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Reference Prices and Bidder Heterogeneity in Secondary Market Online B2B Auctions*

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Online auction environments provide several sources of information that can be used by bidders to form their bids. One such information set that has been relatively understudied in the literature pertains to reference prices available to the bidder from other concurrent and comparable auctions. In this paper, we study how reference prices from such auctions affect bidding behavior on the focal auction. We also study how the impact of these reference prices is moderated by bidder heterogeneity. Bidders are shown to be influenced by two sets of reference prices: internal reference prices from their own historical bidding behavior and external reference prices, formed from other open and just-finished auctions relative to the focal auction. We measure bidder heterogeneity using bidder experience and level of participation in concurrent auctions. Our results show that external reference prices are significantly moderated by bidder heterogeneity. In a departure from current work, we use longitudinal data on auctions and bids in the B2B secondary markets, where goods represent salvage or returned items from big-box retailers and bidders are business buyers. The dataset comprises over 4000 auctions collected from a large liquidator firm in North America and is unique in its comprehensiveness. Our work provides theoretical insights that are complementary to the current set of results from B2C auctions as well as managerial implications for auctioneers in the B2B space.

Keywords: Reference Prices, Bidder Heterogeneity, B2B Auctions, Secondary Markets, First Bid, Bidder Experience, Econometric Analysis

1 Introduction

"... the question of who makes the first bid, to cross the Rubicon and get over what appears to be an unsurmountable hurdle for many listings, still remains, and is worth pursuing" (Dholakia and Soltysinski, 2001, p. 235).

Imagine posting an item up for auction – just as a lottery holder eagerly awaits the drawing of the ‘lucky numbers’, you wait with excitement for the first bid to appear. Will the bid be high, will it be low? While you suspect that the first bid will set the tone for the auction and affect your final profits, a definitive link between the two has yet to be established. While existing work (Ku et al. 2006; Bapna et al. 2008; Simonsohn and Ariely 2008) demonstrating the impact of

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the starting price on the final price *suggests* that the first bid can set the trend for subsequent bidding in an auction, the role of the first bid itself has never been explicitly studied. This paper attempts to address this missing link in the literature, and examine which information in the auction environment influence the first bid in the context of online auctions.

The growth of the online auction platform has allowed researchers to accurately estimate the impact of auction characteristics such as the starting or reserve price (Lucking-Reilly et al. 2000; Mithas and Jones 2007), auction duration (Haruvy and Popkowski Leszczyc 2010), seller reputation (Dellarocas 2006), and an auction’s ending rule (Roth and Ockenfels 2002) on the auction outcomes, with the most important outcome being final price (see Pinker et al. 2003 for comprehensive study on online auctions). More specific bidder behavior, such as sniping, herding and searching, have also been studied (Dholakia and Soltysinski 2001; Bapna et al. 2004; Ku et. al 2006; Simonsohn and Ariely 2008). Much of this work is focused on auction-level outcomes (rather than on individual bids) in the business-to-consumer (B2C) sector, characterized by relatively well-understood and discrete products such as music CDs, laptops and DVDs.

From this body of work, one of the key results pertinent to this paper is that, even when bidding for objects whose value is fairly certain (e.g., DVDs, laptops), bidders are influenced by others’ bidding behavior in the auction. Given this result, it is then natural to ask, as did Dholakhi and Soltysinski (2001), what influences the *first* bid/bidder? While this question is of interest within the well-studied environments of B2C auctions, it is of even greater economic importance in the burgeoning B2B auctions, where the composition of items for sale is widely varied, often ill-specified and prone to uncertain market valuation.

Using panel data from business-to-business (B2B) auctions conducted in the field, we study *at the bid level* the impact of information observable from the bidding behavior of others in the auction environment on the first bid. Specifically, we study how multiple price signals, provided by the prices observed on concurrent auctions for similar products, influence the first bid in an auction when the product’s value is uncertain. In addition, we examine how bidder heterogeneity moderates the influence of these price signals on bids in the focal auction. Our work here adds to the literature thus by studying the *relative* impact of price signals viewed by the bidder on the *bids* in the auction, contingent on *bidder heterogeneity*.

The data for this study comes from the B2B secondary market, where big-box retailers such as Kmart and Target liquidate excess and returned inventory at discounted prices. In an effort to remove excess inventory and returned goods from their warehouses, retailers sell their salvage and returned goods through online auction liquidation sites in bulk-pallet form. Since the pallets

include both customer returns and excess stock times, there is considerable uncertainty regarding the quality and value of the merchandise in each pallet. On these auction sites, other business buyers (such as off-price retailers, eBay power buyers and other such entities) bid for these pallets. The size of this market was at least \$50 billion during the time of our data collection (2008-2009) and has experienced significant growth since. Our data comes from a proprietary dataset of all auction transactions at one such excess inventory auction site, carried out over a period of five years (2003-2008) and includes bidder data as well as specific bid-level data for all auctions during this period. This dataset provides several features that are particularly conducive to the tests we carry out; the seller did not vary the traditional auction parameters studied in the literature, such as starting (reserve) price or auction duration. All auctions were initiated for the same duration (2 days), the same starting price (10% of the pallet’s declared retail value) and with no reserve price. Most importantly, the dataset provides us with visibility into bidder behavior over time and information about the state of the platform (such as current prices on concurrent auctions) at the time of bidding, thereby allowing bid-level analysis, centered around specific variables manifested at the time of the bid.

The marketing literature on reference prices (Mazumdar et al. 2005; Kalyanaram and Winer 1995) provides a useful framework for identifying the relative effect of concurrent price signals on a specific bidder and his/her bid. Reference prices are standards or benchmarks against which the purchase or bid price of a product is judged (Mazumdar et al. 2005). Prior work has identified two main categories of reference prices that affect consumer decision-making; internal reference prices (IRP) and external reference prices (ERP). An internal reference price (IRP) is based on prices or behavior that the consumer has observed in the past; it is primarily self-generated from memory and dynamic. As new prices are observed and assimilated, the IRP is updated appropriately (Yadav and Seider 1998). IRP are thus assumed to be the price the consumer would be willing to pay for a product in general and has a positive impact on the consumers’ willingness to pay. In addition to IRP, consumers also encounter contextual or environmental information that may provide additional reference points for price expectations. These could include prices offered for other products in the same category, prices in competing stores or the presence of advertised sales or promotions (Yadav and Seider 1998; Adaval and Monroe 2002). These are collectively called external reference prices (ERP) since they provide an alternative standard for the price of the product that is rooted in the specific context.

While the role of reference prices has been extensively studied in posted price purchase contexts

in marketing (see Mazumdar et al. 2005 for a comprehensive survey), the effect of reference prices in the auction setting has seen limited work. Unlike posted price contexts, reference prices in auctions tend to change depending on the bids of other bidders and auction parameters such as starting and reserve prices, thereby necessitating research that is more specific to the auction context (Dholakia et al. 2002; Kamins et al. 2004). Existing research studying reference prices in auctions are based on mostly cross-sectional B2C data and have not been privy to the detailed bidding history of individual bidders over time, thus imposing limits on the extent to which differential effects of reference prices can be studied. In contrast, we study reference prices in the B2B context using a longitudinal approach by identifying three types of reference prices that act on bidders as they formulate specific *bids*; (i) the bidder’s IRP, using bidder-specific historical bidding data; (ii) the prices of all open concurrent auctions for comparable goods at the time of bid; (iii) the final prices of auctions for comparable goods that have just finished. This conceptualization of reference prices provides a richer set of environmental information that bidders can use in formulating their bids on the focal auction.

In addition to reference prices captured over time, we are also able to characterize bidder heterogeneity by leveraging historical data on bidding behavior for each bidder in our dataset, a level of analysis hitherto absent in the literature on reference prices in online auctions. We capture two forms of heterogeneity in our analysis; the time-varying bidding *experience* of the bidder (Wilcox 2000; Wang and Hu 2009) and the *participation* of the bidder in comparable and concurrent auctions at the time of the bid. The literature on reference prices notes that accounting for bidder or buyer heterogeneity is critical; indeed, Mazumdar et al. (2005) specifically point out the confounding effects of customer heterogeneity in reference prices research (p. 97) and argue for the use of panel data to tease out the effects of customer heterogeneity. Consistent with these suggestions, in this study, we use panel data to hypothesize and provide evidence for how various reference prices differentially affect bidders and their bids, moderated by bidder heterogeneity at that point in time.

Our work here provides several contributions to the literature. This research is the first, to our knowledge, that (i) quantifies the impact of the first bid on the final price, (ii) studies the manner in which bidders are influenced by internal and external reference prices at the bid level, and (iii) explores the interaction of reference prices and time-varying bidder heterogeneity in the context of online auctions. We provide these results in contexts that are far removed from the well-understood world of consumer goods sold on B2C sites like eBay. Moreover, we model the bidding behavior of professionals in the field, i.e. buyers in a B2B market. Thus, the issue of

generalizability, which may limit results from eBay or experimental data, is less of a problem here. From a methodological viewpoint, we capture arguably the most complete data on reference prices and bidder heterogeneity possible through the use of a proprietary panel dataset. We also account for endogenous entry into the auction, a topic that has been addressed in the auctions literature (Bajari and Hortacsu 2003) but not in the B2B setting.

Our results show that the first bid *is* a significant predictor of the final yield on the auction. Furthermore, we find that information from comparable and concurrent auctions *do* serve as reference prices and are influential on the first bid, but are clearly moderated by bidder heterogeneity, namely bidder experience and participation level. In post-hoc analysis, we use clustering methods (similar to Bapna et al. 2004) to partition the auctions into two clusters based on the type of first bidder observed. We find that while the majority of the bidders are influenced by multiple reference price information as expected, there exist a small but influential set of *super-bidders*. These super-bidders rely heavily on their own internal reference prices and the prices of open auctions in which they are bidding, but tend to ignore other potential reference prices. The identification of these two types of B2B bidders provides several managerial implications and opens up some avenues for future research on bidder heterogeneity in the formation of and reliance on reference prices in online auctions.

Before we discuss our research hypotheses, it is necessary to understand the specific auction setting where we obtained our data. Since the field setting may not be as familiar to readers as B2C sites such as eBay, we describe the B2B auction context, its relevant features and the specific dataset next before moving on to the hypotheses section.

2 Research Site, Context and Dataset

2.1 The Secondary Market B2B Auction Platform

The B2B auction platform that we study deals with the resale of excess and returned *consumer electronics* merchandise from one big-box retailer in North America. As will be evident from our discussion below, the online auction platform we study differs from the commonly studied B2C platforms in three important ways: (i) all bidders are professional resellers who, themselves, vary in their experience bidding on the platform; (ii) there is significant uncertainty regarding the condition of the contents in pallets, and hence its market value; and (iii) multiple comparable pallets are posted concurrently on the auction site by the liquidator (hereafter called the seller) as and when inventory arrives from the retailers, providing some market-level information to the bidders. We elaborate on each of these points below.

The items for sale on the auction site are comprised of excess and returned inventory. When the participating big-box retailers decide to move these excess items from their stores, they create pallets of (frequently) disparate products, and ship them to the seller’s warehouse; the seller has no control over the constitution or quality of the goods auctioned. Pallets, in their entirety, are auctioned on the site in ‘as-is’ format, i.e., neither the retailer nor the seller assume responsibility for the condition of the contents. Since the pallets can include both customer returns and excess stock items, there is considerable uncertainty regarding the quality and value of the merchandise in each pallet. Bidders cannot physically inspect the pallets beforehand, and hence do not know if items are in opened or damaged boxes, or if the items themselves suffer from any defects. There is little, if anything, that the seller or bidders can do with respect to a specific pallet in terms of reducing quality uncertainty in a systematic manner.

Bidders in these auctions are themselves resellers, e.g., flea market vendors, wholesale liquidators, eBay Power sellers, ‘mom and pop’ stores, who vary greatly in their bidding activity and buying volume on the auction site. Their valuation for the pallets is driven in large part by their assessment of the contents’ resale value, adjusted by their (private) channel costs. The resale value of a pallet is largely determined by the condition of its contents, as well as current market trends in the electronics market. The actual condition and composition of the pallet, and hence its resale value, is dependent on factors such as the retailer’s diligence when processing returns (whether the retailer validates the contents of opened boxes), the retailer’s back-store operations (the manner in which inventory is tracked and repackaged into pallets, that are then transported to the seller) and the retailer’s inventory policies (size, frequency and diversity of products ordered). All of these factors contribute to the degree of variability of goods within the pallet and the potential resale value of these items. While some of these factors may be learnt over time by a bidder as pallets won via the auction site are opened and examined, the uncertainty over the composition and resale value of the pallet’s contents is rarely ever eliminated. Finally, the design of the platform does not support feedback or retailer ratings, thereby removing the option of using this data as sources of quality information.

There is, however, potentially relevant valuation information to be gleaned from concurrent auctions for other pallets that are posted on the platform and are visible to the bidder. The big box retailer in our dataset typically ships multiple pallets from the same retail store to one of the seller’s warehouses dedicated to stores in that region. The flow of goods into the warehouse is beyond the seller’s control; it accepts pallets as and when they arrive from the retailers. The need to quickly liquidate excess inventory places considerable pressure on the seller to run multiple

auctions concurrently. The design of the auction platform does not allow the bidder to observe any relevant information about other bidders on both the focal auction and concurrent auctions, nor does it allow the bidder to track the individual bids placed by other bidders – it does, however, allow bidders to see the current winning bids, i.e. highest price only, on concurrent auctions. Given the specific design of the auction environment, and the uncertainty surrounding the pallet’s valuation, it is reasonable to posit that current prices on concurrent auctions (from the same store/warehouse) likely serve as useful sources of information to bidders, giving them a window into their competitor’s assessments of the value of comparable pallets. Thus, the reference prices literature from marketing is particularly suitable here in understanding the impact of these concurrent prices on the bidding behavior on the focal auction.

Auction researchers (Milgrom and Weber 1982) have long acquiesced that, despite the theoretical interest in pure private and common valuation settings, a hybrid valuation model is likely the most appropriate for most auctions. Under a hybrid valuation model, the bidder’s valuation for a pallet is influenced by both his private/idiosyncratic valuation as well as the revealed valuation of other bidders. Given the description of the auction platform above, it follows that an appropriate valuation model for this B2B particular context is that of the hybrid valuation model. While a formal theoretical exposition of the valuation model is out of the scope of this paper, it is worth noting that the model flexibly allows incorporating the two forms of reference prices we study in this paper. External reference prices, formed by the prices on concurrent auctions, represent the (modified) valuations of a collective of other bidders’ maximum willingness to pay. Similarly, internal reference prices capture the private elements of the bidder’s valuation, i.e. they represent the idiosyncratic manner in which the bidder translates pallet-specific information into a maximum willingness to pay. Thus, the affiliated valuation model provides us with a framework to incorporate the influence of both internal reference prices as well as external reference prices on the focal bid observed on the platform.

In the next section, we discuss in greater detail the specific dataset that we use in this paper and the strategy used in variable definitions for reference prices and bidder heterogeneity.

The most commonly adopted hybrid valuation model (cf. Levin 2004) is of the form $v(s_i, s_{-i}) = s_i + \beta \sum_{j \neq i} s_j$. In this valuation model, all bidders have the same value, given by some random variable V . The signals $s_1, \dots, s_n$ are each bidder’s private signal, correlated with V but independent from each other (i.e., $s_i = V + \epsilon_i$ where $\epsilon_1, \dots, \epsilon_n$ are independent). β ($\beta \leq 1$) are also the weights each bidder puts on their own as well as other bidders’ private signals.

2.2 Dataset

We were provided a dataset of all electronics B2B auctions that were conducted on the seller’s online auction platform for the period 2003-2008. This dataset consists of 4308 individual auctions, featuring 1200 B2B buyers (unique bidders). Amongst the 1200 bidders we observe in our data, we see only 569 bidders that appear as first bidders on at least one auction. As mentioned earlier, bidders have incomplete information regarding the condition of the items in the pallets. On the main auction site, bidders are informed as to the total number of items in the pallet Q , as well as the pallet’s declared retail value/price E . Interested bidders are able to click and open a bill of lading, detailing in somewhat vague terms, the contents of the pallet and for each item the number of units and the per unit retail price. The bidding format on the site is similar to that seen on eBay auctions, i.e. proxy auctions. In proxy auctions, bidders submit their maximum willingness to pay (MWTP) for the specific pallet; the auction tool automatically updates a bidder’s current bid until it has reached the bidder’s declared MWTP. The auction ends when no new bid updates occur – the bidder with the highest MWTP wins the auction and pays the second-highest MWTP plus the minimum bid increment. For each auction, we have information regarding all the submitted bids, the identity of the bidders who submitted them (an auction platform generated identification number), and the time of the first bid for each auction ($TOFB$)– rescaled to the interval $(0,1)$ to facilitate discussion. We also collected the number of bids submitted by each bidder, the final price of the auction, the final number of bidders who participated in the auction (N), the physical location of the pallet (the physical warehouse where it is located), the calendar date and time of the posting of the auction, the auction’s starting price,

For the specific category that we study (consumer electronics) and during the period of observation, the seller did not vary the traditional auction parameters studied in the literature, such as starting (reserve) price or auction duration. All auctions were initiated for the same duration (2 days), the same starting price (10% of the pallet’s declared retail value E) and with no reserve price. In addition, all the pallets in our dataset were obtained from the same big-box retailer, thereby controlling for retailer-level idiosyncratic behavior. Thus, the specific set of auctions we study, in addition to the design of the auction platform described in the previous section, provide us with almost experimental-level controls on the auction’s parameters (i.e. starting price, reserve price, duration), which allows us to estimate the effects of reference prices and bidder heterogeneity with few confounding sources of information. Finally, our dataset provides us with complete information over time regarding bidder behavior, the occurrence of successful and unsuccessful bids on

the platform and any outstanding bids at a specific point in time, allowing greater levels of granularity in data definition than possible in most cross-sectional studies on online auctions. We use this additional granularity to define the variables for the two broad constructs we study - reference prices and bidder heterogeneity. We describe these variable definitions next.

2.3 Reference Prices and Bidder Heterogeneity

We focus on three specific reference prices in this study. The first reference price we measure is the bidder’s *internal reference price (IRP)*. The IRP is assumed to be the price that the consumer would be willing to pay for a product based on past purchasing behavior (Mazumdar et al. 2005). The IRP is based on prices or behavior that the consumer has observed in the past; as new prices are observed and assimilated, the IRP is updated appropriately (Yadav and Seider 1998). Therefore, we measure the IRP simply the average normalized final price (as a % of E) of all comparable auctions won by the bidder in a moving window of six months prior to the focal auction. This measure is broadly consistent with other measures of IRP used in the literature (Yadav and Seiders 1998; Rajendran and Tellis 1994). However, for the IRP to be a reasonable reference price for the focal auction, it is necessary to condition it on pallets that are similar to the focal auction’s pallet. Since no two pallets are exactly identical on the B2B auction platform we study, we must define the notion of a ‘comparable auction’. We do so in a manner consistent with Chan et al. (2007), as described below.

At the time of the focal auction, we consider all concurrent auctions that have any overlap in time with the focal auction (see Figure 1) but that are located in the same warehouse. We then calculate the means and standard errors of Q and E for this set of concurrent auctions for the focal auction. The set of *comparable* auctions for the focal auction then contains all auctions that are within one standard deviation of Q and E formed on the set of concurrent auctions; we refer to this set of comparable and concurrent auctions as C&C. This definition allows us to condition the reference prices observed from concurrent auctions such that the aggregate price signals observed are the most proximal for the focal auction. The IRP of the bidder in the focal auction now becomes the average normalized final price of all comparable auctions won by the bidder in the six-month moving window, prior to the observed bid on the focal auction.

Prior work in marketing has identified that consumers’ willingness to pay for a product is also influenced by price information in the surrounding environment (Yadav and Seider 1998; Adaval and Monroe 2002). These prices, such as prices offered for other products in the same category, prices in competing stores or the presence of advertised sales or promotions, are collectively called

external reference prices (ERP). While a bidder on the auction site can neither see the number of submitted bids/bidders at any time, nor the identity of a competing bidders, for the focal auction, bidders can however see the current winning prices of concurrent auctions. These can act as ERPs for the focal auction. Therefore, we identify two sets of ERPs, again by capitalizing on the notion of C&C auctions. From Figure 1, the set of C&C auctions can be divided into two sets. The first set is comprised of C&C auctions that are open when the focal auction begins, but have closed *before* the focal bid is placed in the focal auction; we refer to these as just-finished auctions (JFA). Alternatively, the second set of C&C auctions is still open when the focal bid is placed; these are referred to as open auctions (OA). The average final price of the just-finished auctions (*JFAP*) represents reference prices that are highly informative (Wolk and Spann 2008; Bapna et al. 2009) since they represent a current estimate of other bidders' valuation (cents-on-the-dollar) for comparable pallets. Alternatively, the average current prices of open auctions (*OAP*) serves as a signal of the eventual price of comparable auctions. We examine the effects of both these reference prices on the focal bid. We also measure the number of auctions that are included in the set of open and just-finished auctions, denoted by *NOA* (number of open auctions) and *NJFA* (number of just finished auctions). Finally, of the set of auctions in *NJFA*, it is possible that the focal bidder bid on some auctions (denoted by *NJFA_{bid}*) and was the eventual winner on some auctions (denoted by *NJFA_{won}*).

We capture bidder heterogeneity using two constructs - *bidder experience* and *participation in cross-bidding*. Bidder experience is captured temporally by the number of auctions won by the bidder in the previous six months to the focal auction. The use of a moving window of six months also allows us to account for the effects of bidder inactivity over an extended period of time; in such cases, the value of bidder experience on the platform should reduce. Measuring participation in cross-bidding, i.e. bids in concurrent auctions, again involves the use of the C&C auctions. Cross-bidding behavior suggests that some bidders will likely have multiple bids on concurrent similar auctions, in the manner proposed by Peters and Severinov (2006) and tested by Anwar et al. (2006). It is conceivable that bidders are differentially influenced by those auctions in the C&C set where they have issued bids. To capture this effect, we consider the set of *JFA* and *OA* auctions and only identify those auctions where the bidder has made a bid. The average reference prices from this subset of auctions are therefore denoted as *JFAP_{bid}* and *OPA_{bid}*. Correspondingly,

In robustness tests, we vary this time period to three months (Bruno et al. 2012) with no difference in results. We also consider all won auctions in the past indefinitely (Wilcox 2000) and the number of lost auctions (Wang and Hu 2009). Using all auctions provides weaker empirical results while lost auctions has no impact on bid formation. Finally, we if define experience as the number of bids in the previous months, we see consistent results but with less statistical significance. We use the winning experience in our analysis to stay consistent with the literature.

we also create the reference prices from those auctions where the focal bidder did not have a bid, denoted as $JFAP_{notbid}$ and OAP_{notbid} . These variables capture heterogeneity in bidders by virtue of their participation in the set of concurrent auctions across the observation period of 2003-2008. The summary statistics as well as the correlation table for these variables are also shown in Table 1. Also, the individual variable definitions used in our different analysis throughout this paper are shown in Table 2. Having defined the key variables in our dataset, we propose our research hypotheses in the next section.

3 Theory and Hypotheses

We provide the main arguments for the hypothesized effects of the reference prices and bidder heterogeneity on the first bid value in the B2B auction platform described above. Prior work in internal reference prices argues that it has a strong influence on the valuation and willingness to pay on a given product in the posted-price environment (Rajendran and Tellis 1994). While the effect of ERP both within an auction (such as starting price) and surrounding an auction (such as prices on adjacent auctions) on the *final price* of an auction have been studied in some depth, there is very little work on the role of IRP in the auction context specifically. To the best of our knowledge, only Wolk and Spann (2008) attempt to measure IRP, using a survey for the two products they study (sneakers and MP3 player). In all other cases, IRPs are neither controlled for nor measured, for understandable empirical reasons; longitudinal data is not easily accessible in these environments. Wolk and Spann (2009) show that the IRP does influence the quoted prices in a name-your-own-price environment. In our context, the historical price information that the bidder recalls from won auctions for comparable auctions will weigh heavily on the willingness to pay on the focal auction— the higher the historical IRP, the higher will be transferred valuation to the focal auction. Thus, as a baseline, we propose:

Hypothesis 1 *Higher IRPs will be associated with higher first bids on the focal auction, all else being equal.*

Given our auction environment, there are two natural categories of ERP – the average just-finished auction prices ($JFAP$) and open-auction prices (OAP). $JFAP$ are free of any uncertainty since these auctions are over and therefore, to the focal bidder, will indicate a reasonable anchor of where the focal auction may end. If the bidder observes higher final prices on these auctions on average, it is likely that the private valuation he or she assigns to the focal pallet will be higher as well. Dholakia and Simonsohn (2005) argue that prices on adjacent auctions can serve as signals

of quality. In addition, Dholakia and Soltysinski (2001) show that the tendency to emulate other auctions (the herd behavior bias) is exacerbated when the underlying quality of the product is uncertain. In our setting, clearly there exists quality uncertainty about the pallet. However, the bidder can observe average final prices on C&C auctions which, by virtue of overlapping with the focal auction, provide reference prices that are clearly proximal and easily available to the bidder (Ariely and Simonsohn 2003). Both Ariely and Simonsohn (2003) and Hubl and Popkowski Leszczyc (2003) present evidence that higher starting prices may signal quality and thereby induce consumers to assimilate higher reference prices for the product, thereby leading to higher final prices. Kamins et al. (2004) find that seller-provided reference prices in the form of minimum bids lead to higher prices on average, while Nunes and Boatwright (2004) show that incidental prices on products that are unrelated to the focal auction can also serve as anchors and influence willingness to pay. Extending these arguments, it is likely that final prices on just finished auctions, which represent others' valuations on similar pallets, can function as valid external reference prices and lead to higher willingness to pay for potential first bidders. Therefore, we propose the following hypothesis:

Hypothesis 2 *Higher JFAPs will be associated with higher first bids on the focal auction, all else being equal.*

The dynamics regarding prices observed in open auctions (*OAP*) are somewhat similar to *JFAP* but the information they provide to the bidders is still uncertain since the set of auctions on which they are formed are still unfolding. Higher *OAP*, on average, will induce higher valuations on the focal auctions to the extent that they provide a signal of value. The observed literature on quality signals from external sources (Dholakia and Simonsohn 2005; Kamins et al. 2004) provides reasoning for why *OAP* are likely to influence bidders' willingness to pay. However, it is also possible that the bidder may choose to bid instead on a C&C auction, rather than be the first bidder on the focal auction. Prior work on simultaneous auctions suggests that this is unlikely – Peters and Severinov (2005) argue that cross-bidding behavior will tend to drive bidders to the comparable auction that has a lower current price, which in our case is the auction awaiting the first bid since all starting prices are set at the same level. Therefore, the cumulative effect, we argue, will be to induce the first bidder faced with a higher *OAP* to issue a higher first bid. It is likely that since the information content of *OAP* is less compelling (more uncertain) than *JFAP*, the effect size of the *OAP* may be lower than that of the *JFAP* on the first bid value. We allow the empirical analysis to determine this but propose the following:

Hypothesis 3 *Higher OAPs will be associated with higher first bids on the focal auction, all else being equal.*

Prior literature suggests that reference prices in the auctions context are formed from adjacent or C&C auctions, which is captured by *JFAP* and *OAP*. However, it is unlikely that all such C&C auctions have the same effect on the focal bidder. Prior work has suggested that the act of making certain reference prices explicit or salient, for instance by making the bidder explicitly compare prices across adjacent auctions (Dholakia and Simonsohn 2005), can differentially influence bidding behavior. In a similar vein, Nunes and Boatwright (2004) show that focusing attention on a particular set of incidental prices increases the extent to which they impact willingness to pay, compared to the baseline where no specific attention was directed. In our setting, the notion of salience or attention is captured by the set within C&C auctions where the bidder has actually participated by posting a bid. Therefore, while the set of C&C auctions may be used to set reference prices, the act of bidding on some of these auctions will make the current prices on this subset of auctions more explicit and salient; this salience will show up in the specific bids on the focal auction. Capturing the impact of bidder participation thus introduces a new dimension of bidder heterogeneity that has been understudied in the literature since it is bidder-specific rather than auction or market-specific. We argue that bidders with many bids out on C&C auctions will likely condition their first bid on the focal auction differently than bidders with relatively fewer bids on C&C auctions due to the increased salience of this reference price information. Therefore, we propose:

Hypothesis 4 *The impact of JFAP and OAP on first bid value will be positively moderated by the participation of bidders in JFA and OA.*

Bidder experience has been studied in multiple ways in the literature and has been consistently shown to affect bidding behavior. In an early study, Wilcox (2000) shows that bidders with a high level of winning history, used as a proxy for bidder experience, submit fewer bids and also bid late in the auction. However, subsequent research suggests that winning experience may not necessarily drive bidding behavior (Bajari and Hortacsu 2003; Wang and Hu 2009) captured by willingness to pay, number of incremental bids or time of last bid. Indeed, the losing experience of the bidder appears to have a stronger effect on bidding behavior (Wang and Hu 2009; Park and Bradlow 2005). Due to the ambiguity in the effect of experience on bidding behavior observed in the literature, in the B2B context we study, the role of bidder experience on bidding behavior needs to be established based on an understanding of the specific context rather than extending existing work.

As participation moderates the impact of reference prices, it is also likely that bidder experience makes certain reference prices less influential on bidding behavior (Wilcox 2000). Prior work in the posted-price environment shows that experienced consumers tend to condition more on IRP and less on ERP since experience allows consumers to form more robust internal expectations of value (Rajendran and Tellis 1994; Yadav and Seiders 1998). In the specific context of the online auction, experienced bidders will likely rely more on their historical observations of prices on the focal auction rather than on the dynamics of the current market condition. Therefore, while the impact of higher *JFAP* and *OAP* may signal higher value from the focal auction, the effects of these are likely stronger on inexperienced bidders compared to experienced bidders. Therefore, we propose the following:

Hypothesis 5 *The impact of JFAP and OAP on first bid value will be negatively moderated by bidder experience.*

We have hypothesized the moderating effects of bidder participation and experience on the relationship between ERP and first bids. It is also possible to postulate a three-way interaction between reference prices, participation and experience on the first bid. For instance, it can be argued that the effect of OAP_{bid} and $JFAP_{bid}$ is lower on bidders with experience than on bidders without experience. This analysis is, in effect, a three-way interaction. Providing a priori expectations on the direction of these effects is hard since the proposed moderating effect of experience is negative while that of participation is positive; we cannot clearly identify what the composite effect will be. Therefore, rather than propose a hypothesis, we perform the analysis and allow the data to provide us with guidance. In the next section, we discuss the analysis conducted.

4 Empirical Analysis

We proceed with the empirical analysis in stages so as to provide adequate depth of analysis to the research questions we study. First, we address the importance of the first bid in determining the recovery rate (final price) on the auction. Having established the importance of first bid role, we then study how the first bids are formulated through the influence of reference prices and bidder heterogeneity. Finally, we discuss the results from this analysis, which point to way for further post-hoc analysis reported in Section 5.

4.1 The First Bid's Effect on Recovery Rate

In this section, we confirm that first bids are critical in determining the recovery rate of an auction. We start with a simple OLS model with recovery rate as the dependent variable and the first bid as the key independent variable. Consistent with the literature on final prices in online auctions (Bajari and Hortacsu 2003; Bapna et al. 2004), we include the following covariates - NOA , Q , time of first bid ($TOFB$), Y , number of bidders (N), fixed effects of month/year of auction (to capture seasonality, if any) and physical location of the warehouse (see Table 2 for the summary of variables in recovery rate regression).

The results from the baseline model without first bid are reported in Column 1 of Table 3. On adding first bid to the model, we see the results in Column 2 of Table 3. The regression shows good predictive power and a statistically significant F-statistic, with all covariates showing marginal effects in the expected direction, based on the literature. Most significantly, the coefficient of first bid is positive and the most influential in determining recovery rate.

Prior work on the role of the starting price (Bajari and Hortacsu 2003) suggests that the first bid's effect on recovery rate manifests *through* its influence on number of bidders. For instance, Simonsohn and Ariely (2008) argue that early bidding is a necessary condition for herding to occur, which results in more bidders on the auction and therefore higher final prices. Therefore, we account for the endogeneity of number of bidders in this relationship in the following manner. We instrument for number of bidders using the hour and weekday of the auction dummy variables, which are likely unrelated to the final recovery rate on the auction but may influence the number of bidders. The use of exogenous time variables has been used in prior work as valid instruments (Wooldridge 2002) and we follow this approach. We then estimate a 2SLS regression with number of bidders in the first stage and recovery rate in the second stage. Exclusion conditions require omitting the time dummies from the second stage recovery rate equation. Column 3 of Table 3 shows the first stage results for number of bidders while Column 4 shows the second stage results for recovery rate. The results are consistent with our arguments that first bid is influential in determining recovery rate; all else being equal, an increase of 1% in the first bid value increases the recovery rate by almost 0.4% of E . Having established the critical role of the first bid, we move to testing our research hypotheses on the first bid.

4.2 First Bid Formation

To predict the first value for an auction, we specify a regression model of the following type:

$$FB_{ij} = \beta_0 + \beta_1 Experience_{ij} + \beta_2 IRP_{ij} + \beta_3 ERP_{ij} + \beta_4 BC_{ij} + \beta_5 AC_i + \beta_6 Time_i + \beta_7 Warehouse_i + \epsilon_{ij} \quad (1)$$

Where FB_{ij} is the first bid issued by the bidder j in auction i . Also, $Experience_{ij}$, IRP_{ij} , and ERP_{ij} respectively report on experience, internal, external reference prices of bidder j prior to the time of the first bid on the auction i . BC_{ij} are the control variables for bidder j in auction i which include: the number of incremental bids bidder j submitted in auction i and the number of JFA and OA the bidder j observed prior to the time of the first bid on the auction i ($NJFA$; NOA). Additionally, AC_i represents the control variables for auction i such as Q , Y , and $TOFB$. Finally, we also account for the fixed-effect of time and warehouse location of the auction i . Table 2 summarizes the description of these variables used in Equation (1). The baseline model introduced in Equation (1) does not include interactions to test moderation, which we discuss shortly.

Estimating Equation (1) using OLS is feasible but it is likely that the coefficient estimates of the reference prices and bidder heterogeneity on first bid are biased (Bapna et al. 2004; Bajari and Hortacsu 2003). The bidder's entry into the auction is endogenous, i.e. the focal bidder chooses to enter the auction based on some underlying decision process, which then leads to the formation of the first bid. Ignoring this decision introduces bias into the coefficient estimates of the reference price and heterogeneity variables on the first bid. Jointly estimating fully structural models of entry and bidding is challenging because of the complexity involved in characterizing structural properties of the B2B marketplace, specifically regarding heterogeneous bidder costs, the valuation paradigm (affiliated value versus common value) and computational complexity (Li and Zheng 2009). Therefore, we use a simpler and more parsimonious method to account for endogenous entry by leveraging the availability of panel dataset and the ability to capture the state of the market and the bidder specifically at the time of bidding. We are guided here by the methodology used by Bapna et al. (2009) where, in lieu of a structural model, the effect of endogenous strategic variables are estimated through the use of instruments and reduced form equations.

The approach we use to tackle endogenous entry is as follows. At the point in time when the first bid is entered for the focal auction, there are likely K active bidders on the platform who form the candidate set of bidders for the auction. Recall that all auctions in our sample are of 2 days duration. Therefore, even though there are 1200 buyers registered on the site, it is unlikely that all of them are 'active' on the platform at the time of the auction's posting. Therefore, we first identify

Although FB and most variables in right-hand-side of Equation (1) ($Experience$, IRP , ERP , etc) are also time-dependent, for the sake of exposition simplicity, we suppress the *time* subscript from those variables in the equation.

the K set of ‘latent’ bidders who form the candidate set. For each focal auction, we identify all bidders on the comparable set of JFA and OA auctions who have issued *observable* bids prior to the time of the first bid on the focal auction (t). These bidders then form the pool of latent first bidders on the focal auction, of which one bidder does become the actual first bidder. See Figure 2 for a depiction of this empirical strategy.

The logic for this operationalization is based on three observations. First, all latent bidders thus identified are clearly active on the platform at the time of the focal auction. Second, all these bidders are likely interested in the focal pallet, since they have issued bids for comparable pallets. Third, this approach allows us to capture greater heterogeneity in time-varying bidder characteristics that help in more robust estimation of the entry decision. For instance, we can identify, given the time of first bid on the focal auction, what other outstanding bids the latent bidder has on other auctions, the prices he or she is observing on other concurrent auctions and so on; these variables are likely to influence his or her propensity to bid on the focal auction since they influence his or her valuation for the focal pallet.

Using this approach, for each focal auction, we form a set of K_i latent bidders for each auction i , of whom one bidder chooses to enter the auction. We stack these K_i observations and estimate a discrete choice model wherein each latent bidder k chooses whether to bid or not in auction i . The unit of analysis here is therefore latent bidder-auction and the analysis predicts whether a realized dyad is formed between auction i and bidder k through the first bid. The dependent variable value (*entry*) for the actual first bidder is 1 while it is 0 for all other latent bidders. We use the following variables to parsimoniously predict this choice of entry - bidder experience, $NJFA_{bid}$, $NJFA_{won}$, NOA_{bid} and fixed effects for time of the auction and warehouse location (see Table 2 for a summary of the variables used in the choice of entry model). Since the same auction-level variables appear multiple times within the set of latent bidders for that auction on the right-hand-side, adding these variables directly to the estimation would lead to biased coefficients (Wooldridge 2002). Therefore, we add interaction terms of Q and Y with bidder experience as independent variables, essentially accounting for the extent to which bidders with specific levels of experience will prefer to bid on auctions with certain values of Y and Q . This discrete choice model is estimated using a probit specification and the results are shown in Column 1 of Table 4. The results show that the three bidder-specific variables significantly predict the probability that a bidder will be the first bidder on the focal auction in the expected manner. Bidders who have just won or bid on a set of just finished auctions are less likely to be first bidders on the focal auction given volume of demand, all else being equal. If the bidder has an outstanding bid on a comparable concurrent open auction

(where the bidder is not the current winner), then the odds of the bidder being the first bidder on the focal auction is higher, given the bidder’s interest in similar pallets. More surprisingly, the bidder experience variable is not significant; we return to this finding later in the analysis.

We can now combine the probit model with Equation (1) to correct for bias from endogenous entry. If we assume that all latent bidders for a focal auction i have latent valuations U_{ik} for the auction and that only the bidder with the highest U_{ik} enters the auction, we can model this as a sample selection problem (Heckman 1979). For every latent bidder in every auction, there is an observed variable D_{ik} which is 1 if the bidder becomes the first bidder and 0 otherwise. We only observe the first bid FB on auction i from bidder k when $D_{ik} = 1$. Therefore, we can use the Heckman sample selection two-stage estimation procedure to first estimate the probit model in Table 4, calculate inverse Mills ratios and then estimate Equation (1) as the outcome equation with the first bid as the dependent variable (Maddala 1983).

The results from the baseline estimation of Equation (1), which test the direct effects of reference prices and bidder heterogeneity are shown in Column 1 of Table 5. The moderation hypotheses require interaction terms between the two ERPs and the two source of bidder heterogeneity. Therefore, in subsequent columns, we incrementally add the interaction terms to test the moderation hypotheses. All results reported in Table 5 are based on second-stage Heckman analyses, with the ρ coefficient reported across all columns. Column 2 of Table 5 adds the interaction term between bidder experience and $JFAP/OAP$ respectively to the analysis. In order to test the moderation of bidder participation, we replace $JFAP$ (OAP) by the two subset variables $JFAP_{bid}$ and $JFAB_{notbid}$ (OAP_{bid} and OAP_{notbid}) in the analysis. This allows us to establish the moderation effect. If the marginal effect of reference prices from those auctions in the comparable set where the bidder has previously made a bid is higher than those where no such bids exist, the moderation effect is established. Column 3 of Table 5 replaces $JFAP$ with $JFAB_{bid}$ and $JFAB_{notbid}$ while Column 4 of Table 5 replaces OAP with its subset counterparts. Finally, Column 5 of Table 5 provides the full model.

It is possible that there exists a three-way interaction between the ERPs, experience and participation on the first bid. While we did not provide a formal hypothesis, we test to check if these effects exist in the data. Column 6 of Table 5 extends the results observed from the earlier interaction analysis shown in Column 3 by adding an interaction term of experience and $JFAB_{bid}$. Similarly,

This model is also called the type 2 Tobit model or the generalized tobit model (Amemiya 1985, p. 384). We refer to it here simply as the sample selection model.

ρ indicates the correlation coefficient between error terms in probit model (first stage) and Equation (1) (first bid model). The statistical significance of ρ , reported at the bottom of Table 5, will show to what degree accounting for sample selection is critical for the sake of our analysis.

Column 7 of Table 5 augments Column 4 by adding an interaction term between experience and OAP_{bid} . Column 8 provides the corresponding full model. The results here provide some evidence for the presence of the three-way interaction between bidder experience, participation and external reference prices.

In terms of robustness checks, we re-estimated all the models from Table 5 using OLS. While individual coefficients change, the direction and significance of the results are consistent. OLS also allows for the testing of multicollinearity, which is always a possibility with multiple interaction terms in the same regression. We use variance inflation factors (VIF) to check for collinearity; the maximum and mean VIFs in the analysis are respectively 2 and 1.5, which are below the threshold values indicated by Belsley et al. (1980). We also tested for the presence of outliers, no significant outliers were found in the analysis, which is not surprising given the routinized nature of the B2B secondary market. In roughly 20% of the auctions, the first bidder also issued a second bid, later in the auction. We therefore re-estimated the Heckman model after removing all of these cases, i.e. we only consider auctions where the first bidder issued only one bid. The results are consistent with those shown in Table 5. Finally, a hybrid valuation model rests on the assumption that bidders do respond to price signals from other auctions, i.e. they do not operate in a pure private value auction. To establish that this is the case, we run a simple test for the winner’s curse, in the spirit of Bajari and Hortacsu (2003). For each bidder, we use the past six months of bidding behavior observed to estimate a linear model for N , the number of bidders on an auction. Using this model, we predict N for the focal auction from each bidder’s perspective, using the coefficient estimates from the linear model. We then find a significant and negative relationship between the predicted value of N and the bid value on the auction, indicating that bidders do tend to shade their bids when they expect more bidders to enter the focal auction. This simple test rules out the pure private valuation model (Milgrom and Weber 1982), providing support for the fact that external price signals are indeed likely to be influential on bidding behavior. All the tests reported here are available from the authors upon request.

5 Discussion of Results and Post-Hoc Analysis

We start with discussing the summary statistics that provide some context for our study. From Table 1, we see that the auctions in our context generally provide relatively low yields to the seller, with a mean of 26% of E . The mean first bid is considerably lower at 15.6% of E . Each auction has an average of 5.5 bidders, which is lower than B2C settings but is consistent with recent work in B2B auctions (Langer et al. 2012). The bidders in our sample show considerable heterogeneity in

experience (mean = 13.89, std. dev = 25.72), indicating a mix of experienced and novice bidders. The environment faced by the bidders also varies considerably, as seen in the *NJFA* and *NOA* statistics; the standard deviations show that bidders clearly encounter variability in the number of just finished and open comparable auctions. Finally, we see a small but significant difference between $JFAP_{bid}$ (OAP_{bid}) and $JFAP_{notbid}$ (OAP_{notbid}), suggesting that there is a difference in prices on auctions where the average bidder has a bid versus those where no bids have been issued. However, these variables are highly correlated (as expected) and therefore, we interpret regression results cautiously when the two variables are present together.

Moving to the main results in Table 5, we observe strong statistical support for Hypothesis 1. Across all specifications in Table 5, the coefficient for IRP is positive (0.17, $p < 0.01$). One standard deviation increase in IRP thus leads to a 1.2% of E increase in the first bid. Since the mean of the first bid in our sample is 15.6% of E , one standard deviation increase in IRP results in approximately an increase in first bid of 8% ($1.2/15.6$), i.e. an effect size of 8%. Similarly, Hypotheses 2 and 3 are also supported; the direct effect of $JFAP$ (from Columns 1, 2 and 4 of Table 5) and OAP (from Columns 1, 2 and 3) increase the first bid significantly. One standard deviation increase in $JFAP$ leads to an increase in first bid of 0.2% of E while the increase attributable to one standard deviation increase in OAP is 0.3% of E . The effect sizes for these coefficients on first bid are, respectively, 0.012% and 0.019%, which are relatively low in terms of economic impact.

Hypothesis 4 pertained to the effect of participation on the reference prices. We see that the effect of participation through cross-bidding significantly increases the coefficient of $JFAP$ (Column 3 of Table 5), providing support for the moderation hypothesis; the coefficient for $JFAP_{bid}$ is roughly three times that of $JFAP$, which indicates that a standard deviation increase in $JFAP_{bid}$ is associated with an increase in first bid of 0.45% of E . Interestingly, the coefficient of $JFAP_{notbid}$ is insignificant, indicating that bidders appears to use only those C&C auctions where they have previously bid reference prices. Similarly, the coefficient of OAP_{bid} (Column 4 of Table 5) is much higher than the coefficient of OAP , again providing support for the moderation hypothesis. The effect size of OAP_{bid} , i.e. the incremental contribution of OAP_{bid} on first bid, rises to 0.46%. Again, we find that the average prices of open auctions in which the bidder is not bidding (OAP_{notbid}) is not significant. It is possible that characteristics of the pallets themselves may be leading to different values of $JFAP_{bid}$ (OAP_{bid}) and $JFAP_{notbid}$ (OAP_{notbid}); hence, it is not the reference prices themselves but some specific attributes of the pallets posted by the seller that leads to the observed moderation effect. Two arguments suggest this is not the case. First, the seller's incentives are to place pallets on auction as soon as possible in order to reduce inventory costs. Therefore, there is

little, if any, strategic behavior on the part of the seller in manipulating the concurrence of auctions or pallets, indicating exogeneity of the auction posting process. Second, we compare the the aggregate pallet-level variables, Q and Y , across $JFAP_{bid}$ (OAP_{bid}) and $JFAP_{notbid}$ (OAP_{notbid}) and find no significant differences, indicating that it is likely the salience associated with participation and bidding rather than any specifics of the pallet that leads to the moderation effect.

We see no support for Hypothesis 5 which pertained to the moderation effect of experience. In the case of $JFAP$, the interaction term in Column 2 of Table 5 is insignificant. With respect to OAP , we see the opposite result in Column 2 of Table 5, i.e. the effect of OAP is higher on first bid in the presence of experience. This is contrary to extant work that suggests that experienced bidders are less influenced by external reference prices (Rajendran and Tellis 1994; Yadav and Seiders 1998). We also observe that the direct effect of experience across all specifications is positive, suggesting that experienced bidders bid higher when they are first bidders. This too is inconsistent with prior work, *albeit* in the B2C setting (Park and Bradlow 2005; Gilkeson and Reynolds 2003), showing a negative relationship between bidder’s experience measured by feedback rating and their bid values. One plausible explanation for our result is based on the uncertain nature of these resale markets: in interviews conducted with executives who manage seller organizations, they noted that inexperienced bidders are typically uncertain of the market potential of items (having newly entered into the business) - this uncertainty leads them to bid conservatively (low). However, as the bidders win and gain experience moving items through their own sales channels, their ability to assess the value of a bundle improves and their bids increase accordingly.

When experience is interacted with $JFAP_{bid}$ and OAP_{bid} in a three-way interaction (Columns 6 and 7 of Table 5), we again see results inconsistent with expectations; no significant effect of $JFAP_{bid}$ and a weakly *positive* moderation effect on OAP_{bid} . Recall that the first stage results for endogenous entry (Table 4) also showed an insignificant coefficient for experience, whereas theory suggests that experienced bidders are more likely to bid late and last (Wilcox 2000). Finally, we note that the effect sizes for the external reference prices discussed above are relatively small, especially when compared to prior work, *albeit* in a name-your-own-price auction context (Wolk and Spann 2008). All of these results indicate that there is likely a greater level of heterogeneity in bidding behavior that is masked by the aggregate analysis that we present in Table 5. Through disaggregating bidder behavior by experience and the market environments bidders face, it is possible that we will see results that are more consistent with prior work, in addition to more robust effect sizes. We examine these possibilities through further post-hoc analysis described next.

5.1 Clustering Bidders

Following Bapna et al. (2004), we use a data-driven clustering method to identify latent clusters of bidding behavior that might allow a more detailed analysis of bidder heterogeneity. We use the K -means clustering methodology to identify clusters of bidding behavior at a more granular level. Note that our objective here is to identify clusters of *bidding behavior* rather than bidders; this is an important distinction since our panel dataset captures bidders over a period of years in which their bidding behavior may have changed as a result of increasing experience. We use four variables that characterize the specific bidding context to form our clusters: experience, number of just finished auctions in which the bidder has bid at the time of the focal first bid ($NJFA_{bid}$), the number of open auctions where the bidder has bid (NOA_{bid}), and the number of just finished auctions where the bidder has won ($NJFA_{won}$). These four variables are highly indicative of the bidder’s propensity to be the first bidder on the focal auction (note that they match the independent variables used in the probit analysis reported earlier) and also represent the two sources of bidder heterogeneity we study in this paper (experience and cross-bidding behavior). The k -means methodology will result in finding *two* different clusters of bidding behavior. The summary of statistics of the resulting two clusters are shown in Tables 6 and 7. Cluster 1 comprises of 3369 auctions; representing 78% of the sample, while Cluster 2 is smaller and comprises 942 auctions (22% of the sample).

More critically, Cluster 2 represents a set of bidding behavior that is characterized by high values of experience compared to Cluster 1 (51.5 versus 3.35, difference of means t-test significant at $p < 0.01$). Similarly, Cluster 2 has significantly higher values for first bid, cross-bidding behavior, IRP values and the time of first bid. However, the mean Y and Q are not statistically different across the two clusters, indicating that the different bidding behavior across the clusters is not related to the types of pallets. Finally, the difference in recovery rate across the two clusters is roughly 1% of E and is statistically significant, with Cluster 1 showing a higher recovery rate. Similarly, the number of bidders in an auction are also statistically higher in Cluster 1 compared to Cluster 2. On the basis of the clusters, we posit that Cluster 2 represents a set of highly experienced bidders who actively cross-bid and also tend to bid high when they are the first bidders.

While our clustering was based on bidding behavior rather than on bidder per se, we investigated the composition of the two clusters at a deeper level. Of the 569 unique bidders in our dataset, 535 bidders appear only in Cluster 1 while 3 bidders appear only in Cluster 2 across the dataset. The

We apply Ray and Turi’s (1999) method of determining the most efficient K by calculating the ratio of the intra-cluster distance to the inter-cluster distance, called the validity ratio. The K that minimizes this metric provides a good clustering solution. In our case, the validity ratio is minimized at $K=2$.

remaining 31 bidders appear as first bidders in both clusters across the dataset. Therefore, our clustering appears to be identifying bidders as well, although with a small set of bidders shifting clusters across the panel. When we examine the distribution of bidding behavior of the 31 bidders across the time period of our sample, we note that in most cases, these bidders appear in Cluster 1 in the early years of the panel (in 2003 and 2004) but appear in Cluster 2 more frequently in the later years of the panel. This distribution supports the thesis that these bidders modified their bidding behavior and strategy as they gained experience on the platform. In contrast, the bidders in Cluster 1 appear to still be relatively inexperienced. Not surprisingly, the 34 bidders in Cluster 2 account for more than 21% of the sales on the platform while Cluster 1 accounts for the remaining 79%. We thus term the 34 bidders in Cluster 2 as *super-bidders*. In comparison, Cluster 1 represents a more homogeneous set of bidders who have lower experience and cross-bid less actively.

The clustering results also indicate some interesting dynamics in the relationship between first bids on the auction and the eventual recovery rates that obtain. Auctions where the first bidders are super-bidders see their first bid arrive later in the auction but the first bid value is higher. This tends to reduce the eventual number of bidders in the auction, increase the odds of the first bidder being the eventual winner of the auction but results in a recovery rate that is equal to or slightly lesser than those observed in Cluster 1. Bidders in Cluster 1, on the other hand, bid early, low and are less aggressive in their bidding behavior on the platform, as evidenced by the lower cross-bidding statistics. These bidders are more conservative, allow more bidders to enter the auction and therefore end up with slightly higher prices on average. In addition, the odds of winning are lower for the first bidders from Cluster 1. While these dynamics are based on preliminary analysis, they match with the varying pricing dynamics that Bapna et al. (2008) show using functional data analysis.

Having identified these two clusters, we re-estimate our econometric models on the two clusters separately. The first stage probit results from the sample selection model are shown in Columns 2 and 3 of Table 4 for the two clusters respectively. Similarly, the results of the second stage of the sample selection models are shown in Table 8 for the two clusters. We omit the interaction terms with experience in this table since the clustering accounts for that variable. Columns 1 through 4 of Table 8 provide the first bid results for Cluster 1 while Columns 5 through 8 pertain to Cluster 2. In the interest of space, we only highlight the relevant changes in the results that obtain through the clustering exercise.

In the first stage probit model shown in Table 4, we now see that bidder experience is a significant predictor of entry into the auction. While inexperienced bidders tend to be less likely to be the

first bidders in Cluster 1, we see that in Cluster 2 more experienced bidders are more likely to be the first bidders (see Column 3 in Table 4). These results are consistent with the conclusions drawn by Dholakia et al. (2002) where they argue that experienced bidders tend to include more alternatives in their consideration set of auctions on which to bid. This suggests that experienced bidders may consider more of the available listings and consequently, be more likely to come across an auction listing that has not received any bids as yet. A possible explanation is that Cluster 2 bidders are more confident in their ability to assess value in the pallet from previous experience, they will tend to enter the auction pre-emptively with a higher first bid. The relative lower odds of Cluster 1 bidders to be the first bidder may be driven by their inexperience and resulting difficulty or inability to assess a MWTP for the pallet; hence the desire to first see the bids of others on the focal auction that then help inform their own bid. Therefore, we see that experience has a negative effect on the relative odds of a bidder becoming the first bidder (see Column 2 in Table 4).

Moving to the results in Table 8, we first see that the coefficient for IRP is significantly higher in Cluster 2 than in Cluster 1. Indeed, for Cluster 2, the coefficient of IRP (0.26) suggests an increase in first bid of roughly 1.3% of E . Since the mean first bid in Cluster 2 is 19%, the effect size obtained is almost 7%. The equivalent effect size of IRP in Cluster 1 is roughly 5.5%. Thus, the effect of IRP is higher and more influential in Cluster 2 compared to Cluster 1, which is consistent with expectations given the higher experience levels in Cluster 2 bidders. Both clusters continue to show a positive effect of $JFAP_{bid}$ on first bid; however they differ in the effect size as well as significance level of the variables. While Cluster 1 continues to show effect sizes that are comparable to those observed in Table 5 for both $JFAP$ and $JFAP_{bid}$, Cluster 2's effect sizes are smaller and less significant (at the 10% level) for $JFAP_{bid}$ and insignificant for $JFAP$. Hence, the hypothesized moderation from Hypothesis 4 appears to hold for both clusters, but the role of $JFAP_{bid}$ is considerably diminished for experienced bidders. Finally, the effects of OAP appear to hold in both clusters. As with IRP, the relative weight that bidders in Cluster 2 place on OAP is roughly double that placed by Cluster 1 bidders. The impact of OAP_{bid} on first bid in both clusters is correspondingly higher than OAP , showing that the moderation hypothesis holds across both clusters but differs in magnitude; the effect size of OAP_{bid} on first bid in Cluster 2 is roughly 5.5% but is only 2.6% in Cluster 1.

In summary, the results from the clustering indicate that Cluster 1 appears to be more consistent with prior theory on experience and reference prices in terms of their bidding behavior. Bidders in this cluster condition on their IRP as well as their ERPs. Since these bidders are relatively inexperienced, which in our case translates to fewer auctions won in the past 6 months, their

IRPs are relatively weak signals of the pallet’s market value or of the winning price. Therefore, prior research indicates that they would utilize other salient price signals that are available in the marketplace (Mazumdar et al. 2005) and hence, the influence of $JFAP_{bid}$ and OAP_{bid} . However, prior work argues that experienced bidders are likely to rely primarily on their IRP and be less influenced by other price signals (Yadav and Seiders 1998). Therefore, in Cluster 2, we see evidence of this in the significance and effect size of IRP as well as the non-significance of $JFAP$. However, OAP_{bid} continues to influence first bids in Cluster 2. This result is puzzling at first but there are some potential explanations for this effect, which we describe below.

One explanation is based on the fact that Cluster 2 bidders typically do more cross-bidding, compared to Cluster 1, and therefore are likely to find the prices on these open auctions where they have bid (i.e. OAP_{bid}) particularly salient and easily available (Ariely and Simonsohn 2003). In contrast, $JFAP$ auctions have terminated and final prices have been revealed, making them less salient to the bidder. An alternative explanation is rooted in the differences between the bidders’ average IRP and the ERP values (Mazumdar et al. 2005). For Cluster 2, note that the mean IRP is 0.23 (std deviation = 0.05), which suggests that the bidders possess a strong signal of value from their experience. For these bidders, the mean value of $JFAP$ is 0.19, which is within one standard deviation of the IRP. Thus, for the experienced bidder who has a strong IRP signal, the marginal information content from $JFAP$ is likely redundant and trivial. However, the mean OAP_{bid} , is 0.12, which deviates significantly from the IRP. Additionally, OAP_{bid} provides information on the level of competition in the *current* marketplace for comparable auctions. Of course, we realize that these are candidate explanations and that further work is needed to establish the inter-relationships unambiguously between internal and external reference prices on bidding behavior in the auction setting.

6 Conclusion

In this paper, we started with the objective of addressing specific gaps in the online auctions literature. First, existing research studying reference prices in auctions (Dholakia et al. 2002; Kamins et al. 2004) are based on mostly cross-sectional B2C data from eBay and other similar platforms and have not been privy to the detailed bidding history of individual bidders. Second, due to the absence of bidder-specific characteristics and bidding behavior, this literature is unable to tease out the differential affects of multiple price signals (e.g., bids on comparable/same items or the declared value of the item) on individual bidders and their bids, focusing thereby mostly on auction-level outcomes. Third, extant literature has studied bidder heterogeneity but has not

examined how these factors moderate the use of reference prices. In this paper, we complement and extend this literature by explicitly *studying the role of reference prices on the first bid*, rather than at the auction level, in a B2B context far removed from the well-understood world of consumer goods sold on eBay. Our work here provides several contributions to the literature above and beyond identifying the positive link between the first bid and the final recovery rate of an auction. Our work is the first, to our knowledge, that studies, in one integrated setting, (i) the impact of internal reference prices formed by previous winning prices, measured longitudinally, on individual bids, (ii) the manner in which bidders are influenced by price information (external reference prices) both within and surrounding the focal auction at the bid level, and (iii) the interaction of these external reference prices and bidder heterogeneity on individual bids, specifically the first bid. Our results show that reference prices are influential on the first bid, but are clearly moderated by bidder heterogeneity. In post-hoc analysis, we use clustering methods to partition bidding behavior and show that while the majority of bidders are influenced as expected by reference price information, there exist a small but influential set of ‘super-bidders’ who behave distinctly different in terms of how they use the available reference price information.

From a methodological viewpoint, we capture arguably the most complete data on reference prices and bidder heterogeneity possible through the use of a proprietary panel dataset of B2B auctions. The use of panel data allows us to develop measures for reference prices and bidder heterogeneity at a level of granularity that is not possible in cross-sectional data from platforms such as eBay. This additional granularity allows us to account for endogenous entry into the auction, a methodological issue that has continued to be difficult to account for in empirical auctions research. While our method for modeling endogenous entry is based on some assumptions, we utilize the visibility provided by the full dataset to account for entry in the most parsimonious manner possible. No doubt, more work is required here. Furthermore, our results also lend support to the presence of hybrid valuation models in B2B auctions and would suggest that appropriate hybrid valuation models need to be defined as a function of bidder experience. While our focus here has been on empirical analysis, future theoretical analyses of the hybrid valuation model in ill-defined B2B contexts is warranted and a fruitful avenue for future research. Our results indicate that bidder experience and participation in concurrent auctions may play a significant role in such theoretical analyses of B2B auction contexts.

From a platform design perspective, our results suggest that sellers may benefit from investing in decision support tools or technologies that strategically market (possibly overlooked) auctions to bidders based on their experience levels in order to maximize recovery rates. However, our

results suggest an additional layer of strategic complexity for sellers who undertake such marketing activities. We find that *salience* is a key factor in determining the influence of a reference price, particularly for inexperienced bidders. Inexperienced bidders, by definition, participate in few auctions and win in fewer still, leading to lower IRP values, which provide limited guidance in helping bidders assess values for new auctions. Additionally, given their low auction activity levels, the bulk of the ERPs in the auction environment ($JFAP_{notbid}$ and OAP_{notbid}) are rendered ineffective as sources of guidance for bidding, and a cycle emerges. Inexperienced bidders tend to submit relatively low first bids (based on the low IRP and infrequent use of ERP) and more often than not, lose, thereby remaining inexperienced. All else equal, our research suggest that the seller should invest in decision support tools to increase the salience of C&C auctions in which the inexperienced bidders are not bidding; thereby increasing their first bids and win probabilities by providing them with useful reference information. Experienced bidders, on the other hand, may not need these decision tools since they possess a greater level of depth in their understanding of the dynamics of the auction environment.

For the seller, however, our work indicates a dark side based on the accumulation of bidder experience. While experience helps increase first bids, too much experience can have the deleterious effect of decreasing recovery rates. In our dataset, auctions in which the first bidder is experienced terminated with slightly lower recovery rates. This is (most likely) due to other bidders being deterred from entry into the auction when they see higher first bids and a quicker pace of price increases. This dynamic implies that, in addition to the selection of auction format parameters such as duration and starting price, a rational seller must also consider managing the flow of information (via decision support tools) to bidders strategically based on whether the first bidder belongs to Cluster 1 or Cluster 2, i.e. on the bidder’s experience levels and the actual first bid value. Our analysis suggests that the accumulation of experience will alter the composition of external reference prices used by a bidder (by expanding the set of $JFAP_{bid}$ and OAP_{bid}) and the manner in which he uses them (with a higher reliance on IRP and OAP_{bid}), with the adage of ‘More is Better’ no longer being necessarily true for the seller.

In addition to managing bidders’ information sets through appropriate decision tools so as to influence the impact of ERPs, a savvy seller faces a similarly difficult challenge in deciding whom to attract as a first bidder to particular auction listings. The herding argument would suggest that a first bidder who bids low and early in the auction would attract more bidders and thereby stimulate a higher yield for the seller, in the spirit of Simonsohn and Ariely (2008). However, a higher first bid potentially later in the auction can provide positive externalities on concurrent auctions via the

ERP route, thereby increasing yields. As suggested by Bapna et al (2008), an auction is likely to take a certain trajectory based on whether the first bidder is a Cluster 1 or Cluster 2 bidder; the net effect on seller payoff is still to be determined and represents a topic for further research. In future work, we are currently conducting a set of experiments to test out exactly these relationships in the field and believe there are several insights waiting to be explored in detail.

Finally, looking beyond the first bid leads naturally to the question of how reference prices affect *subsequent* bids in an auction. While the theoretical arguments we make here can be extended to subsequent bids, there are other confounding behavioral effects such as the signal value of earlier bids (Bajari and Hortacsu 2003), herding (Simonsohn and Ariely 2008) and opponent effects (Heyman et al. 2004) that may render the effects of external reference prices and heterogeneity moot as significant predictors of subsequent bids. However, in an effort to explore these possible effects, we expanded our analysis to estimate the effect of reference prices and bidder heterogeneity on all bids in the auction. A simplified OLS analysis indicated that the effect of the ERP variables do not disappear beyond the first bid, as suspected. Bidders continue to be influenced by the reference price signals gleaned from concurrent, comparable auctions. However, as expected, the current price (current winning bid) becomes an significant determinant of the bid value as well. Not surprisingly, the relative weight of the ERP is diminished in this analysis but far from entirely eroded. These results suggest that future work in designing auctions and decision support systems should take into account the tradeoffs inherent in these contexts where reference prices and bidder heterogeneity interact to determine not just the first bids but all bids in an auction. More work is required to clearly understand, in the case of B2B secondary markets, strategic questions for sellers such as deciding what items to place auctions. which items to list simultaenously and how to extract value from the information that is available to heterogeneous bidders.

Figure 1: Reference Prices Formed from Concurrent Auctions

Figure 2: Identifying Potential First Bidders in a Focal Auction

Table 1: Summary statistics and correlation matrix (4308 auctions)

Variable	Mean	St dev	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1 <i>JFAP</i> ^s	0.18	0.09																			
2 <i>JFAP</i> _{bid}	0.15	0.08	0.58																		
3 <i>JFAP</i> _{no} bid	0.18	0.09	0.91	0.43																	
4 <i>OAP</i>	0.12	0.04	-0.08	-0.02	-0.07																
5 <i>OAP</i> _{bid}	0.11	0.03	-0.07	0.05	-0.08	0.60															
6 <i>OAP</i> _{no} bid	0.12	0.04	-0.06	-0.04	-0.04	0.87	0.33														
7 <i>NJFA</i>	4.86	7.03	0.48	0.38	0.48	-0.08	-0.03	-0.06													
8 <i>NOA</i>	4.73	4.76	0.01	0.05	0.02	0.24	0.23	0.24	0.32												
9 <i>NJFA</i> _{bid}	1.18	2.68	0.32	0.59	0.20	-0.02	0.05	-0.04	0.55	0.18											
10 <i>NJFA</i> _{won}	0.22	0.86	0.14	0.30	0.04	-0.03	0.03	-0.04	0.32	0.11	0.66										
11 <i>NOA</i> _{bid}	1.62	2.53	-0.03	0.08	-0.06	0.11	0.28	0.05	0.14	0.56	0.19	0.16									
12 <i>IRP</i>	0.16	0.08	0.02	0.13	-0.01	-0.01	0.07	-0.05	0.03	0.03	0.12	0.14	0.10								
13 Experience	13.89	25.73	0.00	0.15	-0.08	0.00	0.11	-0.07	0.06	0.11	0.25	0.32	0.27	0.44							
14 Number INC Bids	1.52	1.34	-0.03	0.01	-0.03	0.03	0.01	0.05	-0.03	-0.04	-0.01	-0.01	-0.06	-0.07	-0.13						
15 <i>TOFB</i>	0.28	0.27	0.22	0.14	0.19	-0.05	-0.01	-0.05	0.43	0.30	0.24	0.17	0.10	0.08	0.15	-0.06					
16 <i>Q</i>	23.72	17.91	-0.11	-0.13	-0.13	-0.04	-0.05	-0.06	-0.25	-0.31	-0.17	-0.11	-0.20	-0.04	-0.06	0.05	-0.14				
17 <i>Y</i> (100)	1.83	0.43	0.03	0.02	0.04	0.04	0.01	0.03	-0.01	-0.04	-0.02	0.00	-0.03	0.00	-0.05	0.05	-0.15	-0.10			
18 Recovery Rate	0.26	0.06	0.08	0.03	0.10	0.09	0.04	0.08	-0.22	-0.27	-0.13	-0.12	-0.17	0.00	-0.09	0.08	-0.34	0.34	0.23		
19 Number of bidders	5.53	2.15	0.01	-0.07	0.04	0.03	-0.04	0.04	-0.16	-0.20	-0.15	-0.14	-0.17	-0.14	-0.22	0.00	-0.25	0.35	0.17	0.52	
20 <i>FB</i>	0.16	0.06	0.02	0.16	-0.02	0.05	0.16	0.00	-0.06	-0.06	0.10	0.13	0.11	0.37	0.42	-0.11	-0.07	-0.01	0.08	0.19	-0.23

^s In the event that the *JFA* set is null, we utilize the benchmark starting price of 10% for its value; This explains why the mean of the *JFAP* variables are lower than the mean Recovery Rate.

Table 2: List of Variables Used in our Empirical Analysis

Analysis	Variable description
Predicting first bid value in Equation (1)	<p><i>FB</i>: First Bid value of auction as a % of E Experience: Number of all auctions won in past 6 months IRP: Avg. price of comparable auctions won in last 6 months</p> <p><u>ERPs:</u> <i>JFAP</i>: Avg. price of just-finished C&C auctions <i>JFAP_{bid}</i>: Avg. price of just-finished C&C auctions in which bidder bids <i>JFAP_{notbid}</i>: Avg. price of just-finished C&C auctions in which bidder does not bid <i>OAP</i>: Avg. price of open C&C auctions <i>OAP_{bid}</i>: Avg. price of open C&C auctions in which bidder bids <i>OAP_{notbid}</i>: Avg. price of open C&C auctions in which bidder does not bid</p> <p><u>Bidder's control variables:</u> <i>NJFA</i>: Number of just-finished C&C auctions <i>NOA</i>: Number of open C&C auctions Number Inc Bids: Number of bids bidder submits in auction</p> <p><u>Auction's control variables:</u> <i>TOFB</i>: Time of First Bid in auction <i>Q</i>: Quantity of items in each pallet $Y(\\$100) = \frac{E}{Q}$: Avg. per-unit price of items in each pallet (\$100)</p> <p><u>Fixed-effect dummies:</u> Time: Month/year of the auction Warehouse: Physical location of the warehouse the pallet comes from</p>
First stage probit model	<p>Experience: Number of all auctions won in past 6 months <i>NJFA_{bid}</i>: Number of just-finished C&C auctions in which bidder bids <i>NJFA_{won}</i>: Number of just-finished C&C auctions in which bidder wins <i>NOA_{bid}</i>: Number of open C&C auctions in which bidder bids</p> <p><u>Auction's control variables:</u> <i>Q</i>: Quantity of items in each pallet $Y(\\$100) = \frac{E}{Q}$: Avg. per-unit price of items in each pallet (\$100)</p> <p><u>Fixed-effect dummies:</u> Time: Month/year of the auction Warehouse: Physical location of the warehouse the pallet comes from</p>
Predicting Recovery Rate/ Number of bidders	<p><i>FB</i>: First Bid value of auction as a % of E Recovery Rate: Final price of auction as a % of E <i>N</i>: Final number of bidders come in auction</p> <p><u>Bidder's control variables:</u> <i>NOA</i>: Number of open C&C auctions</p> <p><u>Auction's control variables:</u> <i>TOFB</i>: Time of First Bid in auction <i>Q</i>: Quantity of items in each pallet $Y(\\$100) = \frac{E}{Q}$: Avg. per-unit price of items in each pallet (\$100)</p> <p><u>Fixed-effect dummies:</u> Hour/Day: Hour and weekday of the auction Time: Month/year of the auction Warehouse: Physical location of the warehouse the pallet comes from</p>

Table 3: OLS Results Predicting the Recovery Rate and Number of Bidders in B2B Auctions

Dependent Variable:	(1) Recovery Rate	(2) Recovery Rate	(3) N	(4) Recovery Rate
Constant	0.1272*** (0.024)	0.0811*** (0.023)	5.5482*** (1.561)	0.0515* (0.030)
<i>TOFB</i>	-0.0419*** (0.003)	-0.0350*** (0.003)	-1.3329*** (0.114)	-0.0137* (0.008)
<i>Q</i>	0.0007*** (0.000)	0.0006*** (0.000)	0.0405*** (0.002)	0.0000 (0.000)
<i>Y(\$100)</i>	0.0247*** (0.002)	0.0201*** (0.002)	0.9797*** (0.066)	0.0078 (0.006)
<i>NOA</i>	-0.0009*** (0.000)	-0.0009*** (0.000)	-0.0275*** (0.006)	-0.0007*** (0.000)
<i>FB</i>		0.2653*** (0.012)	-9.4904*** (0.475)	0.3871*** (0.053)
Number of Bidders	0.0098*** (0.000)	0.0122*** (0.000)		0.0258*** (0.005)
Dummies (Hour/Day)	No	No	Yes	Used as instrument
Dummies (Time/Warehouse)	Yes	Yes	Yes	Yes
F Stat	176.58**	208***	81.75***	117***
R-Square	0.452	0.505	0.314	0.365
Number of auctions	4308	4308	4308	4308

Notes. Column 1 reports on results from our base model with no first bid value. Column 2 adds the first bid value into base mode. Column 3 will report on the stage 1 of a 2SLS regression predicting the recovery rate. Finally, Column 4 will report on stage 2 results of the 2SLS in which recovery rate is estimated. (Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

Table 4: Probit Regression (First Stage in Heckman Selection Model), DV = Probability of Becoming the First Bidder on the Focal Auction

	All Auctions	Cluster 1	Cluster 2
Experience	0.0000 (0.0001)	-0.0023** (0.001)	0.0007*** (0.000)
Experience $\times$ <i>Q</i>	0.0000 (0.000)	-0.0000 (0.000)	0.0000 (0.000)
Experience $\times$ <i>Y(\$100)</i>	0.0001* (0.0007)	0.0000 (0.000)	0.0004*** (0.0001)
<i>NJF_{bid}</i>	-0.001*** (0.0007)	-0.003*** (0.0008)	0.0000 (0.0008)
<i>NJFA_{won}</i>	-0.022*** (0.001)	-0.021*** (0.003)	-0.016*** (0.003)
<i>NOA_{bid}</i>	0.007*** (0.0005)	0.0087*** (0.0007)	0.001 (0.001)
Dummies (Time/Warehouse)	Yes	Yes	Yes
Log pseudolikelihood	-13827.1	-10448.5	-2884.4
Wald chi2()	2316***	1610***	1099***
Pseudo R2	0.067	0.08	0.14
Number of observations	43565	32619	11037
Number of auctions	4308	3366	942

Notes. Entries in table are marginal effect from Probit regression (dF/dX) with first bids as the unit of analysis. Standard errors are clustered by each focal auction, and are reported in parentheses. (Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$)

Table 5: Heckman Second Stage Results of Reference Prices and Bidder Heterogeneity on First Bid

Dependent Variable:	(1) <i>FB</i>	(2) <i>FB</i>	(3) <i>FB</i>	(4) <i>FB</i>	(5) <i>FB</i>	(6) <i>FB</i>	(7) <i>FB</i>	(8) <i>FB</i>
Constant	0.1095*** (0.009)	0.0881*** (0.009)	0.1121*** (0.008)	0.0951*** (0.009)	0.0988*** (0.008)	0.0964*** (0.024)	0.0841*** (0.023)	0.0902*** (0.009)
<i>TOFB</i>	-0.0202*** (0.003)	-0.0201*** (0.003)	-0.0190*** (0.003)	-0.0195*** (0.003)	-0.0184*** (0.003)	-0.0184*** (0.003)	-0.0183*** (0.003)	-0.0183*** (0.003)
<i>Q</i>	0.0000 (0.000)	0.0000 (0.000)	0.0001 (0.000)	0.0000 (0.000)	0.0001 (0.000)	0.0001 (0.000)	0.0001 (0.000)	0.0001 (0.000)
<i>Y</i> (\$100)	0.0108*** (0.002)	0.0108*** (0.002)	0.0108*** (0.002)	0.0106*** (0.002)	0.0107*** (0.002)	0.0107*** (0.002)	0.0107*** (0.002)	0.0107*** (0.002)
<i>NFA</i>	-0.0001 (0.000)	-0.0001 (0.000)	-0.0000 (0.000)	-0.0001 (0.000)	-0.0002 (0.000)	-0.0001 (0.000)	-0.0000 (0.000)	-0.0001 (0.000)
<i>NOA</i>	-0.0008*** (0.000)	-0.0009*** (0.000)	-0.0008*** (0.000)	-0.0010*** (0.000)	-0.0010*** (0.000)	-0.0010*** (0.000)	-0.0010*** (0.000)	-0.0010*** (0.000)
Experience	0.0007*** (0.000)	0.0003** (0.000)	0.0007*** (0.000)	0.0007*** (0.000)	0.0007*** (0.000)	0.0007*** (0.000)	0.0005*** (0.000)	0.0005*** (0.000)
IRP	0.1714*** (0.016)	0.1711*** (0.016)	0.1661*** (0.015)	0.1682*** (0.015)	0.1635*** (0.015)	0.1639*** (0.015)	0.1647*** (0.015)	0.1651*** (0.015)
Number INC Bids	-0.0026*** (0.000)	-0.0026*** (0.000)	-0.0028*** (0.000)	-0.0027*** (0.000)	-0.0029*** (0.000)	-0.0029*** (0.000)	-0.0029*** (0.000)	-0.0029*** (0.000)
<i>JFAP</i>	0.048*** (0.013)	0.045*** (0.013)		0.045*** (0.013)				
<i>JFAP</i> ×Experience		0.00029 (0.0000)						
<i>JFAP</i> _{bid}			0.0915*** (0.013)		0.0835*** (0.013)	0.0890*** (0.013)	0.0833*** (0.013)	0.091*** (0.013)
<i>JFAP</i> _{bid} ×Experience						-0.0004 (0.000)		-0.0005 (0.000)
<i>JFAP</i> _{notbid}			0.011 (0.021)		0.0124 (0.013)	0.01 (0.012)	0.0118 (0.012)	0.009 (0.012)
<i>OAP</i>	0.0799*** (0.023)	0.0499** (0.024)	0.0760*** (0.022)					
<i>OAP</i> ×Experience		0.0028*** (0.001)						
<i>OAP</i> _{bid}				0.2062*** (0.026)	0.1885*** (0.026)	0.1887*** (0.026)	0.1624*** (0.029)	0.1627*** (0.029)
<i>OAP</i> _{bid} × Experience							0.0018** (0.001)	0.0019** (0.001)
<i>OAP</i> _{notbid}				-0.0025 (0.021)	0.0007 (0.021)	0.001 (0.021)	0.0029 (0.021)	0.0036 (0.021)
Dummies (Time/Warehouse)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of auctions	4308	4308	4308	4308	4308	4308	4308	4308
<i>rho</i>	-0.17***	-0.19***	-0.27***	-0.15**	-0.19***	-0.19***	-0.23***	-0.23***
Number of bidders	569	569	569	569	569	569	569	569

Notes. Entries in columns the second stage of the Heckman selection model. The first 5 columns test Hypotheses 1-4. Column 1 reports on results from our base model. Column 2 adds the interaction term between bidder experience and *JFAP*/*OAP*. Column 3-5 assess the impact of *JFAP*/*OAP* depending on whether or not the first bidder has participated in respectively in any comparable *JFA*/*OA*. Finally, Column 6-8 are used to test a three-way interaction between the *JFAP*/*OAP*, experience, and participation level of the bidder on the first bid value. (Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$).

Table 6: Summary Statistics and Correlation Matrix for Cluster 1 (3369 auctions)

Variable	Mean	St dev	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1 <i>JFAP</i>	0.18	0.09																			
2 <i>JFA_{bid}</i>	0.14	0.07	0.54																		
3 <i>JFAP_{notbid}</i>	0.18	0.09	0.94	0.42																	
4 <i>OAP</i>	0.12	0.04	-0.09	-0.03	-0.08																
5 <i>OAP_{bid}</i>	0.11	0.03	-0.09	-0.03	-0.05	0.57															
6 <i>OAP_{notbid}</i>	0.12	0.04	-0.06	-0.03	-0.05	0.88	0.33														
7 <i>NJFA</i>	4.44	6.55	0.49	0.34	-0.07	-0.03	-0.06	0.25	0.30												
8 <i>NOA</i>	4.44	4.62	0.00	0.03	0.03	0.25	0.22	0.05	0.46	0.13											
9 <i>NJFA_{bid}</i>	0.82	1.96	0.33	0.65	0.25	-0.02	0.05	-0.03	0.46	0.13	0.46										
10 <i>NJFA_{non}</i>	0.09	0.44	0.13	0.28	0.11	0.00	0.06	-0.02	0.22	0.06	0.13	0.07									
11 <i>NOA_{bid}</i>	1.36	2.16	-0.02	0.05	-0.02	0.11	0.28	0.07	0.14	0.52	0.14	0.07	0.02								
12 <i>IRP</i>	0.15	0.08	0.01	0.08	0.01	-0.03	0.04	-0.04	-0.01	-0.01	0.05	0.06	0.09	0.55							
13 <i>Experience</i>	3.36	4.28	-0.02	0.13	-0.05	-0.03	0.04	-0.05	0.00	0.07	0.13	0.15	0.09	-0.04	-0.04						
14 <i>Number INC Bids</i>	1.60	1.47	-0.03	0.03	-0.04	0.04	0.03	0.05	-0.03	-0.03	0.04	0.06	0.08	0.02	0.04	-0.05					
15 <i>TOFB</i>	0.26	0.26	0.22	0.10	0.22	-0.05	-0.02	-0.04	0.40	0.29	0.15	0.04	0.08	0.02	0.04	0.04	-0.14				
16 <i>Q</i>	24.52	18.43	-0.12	-0.11	-0.15	-0.05	-0.05	-0.06	-0.25	-0.31	-0.15	-0.08	-0.19	0.02	-0.07	0.04	-0.15	-0.07			
17 <i>Y(100)</i>	1.84	0.42	0.03	0.03	0.03	0.03	0.02	0.02	0.00	-0.05	0.00	0.01	-0.04	0.00	0.03	0.04	-0.31	0.36	0.23		
18 <i>Recovery Rate</i>	0.26	0.06	0.08	0.04	0.07	0.07	0.03	0.07	-0.21	-0.28	-0.09	-0.07	-0.15	0.04	-0.07	0.08	-0.31	0.36	0.17	0.52	
19 <i>Number of bidders</i>	5.73	2.15	0.00	-0.05	0.00	0.02	-0.04	0.03	-0.15	-0.20	-0.11	-0.10	-0.13	-0.07	-0.12	-0.02	-0.24	0.35	0.17	0.21	-0.17
20 <i>FB</i>	0.15	0.05	0.04	0.14	0.03	0.02	0.11	0.00	-0.05	-0.11	0.07	0.09	0.00	0.28	0.26	-0.06	-0.13	0.04	0.10	0.21	-0.17

Table 7: Summary Statistics and Correlation Matrix for Cluster 2 (942 auctions)

Variable	Mean	St.dev	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1 <i>JFAP</i>	0.19	0.09																			
2 <i>JFA_{bid}</i>	0.17	0.09	0.74																		
3 <i>JFAP_{notbid}</i>	0.17	0.09	0.84	0.52																	
4 <i>OAP</i>	0.12	0.04	-0.05	-0.01	-0.03																
5 <i>OAP_{bid}</i>	0.12	0.04	-0.02	0.06	-0.02	0.70															
6 <i>OAP_{notbid}</i>	0.12	0.04	-0.04	-0.03	-0.01	0.83	0.39														
7 <i>NJFA</i>	6.37	8.37	0.45	0.46	0.45	-0.09	-0.06	-0.04	0.32	0.69	0.45	0.14	0.74								
8 <i>NOA</i>	5.80	5.08	0.01	0.05	0.03	0.23	0.25	0.24	0.32	0.22	0.22	0.14	0.74	0.65							
9 <i>NJFA_{bid}</i>	2.45	4.12	0.36	0.52	0.20	-0.04	0.01	-0.03	0.69	0.45	0.14	0.74	0.65	0.17	0.15						
10 <i>NJFA_{non}</i>	0.67	1.55	0.21	0.33	0.03	-0.07	-0.04	-0.05	0.45	0.22	0.14	0.74	0.65	0.17	0.15	0.02					
11 <i>NOA_{bid}</i>	2.58	3.37	-0.07	0.07	-0.12	0.14	0.25	0.06	0.08	0.65	0.17	0.15	0.02	0.02	0.02	0.24	-0.21				
12 <i>IRP</i>	0.23	0.05	0.03	0.05	0.02	0.05	0.03	0.02	-0.06	-0.08	-0.04	0.02	0.02	0.02	0.02	0.24	-0.21	0.01			
13 <i>Experience</i>	51.52	33.90	-0.05	0.06	-0.17	0.01	0.11	-0.11	-0.09	0.03	0.09	0.19	0.27	0.09	0.09	-0.03	-0.03	-0.10	-0.23		
14 <i>Number INC Bids</i>	1.23	0.66	0.04	0.00	0.06	-0.01	-0.03	0.00	0.04	0.00	0.00	-0.02	-0.06	0.06	0.06	0.00	0.07	0.00	0.09	0.21	
15 <i>TOFB</i>	0.37	0.29	0.21	0.16	0.14	-0.07	-0.03	-0.05	0.46	0.28	0.33	0.26	0.26	0.06	0.06	0.00	0.07	0.00	0.09	0.21	0.24
16 <i>Q</i>	20.83	15.59	-0.06	-0.15	-0.06	0.00	-0.04	-0.06	-0.23	-0.29	-0.19	-0.14	-0.23	-0.17	-0.10	-0.10	-0.15	-0.23	-0.41	0.21	0.51
17 <i>Y(100)</i>	1.80	0.45	0.03	0.02	0.06	0.06	0.02	0.08	-0.01	-0.01	-0.03	0.00	0.01	0.09	-0.10	-0.15	-0.22	0.30	0.18	0.29	-0.24
18 <i>Recovery Rate</i>	0.25	0.06	0.11	0.05	0.17	0.14	0.12	0.13	-0.24	-0.22	-0.18	-0.16	-0.17	0.02	-0.07	0.07	-0.41	0.21	0.24	0.18	0.51
19 <i>Number of bidders</i>	4.83	1.99	0.08	-0.02	0.14	0.07	0.01	0.09	-0.11	-0.12	-0.14	-0.13	-0.18	-0.15	-0.25	0.04	-0.22	0.30	0.18	0.29	-0.24
20 <i>FB</i>	0.19	0.07	-0.05	0.05	-0.11	0.13	0.21	0.05	-0.22	-0.09	-0.03	0.03	0.11	0.26	0.40	-0.22	-0.15	-0.05	0.07	0.29	-0.24

Table 8: Heckman Second Stage Results of Reference Prices and Bidder Heterogeneity on First Bid, Estimated Separately for the Two Clusters from the K-Means Clustering Analysis

Dependent Variable:	Cluster 1				Cluster 2			
	(1) <i>FB</i>	(2) <i>FB</i>	(3) <i>FB</i>	(4) <i>FB</i>	(5) <i>FB</i>	(6) <i>FB</i>	(7) <i>FB</i>	(8) <i>FB</i>
Constant	0.1214*** (0.013)	0.1234*** (0.014)	0.1079*** (0.014)	0.1112*** (0.014)	0.1260*** (0.022)	0.1274*** (0.022)	0.1112*** (0.022)	0.1127*** (0.022)
<i>TOFB</i>	-0.0211*** (0.003)	-0.0200*** (0.003)	-0.0205*** (0.003)	-0.0194*** (0.003)	-0.0094 (0.008)	-0.0087 (0.008)	-0.0093 (0.008)	-0.0086 (0.008)
<i>Q</i>	0.0001** (0.000)	0.0001** (0.000)	0.0001** (0.000)	0.0001** (0.000)	-0.0002 (0.000)	-0.0001 (0.000)	-0.0001 (0.000)	-0.0001 (0.000)
<i>Y(\$100)</i>	0.0098*** (0.002)	0.0098*** (0.002)	0.0097*** (0.002)	0.0097*** (0.002)	0.0087** (0.004)	0.0090** (0.004)	0.0090** (0.004)	0.0094** (0.004)
<i>NFA</i>	-0.0000 (0.000)	-0.0001 (0.000)	-0.0001 (0.000)	-0.0000 (0.000)	-0.0000 (0.000)	-0.0000 (0.000)	-0.0001 (0.000)	-0.0001 (0.000)
<i>NOA</i>	-0.0009*** (0.000)	-0.0009*** (0.000)	-0.0010*** (0.000)	-0.0010*** (0.000)	-0.0003 (0.000)	-0.0002 (0.000)	-0.0005 (0.000)	-0.0005 (0.000)
Experience	0.0019*** (0.000)	0.0019*** (0.000)	0.0018*** (0.000)	0.0018*** (0.000)	0.0002** (0.000)	0.0002* (0.000)	0.0002** (0.000)	0.0002** (0.000)
IRP	0.1306*** (0.019)	0.1302*** (0.019)	0.1283*** (0.019)	0.1280*** (0.019)	0.2555*** (0.040)	0.2590*** (0.040)	0.2585*** (0.040)	0.2622*** (0.040)
Number Inc Bids	-0.0020*** (0.000)	-0.0022*** (0.000)	-0.0021*** (0.000)	-0.0023*** (0.000)	-0.0142*** (0.003)	-0.0141*** (0.003)	-0.0142*** (0.003)	-0.0141*** (0.002)
<i>JFAP</i>	0.0324*** (0.011)		0.0352* (0.011)		0.051* (0.03)		0.044 (0.03)	
<i>JFAP_{bid}</i>		0.0868*** (0.014)		0.0803*** (0.014)		0.0627** (0.028)		0.051* (0.028)
<i>JFAP_{notbid}</i>		0.0131 (0.013)		0.014 (0.013)		-0.009 (0.030)		-0.011 (0.030)
<i>OAP</i>	0.0685*** (0.024)	0.0643*** (0.024)			0.128** (0.053)	0.1320** (0.052)		
<i>OAP_{bid}</i>			0.1837*** (0.029)	0.1686*** (0.029)			0.2555*** (0.053)	0.2491*** (0.053)
<i>OAP_{notbid}</i>			-0.0020 (0.022)	0.0003 (0.022)			0.0013 (0.055)	-0.0003 (0.054)
Dummies (Time/Warehouse)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of auctions	3366	3366	3366	3366	942	942	942	942
<i>rho</i>	-0.02	-0.11*	-0.05	-0.07	-0.52**	-0.54**	-0.47***	-0.49***
Number of bidders	566	566	566	566	34	34	34	34

Notes. Entries in columns report on how reference prices drive the first bid of different clusters of first bidders. Column 1 reports on results from our base model for Cluster 1. Column 2 adds the interaction term between bidder experience and JFAP/OAP. Column 3 and 4 assess the impact of JFAP/OAP depending on whether or not the first bidder has participated in respectively in any comparable JFA/OA for Cluster 1. The corresponding results for Cluster 2 are shown in Columns 5 through 8. (Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1).

References

- Adaval, R., Monroe, K. B. 2002. Automatic Construction and Use of Contextual Information for Product and Price Evaluations. *Journal of Consumer Research*, Vol. 28, No. 4, pp. 572-588.
- Amemiya, T. 1985. Advanced Econometrics. Harvard University Press.
- Anwar, S., McMillan, R., Zheng, M. 2006. Bidding Behavior in Competing Auctions: Evidence from eBay. *European Economic Review*, Vol. 50, pp. 307-322.
- Ariely, D., Simonsohn, I. 2003. Buying, Bidding, Playing or Competing? Value Assessment and Decision Dynamics in Online Auctions. *Journal of Consumer Psychology*, Vol. 13, No. 1/2, pp. 113-123.

- Bajari, P., Hortacsu, A. 2003. The Winner's Curse, Reserve Prices, and Endogenous Entry: Empirical Insights from eBay Auctions. *Rand Journal of Economics*, Vol. 34, Part. 2, pp. 329-355.
- Bapna, R., Goes, P., Gupta, A., Jin, Y. 2004. User Heterogeneity and its Impact on Electronic Auction Market Design: An Empirical Exploration. *Management Information Systems Quarterly*, Vol. 28, Part. 1, pp. 21-44.
- Bapna, R., Jank, W., Shmueli, G. 2008. Price formation and its dynamics in online auctions. *Decision Support Systems*, Vol. 44, Issue. 3, pp. 641-656.
- Bapna, R., Chang, S. A., Goes, P., Gupta, A. 2009. Overlapping online Auctions: Empirical Characterization of Bidder Strategies and Auction Prices. *Management Information Systems Quarterly*, Vol. 22, part. 4, pp. 763-784.
- Belsley, D. A., Kuh, E., Welsch, R. E. 1980. Regression Diagnostics: Identifying Influential Data and Sources of Collinearity. Wiley, New York.
- Bruno, H. A., Che, S., Dutta, S. 2012. Role of Reference Price on Price and Quantity: Insights from B2B Markets. Working paper, January 2012, INSEAD
- Chan, T. Y., Kadiyali, V., Park, Y. 2007. Willingness to Pay and Competition in Online Auctions. *Journal of Marketing Research*, Vol. 44(2), pp. 324-356.
- Dellarocas, C. 2006. How often should Reputation Mechanisms Update a Trader's Reputation Prole?. *Information Systems Research*, Vol. 17, No. 3, pp. 271-285.
- Dholakia. U. M., Simonson, I. 2005. The Effect of Explicit Reference Points on Consumer Choice and Online Bidding Behavior. *Marketing Science*, Vol. 24, No. 2, pp. 206-217.
- Dholakia. U. M., Soltysinski, K. 2001. Coveted or Overlooked? The Psychology of Bidding for Comparable Listings in Digital Auctions. *Marketing Letters*, Vol. 12, Part. 3, pp. 225-237.
- Dholakia. U. M., Basuroy, S., Soltysinski, K. 2002. Auction or Agent (or both)? A study of Moderators of the Herding Bias in Digital Auctions. *International Journal of Research in Marketing*, Vol. 19, No. 2, pp. 115-130.
- Gilkeson, J. H., Reynolds, K. 2003. Determinants of Internet Auction Success and Closing Price: An Exploratory Study. *Psychology & Marketing*, Vol. 20, Issue. 6, pp. 537-566.
- Haruvy, E., Popkowski Leszczyc, P. T. L. 2010. The Impact of Online Auction Duration. *Decision Analysis*, Vol. 7, No. 1, pp. 99-106.
- Hubl, G., Popkowski Leszczyc, P. T. L. 2003. Minimum Prices and Product Valuations in Auctions. *Marketing Science Institute Reports*, Vol. 3, 03-117: pp.115-141.
- Heckman, J. J. 1979. Sample Selection Bias as a Specification Error. *Econometrica*, Vol. 47, No. 1, pp. 153-161.
- Heyman, J., Orhun, Y., Ariely, D. 2004. Auction Fever: The Effect of Opponents and Quasi-Endowment in Product Valuations?. *Journal of Interactive Marketing*, Vol. 18, pp. 7-21.
- Kalayanaram, G., Winer, R. S. (1995). Empirical Generalizations from Reference Price Research. *Marketing Science*, Vol. 14, No. 3, Part 2 of 2: Special Issue on Empirical Generalizations in Marketing, pp. G161-G169.
- Kamins, M. A., Drze, X., Folkes, V. S. 2004. Effects of Seller-Supplied Prices on Buyers' Product Evaluations: Reference Prices in an Internet Auction Context. *Journal of Consumer Research*, Vol. 30, pp. 622-28.
- Ku, G., Galinsky, A. D., Murnighan, J. K. 2006. Starting Low but Ending High: A Reversal of the Anchoring Effect in Auctions. *Journal of Personality and Social Psychology*, Vol. 90, No. 6, pp. 975-98.
- Langer, N., Forman, C., Kekre, S., Sun, B. 2012. Ushering Buyers into Electronic Channels: An Empirical Analysis. Forthcoming at *Information Systems Research*.
- Levin, L. 2004. Auction Theory. Manuscript available at www.stanford.edu/~jdlevin/Econ%20286/Auctions.pdf.
- Li, T., Zheng, X. 2009. Entry and Competition Effects in First-Price Auctions: Theory and Evidence from Procurement Auctions. *The Review of Economic Studies*, Vol. 76, No. 4, pp. 1397-1429

- Lucking-Reiley, D., Bryan, D., Prasad, N., Reeves, D. 2000. Pennies from eBay: The Determinants of Price in Online Auctions. *Journal of Industrial Economics*, Vol. 55, No. 2, pp. 223-233.
- Maddala, G. S. 1983. Limited Dependent and Qualitative Variables in Econometrics, Cambridge: Cambridge University Press
- Milgrom, P., Weber, R. 1982. A Theory of Auctions and Competitive Bidding. *Econometrica*, Vol. 50, No. 5, pp. 1089-1122.
- Mazumdar, T., Raj, S. P., Sinha, I. 2005. Reference Price Research: Review and Propositions. *Journal of Marketing*, Vol. 69, pp. 84-102.
- Mithas, S., Jones, J. L. 2007. Do Auction Parameters Affect Buyer Surplus in E-Auctions for Procurement?/*Production and Operations Management*, Vol. 16, No. 4, pp. 455-470.
- Nunes, J. C., Boatwright, P. 2004. Incidental Prices and Their Effect on Consumer Willingness to Pay. *Journal and Marketing Research*, Vol. 41, pp. 457-466.
- Peters, M., Severinov, S. 2006. Internet Auctions with Many Traders. *Journal of Economic Theory*, Vol. 130, No. 1, pp. 220-245.
- Park, Y. -H., Bradlow, E. T. 2005. An Integrated Model for Bidding Behavior in Internet Auctions: Whether, Who, When, and How Much. *Journal of Marketing Research*, Vol. 42, No. 4, pp. 470-482.
- Pinker, E. J., Seidmann, A., Vakrat, Y. 2003. The Design of Online Auctions: Business Issues and Current Research. *Management Science*, Vol. 49, No. 11, pp. 1457-1484.
- Ranjendran, K. N., Tellis, G. J. 1994. Contextual and Temporals of Reference Price. *Journal of Marketing Research*, Vol. 58, pp. 22-34
- Ray, S., Turi, R. H. 1999. Determination of Number of Clusters in K-Means Clustering and Application in Color Image Segmentation in N M Namazi (ed). Proceedings of the 4th International Conference on Advances in Pattern Recognition and Digital Techniques (ICAPRDT99), Calcutta, India, pp 137-143.
- Roth, A. E., Ockenfels, A. 2002. Last-Minute Bidding and the Rules for Ending Second-Price Auctions: Evidence from eBay and Amazon Auctions on the Internet. *The American Economic Review*, Vol. 92, Part. 4, pp. 1093-1103.
- Simonsohn, U., Ariely, D. 2008. When Rational Sellers Face Nonrational Buyers: Evidence from Herding on eBay. *Management Science*, Vol. 54, No. 9, pp. 1624-1637.
- Wang, X., Hu, Y. 2009. The Effect of Experience on Internet Auction Bidding Dynamics. *Marketing Letters*, Vol. 20, Part. 3, pp. 245-261.
- Wilcox, R. T. 2000. Experts and Amateurs: The Role of Experience in Internet Auctions. *Marketing Letters*, Vol. 11, No. 4, pp. 363-374.
- Wolk, A., Spann, M. 2008. The Effects of Reference Prices on Bidding Behavior in Interactive Pricing Mechanisms. *Journal of Interactive Marketing*, Vol. 22, pp. 2-18.
- Wooldridge, J. 2002. Econometric Analysis of Cross Section and Panel Data. MIT Press, Cambridge.
- Yadav, M. S., Seiders, K. 1998. Is the Price Right? Understanding Contingent Processing in Reference Price Formation. *Journal of Retailing*, Vol. 74, pp. 311-329.