channels, an auction and a negotiation channel, but is unique in that the auction channel is for transactions between dealers (i.e., B2B), while the negotiation channel is primarily B2C. Lee et al. (1999) find that prices in the auctions are significantly higher than in the traditional channel for cars of similar quality.

It is natural to model the use of repeated auctions within a dynamic programming framework. We propose two general models to structure our discussion in this section, a finite horizon model (§4.1) and an infinite horizon model (§4.2). When a firm is using auctions to dispose of surplus inventory, a finite horizon model is most appropriate. When a firm is using auctions as its primary selling channel or using them in parallel with conventional posted-price sales, an infinite horizon model is most appropriate.

In this section, we also outline the important issues in B2B online auctions (§4.3), an area with as yet relatively little research. We consider the decisions faced by a third-party auctioneer who serves as an intermediary between buyers and sellers (§4.4). The auction intermediary is responsible for constructing the infrastructure for the market and defining its rules. Finally (§4.5), we discuss current research on an important topic for repeated auctions, fraud.

4.1. B2C Surplus Auctions

When a firm is using auctions to dispose of surplus inventory, it must make similar auction design decisions as those discussed for isolated auctions in §3. Yet, it must also explicitly account for the opportunities to sell in future auctions. Table 1 defines the notation.

The selling firm faces the following dynamic optimization problem:

$$\underset{k_0,\,T_0,\,R_0}{\text{Max}}\left\{E_{n_0}\left[\sum_{l=1}^{k_0} p_{li} + \delta J_1(q_0 - \min(k_0, n_0))\right] - q_0 T_0 h\right\} + C$$

where

$$J_i(q_i) = \underset{k_i,\,T_i,\,R_i}{\text{Max}}\left\{E_{n_i}\left[\sum_{l=1}^{k_i} p_{li} + \delta J_{i+1}(q_{i+1} - \min(k_i, n_i))\right] - q_i T_i h\right\} + C \qquad \text{for } i > 0,$$

$$k_i \le q_i,$$

$$J_i(0) = 0. \tag{4}$$

Table 1 Finite Horizon Model Notation

q_i—the inventory at the start of auction i (state variable)
k_i—the quantity auctioned in auction i (decision variable)
T_i—the duration of auction i (decision variable)
R_i—the rules of auction i (decision variable)
n_i—the number of bidders in auction i (random variable)
$p_{l,i}$—the final price for the lth item in auction i (random variable)
h—the unit holding cost in dollars per unit time (parameter)
C—the fixed cost of conducting an auction (parameter)
δ—the discount rate (parameter)

McAfee and Vincent (1997) analyze a seller who has a single item to auction and who can attempt to reauction it in a later auction if he fails to receive any bids above his reserve price. They assume that the auctioneer's only decision is the reserve price in each sequential auction. Using a repeated games framework, they show that if the auctions are conducted using second-price or first-price mechanisms, the optimal reserve price trajectory is decreasing and equivalent across mechanisms. The problem they consider is, essentially, a special case of the problem formulated in (4), in which there is a fixed number of bidders in each auction, the auction duration is ignored, holding costs are 0, the auction cost is 0, and the initial inventory is 1.

Pinker et al. (2000) model a firm that uses auctions to dispose of inventory. They use dynamic programming to determine the profit-maximizing way for a firm to allocate its inventory across multiple sequential auctions. They use a special case of (4) in which all the auctions are conducted with a no-reserve second-price mechanism. In a similar fashion as McAfee and Vincent (1997), they also assume that the number of bidders is fixed and thus ignore the auction duration and time between auctions. They do not restrict the initial inventory and do include holding and auction costs and multiunit lots. As a result, they model how the firm must balance the costs of running an auction and inventory holding costs with the price increase provided by smaller lot sizes.

Pinker et al. (2000) also extend the model in (4) by developing a practical Bayesian framework for incorporating results from previous auctions as feedback into design decisions for consecutive auctions of the same item. Using ongoing bidding data, they learn the actual customer valuations for each product and improve their estimate of the spread of the bidder valuation distribution, which is a key parameter in determining the revenue from an auction. Incorporating Bayesian analysis into the multiperiod, multi-item optimization model results in substantial benefits to the seller, primarily when the auction traffic is relatively small, holding costs are high, and there is a relatively large spread in bidders' valuations. They also find that when the spread of the bidder valuation distribution is known, the optimal lot size decreases with each auction. When the spread is learned through Bayesian updating, however, the optimal auction lot size is not monotonically decreasing.

Vulcano et al. (2002) model a firm with a fixed initial inventory that receives bids over time from consumers. They develop a finite horizon dynamic programming model that is a special case of (4) with fixed auction duration and a particular set of auction rules. In each period, the firm makes decisions to accept or reject bids. For the ith highest bid to be accepted, it must exceed the ith highest value threshold set dynamically by the firm. They propose a novel auction scheme in which the bidders reveal their bids and then the firm determines the value thresholds for that auction. They show numerically that this mechanism outperforms multiperiod auctions in which firms commit to a quantity in each auction before observing bids. Their result makes sense because the firm is clearly better off making auction quantity decisions after observing bids than before. This mechanism seems to fit best within the single-leg revenue management context that motivates the paper, however, the auction scheme they propose has yet to be seen in practice.

All of these papers (and one discussed in the next section) on repeated sequential auctions assume that the bidders in one auction are independent of those in all other auctions. Data we have collected (Vakrat 2000) from hundreds of daily B2C online auctions support this assumption, showing that from one day to the next, auctions for the same items yield closing prices with no significant difference. On the other hand, anecdotal evidence suggests that there are bidders who come to online auctions to bargain hunt. These bargain hunters will return repeatedly until they find an auction they can win at a low price. From a modeling perspective, this just means that the bidders in online auctions who expect future auction opportunities have lower valuations for the auctioned good than do bidders who do not plan to participate in other auctions. The result is that in a repeated auction setting, the consumer valuation distribution should be shifted down relative to an isolated auction and possibly more dispersed. Anticipating the effect of this behavior in advance is difficult and suggests that the Bayesian learning framework of Pinker et al. (2000) could be useful to sellers trying to estimate the valuation distribution to inform their auction design choices.

4.2. B2C Auctions as a Regular Sales Channel

Vakrat and Seidmann (1999) compare the price paid at auction with the posted price at the same sites and other sites for 350 auctions conducted on SurplusAuctions.com and Onsale.com (5,174 participants, 7,478 bids, and 1,372 auction winners). They find, on average, 25% discounts over posted prices listed on the same website and 39% discounts when the item was only available on another site; the discount percentage is smaller when the product is more expensive. They develop a model of customer bidding behavior built around a participation cost for the auction derived from the delay cost, with the idea that prices must be lower in auctions for it to be worthwhile to participate and spend time monitoring the auctions and deferring consumption. Their results suggest that auctions can serve as a mechanism for price differentiation.[16] In this context, an interesting question is whether the participants in posted-price and auction channels are different in terms of their valuations of the product being sold.

We have yet to see any theoretical work on the impact of auctions on parallel sales channels like posted price. In this section, we formulate a general model of online auctions used in parallel with a posted-price channel as an infinite horizon dynamic program. When a firm uses auctions as a regular sales channel, they must integrate the auction design decisions with production and pricing decisions. We use the notation in Table 2, suppressing the period subscript, i, and supplement it with the following:

Table 2 Supplemental Notation for the Infinite Horizon Model

f—fixed price offered (decision variable)
y—quantity ordered by seller (decision variable)
n—number of bidders with valuations below the posted price (random variable)
v—number of customers arriving with valuations greater than or equal to the posted price (random variable and function of auction duration)
v^*—number of winning bidders with valuations greater than or equal to the posted price (random variable)
w—unit cost of production (parameter)

The seller must find the policy $\mathbf{u}^*(q) = [k(q),\ T(q),\ R(q),\ f(q),\ y(q)]$ that maximizes the discounted expected profit given by

$$J(q) = \max_{k,T,R,f,y} \Bigg\{ E_{n,v,v^*}, \Bigg[\sum_{l=1}^{k} p_l + \delta J([q - \min(k, n+v^*) - (v-v^*)]^+ + y) + \min(v-v^*, q) f \Bigg] - qTh - yw \Bigg\} + C \qquad \text{for } i > 0,\ k \le q. \tag{5}$$

We do not claim that the above model is precise or practical to solve; its purpose is to illustrate the tradeoffs involved when the firm simultaneously manages an auction channel and a posted-price channel. In (5), customers are assumed to have full knowledge of the existence of both channels. During the delays between auctions, there is only a posted-price channel. Customers with valuations greater than or equal to the posted price will purchase the good if there is a positive inventory. When auctions are in progress, customers immediately decide to participate in the auction or purchase at the posted price. Low-valuation customers (valuations below the posted price) may only participate in the auction. High-valuation customers may purchase directly or join the auction. The decision to join the auction is determined by the customer's expectation of her

[16] A possible explanation for the difference between the auction discount across same-site posted prices and the auction discount across posted prices at different sites is that attempting to price differentiate with auctions forces retailers to lower posted prices.

surplus from the auction. This surplus is determined by the probability of winning the auction, the difference between the auction closing price and the posted price, and the participation cost. As earlier discussed, an important component of the participation cost is the delay involved in waiting for the end of the auction. The time remaining in the auction when the high-valuation customer arrives will influence his participation.

The firm makes several decisions that influence the auction participation decisions and the way the price discrimination occurs. Ideally, the firm would like to use the auction to create a channel for the low-valuation customers without cannibalizing the market for the posted price. Increasing the posted price increases the pool of potential auction participants. Increasing the auction lot size increases the probability of winning for high-valuation customers and, therefore, leads to greater cannibalization of the posted-price channel. Longer auctions increase the number of participants increasing competition, thereby making the posted-price channel more attractive for a larger proportion of the high-valuation customers.[17] We therefore believe that the seller must coordinate the posted price, the auction lot size, and the auction duration to maximize the profits from operating the dual channel. The model in (5) and our discussion of the finite horizon model in the previous section also suggest that auctions can be used as a tool to help manage inventory. When posted-price sales are lower than expected and inventory is high, the firm may increase its use of auctions, by increasing the auction lot size and increasing the frequency of the auctions, to help deplete the inventory and avoid holding costs. Etzion et al. (2003) model the design of parallel auction and posted-price channels.

Van Ryzin and Vulcano (2002) extend Vulcano et al. (2002) to the infinite horizon case and include inventory management decisions analyzing a special case of (5). They show that when using auctions of the type described in their earlier paper, the firm's optimal inventory control policy is a base-stock policy. They then extend their model to the case of a firm simultaneously managing a common inventory for posted-price and auction channels. Yet, their results are limited, as the buyers for each channel are assumed to be independent and the quantity on sale is not revealed, which may dramatically reduce participation.

[17] This statement is based upon the assumption that high-valuation bidders have equal or higher waiting costs than low-valuation bidders.

4.3. B2B Auctions

B2B auctions on the Internet are primarily being conducted in two ways. Some firms are conducting forward auctions to sell off excess inventory ("surplus auctions"), while others are using the reverse auction format to find suppliers ("procurement auctions"). Although there are plans for exchanges using bid/ask double auctions, we have not discovered any evidence of them in operation yet except for ChemConnect.com in the chemical industry.[18] Surplus auctions are similar in structure to B2C auctions, while in procurement auctions, a single buyer makes an RFQ from many potential sellers. Participants in these B2B auctions need to decide on their auction strategies, but the hosts/organizers of the auctions must also make design decisions that fit the business needs of the participants.

Surplus and procurement auctions are different from the B2C auctions we have discussed in several ways. The scale of B2B transactions is much greater than in consumer-oriented transactions, so it is important to identify "qualified" bidders beforehand. A qualified bidder is one who the auctioning firm is confident can satisfy its part of the transaction's requirements. In a surplus auction, we ask whether the bidder is capable of making payment and taking delivery of the goods. In a procurement auction, we ask whether the bidder has the ability to deliver the product as required. Thus, in procurement auctions, the buyer typically has multiple criteria for choosing a supplier, such as price, quality, delivery date, and payment terms. Finally, procurement transactions often involve long-term contracts. Due to the scale and scope of such contracts and the amount of time

[18] Of course, financial securities and commodities exchanges have existed for some time. In this paper, we are concerned with more specialized and more highly processed goods than commodities, for example, a certain grade of copper wire rather than copper itself.

it takes to negotiate them using traditional methods, the effect of the duration of the auction on behavior and participation is much less significant than in B2C auctions.

In surplus auctions, the traditional forward mechanisms like English or Dutch auctions can work well, because from a seller's perspective, qualified buyers can be solely evaluated on price. One way to ensure that only qualified bidders participate in such auctions is to conduct invitation-only auctions, as Eastman Chemicals does, at its EastmanMarketplace.com auction site for chemicals (www.eastmanmarketplace.com). Identifying an appropriate set of bidders is also a service that third-party auction site hosts provide.

Dasgupta and Spulber (1989/1990) model a single buyer who must select a supplier. The buyer does not know the sellers' production costs. They show that it is optimal for the buyer to specify a schedule of price and quantity and then to conduct a sealed-bid auction in which the suppliers bid the quantity they are willing to produce. Chen (2001) proposes a similar mechanism in which the suppliers respond to the price quantity schedule with sealed bids of what they are willing to pay for the contract. The buyer selects the highest bidder and then that supplier selects the quantity that maximizes its profit. Chen (2001) shows that the actual bidding and allocation can be done using any standard auction mechanism. In both these papers, the suppliers are only distinguished by their production costs and the buyer is only interested in a single product type. As a result, it is possible to reduce the problem to some variation of the traditional auction mechanisms. In practice, procurement auctions are much more complex.

The simple traditional auction mechanisms are insufficiently descriptive to capture the complexity of bidding for a contract with multiple components and involving multiple attributes, as occurs in practice. One approach to dealing with multiple attributes used by many reverse auction software providers and hosts is splitting the auction into multiple stages. For example, at Sorcity.com, buyers hold independent auctions for different products or combinations of products they wish to purchase. Each auction is defined by an RFQ, and each RFQ specifies the detailed terms and conditions required by the buyer. Only sellers who can satisfy *all* the terms and conditions can bid on the contract. The buyer will discuss details with the *three lowest bidders* at the end of an auction and choose from these. Some additional criteria beyond price, therefore, are incorporated into the purchase decision. The CompleteSource auction systems provided by Moai Technologies (www.moai.com) provide online negotiation facilities, based on online chat room technologies, for follow up with particular bidders.

In many contexts, there remain important unobservable characteristics of the suppliers who must be inferred from the prices they quote and the context of the auction. For example, in the labor market for information technology (IT) expertise, there are many freelance technology workers bidding on projects. Their experience and quality are unknown to the buyer beyond simple rating systems; RentACoder.com[19] is an example of such a market. Filtering bidders on price before negotiating will not address the problem of identifying the qualified suppliers in this setting. Snir and Hitt (2000) develop a theoretical model of an auction for IT knowledge that involves a stated price and an unobserved quality attribute. They use data from an IT expert auction website, like RentACoder.com, to investigate the behavior of markets for professional services. They find that in such markets, there may be excessive bidding for high-value projects, raising transaction costs for participants, and potentially lowering the quality of the services purchased. They suggest more thorough qualifying of bidders as a mechanism to reduce this problem. Unfortunately, precisely specifying qualifications may be difficult in a professional service market. This is also a limitation of Che (1993) in which a two-dimensional auction model, similar in structure to Dasgupta and Spulber (1989/1990), is developed with quality replacing quantity. The analysis relies on quality being specified by a single

[19] http://www.RentACoder.com. At this website, buyers enter a description of their problem and experts bid for the opportunity to solve the problem. RentACoder employs a payment escrow account to protect buyers who are unsatisfied with the code they receive and serves as an arbitrator for such disputes.

parameter and the buyer knowing the structure of all the suppliers' quality cost functions and the distribution of supplier cost parameters. Milgrom (2000) proposes a mechanism for more general multidimensional attribute auctions, based on the buyer's revealing its utility function to the bidders, and shows that such a procedure would lead to an economically efficient outcome. Given that most firms seek to maximize their own utility rather than achieve economic efficiency for a market, and given that firms may also be reluctant to directly reveal their utility functions to competitors, Milgrom's (2000) results may not be practical.

When a firm is trying to source a multicomponent requirement, such as a bill of materials or transportation services, the situation is even more complex. For example, if a large packaged goods company conducted a reverse auction for its trucking routes, different trucking companies might be bidding on overlapping but nonidentical sets of routes. To simplify the problem, the firm could choose to auction each route independently, but this approach would ignore the important fact that a firm's bid on one route is likely dependent on its success in bidding on other routes.[20] If bidders are allowed to bundle their bids, we have entered the realm of combinational (also called combinatorial) auctions. In combinational auctions, the challenge is to derive rules for ranking bids such that the tasks of computing allocations and selecting bids to place are computationally feasible (Rothkopf et al. 1998, Pekec and Rothkopf 2002, Walsh et al. 2000). The work in this area naturally applies techniques of combinatorial optimization. A discussion of the literature on combinatorial auctions is beyond the scope of this paper.

When a buyer is conducting a multiitem procurement auction in which suppliers bid for portions of the contract because of capacity constraints, the problem is no longer combinatorial but is still complex. Gallien and Wein (2000) propose a "smart market" for such an auction, in which in each round an optimization engine allocates the contracts in a manner that minimizes the buyer's costs by solving a new linear program. A myopic bidding suggestion tool guides the sellers and bidders. This is an attempt to create a framework that addresses the allocation problem faced by the buyer and the bidding problem faced by the seller.

An important element of B2B transactions is their repetition. Buyers value quality and reliability as well as low prices. This means that there might be a preference to send repeat business to suppliers who performed well. Knowing this, suppliers in procurement auctions may bid low to get first-time business with a buyer who will open the door to more lucrative repeat business. A procurement auction makes it easier for a buyer to consider more potential suppliers, weakening its relationship with long-term suppliers. On the other hand, the incentive for first-time suppliers to bid low is diminished if they view long-term relationships as less valuable. It is unclear whether procurement auctions are causing significant changes in buyer-supplier relationships, and it has yet to be studied whether participation in online procurement auctions has expanded the pool of suppliers used by any given firm. There is, in fact, significant skepticism in the industry about the importance and benefits of B2B procurement auctions (Emiliani and Stec 2002a, b; Delaney and Wilson 2000). Although it is acknowledged that purchase costs and transaction times can be dramatically decreased, these benefits are not revolutionizing the supply chain as expected. There is concern that a focus on the potential auctions providing for cost reduction may strain existing buyer-supplier relationships (O'Brien 2001b). The effect of these auctions on supplier relationships underpins the following three main criticisms of procurement auctions:

(1) They are focused on squeezing the suppliers.

(2) The claimed benefits ignore the total costs of purchasing.

(3) They do not encourage better supply chain integration; they are actually a disincentive to relationship-specific investments.

A market built on the premise that one side, the buyer, reaps the entire economic surplus will not attract many suppliers in the long run. There must be gains to both parties to get participation in the

[20] This complexity also arises in wireless spectrum auctions conducted by the Federal Communications Commission. There are synergies for firms from having certain geographic combinations of spectrum rights.

market and sufficient liquidity. As we have discussed above, there are typically multiple dimensions to procurement transactions, and price is only one of them. The greater the degree to which the focus of the auction market is on dimensions other than price, such as reduced transaction costs for both parties, the more likely the market will succeed.

The cost of switching to alternate suppliers based on auction results can be enormous and must be included in the buyer's winner selection process. Furthermore, inexperienced suppliers may impose additional costs on buyers due to poor quality, insufficient or inconsistent capacity, and delivery delays. The buyer must consider all of these potential purchasing costs as well. Finally, the trend in supply chain management has been toward better integration with suppliers. This means sharing information, integrating processes, and so on. If a buyer is switching from supplier to supplier based on auction results, it is impossible to develop the long-term relationships with suppliers that are necessary for both parties to gain from large investments in complementary process improvements.

Many potentially interesting research questions remain for the operations management community regarding the impact of procurement auctions on supply chain management. The following are some examples of open research questions: How does sourcing via an auction with stochastic prices and available quantities affect production and inventory decisions? How does a supplier set prices and service levels when competing against auctions? How does the option of saving through auctions compare to the option of building a relationship with a supplier and achieving cost reductions through integration? Will procurement auctions slow down supply chain integration?

Another effect of repetition on procurement auctions is that it makes it possible to learn about suppliers. A supplier's bids are a reflection of its cost structure. A buyer who knows her supplier's cost structure is in an advantageous position in any negotiations. A reluctance to reveal private information in such repeated transaction environments is one reason Rothkopf et al. (1990) believe that Vickrey auctions are rare. Beil and Wein (2003) devise a mechanism using inverse optimization in which a buyer learns the bidder's cost functions by altering the bid scoring function in each round of a multi-attribute auction. The purpose is to take advantage of this information in devising a scoring function in the final round that maximizes the buyer's utility. Although it may be unrealistic to think that sellers would participate in an auction in which the scoring rules were constantly changing, Beil and Wein's (2003) analysis does make it clear that there is a potential for buyers to improve their utility by using bidding behavior from one auction to design the rules for future auctions.

4.4. Auction Intermediaries

Firms that host auction sites perform several functions. They must communicate supply and demand orders, transform these orders into transactions, and provide sufficient liquidity for the market. These intermediaries provide the infrastructure for the auctions to be conducted over the Internet, provide various value-added services, and serve as a trusted third party who will not manipulate the auctions to anyone's advantage. Firms must decide whether they want to use an intermediary or host their own auctions. Auction hosts, be they third parties, buyers, or sellers, must decide how active a role they will play in the marketplace and what will be their business model.

Interestingly, some firms even host auctions for their own products and competing products. Dell, for example, auctions leased Dell computers on a separate primarily B2C auction site, Dellauction.com, and opens its site to sellers of all computer brands. Dell has made several choices in setting up this site. First, it has chosen to auction leased (used) computers. Second, it has chosen to host its own auctions rather than use a third-party auctioneer. Third, it has chosen to open its site to others. Dell restricts sellers of non-Dell brand products to used equipment and limits the quantity offered. These restrictions prevent competitors from using Dell's site as a major sales channel. The small sellers who use Dell auctions are attempting to "piggyback" on the focused traffic attracted to the site, i.e., they are trying to find market liquidity. For this reason, they have chosen Dell auctions instead of a more generic site like eBay. By hosting its own auctions, Dell is saving fees that otherwise would have gone to auction sites and is more effectively drawing traffic to its other websites. By opening its site to others, Dell is collecting fees from the other sellers, increasing the liquidity of the market for its own auctions, and learning about the demand for competitors' products. So we see that the choice of using an intermediary involves several important trade-offs. There are issues related to cost, liquidity, and marketing.

In B2B procurement auctions, intermediaries also often play an active role in identifying potential suppliers and filtering out those who may not be able to deliver. In the B2B setting, it is in the interest of an auction host to create a mechanism that is not biased toward buyer or supplier. Milgrom (2000) sees the goal of B2B exchange design as economic efficiency. Milgrom's reasoning is that if the mechanism is designed to extract the entire surplus from the sellers, it will eventually be difficult to attract sellers to the auction site. A market without enough participants will quickly collapse.

The importance of market liquidity means that there are positive network externalities in online auctions. The greater the number of participants at an auction site, the greater the attraction it has to potential participants. In theory, one would expect that given the low search costs on the Internet, there would be many intermediaries in each market, because it should be easy for a buyer to find an auction regardless of where it is hosted. In practice, there are giants such as eBay and FreeMarkets. Understanding the factors driving the industrial organization of these auction intermediaries is an open area of research. Intermediaries who want to generate traffic to auctions also face different challenges than traditional retailers. Retailers can stimulate traffic and demand by running promotions based on price discounts. Although buyers expect auction prices to be discounted over those in fixed-price venues, there are no guarantees.

The neutrality of the auction intermediary does not preclude the need to make several choices regarding the business model and operation methods. The auction host must choose a revenue model. Typically, auction sites charge some combination of a listing fee, i.e., a fixed fee for conducting a particular auction, and a percentage of the transaction's value. It is not clear whether they should charge the buyer or the seller, or whether this decision is dependent on whether it is a forward or reverse auction.

The auction host must also determine the degree to which it should be involved in the transaction. The auction host could be simply a bulletin board service in which the sellers are given tools to set up their own auctions with few constraints, as is done on eBay. Alternatively, the auction host could be involved by constraining the auction rules, screening the participants, and offering different forms of guarantees. Teksell.com has its own technicians who certify any previously owned equipment being auctioned on its site. DoveBid.com and others offer inspection services through established third parties like SGS Inc. Sothebys.com offers a three-year warranty on the authenticity of the items sold in its auctions. In the online auction environment, auctioneers have many more options and greater flexibility than they had before. Research has yet to be done to determine guidelines for auction intermediaries in making these business decisions.

4.5. Fraud and Reputation

The anonymity of an online auction creates opportunities for fraud. Traditional auction theory has discussed the effect of auction design on opportunities for collusion, but the Internet offers greater opportunities for misbehaving. Specifically, in C2C online auctions, winning bidders may choose not to pay, and in some cases, they are not bound by any contract to pay the seller. This is a form of ex post bid retraction and if used as a way to conduct bid shielding, it may discourage some participants, thus, hurting the seller.[21] On the other hand, the seller may

[21] An anonymous referee suggested the following example: bidder A asks a colluder, B, to bid $500 for a good on which A has the leading bid of only $10. While B's bid is the highest listed, no new bidders will join the auction. Near the end of the auction, B retracts his bid, allowing A to win for $10. We point out, however, that sites like eBay prevent this behavior by only displaying the lowest bid necessary to be the leading bid. So on eBay, the bidder B's $500 bid would only appear as a $10 plus minimum bid increment bid.

accept payment without providing any product or the promised product, thus, defrauding the bidder. These problems have resulted in two responses. One response has been to design mechanisms to prevent or detect fraud. Another response has been to place value on reputation. There has been recent work on both these responses.

Wang et al. (2001) and Yokoo et al. (2000) consider the problem of false-name bidding in multiunit sealed-bid auctions. False-name bidding occurs when a bidder creates additional identities and splits his demand among these identities. These authors show how false-name bidding can subvert the Generalized Vickrey Auction (GVA) protocol. The GVA was proposed by Varian (1995) as a mechanism for conducting truth-revealing, multiunit sealed-bid auctions and maximizing social surplus. In the presence of false-name bidding, the GVA no longer has its desirable properties. Both Wang et al. (2001) and Yokoo et al. (2000) propose alternative auction mechanisms such that false-name bidding is not incentive compatible for the bidders.

Shilling is another potential form of fraud based on false-name bidding by the seller. In online auctions, sellers can easily create false identities and bid through these identities to boost the bid levels. Kauffmann and Wood (2000) define "questionable bidder behavior" (QBB) as occurring when a bidder bids on an item when the same or a lower bid could have been made on the exact same item in a different concurrent auction that would end sooner than the auction in which the bid was placed. They claim that such behavior is likely to be that of a seller or a colluder involved in shilling. Interestingly, they show empirically that QBB correlates well with auction outcomes and behavior that would be associated with shilling. Looking at 643 QBB bidders out of a population of 6,798 unique bidders, they found that QBB bidders were participating in relatively fewer auctions, won fewer auctions, and bid earlier in the auctions and with higher increments than other bidders. These empirical results could form the basis for developing tools for auction hosts, such as eBay, to identify sellers participating in shilling for possible sanction.

The participant feedback scores provided on eBay[22] create a natural testing ground for the importance of reputation in determining the results of an auction. Lucking-Reiley et al. (1999b), Houser and Wooders (2000), McDonald and Slawson (2002), Dewan and Hsu (2001), and Ba and Pavlou (2002) all conduct empirical studies of the relationship between seller reputation and auction outcomes on eBay, and find that reputation has a small but statistically significant positive effect on price. Lucking-Reiley et al. (1999b) find that the reputation effect is much larger for negative feedback than positive feedback. Houser and Wooders (2000) show that a higher reputation in eBay auctions leads to higher bids, and McDonald and Slawson (2002) find that the number of bids increases with reputation as well.

Dewan and Hsu (2001) compare prices for stamps on a specialty site with eBay and find that the specialty site yields higher prices. This suggests that the reduction in risk or enhanced reputation of the specialty site, because of its added services, has value to consumers. This study is especially interesting, because it is reasonable to think that there is a significant reputation difference between the specialty auctioneer and eBay, and there is some skepticism about the meaningfulness of eBay reputation scores, which could be easily gamed.

Resnick and Zeckhauser (2000, 2001) perform an empirical analysis of buyer and seller feedback on eBay. They do not see an effect on price, but they do see an effect on the probability of a sale. Interestingly, they find that although there is much feedback, it is overwhelmingly positive. This raises many interesting questions. Is there a tendency to avoid negative feedback because of social norms and fear of retaliation? Are sellers who get negative feedback quickly changing their identities? Are sellers preempting bad feedback by sending positive feedback first?[23] The authors posit that the system works because people

[22] On eBay, buyers and sellers can leave comments about each other using a numerical rating: (+1) positive, (0) neutral, and (−1) negative. Only participants in actual transactions, i.e., a seller and a winning bidder, can leave feedback.

[23] From a design perspective, it seems likely that a marketplace like eBay would prefer that there be mainly positive reputations to enhance the reputation of the entire marketplace. We do not suggest

think it is important; sellers do not want negative feedback because they believe that buyers strongly respond to it. Alternatively, poorly rated sellers may be quickly chased away via "stoning," so in equilibrium, few will exist. Given that feedback is predominantly positive on eBay, it is probably not the best setting for tests of reputation effects. Comparisons like the one done in Dewan and Hsu (2001) between two settings in which the reputation differences are substantial will probably be more informative.

Resnick and Zeckhauser (2000, 2001) also make it clear that there is still a need to devise better mechanisms for establishing trust between participants in an online auction or, indeed, in any online marketplace. Dellarocas (2000) develops a formal (mathematical) way to discuss trust issues for online trading. He points out the many flaws in current systems and suggests some possible techniques for improving their design. It is not clear that trust can be effectively developed by a computerized mechanism in a way that would earn the confidence of businesses conducting large-scale transactions. For this reason, many designers of online marketplaces, for example, FreeMarkets, are providing services such as prequalifying suppliers and inspecting goods sold. The major online B2B marketplaces also allow firms to conduct private, invitation-only procurement auctions for the same reasons related to trust and reputation. There has been no research on how issues of reputation, trust, and brand equity have influenced the nature of participation in B2B marketplaces. The main parameters in this discussion are insurance, penalties, and other risk management mechanisms for the buyers, sellers, and intermediaries.

5. Conclusions

The Internet has made auctions a more common and integral part of the way commerce is conducted. The expanded applicability of this trading mechanism and the enormous flexibility granted by the computational power behind online auctions present firms with many important decisions. As a result, there has been great interest in online auctions in the academic research communities, and considerable empirical and analytical research on online auctions has emerged in recent years. Some researchers are basing their work on the analysis of readily available actual auction data. This analysis is being done to identify important empirical phenomena and to inform the development of new theoretical models. Despite some interesting initial results, this work is still at an early stage and has some significant limitations.

It seems that the main focus of the empirical work has been on consumer-oriented auctions, especially on C2C auctions like eBay, and using them to empirically verify previous results from economic theory. There is value in developing our understanding of online auctions by studying simpler environments like C2C auctions, but as researchers, we must avoid focusing our attention on the phenomena that are closest at hand, and in this case, sitting on our desktops. 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.

As a result of the limitations, there remain many important open research questions of management interest. We have identified the following four specific areas that we believe offer opportunities for fruitful and valuable research:

(1) Characterizing the behavior of participants in online auctions and their responses to actual market conditions and rules.

(2) Defining the optimal design of online auctions, taking into account newly relevant issues.

(3) Integrating auctions into the ongoing operations of the firm and quantifying the effects of auctions on critical business decisions such as procurement, marketing, production and inventory control, and supply chain management.

(4) Developing statistical estimation techniques and optimization methodologies for effectively mining the rich consumer data generated by auctions to predict behavior and to dynamically improve operational decisions.

that eBay manipulates participant feedback, but there does appear to be an incentive for them to discourage many negative feedback comments.

This paper should serve to make online auctions a more accessible research area for management scientists. We also expect that the boundaries of knowledge we have delineated and the open research questions we have identified should serve as a challenge to the intellectual curiosity and talents of our peers.

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