ABSTRACT

Title of dissertation:	Essays on Information Flows and Auction Outcomes in Business-to-Business Market: Theoretical and Empirical Evidence
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In this dissertation, I have three separate essays in the context of Business-to-Business (B2B) auctions; in each I introduce a complex problem regarding the impact of information flows on auction's performance which has not been addressed by prior auction literature. The first two essays (Chapter 1 and 2) are *empirical* studies in the context of online secondary market B2B auctions while the third essay (Chapter 3) is a *theoretical* investigation and will contribute to the B2B procurement auction literature. The findings from this dissertation have managerial implications of how/when auctioneers can improve the efficiency or success of their operations.

B2B auctions are new types of ventures which have begun to shape how industries of all types trade goods. Online B2B auctions have also become particularly popular for industrial procurement and liquidation purposes. By using online B2B auctions companies can benefit by creating competition when auctioning off goods or contracts to business customers. B2B Procurement auctions— where the buyer runs an auction to procure goods and services from suppliers— have been documented

as saving firms millions of dollars by lowering the cost of procurement. On the other hand, B2B auctions are also commonly used by sellers in 'secondary market' to liquidate the left-over goods to business buyers in a timely fashion.

In order to maximize revenues in either both industrial procurement or secondary market settings, auctioneers should understand how the auction participants behave and react to the available market information or auction design. Auctioneers can then use this knowledge to improve the performance of their B2B auctions by choosing the right auction design or strategies.

In the first essay, I investigate how an online B2B secondary market auction environment can 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. I will examine how reference prices from such auctions affect bidding behavior on the focal auction conditioning on bidders' types. I will use longitudinal data of auctions and bids for more than 4000 B2B auctions collected from a large liquidator firm in North America.

In the second essay, I report on the results of a field experiment that I carried out on a secondary market auction site of another one of the nation's largest B2B wholesale liquidators. The design of this field experiment on iPad marketplace is directly aimed at understanding how (i) the starting price of the auction, and (ii) the number of auctions for a specific (model, quality), i.e., the supply of that product, interact to impact the auction final price. I also explore how a seller should manage the product differentiation so that she auctions off the right mix and supply of

products at the reasonable starting prices.

Finally, in the last essay, I study a *norm* used in many procurement auctions in which buyers grant the 'Right of First Refusal' (ROFR) to a favored supplier. Under ROFR, the favored supplier sees the bids of all other participating suppliers and has the opportunity to match the (current) winning bid. I verify the conventional wisdom that ROFR increases the buyer's procurement cost in a single auction setting. With a looming second auction in the future (with the same participating suppliers), I show that the buyer lowers his procurement cost by granting the ROFR to a supplier. The analytical findings of this essay highlights the critical role of information flows and the timing of information-release in procurement auctions with ROFR.

Essays on Information Flows and Auction Outcomes in the
Business-to-Business Market: Theoretical and Empirical Evidence

by

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Dedication

To my father and mother whom without their love and support this dissertation would not have been made possible.

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I have a great deal of gratitude for all of the individuals who made this dissertation possible. While words cannot convey this gratitude accurately, I would first and foremost like to thank my advisor, Professor Wedad Emaghraby. Her love, support, patience and guidance over the last five years were instrumental to accomplishing the three projects of this dissertation. It has been a pleasure to work and learn from such an extraordinary person. Secondly, I would like to thank Dr. Anandasivam Gopal for his assistance and guidance in providing me with the foundation to become a empirical scholar. His vision and insight played a critical and supportive role in the completion of the first two projects of my dissertation. For everything you have done for me, I thank you.

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unfailing support I needed to complete the journey of my dissertation.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Chapter 1

Reference Prices and Bidder Heterogeneity in Secondary Market

Online B2B Auctions

1.1 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 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 essay attempts to addresses 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 in this essay 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[1]. 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%

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[1]http://www.ecommercebytes.com/cab/abn/y09/m09/i08/s01

3

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

4

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 in this essay 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.

1.2   Research Site, Context and Dataset

1.2.1   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' 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[2]. 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 work, it is worth noting that the model flexibly allows incorporating the two forms of reference prices we study in this essay. 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 a 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 chapter and the strategy used in variable definitions for reference prices and bidder heterogeneity.

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[2]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 $s_1,..,s_n$ are each bidder's private signal, correlated with V but independent from each other (i.e., $s_i = V + \epsilon_i$ where $\epsilon_1,..,\epsilon_n$ are independent). β ($\beta \leq 1$) are also the weights each bidder puts on their own as well as other bidders' private signals.

1.2.2 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. When auction ends, 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, and 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.

1.2.3 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 1.1) 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 1.1, 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.[3] 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

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[3]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.

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, 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 1.1. Also, the individual variable definitions used in our different analysis throughout this chapter are shown in Table 1.2. Having defined the key variables in our dataset, we propose our research hypotheses in the next section.

1.3   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 is not easily accessible in these environments. Wolk and Spann (2008) 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). $JFAP$ is 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 Simonson (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 Simonson 2003). Both Ariely and Simonson (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 $JFAP$s 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 Simonson 2005; Kamins et al. 2004) provides reasoning for

19

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 Simonson 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 that the effect of OAP_{bid} and $JFAP_{bid}$ is lower on bidders with experience than on bidders without experience. This anal-

ysis 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.

1.4 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 final price of the auction. Having established the importance of first bid role, we then study how the first bids are formulated through the influence of references prices and bidder heterogeneity. Finally, we discuss the results from this analysis, which point to way for further post-hoc analysis reported in Section 2.5.

1.4.1 The First Bid's Effect on Recovery Rate

In this section, we confirm that first bids are critical in determining the final price of an auction, We start with a simple OLS model with final price 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 1.2 for the summary of variables in final price regression).

The results from the baseline model without first bid are reported in Column 1 of Table 1.3. On adding first bid to the model, we see the results in Column 2 of Table 1.3. 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 final price.

Prior work on the role of the starting price (Bajari and Hortacsu 2003) suggests that the first bid's effect on final price 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 price 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 final price in the second stage. Exclusion conditions require omitting the time dummies from the second stage final price equation. Column 3 of Table 1.3 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 final price; all else being equal, an increase of 1% in the first bid value increases the final price of auction 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.

1.4.2 First Bid Formation

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

$$FB_{ij} = \beta_0 + \beta_1 Experience_{ij} + \beta_2 IRP_{ij} + \beta_3 ERP_{ij} + \beta_4 BC_{ij} + \beta_5 AC_i$$

$$+ \beta_6 Time_i + \beta_7 Warehouse_i + \epsilon_{ij} \tag{1.1}$$

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 1.2 summarizes the description of these variables used in Equation 1.1 [4]. The baseline model introduced in Equation 1.1 does not include interactions

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[4] Although FB and most variables in right-hand-side of Equation 1.1 ($Experience$, IRP, ERP, etc) are also time-dependent, for the sake of exposition simplicity, we suppress the *time* subscript

to test moderation, which we discuss shortly.

Estimating Equation 1.1 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

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from those variables in the equation.

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 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 1.2 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 1.2 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 1.4. 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 1.1 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 1.4, calculate inverse Mills ratios and then estimate Equation 1.1 as the outcome equation with the first bid as the dependent variable (Maddala 1983)[5].

The results from the baseline estimation of Equation 1.1, which test the direct effects of reference prices and bidder heterogeneity are shown in Column 1 of Table 1.5. 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 1.5 are based on second-stage Heckman analyses, with the rho coefficient[6] reported across all columns. Column 2 of Table 1.5 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)

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[5]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.

[6]rho indicates the correlation coefficient between error terms in probit model (first stage) and Equation 1.1 (first bid model). The statistical significance of rho, reported at the bottom of Table 1.5 will show to what degree accounting for sample selection is critical for the sake of our analysis.

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 1.5 replaces $JFAP$ with $JFAB_{bid}$ and $JFAB_{notbid}$ while Column 4 of Table 1.5 replaces OAP with its subset counterparts. Finally, Column 5 of Table 1.5 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 1.5 extends the results observed from the earlier interaction analysis shown in Column 3 by adding an interaction term of experience and JFA_{bid}. Similarly, Column 7 of Table 1.5 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 1.5 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 1.5. 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.

1.5 Discussion of Results and Post-Hoc Analysis

We start with discussing the summary statistics that provide some context for our study. From Table 1.1, 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 1.5, we observe strong statistical support for Hypothesis 2.3. Across all specifications in Table 1.5, 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 2.3 and 3 are also supported; the direct effect of $JFAP$ (from Columns 1, 2 and 4 of Table 1.5) 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 2.3 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 1.5), 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 1.5) 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 1.5 is insignificant. With respect to OAP, we see the opposite result in Column 2 of Table 1.5, 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 1.5), 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 1.4) 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 1.5. 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.

1.5.1 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

35

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 work (experience and cross-bidding behavior). The k-means methodology will result in finding *two* different clusters of bidding behavior[7]. The summary of statistics of the resulting two clusters are shown in Tables 1.6 and 1.7. 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

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[7]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 $K=2$.

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 final price across the two clusters is roughly 1% of E and is statistically significant, with Cluster 1 showing a higher final price. 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 first bidders in our dataset, 535 bidders appear only in Cluster 1 and 3 bidders appear only in Cluster 2 across the dataset. The 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 final prices 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 final price 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 1.4 for the two clusters respectively. Similarly, the results of the second stage of the sample selection models are shown in Table 1.8 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 1.8 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 1.4, 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 1.4). 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 1.4).

Moving to the results in Table 1.8, 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 1.8 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 2.3 appears to be 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 Simonson 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

41

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.

1.6 Conclusion

In this essay 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 work 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 final price 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 empir-

ical 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 final prices. 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 final prices. In our dataset, auctions in which the first bidder is experienced terminated with slightly lower final prices. 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 simultaneously and how to extract value from the information that is available to heterogeneous bidders.

1.7 Figures and Tables

Figure 1.1: Reference Prices Formed from Concurrent Auctions
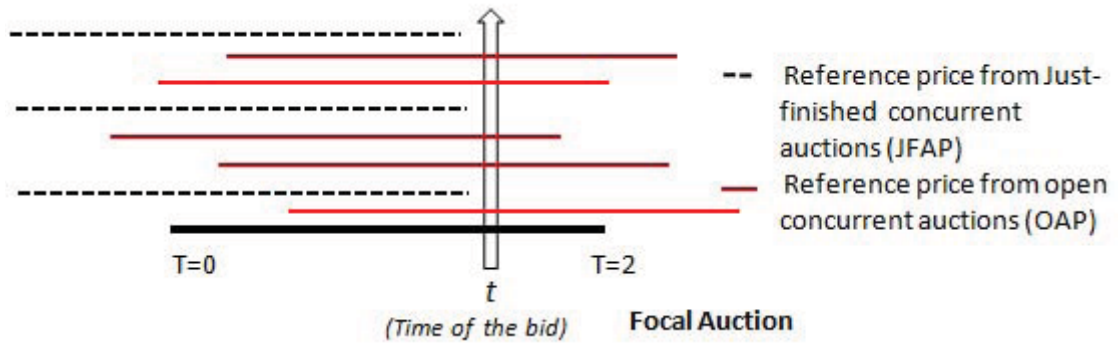
Figure 1.2: Identifying Potential First Bidders in a Focal Auction
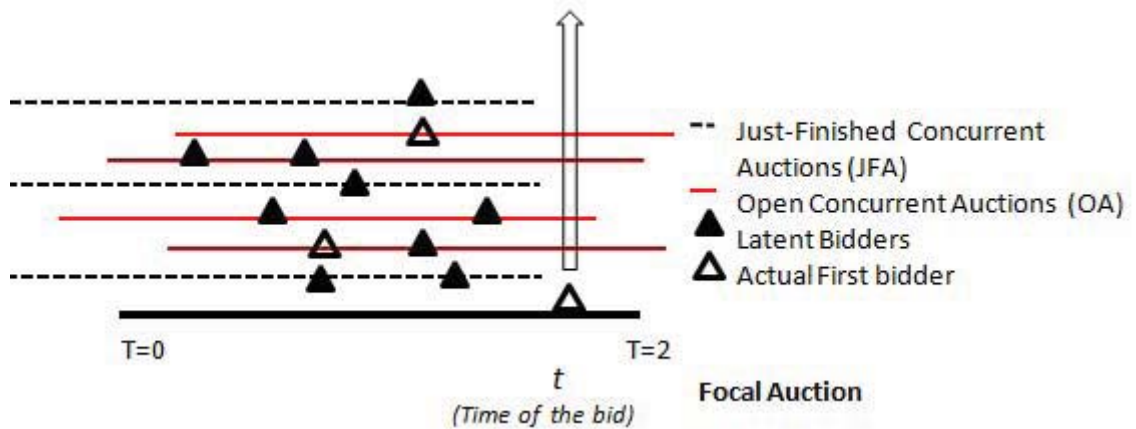
Table 1.1 Summary statistics and correlation matrix (4308 auctions)

	Variable	Mean	St dev	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	$JFAP^8$	0.18	0.09																			
2	$JFAP_{bid}$	0.15	0.08	0.58																		
3	$JFAP_{notbid}$	0.18	0.09	0.91	0.43																	
4	OAP	0.12	0.04	-0.08	-0.02	-0.07																
5	OAP_{bid}	0.11	0.03	-0.07	0.05	-0.08	0.60															
6	OAP_{notbid}	0.12	0.04	-0.06	-0.04	-0.04	0.87	0.33														
7	$NJFA$	4.86	7.03	0.48	0.38	0.48	-0.08	-0.03	-0.06													
8	NOA	4.73	4.76	0.01	0.05	0.02	0.24	0.23	0.24	0.32												
9	$NJFA_{bid}$	1.18	2.68	0.32	0.59	0.20	-0.02	0.05	-0.04	0.55	0.18											
10	$NJFA_{won}$	0.22	0.86	0.14	0.30	0.04	-0.03	0.03	-0.04	0.32	0.11	0.66										
11	NOA_{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	IRP	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	$TOFB$	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	Q	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	$Y(100)$	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	Final price	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	FB	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

[8] 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 final price.

Table 1.2 List of Variables Used in our Empirical Analysis of Chapter 1

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

Table 1.3 OLS Results Predicting the Final Price and Number of Bidders in B2B Auctions

	(1)	(2)	(3)	(4)
Dependent Variable:	Final Price	Final Price	N	Final Price
Constant	0.1272***	0.0811***	5.5482***	0.0515*
	(0.024)	(0.023)	(1.561)	(0.030)
$TOFB$	-0.0419***	-0.0350***	-1.3329***	-0.0137*
	(0.003)	(0.003)	(0.114)	(0.008)
Q	0.0007***	0.0006***	0.0405***	0.0000
	(0.000)	(0.000)	(0.002)	(0.000)
$Y(\$100)$	0.0247***	0.0201***	0.9797***	0.0078
	(0.002)	(0.002)	(0.066)	(0.006)
NOA	-0.0009***	-0.0009***	-0.0275***	-0.0007***
	(0.000)	(0.000)	(0.006)	(0.000)
FB		**0.2653*** **	-9.4904***	**0.3871*** **
		(0.012)	(0.475)	(0.053)
Number of Bidders	0.0098***	0.0122***		0.0258***
	(0.000)	(0.000)		(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 final price. Finally, Column 4 will report on stage 2 results of the 2SLS in which final price is estimated. (Standard errors in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$).

Table 1.4 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	-0.0023**	0.0007***
	(0.0001)	(0.001)	(0.000)
Experience$\times Q$	0.0000	-0.0000	0.0000
	(0.000)	(0.000)	(0.000)
Experience$\times Y(\$100)$	0.0001*	0.0000	0.0004***
	(0.0007)	(0.000)	(0.0001)
NJF_{bid}	-0.001***	-0.003***	0.0000
	(0.0007)	(0.0008)	(0.0008)
$NJFA_{won}$	-0.022***	-0.021***	-0.016***
	(0.001)	(0.003)	(0.003)
NOA_{bid}	0.007***	0.0087***	0.001
	(0.0005)	(0.0007)	(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 1.5 Heckman Second Stage Results of Reference Prices and Bidder Heterogeneity on First Bid

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable:	FB	FB	FB	FB	FB	FB	FB	FB
Constant	0.1095***	0.0881***	0.1121***	0.0951***	0.0988***	0.0964***	0.0841***	0.0902***
	(0.009)	(0.009)	(0.008)	(0.009)	(0.008)	(0.024)	(0.023)	(0.009)
$TOFB$	-0.0202***	-0.0201***	-0.0190***	-0.0195***	-0.0184***	-0.0184***	-0.0183***	-0.0183***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Q	0.0000	0.0000	0.0001	0.0000	0.0001	0.0001	0.0001	0.0001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Y(\$100)$	0.0108***	0.0108***	0.0108***	0.0106***	0.0107***	0.0107***	0.0107***	0.0107***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
NFA	-0.0001	-0.0001	-0.0000	-0.0001	-0.0002	-0.0001	-0.0000	-0.0001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
NOA	-0.0008***	-0.0009***	-0.0008***	-0.0010***	-0.0010***	-0.0010***	-0.0010***	-0.0010***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Experience	0.0007***	0.0003**	0.0007***	0.0007***	0.0007***	0.0007***	0.0005***	0.0005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
IRP	0.1714***	0.1711***	0.1661***	0.1682***	0.1635***	0.1639***	0.1647***	0.1651***
	(0.016)	(0.016)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Number INC Bids	-0.0026***	-0.0026***	-0.0028***	-0.0027***	-0.0029***	-0.0029***	-0.0029***	-0.0029***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$JFAP$	0.048***	0.045***		0.045***				
	(0.013)	(0.013)		(0.013)				
$JFAP\times$Experience		0.00029						
		(0.0000)						
$JFAP_{bid}$			0.0915***		0.0835***	0.0890***	0.0833***	0.091***
			(0.013)		(0.013)	(0.013)	(0.013)	(0.013)
$JFAP_{bid}\times$Experience						-0.0004		-0.0005
						(0.000)		(0.000)
$JFAP_{notbid}$			0.011		0.0124	0.01	0.0118	0.009
			(0.021)		(0.013)	(0.012)	(0.012)	(0.012)
OAP	0.0799***	0.0499**	0.0760***					
	(0.023)	(0.024)	(0.022)					
$OAP\times$Experience		0.0028***						
		(0.001)						
OAP_{bid}				0.2062***	0.1885***	0.1887***	0.1624***	0.1627***
				(0.026)	(0.026)	(0.026)	(0.029)	(0.029)
$OAP_{bid}\times$ Experience							0.0018**	0.0019**
							(0.001)	(0.001)
OAP_{notbid}				-0.0025	0.0007	0.001	0.0029	0.0036
				(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Dummies (Time/Warehouse)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of auctions	4308	4308	4308	4308	4308	4308	4308	4308
rho	-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 1.6 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	$JFAP$	0.18	0.09																			
2	$JFAP_{bid}$	0.14	0.07	0.54																		
3	$JFAP_{notbid}$	0.18	0.09	0.94	0.42																	
4	OAP	0.12	0.04	-0.09	-0.03	-0.08																
5	OAP_{bid}	0.11	0.03	-0.09	0.02	-0.09	0.57															
6	OAP_{notbid}	0.12	0.04	-0.06	-0.03	-0.05	0.88	0.33														
7	$NJFA$	4.44	6.55	0.49	0.34	0.50	-0.07	-0.03	-0.06													
8	NOA	4.44	4.62	0.00	0.03	0.03	0.25	0.22	0.25	0.30												
9	$NJFA_{bid}$	0.82	1.96	0.33	0.65	0.25	-0.02	0.05	-0.03	0.46	0.13											
10	$NJFA_{won}$	0.09	0.44	0.13	0.28	0.11	0.00	0.06	-0.02	0.22	0.06	0.46										
11	NOA_{bid}	1.36	2.16	-0.02	0.05	-0.02	0.11	0.28	0.07	0.14	0.52	0.14	0.07									
12	IRP	0.15	0.08	0.01	0.08	0.01	-0.02	0.04	-0.04	-0.01	-0.01	0.05	0.06	0.02								
13	Experience	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	0.55							
14	Number INC Bids	1.60	1.47	-0.03	0.03	-0.04	0.04	0.03	0.05	-0.03	-0.03	0.04	0.06	-0.04	-0.02	-0.04						
15	$TOFB$	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	-0.05					
16	Q	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	-0.14				
17	$Y(100)$	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	-0.15	-0.07			
18	Final Price	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	0.23		
19	Number of bidders	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	0.52	
20	FB	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 1.7 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	$JFAP$	0.19	0.09																			
2	$JFAP_{bid}$	0.17	0.09	0.74																		
3	$JFAP_{notbid}$	0.17	0.09	0.84	0.52																	
4	OAP	0.12	0.04	-0.05	-0.01	-0.03																
5	OAP_{bid}	0.12	0.04	-0.02	0.06	-0.02	0.70															
6	OAP_{notbid}	0.12	0.04	-0.04	-0.03	-0.01	0.83	0.39														
7	$NJFA$	6.37	8.37	0.45	0.46	0.45	-0.09	-0.06	-0.04													
8	NOA	5.80	5.08	0.01	0.05	0.03	0.23	0.25	0.24	0.32												
9	$NJFA_{bid}$	2.45	4.12	0.36	0.52	0.20	-0.04	0.01	-0.03	0.69	0.22											
10	$NJFA_{won}$	0.67	1.55	0.21	0.33	0.03	-0.07	-0.04	-0.05	0.45	0.14	0.74										
11	NOA_{bid}	2.58	3.37	-0.07	0.07	-0.12	0.14	0.25	0.06	0.08	0.65	0.17	0.15									
12	IRP	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								
13	Experience	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	0.24							
14	Number INC Bids	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	-0.03	-0.21						
15	$TOFB$	0.37	0.29	0.21	0.16	0.14	-0.07	-0.03	-0.05	0.46	0.28	0.33	0.26	0.06	0.00	0.07	0.01					
16	Q	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	0.06	0.00	-0.10				
17	$Y(100)$	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	0.09	-0.15	-0.23			
18	Final Price	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		
19	Number of bidders	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	0.51	
20	FB	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 1.8 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

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

Chapter 2

The Impact of Auction Starting Price and Supply of Products in Secondary Market: Evidence from a Field Experiment in online B2B Auctions

2.1 Introduction

In the Business-to-Business (B2B) secondary market, large retailers (such as Sears, Target, or Walmart) can liquidate their excess and customer-returned inventory to business buyers (such as off-price retailers, flea markets, or eBay power sellers). This customer-returned merchandise is a used product that was sold to a customer, who then either physically brought the item back to a store or mailed it to a specified location. Although there is no single definition of secondary markets, there are some reports that estimate the size of the US returns market alone to be at least $50 billion. In such a supply chain environment, many retailers have shifted the responsibility of disposing of this leftover inventory to large wholesale liquidators who have their own online marketplaces and large networks of buyers. Hundreds of billions of dollars worth of returned inventory is now finding its way to online marketplaces where buyers can buy it without the big markup added by a middleman. B2B auctions are a common sale mechanism used by these wholesale liquidators.

Due to the nature of secondary market, used products in secondary markets can arrive at the wholesale liquidator's in a range of state-of-quality conditions. The quality conditions are graded from salvage (the lowest quality level) to excellent. The used products of the same quality condition are then bundled together and sold as a whole pallet in B2B auctions. At this point, one seller's decision will come to determine the *auction starting price*, which is the minimum price at which a seller is willing to sell the pallet. The auction starting price is often determined based on prior sale data or on pricing information gathered from other Business-to-Consumer or Consumer-to-Consumer online markets (e.g., Amazon, Terapeak) for comparable product types.

With fast liquidation being a critical part of their daily business model, wholesale liquidators often run several auctions simultaneously for identical and comparable products, whereby comparable products differ according to quality condition and models of the product– vertically differentiated products. Vertical differentiation occurs in this market where the several goods that are present can be ordered according to their model (from newest to oldest) or quality condition (from the highest to the lowest). As wholesale liquidators now operate as multi-product firms, in addition to choosing the starting price, another challenge these firms face on a daily basis is to determine the supply of these products the number of posted auctions for each product. Although posting several auctions simultaneously can of course increase the speed of the liquidation process, its net effect on the wholesale liquidator's total profit is unclear. Posting several auctions for identical and/or comparable products at different starting price levels can depress overall profits by directly in-

creasing the competition in supply. Additionally, if the auction starting price levels for these products are within the same ranges, products may become vertically less differentiated but more substitutable. Due to rise in demand substitution, we may now face an interconnected market in which some bidders have the opportunity to substitute their favorite quality and models of the product for others with lower or similar bids, while still satisfying their original needs.

Further complicating the market dynamics is the price revelation process that is inherent in auctions. The seller does not dictate a selling price in order to make products differentiated, but rather sets the tone for the auction via her starting price or adjusting the supply of the products in market. Both the starting price of auction and product's supply (adjusted via the number of daily auctions) can vary the degree to which demand substitution occurs across different market, and this can impact the final price.

In such an auction environment, one important and open question to ask is how a seller should manage positioning her products in the market by, for instance, auctioning off the right mix and supply of products at a reasonable starting price. Although, product positioning or product assortment problem has received plenty of attention in the marketing and operations literature in recent years (e.g., Kök et al. 2006), it is as yet unexplored in the auction literature. The first step to tackle such a strategic question is to have the knowledge of how an auction's final price is driven by all different factors from the same or different market. Prior auction literature fails to address this question due to lack of access to a clean and controlled environment in which researchers can be in control of auction and market specifics

(e.g., the auction starting price and number of auctions) while the characteristics of the products (e.g., models, qualities) are exogenously determined through the sellers production processes.

In this essay, we address this gap by running a controlled field experiment on the auction site of one of the nation's largest online auction wholesale liquidators. The design of this field experiment was directly aimed at understanding the extent to which (i) the starting price of the auction, and (ii) the number of auctions for a specific (model, quality), which implies the market supply for that product, interact to impact an auction's final price.

In terms of existing related literature, prior research has extensively studied a number of factors (e.g., starting price, reserve price, auction duration, seller's reputation, auction formats, and auction ending rules) that impact the final price/success of auctions (see Pinker at al. 2003 for a comprehensive study of online auctions). In particular, prior studies report on mixed results with regard to the relationship between auction starting price and final price conditional on sale. On the one hand, other work (e.g., Bajari and Hortacsu 2003; Lucking-Reiley et al. 2007) argue that starting price could work as an indicator for the auction's products value, which impacts the consumer's valuation construct. This justifies the positive relationship between auction starting price and final price. On the other hand, some branches of literature (e.g., Ku et al. 2005 and 2006) report a negative relationship between auction starting price and final price since a low starting price might increase the attractiveness of entering into the auction (entry decision), leading to high final price. Other branches of literature (e.g., Dholakia et al. 2002) also consider the

starting price presence as the single most important factor in a buyer's decision to bid for a listing.

Although most works in this area treat auctions in isolation without accounting for interaction with adjacent and open auctions, some auction works explore the influence of the starting price in other comparable auctions (which are simultaneously available) on the final price of the focal auction. In this regard, some works (e.g., Nunes and Boatwright 2004, Häubl and Popkowski-Leszczyc 2003) show that consumers use price cues such as starting prices observable from other comparable auctions as a basis for constructing their own valuations of an auctioned product. One common ground for this stream of literature is that they ignore how the relative distance between the starting price of the focal auction and other comparable goods can change the consumer valuation and, hence, the final price. One related work, Ariely and Simonson (2003), confirms via an experiment that there is a positive relationship between auction starting price and final price, but only when comparable items are *not* available in the immediate context.

Finally, regarding the amount of supply for a product in the market– capture via number of available auctions– and final price of the auctions, there is only a handful of papers controlling for number of similar available auctions in their analyses. The most related one is Chan et al. (2007) who shows the negative impact of number of available auctions and competition in supply on bidders willingness to pay. Dholakia et al. (2002) also investigates the degree of herding bias (buyers tend to bid for listings with existing bids) across bidders as a function of the listing volume for that category. They show that when they are few auctions open– because

of few alternative to learn, bidders tend to focus more on the attribute of auctions like existing bids or auction starting price. On the other hand, when they more listings to choose, the buyer may now need to rely less on auction's attribute. They also argue that when there a few listings in the market, popularity diminishes, and this attract few new bidders in aggregate to participate.

In a departure from prior literature, which mainly focuses on the impact of auction starting price and market supply in isolation from the larger market context, we use a dataset collected from a unique field experiment to account explicitly for the substitution/market effects raised from the starting price and market supply- the number of all (generation, quality) auctions simultaneously open. We show how the starting price and amount of supply for different related (comparable) markets influence each market's final price. To support our findings, we raise some arguments about demand substitution, the bidders entry decisions, and value signaling effect.

We ran the field experiment on a set of electronic products that are well-understood and clearly specifiable: iPad tablets. We conducted the experiment on two sets of products: used 2rd generation iPads ($iPad2$) and 3rd generation iPads ($iPad3$). The pallet therefore contain iPads of the same generation (i.e. all $iPad3$) of two grades of quality: $light\text{-}use$ and $moderate\text{-}use$ (a lower quality level). The experiment included 22 days of auctions, excluding the holiday season, within a window of three months. The experiment consisted of 632 successful auctions totaling over $1 million revenues. The goods in each auction in the sample consisted of a pallet of similar iPads that were similar in terms of quality and generation.

Our findings from the experiment shed light on predicting the final price of

auctions in interconnected markets conditioning on the auction starting price and the supply of products in each market. First, we find evidence of some bidders substituting bids on higher-end products for lower-end products. We can find that an increase in the starting price of low-quality *iPad2* auctions will kick in an upward demand substitution, so that bidders may now more likely to participate in auctions of high-quality *iPad2*s or *iPad3*s. Another significant finding is that an increase in auction starting price of a high-quality product of an older generation (light-use *iPad2*) will have a negative effect on the final prices of all auctions for the newer generation of products (light-use *iPad3*). We also tease out some patterns of demand substitution across generations and quality class, depending on the amount of supply in each market. For instance, we can show that an increase in the number of low-quality auctions increases the final price of high-quality product. Finally, we identify the diminishing importance for the starting price in auctions of a product when the product's supply increases.

In terms of the contribution, our field experiment provides the first empirical evidence in support of demand substitution in a B2B auction marketplace across different comparable markets. We find clear examples of some bidders substituting bids on higher-end products for lower-end products. We also provide a more nuanced understanding of the impact of starting price on the final price of a focal auction conditioning on the starting price levels of other available comparable products. To the best of our knowledge, we are among the first researchers who have accounted simultaneously for auction's starting price of all related products in the market as well as their market's supply amount when studying the perfor-

mance of auctions for a particular product. We should also point out that despite the challenges we faced to comply with sellers daily operational requirements, the scale of our field experiment was by far one of the most extensive run in a real B2B marketplace with business buyers. Finally, this essay also discusses preliminary results on the under-studied issue of product differentiation and its implication on the positioning of different auctions in a B2B secondary market. We provide sellers in the secondary market with some managerial implications about auctioning off their products (varying with the model and quality).

The remainder of this essay is organized as follows. In the next section, we begin with discussing the specific B2B marketplace we explore in this essay. Then, we discuss the studied marketplace and describe the experimental design and the data. In Section 2.3, we review the theory and hypotheses. The empirical analysis and a discussion of the results are presented respectively in Section 2.4 and 2.5. Finally, in Section 2.6, we close the essay with conclusions, some managerial implications and some potential avenues for future research.

2.2 Auction Marketplace, Experimental Design, and Data Description

Before we discuss our experimental design and the data we collected, we describe the B2B auction marketplace we study in this essay. The company under study is a publicly traded company and one of the leading B2B online auction marketplaces for surplus merchandise in the US secondary market. It enables buyers

and sellers to transact in an efficient, automated online auction environment offering over 500 product categories. Its marketplaces provide more than a million professional buyers with access to a global, organized supply of wholesale surplus assets in a variety of conditions, presented with digital images and other relevant product information. The company sells bulk inventory merchandise, including returns, closeouts, refurbished merchandise, etc

The customer-returned merchandise, which is the focus of this study, is a used product that was sold to a customer who then either physically brought the item back to a store or mailed it to a specified location. The customer's reasons for returning the product may not have any correlation to its usefulness (i.e., its size, color, model, etc.), and as a result the product may be in fine working order. The majority of returns, however, do have some operational and/or cosmetic problem (e.g., scratches). They generally do not come in the original packaging and often do not have any of the advertised documentation or additional parts and/or accessories. The used products are offered in different categories, from consumer electronics to apparel and scientific equipment.

The returned merchandise comes in a variety of conditions from big-box stores such as Sears, Target, and Walmart. The big-box stores will only provide the wholesale liquidators with a product manifest, which includes the number and retail declared value/price of each product. In fact, the big-box stores are not aware of the true quality condition of their own merchandise. Based on their historical transactions, the wholesale liquidators will offer the price at which they acquired it. First, the wholesale liquidators begin processing the items in the warehouses. They sort,

test and grade the items into one of the following conditions: *light-use* (the high-quality condition), *moderate-use*, *heavy-use*, or *salvage* (the worst quality condition). The final task is to make up pallets of similar products with the same quality grade by fulfilling certain guidelines, i.e. the total retail value of pallets may not exceed a certain dollar value, such as $2500.

Due to the nature of returned products, their market value is uncertain, which can translate into the uncertainty in the final price of auctions as well. This uncertainty in the final price of auctions can still exist even across the same type of products as they are auctioned off under different auction and market-specific conditions (e.g., with a different auction starting price or a different number of similar/identical auctions). Besides, as fast liquidation is the part of daily business, wholesale liquidators need to auction off multiple pallets of comparable or identical products simultaneously on their auction marketplace. The flow of goods from the warehouses to the auction marketplace is highly dependent on the inventories ages and on timing guidelines for selling the products by a certain time.

Going to the demand side, the bidders in the B2B auction platform we studied are professional buyers who purchase the pallets of products to resell them at higher prices after-market. The bidders pool can include flea market vendors, eBay power sellers, offline/online retailers, exporters, 'mom and pop' stores, etc. Having faced several listings and comparable auctions open at each time, these bidders (potential buyers) will find the opportunity to bid across multiple auctions while choosing the best deal, i.e. bidding at auctions with the lowest standing bid.

In the next section, we describe the experimental design we use to collect the

dataset needed to answer our research questions.

2.2.1 Experimental Design

In this section we report on the results of a field experiment we ran between November 2012 and January 2013 on the B2B online auction site of one of the nation largest wholesale liquidators. The design of this field experiment was directly aimed at understanding how (i) the starting price of the auction, and (ii) the number of auctions for a specific (model, quality), which implies the market supply for that product, interact to impact an auction's final price.

In order to reduce unobservable heterogeneity in the auction environment and to standardize the items for auction to the maximum extent possible, we ran the field experiment on a set of electronic products that were well understood and clearly specifiable– iPad tablets. Different generations of iPads gross millions of retail dollars annually for the seller where we stage the experiment. Besides, due to the growing popularity of tablet markets, i.e., Apple products, worldwide since 2010[1], it is expected that the seller will keep purchasing and receiving, in particular, millions of dollars worth of used Apple iPads annually from big retailers over the next few years.

The primary advantage of data collected from a field experiment versus data collected from a naturally occurring market with all its unobservable noises is the

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[1]In July of 2012, Apple exceeded the 85 million mark for iPad tablets sold since the product's launch in April of 2010 (Apple's Share of the Tablet Market Nears All-Time High, by Dan Graziano, Aug 14. 2012, http://bgr.com/2012/08/14/ipad-market-share-all-time-high).

ability to control on variables of interest and isolate their effects of changes on some outcome variables. However, in a real marketplace with all real buyers, one might not be able to design a full-factorial experiment (see Lusk and Shogren 2007, Chapter 4) without disrupting the daily operations of the marketplace. Instead, to the extent possible, the researchers could randomize assigning different values for all variables of interest to the treatments while having fair control on other variables that ideally should be exogenously determined.

That said, we conducted the experiment on two models of iPad tablets - returned 2nd generation iPads (*iPad2*) and 3rd generation iPads (*iPad3*) of varying levels of prior use. The experiment included 22 days of auctions, excluding the holiday season, and consists of 632 *successful* auctions totaling over $1 million revenues. The pallet of goods in each auction in the sample consisted of similar iPads, in terms of quality and generation, as is common in the secondary B2B market, with an average size of 4.5 units (std. dev.=0.73). The pallet could therefore contain iPads of the same generation (i.e. all *iPad3*s) of two grades of quality: *light-use* and *moderate-use*. As the quality grade and characteristics of the products are exogenously determined through the seller's production processes, the seller can potentially influence the outcomes of the auctions by manipulating the starting price or the amount of supply through posting needed number of auctions across different models and quality grades.

As part of the experimental design, we were allowed the opportunity to randomly set starting prices and the number of auctions[2] for each set of auctions (across

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[2]Due to the fact that our seller has a policy to make a pallet of iPads with average size of 4.5

generations and quality levels) on a given day (within acceptable ranges), thereby guaranteeing the exogeneity of these parameters. Thus, the design of the experiment allows us to tease out the effects of varying starting prices and amount of supply on auctions final prices across the generational and quality dimensions.

For each of the 22 days, we determined the starting price and number of auctions for each of the four sets of iPad product markets (*light-use/iPad2*, *moderate-use/ iPad2*, *light-use/iPad3*, *moderate-use/iPad3*). We synchronized the start of the auctions so as to have them open simultaneously each day. Also to further ensure homogeneity across days, we convinced the seller (unlike the current practice) to run auctions every two days (auctions last approximately two days) instead of every day. We should note that running auctions every two days will avoid any uncontrolled competition stemming from overlap across auctions that did not begin on the same day, and therefore improve the precision of our experiment.

The starting prices of auction for each (generation, quality) pair was fixed within a day and was set in consultation with the channel manager. Given the relative abundance of *iPad2*s inventory compared to *iPad3*s, we were allowed to manipulate the starting price for *iPad2*s. We identified a reasonable *low* and *high* starting price for light and moderate-use auctions of *iPad2*, respectively, rendering us four different combinations of starting price pairs. The low (high) starting price for light-use *iPad2* was 55% (70%) of per-unit retail value ($399); the low (high) starting price for moderated-use *iPad2* weas 50% (65%) of per-unit retail value

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units (std. dev.=0.73), she can manipulate the amount of supply for any particular product only via posting number of auctions needed to meet her supply target.

($399). The low and high starting prices for each quality class of *iPad2* is defined so that their average comes to approximately the mean starting prices the seller used before the experiment period (i.e., 66% for light-use *iPad2* and 62% for moderate-use *iPad2*).

Going to starting prices of *iPad3* auctions, due to the limitation in number of experimented days and the inventory of *iPad3*s within the firm for the experiment's duration, we fixed the starting price level of *iPad3* auctions as the percentage of per-unit retail value ($499 or $599[3] throughout the experiment to rule out the effects of their changes on the final prices.

We provided the iPad channel specialist with the randomized list of *iPad2*'s starting prices (one of four combinations of starting price pairs) for each next few days in advance. While we were able to exert full control over the starting prices, the number of auctions posted was at the occasional mercy of inventory availability within the firm. In each given day, on average we had 12.4 light-use *iPad2*, (min=0, max=27), 4.5 moderate-use *iPad2* (min=0, max=10), 8.6 light-use *iPad3* (min=0, max=17) and 3.2 moderated-use *iPad3* (min=0, max=8). Table 2.2 reports on the exact daily number of auctions for each market, as well as the randomly selected low or high starting price level for *iPad2* auctions, if any exists. Table 2.3 also summarizes the frequency and number of auctions for each market (varying across model and quality) across four different combinations of *iPad2*'s starting price pair. As Table 2.3 demonstrates, we have almost a balanced and homogeneous sample for each combination of starting price pairs in terms of the conditions under which

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[3]The price difference for per-unit of *iPad3* is due to the memory size (16GB versus 32GB).

the experiment is run. This will support our randomized block designs, which can increase the precision of the field experiment.

At the end, it is noteworthy that our field experiment is unique in different aspects. First, the ability to run a field experiment in a real and well-known B2B auction marketplace on this scale for over three months is rarely seen in the experimental auctions domain. Secondly, the bidders in the experiment are composed of real and rational business buyers, and the randomization applied across the experiment will guarantee the buyers lack of knowledge about manipulation of auction starting prices and the amount of supply for each iPad's market by the seller, which is a key condition to corroborate our randomized experiment. Furthermore, since the degree to which demand substitution occurs is driven by those bidders who occasionally switch across different markets, we can show that more than 50% of bidders were interested in both generations of iPads during the experiment. These key bidders were also winners in more than 80% of the auctions (more than 85% of seller's gross revenue). Finally, unlike some prior auction literature that ran field experiments or tracked auctions on eBay for relatively cheap goods (music CDs, books, movie DVDs), we focused on a relatively expensive and well-understood consumer electronic device, the iPad tablet, which grosses million dollars in annual sales for the seller.

In the next section, we discuss in detail the specific dataset we use in this essay, variable definitions, and some summary of statistics.

2.2.2 Description of the Data

The data collected from the 22 days of experiment consists of 632 auctions across 4 markets: 272 light-use *iPad2* auctions, 100 moderate-use *iPad2* auctions, 189 light-use *iPad3* auctions, and finally 71 moderate-use *iPad3* auctions. On the main auction site, as we can see in Figure 2.1, bidders are given information about the total number of items on pallet Q, as well as the pallets declared retail value (extended cost) E. For each auction in progress, the bidders can also observe the existing number of bids and the highest current auction price, as well as the remaining time for the auction. Similar to the auction mechanism used by the wholesale liquidator studied in essay one, the seller under investigation in this essay also uses the bidding format seen on eBay auctions, i.e. proxy auctions. As 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. When the auction ends, the bidder with the highest MWTP wins and pays the second-highest MWTP plus the minimum bid increment.

In this essay, the dependent variable of interest is auction's final price which we are interested in predicting as a function of auction starting price and market' supply amount for all available products while sustaining full experimental control on other explanatory variables. Hence, the unit of our analysis is auction. We collected the following information at the auction level. For each auction, we collected the auction starting price (which can be either low or high for *iPad2* and constant for *iPad3*), Q, the quality condition of the pallet, the per-unit retail value of the pallet Y ($Y=E/Q$,

$Y \in \{\$399, \$499, \$599\}$); the number of unique bidders in the same auction N^4; final price of the auction (the price of the second-highest MWTP on the auction); the starting and ending times of the auction; and physical location of auction (which is one of two separate warehouses).

As we run our analysis on auctions of pallets which have nonidentical declared retail values even within a same model-quality class of iPads, we operationalize the final price (our dependent variable) by calculating the final price of the auction as a percentage of the pallets declared retail value E. This rescale the auction's final price to the interval (0,1). Furthermore, throughout our iPad experiment, all the iPad pallets come from a single seller. Also, auctions lasted for roughly for two days on the marketplace. The same seller and auction length will provide us with a full experimental-level control on the seller's reputation and auction length parameter; previous literature reports on the existing relationship between them and the auction's final price (*cf* Hou 2007). Hence, we can dismiss any effects in changes from these two parameters on the auction's final price, and link the changes in the auction's final price to our treatment variables: auction starting price and number of auctions in each market.

In terms of starting price parameters, as the starting price of *iPad3* auctions was constant across 22 days of experiment, we exclude them from our explanatory variable lists. On the other hand, we measured the starting price level of light-use

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[4]We also collected the total number of submitted bids per auction, but as bidders submitted on average 1.04 bids (std. dev.=0.12) in each auction, both number of bidders and total bids represent the same information.

iPad2 auctions using a binary variable of $iPad2Light_{high}$ that indicates whether the starting price level of light-use *iPad2* was set to be *high* in the auction (1 when it is true, 0 otherwise). Similarly, $iPad2Mod_{high}$ is a binary variable that indicates whether the starting price level of moderate-use *iPad2* in the auction is *high* (1 when it is true, 0 otherwise). Although we are able to capture all four possible combinations of starting price pairs in the market (described earlier) with $iPad2Light_{high}$ and $iPad2Mod_{high}$ binary variables, we still need to account for their interaction. The variable $iPad2Light_{high} \times iPad2Mod_{high}$ shows whether the starting price level of both light-use and moderate-use *iPad2* is *high* (1 when it is true, 0 otherwise). The $iPad2Light_{high} \times iPad2Mod_{high}$ will help us later to tease out the starting price effect of light-use (moderate-use) *ipad2* auctions on its own auction final price conditioning on the starting price level of moderate-use (light-use) *ipad2* auctions.

Going to our other variable of interest; the supply amount of products in each market, we need to measure the aggregated number of daily auctions for each available market of light-use *iPad2*, moderate-use *iPad2*, light-use *iPad3*, and moderate-use *iPad3*. Use of these four variables enables us to account for competition *within* a market or the potential demand substitution *between* markets. Table 2.4 provides a summary and brief definition of all the variables used in this essay.

Regarding the bidders pools throughout the 22 days of the experiment, we can identify 128 unique bidders among whom 57 bidders participate in more than a single auction. Out of these 57 bidders, there are 10 interested only in *iPad2* and 17 interested only in *iPad3*, while the remaining 30 bidders (more than 50% of bidders) participated in both markets. We should also note that these 30 cross-bidders are

those who are potentially subject to substitute different generations of iPads. Also, they are key bidders in our market as they win in more than 80% of auctions (providing more than 85% of the seller's gross revenue). These 30 cross-bidders are also equally interested in both quality-grade classes within each generation. That most winners in this market can occasionally substitute iPad products from different generations and quality grades will motivate us even further to question the existence of demand substitution in such an interconnected auction marketplace.

Finally, as the objective of this essay to investigate the impact of all available starting prices and number of available auctions on final auction final price beyond a single isolated market (or a single auction), we will ask our research questions separately for each of the four markets (*light-use/iPad2*, *moderate-use/ iPad2*, *light-use/iPad3*,and *moderate-use/iPad3*). This is due to the fact that each market can fundamentally operate differently; due to its own characteristics and that to which degree they are differentiable from buyers' perspective. Hence, such an explicit market segmentation will help us to increase the uniformity of the conditions under each market when answering our research questions.

Table 2.5 reports on summary of statistics as well as the correlation matrix for auction/market variables used throughout our different analyses.

Having defined the key variables in Table 2.4 and their summary of statistics in Table 2.5 for each market, we now move forward by proposing our research hypotheses in the next section.

73

2.3 Theory and Hypotheses

In this section, we provide the arguments to introduce our research hypotheses to investigate the effects of the auction starting price and the amount of product supply on the final price in the B2B secondary market auctions described earlier. We begin with positing hypotheses on testing the impact of the starting price of high-quality (i.e. *iPad2 light-use*) and low-quality products (i.e. *iPad2 moderate-use*) on the overall performance of all available product markets varying via model and quality. We will conjecture about the effect of supply amount of the product, captured by number of auctions, on the performance of these markets, as well as the moderation effect of product's supply on the starting price/final price relationship. Before delving into our hypotheses, we should point out that throughout this section we construct our hypotheses at the abstract level and only for those markets which the number of observations and the experiment's design would allow. Hence, although we construct our hypotheses at the abstract level, it is likely that due to insufficient statistical support, we cannot test some of our hypotheses for a specific market.

Prior literature on the auction starting price (aka reserve price) and its impact on final prices (or winning bids) is extensive. In this regard, there are two conflicting theories. First, one branch of the literature (e.g., Bajari and Hortacsu 2003; Lucking-Reiley et al. 2007) argues that the auction starting price could work as an anchor (Tversky and Kahneman 1974), or more specifically as a reference price (e.g., Wolk and Spann 2008; Bruno et al. 2012). When the auction starting price serves

as a reference price or value/quality indicator, bidders may perceive a high value or quality for the focal product. This will increase their willingness-to-pay, leading to a higher final price. Although most work in this area treats auctions in isolation without accounting for interaction with adjacent and other open auctions, more recent research further explores the starting price/final price relationship in the presence of other comparable auctions that are simultaneously open. In this regard, some work (Nunes and Boatwright 2004, Häubl and Popkowski-Leszczyc 2003) provides evidence suggesting that consumers use price cues available in purchase and external environments (i.e., starting price of other auctions) as a basis for constructing their own valuations for an auctioned product.

Kamins et al. (2004) also show that, on average, seller-provided reference prices in the form of starting price raise the final price. Similarly, Li et al. (2005) associate the positive effect of starting price on final price to the quality signaling effect which helps bidders to construct their valuation. Finally, Brint (2003) finds that this positive relationship holds only when the item's value is difficult to determine.

On the other hand, some other branches of literature report a negative relationship between the auction starting price and the final price. They argue that a high starting price creates entry barriers into an auction, which will naturally decrease the final price. For instance, Ku et al. (2005) and (2006) both argue that a high starting price creates entry barriers into an auction, as opposed to a lower starting price which facilitates participation. Ku et al. (2006) also argue that the low starting price will escalate the commitment among early bidders which may lead to additional bids which will result in pushing final price higher. Furthermore, Si-

monsohn and Ariely (2008) confirm that conditioning on current price, low starting price auctions are more likely to receive additional bids. Li et al. (2005) also associate the negative positive effect of starting price on final price to the common value effect (e.g., auction fever). According to their argument, the bidder's valuation is affected by other bidder's behaviors. Hence, the more competitive the bidding process, the higher the final price, and this will lead to a negative relationship between starting price and final price.

Spann et al. (2011) (who study how bid elicitation affects retailer profit) also show that high prices can impact the construction of bidders' beliefs about the potential bid value of the winning bid, which can negatively impact the entry decision. Field experiments have established this relationship (Reiley 2006). As Choi et al. (2010) report, when the bidder entry is endogenous (which is the case in all auctions), the higher starting price does not hurt the entry to such an extent as to offset the positive impact of the starting price on the winning bid. This suggests that the auctioneer is unlikely to benefit by setting no starting price at the auction.

As Ariely and Simonson (2003) also discuss, the degree to which the positive or negative effect of the starting price on the final price will determine the net effect of the overall starting price will depend on the context and consumer types (i.e., quality-sensitive versus price-sensitive consumers). In this regard, Simonsohn and Ariely (2008) predict and successfully test on eBay's auctions of DVD movies that sellers' expected revenue from a low and a high starting price is the same.

As we study a B2B secondary market with existing after-market where the true value of items is not certain due to the used condition, we conjecture that the

positive impact of starting price on final price through signaling effect dominates its negative impact due to the lowering the number of bidders. Thus, as a baseline, we propose:

Hypothesis 1: *An increase in auction starting price of a (generation, quality) class will increase the final price in auctions of that product.*

Most prior literature has focused on studying the relationship between the auction starting price and the final price in isolation of the larger market context. However, given our B2B auction environment in which we can have several co-existing identical/comparable markets (varying across models and quality conditions) simultaneously open, it is not yet known how the relationship posited in Hypothesis 1 would change conditioning on the starting price of other available related products (i.e., products with lower or higher-quality)– if any other product exists at all.

From the marketing auction literature (e.g., Dholakia and Simonson 2005), we learn that prices from identical adjacent auctions (i.e., starting prices) can serve as signals of value and quality. In the extreme, Nunes and Boatwright (2004) also support the claim that even incidental prices on the *unrelated* product available at the time can still influence bidders' willingness-to-pay and potentially the auction's final price. Nevertheless, there is still an open question about how the relative distance between the starting price of focal auction and that of the other comparable goods can change the consumer's valuation and final price in the focal auction.

From demand substitution perspective, we can argue that when the price for a low-quality product becomes closer to that of the high-quality comparable products, the demand for the latter one will increase, as an indication for upward substitu-

tion. Hence, we should expect higher number of bidders to come in auctions of high-quality product– leading to higher final price. Conversely, if a seller increases the starting price of auctions in high-quality products, she may decrease the potential substitution effect from low-quality to high-quality market. In this situation, an increase in auction starting price of high-quality products will drive away those potential bidders who could have participated in auctions of the high-quality products if they could have submitted bids when the starting price had been lower. The emerging negative effect of reduction in substitution and number of new bidders from lower-quality market may now weaken the positive impact of starting price on final price, as we discussed in Hypotheses 1.

Another related work here is Ariely and Simonson (2003) which experimentally show that there exist the positive relationship between the auction starting price and final price (H1) but only when comparable items are not available in the immediate context. They argue that the salient external reference prices are likely to diminish the influence of value cues. For instance, to the extent that consumers can easily compare the focal item with comparable items, the effect of starting price and other cues is likely to be reduced. Coming to our low/high-quality comparable iPad markets, the presence of starting price of a low-quality comparable products in the market and its comparison with the starting price of the focal high-quality products can provide the bidders with more information about the high-quality products so that they now rely less on the quality signaling effect of starting price in high-quality market which was discussed in Hypotheses 1. This will then weaken the relationship in Hypotheses 1.

Coming to our auction context, since the starting price of both low-quality and high-quality *iPad2* products is designed to vary on a daily basis, we can extend the Hypothesis 1 by revisiting the question of the starting price and final price relationship for high-quality *iPad2* conditioning on the starting price level of the low-quality *iPad2* available at the same market[5]. According to above arguments and theory, we conjecture that an increase in auction starting price of a non-focal low-quality product will weaken the relationship stated in Hypotheses 1 in the market for the high-quality products. Thus, as a baseline, we propose:

Hypothesis 1B: *An increase in auction starting price of low-quality products will weaken the effect of auction starting price of high-quality products on their own final prices.*

As we discussed above in our B2B auction context, the closer the starting price of low and high-quality products, the higher likelihood for substitution between them– mostly upward substitution such that some bidders may now have an opportunity to substitute the low-quality products with higher quality models of the product for relatively low enough bids. This also can be argued in the same spirit of Anwar et al. (2006), which provides empirical evidence to validate cross-bidding behavior of bidders across identical competing auctions and to show that bidders tend to bid on auctions with the lowest standing bid. In other words, when choosing between two auctions with close starting prices, some bidders may desire high-quality

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[5]As the majority of *iPad2* and *iPad3* products are in high-quality condition, we might not be able statistically to tease out the impact of the auction starting price of low-quality products on its own final price conditioning on the auction starting price of the high-quality products.

items whose starting price is not higher than the starting price of low-quality items.

Similar to our reference price discussion from market literature (Nunes and Boatwright 2004; Dholakia and Simonson 2005) in Hypotheses $1B$, we can first argue that prices (e.g., starting price) from adjacent auctions can serve as external reference price to increase the bidders' willingness to pay for potential bidders in an auction for the high-quality product.This will drive up the auction final price. Also, from our prior discussion for Hypotheses $1B$ we can conjecture that when the price for a low-quality product or the high-quality products of an old version becomes closer to that of the high-quality comparable products (either from old or new version)[6], the demand for the latter market will increase. As a result, we can expect a higher final price in auctions of high-quality products. For the same exact arguments, we could posit the similar prediction between starting price of low-quality products of an older version and final price of in auctions of low-quality products of a newer version; since the latter should be preferred and ranked higher by bidders when making purchase decision in the absence of any price consideration.

To test above arguments in our B2B auction context, we will propose as follows

Hypothesis 2A: *An increase in auction starting price of low-quality products will increase the final price in auctions of high-quality products.*

Hypothesis 2B: *An increase in auction starting price of low-quality products of an older version will increase the final price in auctions of low-quality products*

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[6]The practical implication of the argument raised here is commonly used by the offline retailers such that in order to sell more of a particular product, sellers may need to offer a cheaper product (http://www.productfocus.com/pricing_psychology.php).

of a newer version.

Finally, another interesting question one could ask regarding starting prices of different products is how the change in starting price of a high-quality product of an older generation (e.g., light-use *iPad2*) will affect final prices of all auctions for a high-quality but newer generation of products (i.e., light-use *iPad3*). Note that this question cannot be addressed by the Hypothesis $2A$ or $2B$, as we now focus on the starting price of the high-quality products.

There could be different arguments from prior literature in predicting the direction of this relationship. First, again from marketing literature, it is plausible that prices (e.g., starting price) from adjacent auctions can serve as external reference price to increase the bidders' willingness to pay for potential bidders in an auction in a focal auction, open simultaneously in another market. Hence, this may drive up the final price in focal auction. Accordingly, one conjecture would be that an increase in auction starting price of high-quality products of an older version will increase the final price in auctions of high-quality product.

On the other hand, we can also argue that as the newer generation of products typically tends to be more expensive across all quality levels than the older generation (i.e., the retail value for a new *iPad2* is \$399 while this price is \$499 or \$599 for a new *iPad3*), the likelihood of downward demand substitution (from *iPad3* to *iPad2*) is higher when an alternative older version of the product is made more attractive through a higher starting price. In effect, the high-quality *iPad2* becomes a viable substitute for all high-quality *iPad3* products available in the market through the signal of the higher starting price on the *iPad2*. As a result, the potential downward

81

substitution may lower the final price in auctions of high-quality *iPad3*.

Another valid argument could be raised here, in the same spirit of Spann et al. (2011), is that when the auction's starting price of a product of an older generation goes up, bidders who are interested in the newer generation version of the product may now perceive more value which is used to shape their beliefs about what bid amount will be successful. For bidders, the higher auction's starting price of the product from an older generation may now necessitate higher bids to submit in order to win in auction of the new version product. As a result, bidders may lose their interest to participate in auction of new-version product. This may lead some bidders to withdraw from the market and postpone their purchase of the new-version product. Hence, another possible conjecture here could be that an increase in auction starting price of high-quality products of an older version will decrease the final price in auctions of high-quality product.

We will allow the empirical analysis to determine the extent to which above arguments are valid, but we propose the following:

Hypothesis 3: *An increase in auction starting price of high-quality products of an older version will decrease the final price in auctions of high-quality products of a newer version.*

With regards to the amount of supply for each product– which is adjusted by number of open auctions, we speculate an increase in the number of open auctions for a (generation, quality) class of products will decrease the final price in auctions of that product. This is in the same spirit of Chan et al. (2007), who study the negative impact of number of similar auction on bidders willingness to pay. Another related

argument raised in Dholakia et al. (2002) is that in a market with relatively large number of auction listings, there is less likelihood for an auction being overlooked. Thus, bidders will bid in greater number the auctions rather than being gravitated toward those auctions with already existing bids. This could naturally reduce the average number of bidders per auction. Consistent with this literature, we predict that the presence of competition due to high supply of products, as a result, more number of auctions will lower the number of bids per auction, and this leads to the lower final prices (Ariely and Simonson 2003). Therefore, we propose the following hypothesis:

Hypothesis 4: *An increase in supply for a (generation, quality) class will decrease the final price in auctions of that product.*

Due to the characteristics of our auction marketplace, which can host simultaneously different types of markets (varying across model and quality condition), we can also investigate how the performance of a focal auction interacts with the number of the auctions in all non-focal markets. For instance, we want to find out how the number of open auctions in the low-quality *iPad2* market will impact the auction's performance in the market for the high-quality *iPad2* and *iPad3*, or vice versa.

As Dholakia et al. (2002) mention, when listing volume increases, bidders have more options to choose and learn. This will then attract more bidders into the auction marketplace and increase the activity level in the market such that it results in lower number of overlooked auctions in the market. Higher activity level at the

aggregated level[7] can signal quality and value into the bidders' valuation problem when assessing the true value for the superior product on the vertical differentiation ladder. As bidders may now perceive higher value for the high-quality products (e.g., Kamin et al. 2004), they are more likely to bid in the market with higher quality products. This will increase the number of bidders and naturally final price in the market of high-quality products. Accordingly, we conjecture that an increase in supply for low-quality products will increase the final price in auctions of high-quality products

On the other hand, similar to our discussion regarding upward substitution in Hypothesis $2A$ and $2B$, it is likely that bidders from low-quality market will switch to the auctions of high-quality market if the auctions in the high-quality market look more attractive. We know from Hypothesis 4 that more supply of iPads in high-quality market will reduce the final price in these auctions, and, hence, this may attract some bidders from low-quality to the high-quality market. Thus, we can expect to see a decrease in final price of auctions in the market of low-quality products.

Therefore, we propose the following hypotheses:

Hypothesis 4A: *An increase in supply for low-quality products will increase the final price in auctions of high-quality products.*

Hypothesis 4B: *An increase in supply for high-quality products will decrease the final price in auctions of low-quality products.*

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[7]Note that according to Hypothesis 4 due to more supply of goods, we might expect lower number of bidders and final price per auction.

The last interesting question which has not been explicitly tested in prior literature is studying the importance of starting price of final price in a focal auction depending on the amount of supply for that product in the market. There are some insightful arguments and findings from literature which can help us to conjecture about above question. First, Dholakia et al. (2002) report when the volume of similar listings goes up, due to more existing alternatives, the influence from other auctions or bidders (e.g., herding bias) in bid formation decreases. Hence, we can posit that the importance of starting price in driving the final price (Hypothesis 1) will diminish if there are more supply of the products in the market. Furthermore, from Ariely and Simonson (2003), we can conclude that the salient external reference prices are likely to diminish the influence of value cues. As a result, to the extent that consumers can easily compare the focal item with comparable items due to more supply of the product, the effect of starting price on final price is likely to be reduced.

Motivated by above arguments, we propose the following hypothesis:

Hypothesis 5: *An increase in supply for a (generation, quality) class will weaken the effect of auction starting price of that product on its own final price.*

In the next section, we discuss the empirical analysis conducted before reporting on the results in Section 2.5.

2.4   Empirical Analysis

In this section, we proceed with the empirical analysis in order to answer our research hypotheses questions. We use a linear model estimation approach to the link auction's starting price and amount of supply in each market to the auction's final price, while having control of the other auction parameter variables. Based on the hypotheses developed in the previous section, the following generalized model will be used:

$$Final\ Price = f\big(Q, Y, iPad2Light_{high}, iPad2Mod_{high},$$

$$iPad2Light_{high} \times iPad2Mod_{high}, NiPad2Light, NiPadMod, NiPad3light,$$

$$NiPad3Mod, Control\ Variables\big) \tag{2.1}$$

In the above regression model, Q and Y simply capture the pallet-specific which may also influence the bidders willingness to pay, all else being equal. For example, the number of *iPad3* units available in a pallet and whether each *iPad3* has a 16GB memory may change the percentage of which the pallet will be recovered in auctions. Control variables also include the fixed effects of the starting/ending time of auctions and the physical location of the warehouse. Table 2.4 summarizes the description of all variables used in above equation.

We should note that unlike prior literature, which uses N (the unique number of bidders in the same auction) in predicting the final price (e.g., Bajari and Hortacsu 2003), we will not use N in the aforementioned model. As a result, our approach here is to study the impact of the auction starting price and number of auctions on the final price, which are due to either change in N or some other reason (i.e.,

reference price argument). Nevertheless, we use the co-variate N to explain some of our findings[8].

The ordinary least square method (OLS) is used to estimate the regression model in predicting the final price. The results will be shown in Table 2.6 and 2.7 for auctions run between day 1 and 22 of our experiment in which the starting price of *iPad3* auctions is fixed. As a result, the starting price of *iPad3* is excluded from our analysis and RHS variables in Equation 2.1 To answer our research hypotheses, we first create a basic model for each particular market/markets (base model). Then, to be able to discern the impact of each variable individually, we will add the variables of interest one by one. This will allow us to identify the most robust variables while holding all other variables constant. This is also a cautious approach when we later interpret regression results if two variables, in particular the iPad's supply in different markets, are highly correlated. Hence, Table 2.6 and 2.7 is designed such that we are able to test different hypotheses which are specific and related to *a* particular market through the different columns.

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[8]We also have done a parallel analysis to our current one in which we included N in predicting the final price of auctions. We treated N as an endogenous explanatory variable which is determined during the course of the auction. We argue that the number of available auctions (for both focal and all non-focal market) will impact the auction's final price via the number of bidders. Hence, we can use the number of auctions, which determines the supply of the products, as valid *instruments* to account for endogeneity of the number of bidder. We used $2SLS$ regression with the number of bidders in the first stage and final price in the second stage. The results from $2SLS$ regression models are consistent with our findings from the current analysis reported in Table 2.6 and 2.7.

Table 2.6 shows the result of the estimation for final price in light-use (Columns 1-6) and moderate *iPad2* auctions (Columns 7-11). Note that the light-use *iPad2* market has the highest number of observations (272 auctions) in our experiment, in which we manipulated the starting price level (10 days have a *low* starting price while 9 days have a *high* starting price). In addition, light-use *ipad2* auctions, on average, have the highest final price per auction compared to others (mean=0.77, st. dev.=0.04; from Table 2.5).

Column (1) in Table 2.6 reports on the base model in predicting the final price of a light-use *iPad2* auction including the starting price dummies ($iPad2Light_{high}$, $iPad2Mod_{high}$) for both light-use and moderate *iPad2* auctions, as well as their interaction term ($iPad2Light_{high} \times iPad2Mod_{high}$). We will add this interaction term as we are also interested in studying how the relative difference between the starting price of the adjacent market, which may determine the degree of demand substitutability across markets, will affect the final price. As a result, the interaction term can differentiate between the impact of starting price in each market conditional on the starting price level in the other market. The model in Column (1) also includes the number of available auctions for the focal light-use *iPad2* market ($NiPad2Light$).

In Column (2), we will add the interaction term between the starting price dummy for light-use *iPad2* auctions and the number of auctions in the same market ($iPad2Light_{high} \times NiPad2Light$) to our base model of Column (1) of Table 2.6. This allows us to establish the moderation effect and to test whether the main effect of a focal auction's starting price variation is weakened or intensified by the

number of auctions in the the same market. In Column (3) of Table 2.6, we will add $NiPad2Mod$ into the base model as the moderate-use $iPad2$ market could have, arguably, the most comparable iPad-to-iPad in the focal auction. As we can see, the regression model in Column (3) demonstrates a better predictive power and is statistically significant in F-statistics compared to that of Column (1).

Columns (4) through (6) in Table 2.6 will respectively add $NiPad3light$ and $NiPad3Mod$ into the model of Column (3) as the $iPad3$ may also be substituted for the $iPad2$ in the focal auction. The results from Columns (4)-(6) will also confirm that accounting for the number of auctions from a newer model of the product (whether at the same or lower-quality level) may play a role in determining the final price in the focal $iPad2$ auctions. Column (6) in Table 2.6 will illustrate the model which includes the starting price dummies and iPad's supply in all four markets. The results from Column (6) will confirm the importance of the starting price level and the amount of iPad's supply in non-focal auctions on the performance of the focal auction.

Likewise, we can repeat our step-wise analysis in Columns (1)-(6) of Table 2.6 for the moderate-use $iPad2$ and report them in Columns (7)-(11) of Table 2.6. However, it is expected that due to the lower number of observations for moderate-use $iPad2$ auctions (100 auctions), we may not have a statistically significant impact for the starting price level in $iPad2$ auctions and the variables which represent number of auctions in the moderate-use $iPad2$ market. Hence, we will only validate those hypotheses for which we can find support[9].

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[9]Due to the limiting number of the days to run experiment, our experiment was originally

As light-use *iPad3* auctions are the second most populated auction sample in our experiment (189 auctions), we will report on the performance of this market as a function of starting prices in the *iPad2* market and the number of auctions in all four markets. Table 2.7 presents the result for regression model in estimating the final price of light-use (Columns 1-5) and moderate *ipad3* auctions (Columns 6-10). We will repeat our analysis in Columns (1)-(11) (except for Column 2) of Table 2.6 in Table 2.7 to represent the *iPad3* market.

To test for multicollinearity– which may exist across the amount of iPad's supply (or number of auctions) in different variables, we computed the variance inflation factors (VIF). The highest VIF across all regression models is 7.2, which is lower than 10, which is below the threshold value reported by Belsley et al. (1980). As a result, multicollinearity cannot be an issue in our empirical analysis. We will present the discussion of results as well as alternative explanations for our findings in the next section.

2.5   Discussion of Results

In this section, we begin by discussing the summary statistics in order to have a better understanding of how each of the four markets operated. First, one surprising observation from Table 2.5 is that there are, on average, less than 3 bidders who have participated in auctions of *iPad2* and *iPad3*. This number is definitely lower than B2C settings (e.g., Simonsohn and Ariely 2008) and also less than our other

designed to reveal some information about the performance of the light-use iPad marketplace (high-quality products) which accounts for the seller's most gross revenue.

studied B2B marketplace in essay one. The low number of bidders (mean=2.69, std. dev=0.7) in each auction of our marketplace can highlight the critical role of the starting price in further driving the auction's performance; as Reiley (2006) argues, the gains to setting an optimal starting price becomes significantly bigger if the number of bidders is reduced. Besides, the low mean and variance for the number of bidders in each auction may also imply that we study a market in which bidders had a fair amount of information about the true value of the items, and they were not willing to participate in auctions that went beyond certain prices. In such a marketplace, it is plausible that a seller can significantly benefit by attracting one more additional bidder into an auction, and this may be achievable via varying the substitution effect across different markets.

In terms of the final price of auctions, from the Table 2.5 and our pair-wise t-tests with p-values $<.01$, we can conclude that light-use *iPad2* auctions has the highest final prices (mean=0.77, std. dev=0.04), moderate-use *iPad2* auctions has the second highest final prices (mean=0.74, std. dev=0.05), light-use *iPad3* auctions has the third highest final prices (mean=0.73, std. dev=0.03), and finally, moderate-use *iPad3* has the worst final prices (mean=0.70, std. dev=0.04) among all four markets.

That higher-quality products on the vertical differentiation ladder result in higher prices is not surprising, but that the older model of a product recovers at the higher prices compared to its newer version counterpart needs some explanation. From our findings (i.e., the negative coefficients of Y in Table 2.7) and also from consultation with the channel manager, we can conclude that buyers are willingness

to pay higher prices, as the percentage of E, for pallets with cheaper per-unit value Y. There could be different unknown reasonings for this which is not at the scope of this essay to explore. For instance, bidders' financial constraint (Che and Gale 1998) may make smaller bidders participate more likely in auctions with cheaper retail value. Hence, we can expect more number of bidders, and consequently higher final prices for pallets with cheaper units. As the *iPad2* has large Y (\$399) compared to the *iPad3* (\$499 or \$599), for a given condition grade, we can expect higher final prices for the *iPad2*. Furthermore, another reason for such an outcome could be the small difference between the auction's starting prices in *iPad3* and starting prices in *iPad2*. As we will show later, this closeness in starting prices may dampen the final prices in the *iPad3*.

Going to our hypotheses testing, we divide our discussion of results into three parts. First, we test the hypotheses related to the auction's starting prices (Hypotheses 1, 1B, 2A, 2B and 3). We will then report the results on testing the hypotheses 4, 4A and 4B in regard to the supply of iPads through number of auctions. Finally, we finish our discussion with testing the moderation effect of number of open auctions (supply of product) on starting price/final price relationship (Hypothesis 5).

2.5.1 The Impact of Starting Prices on Auctions' Final Price

We can only test hypotheses 1 and 1B across *iPad2* markets with varying starting prices. First, from Column (1)-(5) of Table 2.6, while controlling the start-

ing price of moderate-use $iPad2$ auctions and the interaction term between two starting price dummies, we find enough evidence to support a positive and statistically significant impact of $iPad2Light_{high}$ dummy variable on the final price of light-use $iPad2$ auctions. While the coefficient for $iPad2Light_{high}$ in Columns (1) and (3)-(5) is somewhere between 0.015 and 0.025, in Column (2), this number is significantly higher due to the interaction term of $iPad2Light_{high} \times NiPad2Light$. Finally, there is only a weakly positive coefficient at p-value>0.1 significance for $iPad2Light_{high}$ in Column (6) of Table 2.6. Hence, we cannot reject this hypothesis in the light-use $iPad2$ market. One plausible explanation for the lack of statistical significance in the positive relationship between $iPad2light_{high}$ and the final price in Column (6) of Table 2.6 is the possible negative correlation between $iPad2light_{high}$ and $NiPad3Light$ (added in Column 6 compared to Column 5) (See Table 2.5).

Hypothesis $1B$ investigated the main impact of the starting price of the light-use $iPad2$ auction by conditioning on the starting price level of moderate-use $iPad2$ auctions simultaneously open. The motivation for Hypothesis $1B$ arose as we predicted the closeness between the starting price level of a low and high-quality market may influence the degree to which the substitution varies across two markets, which can impact the auctions' performance. We will do this investigation by adding the interaction term between the two starting price dummies in the $iPad2$ market ($iPad2Light_{high} \times iPad2Mod_{high}$) across all specifications in Table 2.6. As we can see in Columns (1)-(6) of Table 2.6, we observe a negative and statistically significant coefficient for $iPad2Light_{high} \times iPad2Mod_{high}$[10]. That said, we can provide enough

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[10]Again, due to the possible negative correlation between $iPad2light_{high}$ and $NiPad3Light$ in

empirical evidence to support Hypothesis 1B for the light-use $iPad2$ market, and conclude that the positive impact of an increase in the starting price level of the light-use $iPad2$ auction (already established in Hypothesis 1) *shrinks* when the starting price level in moderate-use $iPad2$ auctions increases ($iPad2Mod_{high}=1$). To the extreme, this will turn the overall net impact of the starting price of the light-use $iPad2$ on its own final price *negative* (the sum on coefficients of $iPad2Light_{high}$ and $iPad2Light_{high} \times iPad2Mod_{high}$) across all Columns (1)-(6).

In substantive terms and as we discussed in Section 2.3, the new finding of Hypothesis 1B implies that substitution from the moderate-use $iPad2$ to light-use $iPad2$ market exists and its absence can hurt the light-use $iPad2$ market. In effect, when starting prices for the moderate-use $iPad2$ auctions are *high* (65%), some bidders can now choose to bid on the auctions of the light-use $iPad2$ whose starting price is lower (55%). In this situation, if a seller decides to increase the starting price level of the light-use $iPad2$ from 55% to 70%, this might drive away those bidders who used to submit bids in the light-use $iPad2$ auction when the starting price was at 55%. As a result, we will expect a reduction in the bidders' traffic in light-use $iPad2$ market when $iPad2Light_{high}=1$ compared to when $iPad2Light_{high}=0$ (2.3 *versus* 3.1 bidders, a difference of means t-test significant at $p<0.01$), thereby lowering the final price.

Moving to Columns (7)-(11) of Table 6.2 which report on the moderate-use $iPad2$ markets, across all specifications, we can neither support nor reject the Hy-

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Column (6) of Table 2.6, the coefficient for $iPad2Light_{high} \times iPad2Mod_{high}$ is smaller compared to the Columns (1)-(5).

pothesis 1. One main reason for this result is the low number of observations under each combination of starting price pairs in the moderate-use $iPad2$ market (see Table 2.3), which is not enough for the sake of testing for the Hypothesis 1. Nevertheless, we can still see the positive sign for coefficient of $iPad2Mod_{high}$ in Columns (7)-(11) of Table 2.6.

Hypotheses $2A$ and $2B$ pertained to the effect of the starting price of low-quality products on the final price of higher-quality products or the low-quality products of a newer generation. We can test Hypotheses $2A$ and $2B$ for both light-use $iPad2$ and $iPad3$ markets. First, across all specifications reported in Columns (1)-(6) of Table 2.6, we see that the coefficient of $iPad2Mod_{high}$ is significant and positive, providing support for Hypothesis $2A$ in the light-use $iPad2$ market. The effect size for the coefficient of $iPad2Mod_{high}$ simply implies that when the starting price of the moderate-use $iPad2$ auction increases from low (50%) to high (65%), the final price in light-use $iPad2$ auctions improves by 2-3%. Furthermore, as we find out from Columns (1)-(6) of Table 2.6, the increase in the final price of light-use $iPad2$ auctions due to the increase in the auction's starting price of the moderate-use $iPad2$ is *higher* when $iPad2Light_{high}=0$ (no impact from the coefficient of $iPad2Light_{high} \times iPad2Mod_{high}$). This is again due to the rise in substitution from moderate-use to light-use $iPad2$ market when the difference between the starting prices of both iPad markets is small.

Similarly, from Columns (1)-(5) of Table 2.7, we can support the Hypothesis $2A$ with regard to the effect of the starting price in auctions of a low-quality market (moderate-use $iPad2$) on the final price of auctions for high-quality product

95

(light-use *iPad3*. Across all specifications in Columns (1)-(5) of Table 2.7, we can observe a positive and statistically significant coefficient for $iPad2Mod_{high}$ (0.015-0.025, $p<0.01$). This positive coefficient implies that, all else being equal, if the starting price of the moderate-use *iPad2* auction goes up from low (50%) to high (65%), the final price in light-use *iPad3* auctions improves around 2%, and this will again validate the Hypothesis 2*A*.

Coming to Hypothesis 2*B* and from Columns (6)-(10) of Table 2.7, we can support Hypothesis 2*B*. The positive and statistically significant coefficient for $iPad2Mod_{high}$ in the regression model of Columns (6)-(10) in Table 2.7 will indicate when the starting price of the moderate-use *iPad2* auction increases from low (50%) to high (65%), the final price in moderate-use *iPad3* auctions improves by more than 3%. Note that as the starting price of moderate-use *iPad3* auctions is fixed at 62%, which is between the low and high starting price of moderate-use *iPad2* auctions, the substitution argument still holds and will explain this result between moderate-use iPad products of the old and new generation.

Finally, Hypothesis 3 predicted that the starting price of high-quality products of an older generation has a positive impact on the final price of high-quality products of a newer generation. We can only test this hypothesis in the light-use iPad markets. From Columns (1)-(5) of Table 2.7, we see that across all specifications, the impact of $iPad2Light_{high}$ on the final price of light-use *iPad3* auctions is statistically significant and negative, all else being equal. Therefore, we have empirical evidence to support Hypothesis 3. The effect size of $iPad2Light_{high}$ coefficient on the final price of the light-use *iPad3* auctions is somewhere between -0.02 and -0.033 (de-

pending on the model specification) at the 0.01 p-value significance. As we discussed earlier, one possible driver of this result is a decrease in the average number of final bidders in each auction of light-use *iPad3* product. In effect, the high-quality *iPad2* may now become a viable substitute for all high-quality *iPad3* auctions available in the market. Also, a potential winner in the auction of light-use *iPad3* may now have a belief about paying a higher final price due to the high starting price in light-use *iPad2* auctions. As a result, some potential bidders in light-use *iPad3* auctions may withdraw and postpone their purchase decision, leading to lowering the final price in light-use *iPad3* auctions

Hypothesis 3 would suggest that a seller could improve the auctions' performance of the most premium products (i.e., light-use *iPad3* in our market) by differentiating this market from others, i.e., choosing a very high starting price compared to other inferior markets. This result looks surprising at first glance, however, we can find much supportive evidence in offline markets in which sellers of premium goods are suggested to position their premium goods in strategic locations, expecting consumers to see these high-priced items first before seeing other cheaper substitutable products.

2.5.2 The Impact of Number of Auctions (Supply of Products) on the Auctions' Final Price

Moving to our hypotheses with regard to supply of the iPad product– determined by number of auctions, we begin by testing Hypothesis 4. Hypothesis 4 is

the most preliminary prediction about the competition effect from other identical auctions on the performance of a focal auction, all else being equal. We can independently test the Hypothesis 4 on four markets. First, Columns (1)-(6) of Table 2.6 will consistently report on a negative and statistically significant coefficient for $NiPad2Light$ in validation of the Hypothesis 4 in the light-use $iPad2$ market. In terms of the effect size, one standard deviation increase in $NiPad2Light$ (5.9 auctions) will lead to, on average, a 1-1.5%of E decrease in the final price in the light-use $iPad2$ market. Furthermore, from Columns (1)-(5) of Table 2.7, we observe a negative and statistically significant coefficient for $NiPad3Light$ which negatively affects the final price of light-use $iPad3$ auctions. Likewise, one standard deviation increase in $NiPad3Light$ (4.2 auctions) will lead to, on average, a 1-1.5% of E decrease in the final price in the light-use $iPad3$ market.

Going to the moderate-use $iPad3$ market, we can still provide enough empirical support for Hypothesis 4 due to the negative coefficient of $NiPad3Mod$ (-0.0035, $p<0.01$) in Columns (7)-(8) of Table 2.7. However, we cannot confirm Hypothesis 4 in the moderate-use $iPad3$ market from Column (6), and (9)-(10) of Table 2.7. One main reason for this could be the significant positive correlation between $NiPad3Mod$ and $NiPad2Mod$ in the moderate-use $iPad3$ market (See Table 2.5). Finally, we can neither support nor reject Hypothesis 4 for the moderate-use $iPad2$ market in Columns (7)-(11) of Table 2.6. Nevertheless, we can still see the negative sign for coefficient $NiPad2Mod$ across all specifications, consistent with the prediction of Hypothesis 4.

Hypothesis $4A$ predicted the positive impact of the number of auctions in

low-quality products on the final price in auctions of high-quality products. First, Columns (2)-(3) of Table 2.6 report on a positive and statistically significant coefficient for $NiPad2Mod$ in predicting the final price of light-use $iPad2$ auctions. Furthermore, Column (6) of Table 2.6 will also show a positive and statistically significant coefficient for $NiPad3Mod$ while that of $NiPad2Mod$ is insignificant. We believe the reason for this sudden lack of significance of the $NiPad2Mod$ coefficient is a high correlation between $NiPad3Mod$ and $NiPad2Mod$ (r=0.72). Nevertheless, the evidence from Columns (2), (3) and (6) of Table 2.6 is enough to support Hypothesis $4A$ for the light-use $iPad2$ market.

On the other hand, we can only find support for Hypothesis $4A$ in the light-use $iPad3$ market in which the low-quality market belongs to the same generation as the high-quality products. In other words, while from Columns (3) of Table 2.7, we can find a positive coefficient on $NiPad3Mod$ (0.004, p<0.01) in support of Hypothesis $4A$, we cannot find support for Hypothesis $4A$ in the light-use $iPad3$ market from Columns (4)-(5) of Table 2.7. The reason for that is when both $NiPad3Mod$ and $NiPad3Mod$ variable co-exist (Columns 4, 5 of Table 2.7), we will see an unexpected negative coefficient on $NiPad2Mod$. We do not yet have a valid explanation for this result. That said, we can only support the claim for Hypothesis $4A$ in the light-use $iPad3$ market only when the low-quality market belongs to the same model (i.e., $iPad3$ generation).

Finally, in regard to Hypothesis $4B$, we could only find support for the impact of the number of auctions from a high-quality market on the auction's final price of the low-quality market only if both low and high-quality markets belong to the

same model (i.e., same iPad generation). First, for the moderate-use *iPad2* market, Columns (8)-(11) of Table 2.6 consistently show a negative and statistically significant coefficient for $NiPad2light$ (respectively -0.0027, -0.0035, -0.0027, -0.0038, $p{<}0.01$) in support of Hypothesis $4B$. In terms of the effect size, one standard deviation increase in $NiPad2Light$ (5.5 auctions) will lead to roughly a 1%-1.5% of E decrease in the final price in the moderate-use *iPad2* auction. Going to the moderate-use *iPad3* market and $NiPad2light$ coefficient in Columns (7)-(10) of Table 2.7, we can still support Hypothesis $4B$ across the *iPad3* generation. One standard deviation increase in $NiPad3Light$ (3.2 auctions) will lead to roughly a 1% of E decrease in the final price in moderate-use *iPad3* auction.

2.5.3 The Moderation Effect of Number of Auctions on the Main Effect of Starting Prices on Auctions' Final Price

As our last prediction, we hypothesize the moderation effect of the number of identical auctions on the impact of an auction's starting price on its own final price. We could only test this hypothesis on the light-use *iPad2* market due to the relatively large number of observations in this market. This hypothesis can have a very important implication for the seller as its prediction can guide the seller to either increase or decrease the auction's starting price depending on the number of auctions in that market. Column (2) of Table 2.6 is used to this hypothesis. As we can see the negative and statistically significant coefficient for the interaction term of $iPad2Light_{high} \times NiPad2Light$ (-0.0046 $p{<}0.01$) will validate Hypothesis

5. This implies when market will supply more identical iPads, the positive impact of $iPad2Light_{high}$ on light-use $iPad2$ final price will decrease. Consequently, the seller may now afford to choose a low starting price to benefit more from increasing in bidder's entry into the auctions (i.e., Ku et al. 2005, 2006).

2.6   Conclusion

In this essay, we started with identifying the gap in the online B2B auctions with regards to product differentiation in used secondary market. We address this gap by running a controlled field experiment on the auction site of one of the nation's largest online auction wholesale liquidators. The objective of our experiment is to investigate the formation of auction's final price across different comparable/related markets (varying via model and quality), beyond a single market (or a single auction) which is the focus of most prior literature (e.g., Bajari and Hortacsu 2003; Lucking-Reiley et al. 2007). One main challenge in studying a particular market in such an interconnected marketplace is the ability to tease out the impact of other markets from its own, which can drive the performance of auctions.

Having fair control on auction and market specifics (e.g., the auction starting price and number of open auctions in all existing markets) while exogenously determining the characteristics of the products (e.g., models, qualities), we designed a field experiment which was directly aimed at understanding the extent to which (i) the starting price of the auction, and (ii) the number of auctions for a specific (model, quality) which implies the amount of supply for that product, interact to

impact an auction's final price.

Our work in this essay contributes to the operations management and auction literature by providing the first empirical evidence in support of demand substitution in a B2B auction of used products across different comparable markets. Our results also provide a more nuanced understanding of the impact of starting price on the final price of a focal auction conditioning on the starting price levels of other available competing products. Furthermore, we are among the first researchers who have accounted simultaneously for both starting price and the supply of different products when studying the performance of auctions for a particular product. We should also point out that despite the challenges we faced to comply with sellers daily operational requirements, the scale of our field experiment was by far one of the most extensive run in a real B2B marketplace with business buyers.

Our result suggests that, consistent with prior literature, an increase in the starting price of a focal auction will positively impact the final price of its own auction; however, this relationship is negativity moderated by the high starting price level in an auction from a comparable market simultaneously open. This result is driven due to the potential substitution from the non-focal auction to the focal auction, in particular when starting price of both non-focal and focal auctions is close. However, the increase in starting price of focal auction will attenuate the substitutability, thereby lowering the flow of bidders from the non-focal auction to the focal auction. This will then negatively impact the final price in the focal auction.

Our finding also supports the an increase in the auction's starting price in a

low-quality market will positively impact the final price in an auction of a higher quality or new generation model product. From managerial viewpoint, this result suggests that if, as is the case with many wholesale liquidators, the objective is to improve the performance of higher-quality or newer-generation inventory, then the seller would be well advised to set the lower-end product's starting price *high* so as to improve the substitution from an inferior product to a superior one. On the contrary, it is plausible that the seller should do the opposite if her objective is the fast-removal of lower-end products in order to prevent directing bidders to higher-end auctions.

We find evidence that an increase in auction starting price of a high-quality product of an older generation (light-use *iPad2*) will have a negative effect on the final prices of all auctions for the newer generation of products (light-use *iPad3*). This noble result in B2B auction context is consistent with the current practice in offline retail markets in which the sellers of premium goods are suggested to position their premium goods in strategic locations, expecting consumers to see these high-priced items first before seeing other cheaper substitution products.

We also tease out some patterns of demand substitution across generations and quality class, depending on the amount of which products are supplied. We have successfully tested and showed that an increase in the number of auctions in high-quality product will decrease the final price in auctions of low-quality products. This finding will simply show that an increase in the supply of products in high-quality products will decrease the average auction's price in the market of the lower-quality products. On the other hand, we also showed that the opposite statement is true

with this caveat that the supply of products from low-quality products will benefit the auction's performance of the higher-quality products only if they belong to the same model of the low-quality market.

Finally, we identify a diminishing importance for the starting price as the market supplies more products. This finding has implications for development some guidance in choosing the appropriate starting price depending on the volume of posted auctions. For instance, a seller can still benefit from posting a low starting price if she is in need of liquidating a lot of products for a given day. A common concern here raised by the managers of B2B secondary marketplace is the fact that a low starting price can significantly put making a certain profit at risk; therefore, to hedge this risk, they choose a high starting prices which may also be hurtful due to the low bidders' participation rate in the auction. That said, this result recommends that if the seller is in need of auctioning off many products, choosing a low starting price can be beneficial compared to a high starting price, as the former would attract more bidders into the auction leading to increase the final price.

From the product assortment and policy making perspective, our findings about the formation of the final price in iPad interconnected market can provide a seller with some preliminarily managerial implications to strategically manage auctioning off the right mix of products at the right starting price. As a B2B seller of secondary market merchandise, disregarding the strategic consideration in positioning the products in a marketplace, like iPad tablet, with no intense competition (less than 3 bidders per auction) may lead to suboptimal outcomes for the seller. For instance, a 4% decrease in final price of auctions (one std. dev) in the studied

iPad marketplace can translate into $ 50000-$ 60000 less revenue on a $ 1 million market. As a large seller (like the one we studied in Essay 1) can post auctions with the annual worth of a $billion, a few percentage increase in auctions' final prices can lead to million dollars of excess revenue. The decision of choosing the right price for the right mix of products is highly dependent on the inventory constraint. For instance, if in our studied iPad marketplace, the seller is left with a lot of light-use *iPad2* auctions, it is recommend to first post a several auctions for the lower-quality product whose starting price is chosen high in order to benefit from substitution effect. Also, it is beneficial in order to intensify the substitution effect, the seller chooses a low auction's starting price in light-use *iPad2* market.

There are a number of limitations in our experiment and analysis that should be acknowledged and perhaps addressed in future research. First, we should point out that that our experiment will fail answering the question of which, how a seller can maximize the expected daily profit. In fact, answering to such a question necessitates running more extensive field experiments with higher number of days and treatments (desirably at the full-factorial form) while manipulating for more level of starting prices in all four markets, as well as different level for supply of iPads in each market. Another potential avenue for future research is to investigate the behavior of bidders and their choice models in such an interconnected market, in which some bidders (i.g., cross-bidders) will substitute their bids in different markets. Understanding such bidders' behavior can help the seller to identify the key bidders who can be explicitly encouraged to bid or not bid in a particular auction through some appropriate decision tool.

2.7   Figures and Tables

Figure 2.1: The Snapshot of the Results Page for iPad Marketplace

	Auction Title	Condition	Seller	Qty	Lot Price	Bids	Location	End Time ▲	Watch
	Salvage Apple iPads - Original MSRP $3,716.53	Salvage	techexcess	5	$100.00	0	Texas	03/22/2013 07:35 PM	⊕
	Salvage Apple iPads - Original MSRP $3,613.53	Salvage	techexcess	5	$100.00	1	Texas	03/22/2013 08:00 PM	⊕
	Salvage Apple Ipads - Original MSRP $3,323.94	Salvage	techexcess	4	$100.00	1	Texas	03/22/2013 08:20 PM	⊕
	Salvage Apple Ipads - Original MSRP $3,784.51	Salvage	techexcess	6	$160.00	4	Texas	03/22/2013 09:20 PM	⊕
	Light Use Apple iPads - Original MSRP $1,827.99	Returns	techexcess	3	$775.00	2	Texas	03/23/2013 09:10 AM	⊕
	Salvage Apple iPads - Original MSRP $3,124.52	Salvage	techexcess	5	$100.00	0	Texas	03/23/2013 10:15 AM	⊕

Notes. The 'Lot Prices' will show the current highest price for each auction while 'Bids' reports on number of existing bids.

Table 2.1: Starting Price Level for All Markets

Quality Grade	iPad2		iPad3
	Low	*High*	*Fixed*
Light-use	55%	70%	66%
Moderate-use	50%	65%	62%

Table 2.2: The Starting Price Profile and Number of Auctions for days of Experiment

Day	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22
Light-use *IPAD2* (# of Auctions)	0	23	27	0	17	5	0	10	4	11	16	12	12	8	18	15	10	12	16	21	18	17
Moderate-use *IPAD2* (# of Auctions)	0	1	10	0	7	1	0	10	2	9	8	2	2	4	6	7	5	4	7	2	3	10
Light-use *IPAD2* (Starting price)	–	High	Low	–	High	Low	–	Low	Low	Low	High	Low	High	High	High	Low	High	High	High	Low	Low	Low
Moderate-use *IPAD2* (Starting price)	–	High	Low	–	Low	High	–	Low	High	High	High	High	Low	High	Low	Low	Low	Low	High	High	Low	High
Light-use *IPAD3* (# of Auctions)	16	17	13	14	8	0	9	8	4	6	8	6	7	8	8	8	2	0	9	15	14	9
Moderate-use *IPAD3* (# of Auctions)	1	2	7	0	5	0	0	8	5	8	4	4	4	4	3	4	4	0	4	1	0	3

Notes. In three days of the experiment (Day=1, 4, 7), we have no posted *iPad2* auctions.

107

Table 2.3: Breakdown of Auctions for Each Combination of iPad2's Starting Price Pair

	Combination 1	Combination 2	Combination 3	Combination 4
Light-use *IPAD2* (Starting price level)	*High*	*High*	*Low*	*Low*
Moderate-use *IPAD2* (Starting price level)	*High*	*Low*	*Low*	*High*
Number of days in experiment	4	5	4	6
Total Number of light-use *iPad2* Auctions	63	69	70	70
Total Number of moderate-use *iPad2* Auctions	20	24	30	26
Total Number of light-use *iPad3* Auctions	42	25	43	40
Total Number of moderate-use *iPad3* Auctions	14	16	19	21
Avg. Number of Daily light-use *iPad2* Auctions	15.8	13.8	17.5	11.7
Avg. Number of Daily moderate-use *iPad2* Auctions	5	4.8	7.5	4.3
Avg. Number of Daily light-use *iPad3* Auctions	10.5	5	10.8	6.7
Avg. Number of Daily moderate-use *iPad3* Auctions	3.5	3.2	4.8	3.5

Table 2.4: List of Variables Used in Empirical Analysis of Chapter2

Variable	Definition
Final Price	The price of the second-highest maximum-willingness-to-pay on the auction as a % of E
N	The final number of unique bidders in the same auction
Q	The number of items in each pallet
E	$ declared/retail price of all items in each pallet
Y	Avg. per-unit $ declared/retail price in each pallet (E/Q)
$iPad2Light_{high}$	Dummy variable indicating whether light-use *iPad2* auction has high starting price (=1) or low starting price (=0)
$iPad2Mod_{high}$	Dummy variable indicating whether moderate-use *iPad2* auction has high starting price (=1) or low starting price (=0)
$NiPad2Light$	Number of daily posted light-use *iPad2* auctions
$NiPad3Mod$	Number of daily posted moderate-use *iPad2* auctions
$NiPad3Light$	Number of daily posted light-use *iPad3* auctions
$NiPad3Mod$	Number of daily posted moderate-use *iPad3* auctions

Table 2.5: Summary of Statistics and Correlation Matrix for iPad2 and iPad3 Markets

Market		Variable	Observations	Mean	Std. Dev.	1	2	3	4	5	6	7	8	9
Light-use iPad2	1	Final Price	272	0.77	0.04									
	2	N	272	2.84	0.74	0.52*								
	3	Q	272	4.39	0.84	-0.05	-0.29*							
	4	Y^1	272	399	0									
	5	$iPad2Light_{high}$	272	0.49	0.50	0.15*	-0.30*	0.16*						
	6	$iPad2Mod_{high}$	272	0.49	0.50	0.21*	0.15*	0.032		-0.023				
	7	$NiPad2Light$	272	17.19	5.95	-0.41*	-0.28*	0.23*		-0.17*	-0.15*			
	8	$NiPad2Mod$	272	6.00	3.57	0.04	0.24*	0.00		-0.22*	-0.28*	0.25*		
	9	$NiPad3Light$	272	10.53	4.71	-0.34*	-0.27*	0.35*		-0.22*	0.24*	0.69*	-0.1	
	10	$NiPad3Mod$	272	4.10	2.60	0.15*	0.30*	-0.11*		-0.05	-0.13*	0.14*	0.72*	0.05
Moderate-use iPad2	1	Final Price	100	0.74	0.05									
	2	N	100	2.70	0.70	0.28*								
	3	Q	100	4.85	0.58	-0.06	-0.33*							
	4	Y^1	100	399	0									
	5	$iPad2Light_{high}$	100	0.44	0.50	0.20*	-0.13	-0.15						
	6	$iPad2Mod_{high}$	100	0.46	0.50	0.25*	-0.1	0.06		-0.01				
	7	$NiPad2Light$	100	15.82	5.91	-0.44*	-0.35*	-0.01		-0.14	-0.25*			
	8	$NiPad2Mod$	100	7.64	3.07	-0.17*	-0.18*	0.08		-0.41*	-0.1	0.36*		
	9	$NiPad3Light$	100	9.37	3.54	-0.22*	-0.18*	0.1		-0.40*	0.1	0.61*	0.35*	
	10	$NiPad3Mod$	100	5.02	2.53	-0.1	-0.24*	0.01		-0.26*	-0.1	0.10	0.68*	0.32*
Light-use iPad3	1	Final Price	189	0.73	0.03									
	2	N	189	2.57	0.78	0.89*								
	3	Q	189	4.25	0.73	0.30*	0.11							
	4	Y	189	529.16	46.02	-0.38*	-0.37*	-0.51*						
	5	$iPad2Light_{high}$	189	0.35	0.48	-0.12*	-0.21*	0.21*	-0.01					
	6	$iPad2Mod_{high}$	189	0.43	0.50	0.21*	0.17*	0.12*	0.03	0.28*				
	7	$NiPad2Light$	189	13.79	8.84	-0.18*	-0.25*	0.18*	0.02	0.23*	0.27*			
	8	$NiPad2Mod$	189	4.60	4.02	0.10	0.01	-0.06	0.03	0.06	0.02	0.50*		
	9	$NiPad3Light$	189	12.68	4.26	-0.36*	-0.26*	-0.03	-0.01	-0.24*	-0.05	0.02	-0.5*	
	10	$NiPad3Mod$	189	3.90	2.37	0.18*	0.20*	-0.29*	-0.03	0.11	-0.04	0.12*	0.68	-0.34*
Moderate-use iPad3	1	Final Price	71	0.70	0.04									
	2	N	71	2.48	0.69	0.73*								
	3	Q	71	4.56	0.58	0.27*	0.03							
	4	Y	71	532.80	47.64	-0.42*	-0.10	-0.75*						
	5	$iPad2Light_{high}$	71	0.42	0.50	0.05	-0.14	0.01	-0.01					
	6	$iPad2Mod_{high}$	71	0.49	0.50	0.48*	0.33*	0.25*	-0.10	-0.05				
	7	$NiPad2Light$	71	14.52	6.76	-0.25*	-0.20*	-0.12	0.03	0.03	-0.27*			
	8	$NiPad2Mod$	71	7.07	3.55	-0.28*	-0.171	-0.04	0.05	-0.32*	-0.28*	0.45*		
	9	$NiPad3Light$	71	9.66	3.18	-0.26*	-0.15	-0.01	0.15	-0.23*	0.01	0.50*	0.14	
	10	$NiPad3Mod$	71	5.68	2.04	-0.27*	-0.13	-0.05	0.11	-0.45*	-0.16	0.05	0.62*	0.14

Notes. [1] Y for *iPad2* is fixed and \$399. All correlations significant at $p<0.1$ is denoted by *.

Table 2.6: OLS Results Predicting the Final Price in iPad2 Auctions

Dependent Variable:	Light-use iPad2						Moderate-use iPad2				
Final Price	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Constant	0.7890***	0.7685***	0.7796***	0.7804***	0.7650***	0.7528***	0.8386***	0.8661***	0.8542***	0.8625***	0.8639***
	(0.029)	(0.029)	(0.029)	(0.028)	(0.030)	(0.030)	(0.066)	(0.063)	(0.064)	(0.068)	(0.067)
Q	0.0057	0.0075**	0.0041	0.0065*	0.0038	0.0077***	-0.0236**	-0.0219**	-0.0224**	-0.0218**	-0.0228**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
$iPad2Light_{high}$	0.0141**	0.0903***	0.0213***	0.0155**	0.0211***	0.0112	0.0030	0.0013	0.0105	0.0014	0.0118
	(0.007)	(0.018)	(0.007)	(0.008)	(0.007)	(0.008)	(0.015)	(0.014)	(0.016)	(0.014)	(0.016)
$iPad2Mod_{high}$	0.0249***	0.0350***	0.0319***	0.0341***	0.0306***	0.0331***	0.0107	0.0028	0.0021	0.0026	0.0027
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.014)	(0.013)	(0.013)	(0.014)	(0.013)
$iPad2Light_{high} \times iPad2Mod_{high}$	-0.0228**	-0.0262**	-0.0270**	-0.0227**	-0.0265**	-0.0188*	0.0021	0.0077	-0.0001	0.0076	-0.0012
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.020)	(0.019)	(0.020)	(0.019)	(0.020)
$NiPad2Light$	-0.0030***	-0.0021***	-0.0032***	-0.0024***	-0.0030***	-0.0014*		-0.0027***	-0.0035***	-0.0027***	-0.0038***
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)		(0.001)	(0.001)	(0.001)	(0.001)
$iPad2Light_{high} \times NiPad2Light$		-0.0046***									
		(0.001)									
$NiPad2Mod$			0.0030***	0.0023***	0.0016	-0.0007	-0.0030	-0.0011	-0.0009	-0.0013	-0.0001
			(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
$NiPad3Light$				-0.0017*		-0.0029***			0.0023		0.0027
				(0.001)		(0.001)			(0.002)		(0.002)
$NiPad3Mod$					0.0026	0.0050**				0.0005	-0.0017
					(0.002)	(0.002)				(0.003)	(0.004)
Dummies (location/auction time)	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Number of auctions	272	272	272	272	272	272	100	100	100	100	100
F Stat	10.16***	11.97***	11.48***	10.75***	10.57***	10.54***	3.97***	5.31***	4.98***	4.73***	4.51***
R-Square	0.236	0.291	0.283	0.292	0.288	0.308	0.258	0.347	0.359	0.347	0.360

Notes. Entries in columns report on how starting price and number of auctions in each market will impact the final price in iPad2 auctions. Column (1) reports the base model for light-use iPad2 auctions. Column (2) is used to test an interaction term between starting price and number of light-use iPad2 auctions. Column (3)–(6) will assess the impact the amount of supply for other markets on the final price of light-use iPad2 auctions. The corresponding results for moderate-use iPad2 auctions are shown in Columns (7) through (11). (Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.01).

110

Table 2.7: OLS Results Predicting the Final Price in iPad3 Auctions

Dependent Variable: Final Price	Light-use iPad3					Moderate-use iPad3				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Constant	0.8289***	0.8120***	0.8061***	0.8021***	0.8019***	1.1444***	1.1648***	1.1678***	1.1618***	1.1649***
	(0.045)	(0.047)	(0.044)	(0.044)	(0.043)	(0.133)	(0.128)	(0.130)	(0.130)	(0.136)
Q	0.0178***	0.0180***	0.0161***	0.0160***	0.0157***	-0.0256*	-0.0206	-0.0210	-0.0205	-0.0208
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Y	-0.0001**	-0.0001**	-0.0001***	-0.0001**	-0.0001***	-0.0005***	-0.0004***	-0.0004***	-0.0004***	-0.0004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$iPad2Light_{high}$	-0.0304***	-0.0299***	-0.0209***	-0.0339***	-0.0286***	0.0043	-0.0104	-0.0101	-0.0109	-0.0105
	(0.007)	(0.007)	(0.006)	(0.006)	(0.007)	(0.011)	(0.012)	(0.012)	(0.012)	(0.013)
$iPad2Mod_{high}$	0.0254***	0.0244***	0.0263***	0.0157***	0.0189***	0.0361***	0.0321***	0.0316***	0.0312***	0.0312***
	(0.006)	(0.006)	(0.005)	(0.005)	(0.006)	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)
$iPad2Light_{high} \times iPad2Mod_{high}$	-0.0017	-0.0016	-0.0059	0.0072	0.0028	-0.0044	0.0128	0.0127	0.0136	0.0132
	(0.009)	(0.009)	(0.008)	(0.008)	(0.009)	(0.014)	(0.015)	(0.016)	(0.016)	(0.017)
$NiPad2Light$			-0.0012***		-0.0006*			-0.0001		-0.0001
			(0.000)		(0.000)			(0.001)		(0.001)
$NiPad2Mod$				-0.0048***	-0.0035***				-0.0003	-0.0002
				(0.001)	(0.001)				(0.001)	(0.002)
$NiPad3Light$	-0.0042***	-0.0037***	-0.0023***	-0.0036***	-0.0029***		-0.0036**	-0.0035**	-0.0036**	-0.0035*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)		(0.001)	(0.002)	(0.001)	(0.002)
$NiPad3Mod$		0.0013	0.0040***	0.0091***	0.0083***	-0.0034	-0.0053**	-0.0053**	-0.0050	-0.0051
		(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)
Dummies (location/auction time)	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Number of auctions	189	189	189	189	189	71	71	71	71	71
F Stat	18.61***	16.94***	19.54***	16.94***	20.97***	5.99***	6.48***	5.78***	5.8***	5.58***
R-Square	0.483	0.488	0.548	0.566	0.574	0.469	0.519	0.520	0.520	0.520

Notes. Entries in columns report on how starting price and the number of auctions in each market will impact the final price in *iPad3* auctions. Column (1) reports the base model for light-use *iPad3* auctions. Columns (2)-(5) will assess the impact of iPad's supply in other markets on the final price of light-use *iPad3* auctions. Likewise, the corresponding results for moderate-use *iPad3* auctions are shown in Columns (6) through (10). (Standard errors in parentheses,
*** p<0.01, ** p<0.05, * p<0.01).

Chapter 3

ROFR-of-First-Refusal in Sequential Procurement Auctions

3.1 Introduction

Procurement auctions – where a buyer runs an auction to procure goods and services from suppliers – have ostensibly saved firms millions of dollars in direct costs of procurement. For instance, General Electric claimed a saving of $600 million (a net saving of more than 8%) in 2001, and Ariba, a leading software vendor for online auctions, reports that it consistently saved its customers an astonishing 20% on purchases worth more than $30 billion between 1995-2001 by using procurement auctions, *cf.* Engelbrecht-Wiggans and Katok (2006).

Several appealing features of classical procurement auctions, such as transparency, supplier-competition, etc., contribute to the cost savings, *cf.* Elmaghraby (2003). But the one standout feature that exerts an inexorable downward pressure on bids (and hence procurement cost) is that the winner of the auction is de facto the lowest bidder (*cf.* Elmaghraby 2003, Li and Scheller-Wolf 2009, Chen and Vulcano 2009, and Zhang 2010). The conflation of the lowest bid and 'allocation' (winner determination) scuttles any possibility of a long-term buyer-supplier relationship since, in each auction, a different supplier may end up being the lowest bidder, and hence the winner. Not surprisingly then, in recent surveys (Sawhney 2003, Jap 2007),

more than 95% of the suppliers viewed procurement auctions as toxic to long-term buyer-supplier relationships. Additionally, because the allocation is based solely on the lowest bid, the buyer too is forced to award a contract to less preferred or unfamiliar suppliers. As a result, one key reason of using procurement auctions – that of low procurement cost – does not always materialize either. Such savings in direct cost often disappear due to post-auction negotiations, or are diluted by increases in indirect costs of procurement, such as administrative hassles of dealing with a new supplier. For example, GE later claimed that as much as 50%, or about $300 million, a staggering proportion of the aforementioned $600 million saving, was lost due to frictions in executing contracts with new suppliers.

To offset the key disadvantage of classical procurement auctions, many academicians and practitioners have explored decoupling allocation from the bids received ('price discovery'). In specific, the winner may not necessarily be the lowest bidder – the final winner is at the buyer's discretion and may be based on both tangible and intangible factors, such as quality, lead time, etc. (Wan and Beil 2009, Engelbrecht-Wiggans *et al.* 2007, and Kostamis *et al.* 2009). As Elmaghraby (2007) notes: "...auctions should be viewed as one tool to *enable price discovery*...and *should not be considered a substitute for negotiation* [i.e., allocation]..." [page 410, emphasis added].

An auction *combined with* the *Right-of-First-Refusal* (ROFR) is a popular, yet simple, mechanism to decouple price-discovery and allocation. Under ROFR, the buyer runs an auction and collects the submitted bids. She then offers the 'preferred' bidder – the one who enjoys the right-of-first-refusal – the opportunity to match

the best offer that the buyer has. Thus, in the context of *procurement* auctions, the preferred supplier has an opportunity to win the contract by preferentially matching the *lowest* bid of the competing suppliers.

ROFR is historically the norm in many industries such as music, entertainment, real-estate, etc., where the incumbent is typically bestowed with ROFR. For instance, in 2001, Paramount Studios – the producer of the successful TV show Frasier – had to renegotiate the broadcasting right of Frasier after the original contract with NBC expired. NBC, as the incumbent network, enjoyed the right-of-first-refusal. The contract explicitly stated that NBC had "...10 days to match [CBS] terms." (Grosskopf and Roth 2009). Similarly, in the National football league (NFL), the incumbent team has the right to match the best offer a player has once he is eligible to change teams (Lee 2008).

Even in industries unencumbered by the above historical underpinnings, ROFR may still be awarded to incumbents. For example, there was a recent uproar in the automotive industry where suppliers complained that buyer used procurement auction to "...see how low suppliers are willing to bid – but the buyer has no intention to re-source...instead the *buyer goes to the existing [preferred] supplier to beat down [match] the price.*" [Kisiel 2002, emphasis added.]

ROFR may often be awarded surreptitiously or implicitly to a bidder. In 1999, Jinro Ltd, a bankrupt Korean brewery, was up for sale. However, the bid by Coors, a U.S. firm, was leaked to a preferred local brewery, The Oriental Brewery Company (OBC), despite explicit rules against such leakage. Based on the bid by Coors, OBC then resubmitted a (slightly) higher bid and won the auction. (Modern Brewery

Age, 1999.) Political pressure may also result in an implicit ROFR. In 2003, Airbus sought bids for engines to its A400M military aircraft. Pratt & Whitney of US and EuroProp International, a consortium of European engine manufacturers, were the major bidders. Although Pratt & Whitney's bid was more competitive, but succumbing to pressure from France and Germany who wanted European engines, Airbus implicitly granted ROFR to EuroProp which matched Pratt & Whitney's bid and won the contract, Lunsford (2003).

(To emphasize, in all the above examples, there is a separation of price discovery and allocation – the allocation being made, to the extent possible, to a preferred firm through an explicit or an implicit ROFR.)

Notwithstanding the many reasons for granting ROFR, the overwhelming conclusion – from both practitioners and academicians alike – is that, in the absence of side-payments to confer the ROFR, the only firm that benefits from ROFR is the preferred supplier. In particular, ROFR creates incentives for the nonpreferred supplier(s) to bid less aggressively (i.e., bid high in a procurement context) which increases the procurement cost for the buyer, *cf.* Chouiard (2005), Bikhchandani *et al.* (2005) and Elmaghraby (2007).

The theoretical result that ROFR raises the procurement cost hinges on the analysis of a single (one-shot) auction. Whereas a one-shot procurement setting may be justified in many instances, in many others suppliers repeatedly compete with each other over time; for example in the procurement of defense goods and services (Burnett and Kovacic 1989, Klotz and Chatterjee 1995), in federal and state procurement contracts, etc. (*cf.* Cason *et al* 2011). A key question that then arises

is whether the single-auction outcome – that ROFR raises the buyer's procurement cost – holds true more generally within repeated (or sequential) auctions?

The short answer is no. We establish that in several reasonable contexts where buyers runs sequential auctions, granting ROFR to a preferred supplier lowers the buyer's total procurement cost when compared to auctions without ROFR. This result arises due to aggressive bidding by the nonpreferred supplier, in direct contrast to one-shot auctions with ROFR, which in turn is an outcome of *information flows* generated endogenously through ROFR in sequential auctions.

In specific, in this chapter we show that in the context of two sequential procurement auctions with two bidders (or suppliers) – a *preferred* supplier who enjoys ROFR and a *nonpreferred* supplier without ROFR – granting ROFR to the preferred supplier in only the first auction precipitates an earlier release of information, compared to a benchmark of running two sequential procurement auctions without ROFR. Such early release of information exacerbates the strategic interactions between the suppliers in sequential auctions with ROFR, which a one-shot ROFR auction snuffs out prematurely. In particular, the buyer reveals the bid of the nonpreferred supplier to the preferred supplier in the first auction with ROFR, thus putting the nonpreferred supplier at an informational disadvantage in the second auction. In order to blunt this informational advantage enjoyed by the preferred supplier, the nonpreferred supplier bids extremely aggressively to win the first auction with ROFR – so much so that it decreases the buyer's total procurement cost over the two auctions compared to a benchmark case of running both the sequential auctions without ROFR. As noted above, this result is in stark contrast and

contrary to known results on the impact of ROFR on buyer's procurement cost in single-auction settings (where nonaggressive bidding by the nonpreferred supplier raises the buyer's procurement cost).

3.2 The Model

A buyer wishes to procure Q units of a product at $T = 1$ and Q units at $T = 2$. She runs an auction in each time period to procure her goods – auction 1 at $T = 1$ and auction 2 at $T = 2$. For ease of exposition, we assume $Q = 1$. The buyer faces two potential suppliers – a preferred supplier (PS) who enjoys ROFR if the buyer decides to run an auction with ROFR and a nonpreferred supplier (NPS) who does not have ROFR – both of whom bid in *both* auctions. (The buyer's preference for awarding ROFR to the preferred supplier is exogenously determined.) We index the three players – the *b*uyer, the *p*referred supplier and the *n*on-preferred supplier – by b, p and n respectively.

Each supplier incurs a (per unit) production/supply cost if he is selected to supply the product in period T; this cost can either be *high* (denoted by C_H) or *low* (denoted by C_L), with $C_H > C_L$. Each supplier independently draws his cost at $T = 1$, and he keeps this cost across both auctions at $T = 1$ and at $T = 2$. The probability of drawing a high cost is $q_1 \in (0, 1)$ and the probability of drawing a low cost is $(1 - q_1)$. Although the actual realization of these costs is private information, the probability distribution is common knowledge. Consistent with standard terminology in such games of incomplete information, the supplier that draws a high cost is referred to as the high *type,* while the supplier that draws

a low value of cost is referred to as the low *type*.

In an auction with ROFR, the following events take place. After the initial bids are placed by the two suppliers, the NPS's bid is revealed to the PS. If the PS's bid is the higher of the two, he then has the opportunity (but not an obligation) to revise his bid to match the NPS's lower bid[1]. Once the decision to 'match or not' is made by the preferred supplier, the lowest standing bid is declared the winner.

Alternatively, the buyer can run a (standard) 1st price auction, where the supplier with the lowest bid wins and is paid his bid. (If an auction is run as 1st price, then neither supplier enjoys ROFR, and the monikers of preferred and nonpreferred suppliers are merely placeholders to distinguish the two suppliers.) Elmaghraby (2007) notes that most procurement auction in practice are 1st -price.

The sequence of events is as follows. At $T = 1$, the buyer announces her procurement mechanism for both auctions (each auction is run either as 1st-price or as ROFR); and the suppliers independently draw their costs. At the end of each procurement event, the buyer announces the winning bid and the winner. Dimitri *et al.* (2006) note that announcing only the name and bid of the winner dominates the usage of other disclosure policies in practice (pg. 28, Fig 2.56). Additionally, as we shall see in Section 3.5, focusing on this particular disclosure mechanism allows us to tease out the impact of the timing of information flows on sequential auctions with ROFR.

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[1]It stands to reason that the buyer does not permit the preferred supplier from raising his bid – and therefore increasing the buyer's procurement cost – if the preferred supplier's initial bid is lower than the nonpreferred supplier's.

Four mechanisms (or subgames) potentially arise in our model: (i) $(ROFR, 1^{st})$, (ii) $(1^{st}, ROFR)$, (iii) $(ROFR, ROFR)$, and (iv) $(1^{st}, 1^{st})$, where the first element in $(\cdot, \cdot)$ is the auction type for $T = 1$ and the second element the auction type for $T = 2$. No auction in a period is indexed by $\emptyset$, e.g., $(ROFR, \emptyset)$ denotes a setting where a ROFR-auction is held at $T = 1$ and no auction takes place at $T = 2$.

Suppliers are risk-neutral expected profit maximizers, while the buyers seeks the lowest (expected) procurement cost for the two products. There is no collusion between bidders and there is no participation fee. Without loss of generality, we normalize C_L to zero. We index the equilibrium bid of a supplier $i \in \{p, n\}$ with the cost of $j \in \{L, H\}$ at time $k \in \{1, 2\}$ by b^i_{jk}.

3.3 Sequential Auctions and ROFR

Sequential auctions are underlined by repeated interactions over time between buyers and suppliers. Typically, a myopic strategy – of maximizing total profits by optimizing over individual auctions without heed to future interactions – is suboptimal. A myopic strategy may indeed be optimal in isolated instances, such as when future outcomes are independent of the past; for example, when, in each auction, suppliers draw a new independent value of cost. However, in most cases, such as in our model, where current (and past) outcomes can reveal critical information to the competitor (such as high or low cost), and when such information can be used strategically in future auctions, a myopic strategy may be suboptimal. Specifically in our modeling context, the players *must* take into account the impact of their bids and the information released at $T = 1$ on the *beliefs* and strategies of the players at

$T = 2$.

Hence, in order to understand if and when it is optimal for a buyer to use a ROFR in *sequential* auctions, we must therefore understand and isolate the following elements of information flows which are either absent or inconsequential in a single-auction setting: (i) *what* information is revealed in auction 1; (ii) *when* is information revealed (timing); and (iii) the *impact* of revealed information on the beliefs (and hence strategies) of players in auction 2, and then folding back, the impact on strategies in auction 1.

3.3.1 Literature Review

There are two main streams of work that are pertinent to our own: (i) Sequential auctions and (implicitly) the degree to which the potential to learn over time strategically impacts bidders' behavior, and (ii) ROFR within a (single) auction.

Sequential auctions There is a small body of literature that addresses procurement in a setting where bidders compete against each other over time, and hence, learning can occur. This literature (mostly) focuses on 1st-price auctions in a two period setting. Other key model features – namely, the number of bidders, the valuation structure (whether discrete or continuous type space, as well as whether the valuations are *common* or *private*), information disclosure policy (what information is revealed by the auctioneer between auctions), and finally the form of resulting equilibrium (*separating, semipooling or pooling*) – are summarized in Table 1 below.

Within sequential auctions, a key pattern emerges between the information disclosure policy and the resulting equilibrium: When the auctions are run under the *all-bid* revelation policy, win or lose, the suppliers' bids are revealed at the end

of each auction. Hence, bidders have a strong incentive to mask their type and semi-pooling equilibria generally emerge.[2] When the auction is run under a less informative feedback format (e.g., only the winner is announced, or both the winner and winning bid are announced), then bidders understand that their information is only revealed if they win. Consequently, the double-whammy of losing both the informational advantage and the auction is absent; hence the bidders find it optimal to reveal their true types in equilibrium, i.e., a separating equilibrium emerges.

In our analysis in this chapter, we find that although only the winning bid and the winner is disclosed at the end of each auction, the information release within ROFR can mimic all-bid revelation. Despite that, a separating equilibrium can emerge which lowers the procurement cost of the buyer.

Chouinard and Yoder (2007) is the only paper (other than our own) which investigates the role of a ROFR within sequential auctions. They characterize the set of Nash equilibria in an infinite sequence of auctions. In each auction, there is one incumbent that enjoys ROFR and one *new* entrant. If the incumbent wins, he continues on to the next auction and faces a new entrant. If the entrant wins, he becomes the incumbent (with ROFR) in the next auction and the current incumbent leaves the game. Given new participants in each auction, the game reduces to a series of independent auctions (with ROFR) in which no learning exists across auctions. Table 3.1 will show the summary of literature on sequential auctions.

ROFR in a single auction The second stream of papers discuss the effect of

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[2]The one exception to this is Ortega (1968); the separating equilibrium arises due to the presence of two bidders whose valuations are drawn from continuous distributions.

granting ROFR within a single-auction framework. Researchers are divided as to the benefits of offering an ROFR in an auction. For example, Chouiard (2005) and Bikhchandani et al. (2005) find that granting an ROFR to the preferred supplier leads to inefficiency in the auction (the lowest cost supplier does not necessarily win), and that the resulting inefficiency increases the right-holder's expected profit at the expense of the auctioneer and other bidders.

Although the impact of an ROFR, when considered in isolation may be detrimental to the buyer, its overall impact can change when the initial allocation of the ROFR is considered. For example, Lee (2008) studies procurement auction where suppliers have private and asymmetric cost structure. He concludes that, if the buyer knows the suppliers' cost distributions and is able to identify which supplier is associated with which distribution, the buyer may gain by granting the ROFR to the inefficient supplier (the one with the higher cost distribution). This result is reminiscent of Myerson (1981) result regarding the optimal use of differential reserves when facing asymmetric bidders. Other researchers (Burguet and Perry 2005, Choi 2009) have concluded that while granting an ROFR for free will never benefit the buyer, he may benefit if he sells the ROFR before the auction to the bidder with the highest willingness to pay. In contrast, we demonstrate that even without transfer payments or asymmetric supplier cost distributions, the buyer can be strictly better off awarding an ROFR within sequential auctions settings.

ROFR may also arise implicitly due to corruption between a bidder and an auctioneer (or his agent); for instance, a corrupt auctioneer may reveal the bid of a bidder to the dishonest bidder in exchange for a monetary payoff, *cf.* Porter

and Shoham (2004), Burguet and Perry (2007) and Arozamena and Weinschelbaum (2009). However, all these paper consider single auctions with continuous types.

In summary, whereas sequential auctions without ROFR and single-shot auctions with ROFR are reasonably well-studied, there is no paper that meaningfully analyzes ROFR within sequential auctions (as noted above, in Chouinard and Yoder (2007) the sequential auctions reduce to a series of auctions with no learning). Our analysis in this chapter fills the gap.

3.4 Analysis

We now establish the Perfect Bayesian Nash Equilibria of the entire game by solving backwards beginning at $T = 2$. Before we proceed with the formal analysis, we characterize the rather simplistic strategy of the high-cost suppliers (preferred or non-preferred) in our setting (with or without ROFR).

Lemma 1 *The high-cost suppliers bid C_H in any auction with or without ROFR and always make zero profit in equilibrium.*

The lemma allows us to focus much of the discussion on the strategies and payoffs of the low-cost suppliers without getting unduly distracted by the high types. Nevertheless, for completeness, all propositions that follow explicitly state the strategies and payoffs of the high types as well.

3.4.1 Equilibrium at $T = 2$

In the second auction, a supplier may face a ROFR-auction or a 1st-price auction. At the start of $T = 2$, suppose the PS believes that with probability $q_2^p \in [0, 1]$ the NPS has a high cost, and suppose the NPS believes that with probability $q_2^n \in [0, 1]$

the PS has a high cost.

Proposition 1 delineates the equilibrium for a ROFR-auction at $T = 2$ thereby establishing the equilibria at $T = 2$ under $(ROFR, ROFR)$ and $(1^{st}, ROFR)$; while Proposition 2 delineates the equilibrium at $T = 2$ for a 1st-price auction thereby establishing the equilibria at $T = 2$ under $(ROFR, 1^{st})$ and $(1^{st}, 1^{st})$. (As we prove, the equilibria of the second auction are linked to the strategies and outcomes of the first auction only through the suppliers' beliefs. Hence, the general, and possibly asymmetric, belief structure noted above allows us to capture all these feasible equilibrium paths.) Note that since $T = 2$ is the terminal period, the results of Propositions 1 and 2 can be also interpreted as the equilibria of a one-shot ROFR-auction and a one-shot 1st-price auction respectively, and our propositions are written as such.

Proposition 1 *The unique Perfect Bayesian Nash Equilibrium of a one-shot ROFR-auction is:*

(i) The low-cost nonpreferred supplier bids at $C_H - \epsilon$, with $\epsilon \to 0$. The high-cost nonpreferred supplier bids at C_H.

(ii) The preferred supplier (of either type) initially bids at C_H. Subsequently, the low-cost preferred supplier <u>always</u> matches the nonpreferred supplier's bid; the high-cost preferred supplier matches the non-preferred supplier's bid whenever the non-preferred supplier's bid equals C_H.[3]

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[3] If the nonpreferred supplier's bid is greater than C_H, which is off the equilibrium path, then the preferred supplier wins the auction without matching. Moreover, the belief structure plays no role in the equilibrium outcome and therefore has been suppressed for brevity.

(*iii*) *The buyer's expected procurement cost is* C_H.

It is a dominant strategy for the preferred supplier to initially bid C_H. For two reasons: (*i*) he can subsequently *choose* whether to match the nonpreferred supplier's bid; and (*ii*) if the PS indeed matches, initially bidding at C_H affords the PS the highest winning margin (as against inadvertently bidding lower than the NPS).

In a single ROFR-auction, the low-cost PS *always* wins auction 1 by matching the NPS's bid – matching nets the PS nonnegative profits, while not matching nets him 0. On the other hand, a high-cost PS matches NPS's bid only if the bid equals C_H; matching a bid less than C_H results in negative profit for the high-cost PS. Thus, because a low-cost NPS can only win against a high cost PS, the low-cost NPS bids as close to C_H as possible, thereby maximizing margins while winning (with certainty) against a high-cost PS.

It is interesting to note that (*i*) the equilibrium of a one-shot ROFR-auction does not depend on the beliefs, provided that they are strictly bounded above 0 and below 1; and (*ii*) the equilibrium is extremely 'unaggressive' (i.e. the equilibrium bids are very high). Neither of these statements are true for a one-shot 1st-price auction, outlined below. Recall that q_2^p and q_2^n are not necessarily equal to q_1 (the beliefs at $T = 1$) and need not be equal to each other (asymmetric beliefs).

Proposition 2 *The unique Bayesian Nash equilibrium of a single first-price auction without ROFR, in terms of the strategies and the payoffs of the three players is:*

(*i*) *If* $q_2^p = q_2^n = 0$, *then both suppliers bid zero* $(b_{L2}^p = b_{L2}^n = 0)$ *and earn a profit of* 0. *The buyer's procurement cost is* 0.

(*ii*) If $q_2^p = q_2^n = 1$, then both suppliers bid C_H ($b_{H2}^p = b_{H2}^n = C_H$) and earn a profit of 0. The buyer's procurement cost is C_H.

(*iii*) For all other cases,

(*a*) a low-cost supplier i with the belief of $Max\,(q_2^p, q_2^n)$ draws his bid (b_{L2}^i) from a continuous distribution with a cumulative distribution function

$$F(b_{L2}^i) = \frac{b_{L2}^i - Max\,(q_2^p, q_2^n)\,C_H}{(1 - Min\,(q_2^p, q_2^n))b_{L2}^i}, \quad b_{L2}^i \in [Max\,(q_2^p, q_2^n)\,C_H\,,\ C_H)$$

Moreover, this supplier has an atom at C_H [4], i.e., he bids C_H with a probability of

$$\frac{Max\,(q_2^p, q_2^n) - Min\,(q_2^p, q_2^n)}{1 - Min\,(q_2^p, q_2^n)}.$$

(*b*) a low-cost supplier i with the belief of $Min\,(q_2^p, q_2^n)$ draws his bid (b_{L2}^i) from a continuous distribution whose cumulative distribution function (cdf) is

$$G(b_{L2}^i) = \frac{b_{L2}^i - Max\,(q_2^p, q_2^n)\,C_H}{(1 - Max\,(q_2^p, q_2^n))b_{L2}^i}, \quad b_{L2}^i \in [Max\,(q_2^p, q_2^n)\,C_H\,,\ C_H)$$

(*c*) a high-cost supplier i bids C_H ($b_{H2}^i = C_H$).

(*d*) a low-cost supplier earns an expected profit of $Max\,(q_2^p, q_2^n)\,C_H$ whereas a high-cost supplier earns an expected profit of 0. The buyer's expected procurement cost is $Max\,(q_2^p, q_2^n)\,[2 - Max\,(q_2^p, q_2^n)]C_H$.

A similar proposition with two bidder types is analyzed in Thomas (1996) for 'forward' auctions. We briefly elaborate on the relevant technical details below.

In part (*i*) of Proposition 2, both suppliers believe that the other has a low cost (i.e., $q_2^p = q_2^n = 0$). Since beliefs are fulfilled in equilibrium, this results in an

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[4]To be strict, the atom is placed at $C_H - \epsilon$ to prevent ties with the high-cost supplier. Since ϵ is arbitrary small, we ignore it for simplicity.

unbridled (Bertrand) price competition which precipitates the equilibrium bids to the suppliers' marginal costs of zero (since $C_L = 0$), and hence zero procurement cost for the buyer in auction 2.

In a similar vein, in part (ii) of Proposition 2, each supplier believes that the other has a high cost (i.e., $q_2^p = q_2^n = 1$). Thus, the equilibrium bids, and thereby the buyer's procurement cost, are polarized to the other extreme at C_H.

In all other cases, at least one supplier is unsure about the cost of the other supplier, i.e., at least one supplier has a posterior belief which is bounded strictly away from both 0 and 1 (part (iii) of Proposition 2). Whereas a high-cost supplier bids C_H, a low-cost supplier plays a mixed strategy with support between $Max(q_2^p, q_2^n)C_H$ and C_H in auction 2.

Not withstanding the different bid distributions of the two low-cost suppliers in case (iii), both low-cost suppliers make the same expected profit in equilibrium. More importantly, this expected profit is *increasing in the maximum of the two beliefs*, namely $Max(q_2^p, q_2^n)$. Hence, it behooves *both* low-cost PS *and* NPS to manage the beliefs in $T = 1$ so as to keep the maximum belief (i.e., the probability of facing a high-cost opponent) as high as possible.

To summarize our results from this section, the payoff in (the terminal) auction at $T = 2$, which is identical to a one-shot auction, is determined by Proposition 1 for a ROFR-auction or Proposition 2 for a 1st-price auction. As we show, the beliefs at the start of $T = 2$ are critical to the payoffs in that period, especially when the buyer does not offer an ROFR (Proposition 2). These beliefs emerge endogenously from strategies and outcomes in auction 1.

We now establish the equilibria for the metagame by turning our attention back to $T = 1$.

3.4.2 Equilibrium at $T = 1$

Recall that the buyer is faced with four possible procurement mechanisms: (i) $(ROFR, 1^{st})$, (ii) $(1^{st}, ROFR)$, (iii) (ROFR, ROFR), and (iv) $(1^{st}, 1^{st})$. To conserve space, we only focus on cases (i) and (iv) in the main text; a complete analysis of cases (ii) and (iii) is available with the authors. As we prove, cases (ii) and (iii) are dominated by cases (i) and (iv).[5] Case (i) is analyzed in Section 3.4.2.1 whereas case (iv) is analyzed in Section 3.4.2.2. In both cases, the second (terminal) auction is devoid of ROFR and run as a standard 1st price, analyzed in Proposition 2.

And, as we prove in Proposition 2, when the second auction is run as 1st price, the profit in auction 2 is determined by the beliefs going into $T = 2$. Unless *both* beliefs are zero, i.e., unless both suppliers know for sure that the other supplier has low cost, both low-cost suppliers make non-zero profit in equilibrium. Additionally, the low-cost suppliers' profits in auction 2 are *increasing* in the maximum of the two beliefs. Hence, a consideration of auction 2 (and hence total profits) while deciding the strategies in auction 1, in both cases (i) and (iv), boils down to a consideration of beliefs at the end of auction 1.

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[5]When the terminal auction is run with ROFR, as in cases (ii) and (iii), the outcome, detailed in Proposition 1, is independent of beliefs at the end of auction 1. Hence, the two auctions are independent of each other despite being sequenced in time. The fact that cases (ii) and (iii) are dominated by cases (i) and (iv) underlines the importance of 'linking' the two auctions through learning, *a la* section **??**.

3.4.2.1 Case (i): $(ROFR, 1^{st})$

Auction 1 with ROFR is a dynamic game of incomplete information. The non-preferred supplier *signals* his type to the preferred supplier by his bid, and the preferred supplier in turn signals his type by matching (or not) the nonpreferred supplier's bid[6]. Strategies forge beliefs; as in typical signaling games, posterior beliefs are derived, wherever possible, from equilibrium strategies using Bayes' rule. Off-equilibrium beliefs are filtered through the Intuitive Criterion of Cho and Kreps (1987).

The strategy space of the low-cost nonpreferred supplier can be broken into two disjoint subsets: bid at C_H (*pool* with the high type) or bid lower than C_H (*separate* from the high type). Bidding at C_H is suboptimal from the perspective of auction 1 alone; NPS surely loses auction 1 (as we prove, both types of preferred supplier match his bid). The advantage emerges in shaping the PS's beliefs (regarding the NPS's cost) which possibly reap reward in auction 2: at a minimum the NPS can hide is true cost and, at best, erroneously convince PS that he has high cost, i.e., he can induce posterior beliefs held by the preferred supplier that range anywhere between the prior of q_1 and 1 depending on equilibrium strategies. In contrast, by bidding lower than C_H, NPS unambiguously conveys his low cost to PS (by lemma, 1 high-cost suppliers bid C_H), precipitating PS's posterior belief to zero and thereby

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[6]The nonpreferred supplier only observes whether he won the auction or not. For a bid $< C_H$ by the nonpreferred supplier, he wins the auction if and only if the preferred supplier does not match. Hence, the nonpreferred supplier can perfectly infer the preferred supplier's decision to match or not.

(possibly) compromising auction 2 payoffs. But on the upside, he surely wins the first auction when facing a high-cost PS and, unlike in a single auction with ROFR, he *can* win the first auction even when facing a low-cost PS.

Consider now the preferred supplier. The strategy space of PS has two elements: the initial bid and whether to match NPS's bid. As in a one-shot auction with ROFR, it is optimal for PS to bid C_H and avoid inadvertently bidding lower than NPS. The original bid of C_H is anticipated by NPS and serves no role in forming new beliefs or in determining the winner of the first auction. We therefore analyze the tension inherent in the second decision made by the PS: whether to match the NPS's bid.

If NPS bids at C_H, it is a dominant strategy for both types of PS to match and win auction 1 – even with the most favorable belief induced on NPS by not matching, the resulting profit in auction 2 is insufficient to compensate the loss of losing auction 1. In fact, a high-cost PS will only match a bid of C_H. But the low type PS may find it profitable to match a bid less than C_H.

A low-cost PS presented with a bid below C_H faces the following tension: By matching the bid, he signals himself to be a low type (*separating* from the high type who cannot match a bid lower than C_H) and wins auction 1. However, NPS then knows that the PS has low cost (NPS's posterior belief is now zero). Since the NPS has already signaled his low cost by bidding lower than C_H, both players know their opponent has low cost; consequently, both get zero profit in auction 2. However, by not matching (i.e., by *pooling* with the high type), the low-cost PS loses auction 1 but preserves the uncertainty on his cost: the nonpreferred supplier has no way

to differentiate whether the preferred supplier *could not* match since he has a high cost, or *chose* not to match. The preferred supplier loses auction 1 but leaves the possibility of earning profit in auction 2 by maintaining uncertainty on his cost.

The above tensions in the strategies of the two suppliers are resolved in two different ways depending on the probability q_1 of initially drawing a high cost. For $q_1 \geq (1/2)$ there exists an equilibrium in pure strategy of Proposition 3 – the low-cost NPS separates from the high type, whereas the low-cost PS pools with the high type. For $q_1 < (1/2)$, there is no equilibrium in pure strategies for the nonpreferred supplier. Hence we delineate a mixed strategy equilibrium of Proposition 4, where the low-cost NPS mixes between pooling and separating whereas the PS continues with the pooling strategy of Proposition 3. (Since the terminal auction at $T = 2$ has already been analyzed in Proposition 2, we only delineate the equilibrium at $T = 1$ in the propositions below.)

Proposition 3 *Under the procurement mechanisms* $(ROFR, 1^{st})$, *the Perfect Bayesian Nash equilibrium of auction 1 when* $q_1 \geq (1/2)$ *is as follows:*

(i) The low-cost preferred supplier initially bids at C_H $(b_{L1}^p = C_H)$, *and he matches the nonpreferred supplier's bid iff the nonpreferred supplier's bid is greater than* $q_1 C_H$. *The high-cost preferred supplier bids at* C_H $(b_{H1}^p = C_H)$, *and he matches the nonpreferred supplier's bid iff the nonpreferred supplier's bid equals* C_H.

(ii) A low-cost nonpreferred supplier bids $q_1 C_H$ $(b_{L1}^n = q_1 C_H)$. *A high-cost nonpreferred supplier bids at* C_H $(b_{H1}^n = C_H)$.

(iii) The posterior belief of the preferred supplier at the end of auction 1 condi-

tional on the nonpreferred supplier's bid b_{j1}^n, is:

$$\Pr\left\{nonpreferred\ supplier\ has\ high\ cost\Big|b_{j1}^n\right\} = q_2^p = \begin{cases} 0\ if\ b_{j1}^n < C_H \\ \\ 1\ otherwise \end{cases} \tag{1}$$

(iv) The posterior belief of the nonpreferred supplier at the end of auction 1, conditional on the nonpreferred supplier bid b_{j1}^n and the preferred supplier's decision to match or not, is:

$$\Pr\left\{preferred\ supplier\ has\ high\ cost\Big|b_{j1}^n,\ match\ or\ not\right\} = \tag{2}$$

$$q_2^n = \begin{cases} 0\ if\ b_{j1}^n < C_H\ and\ the\ preferred\ supplier\ matches \\ \\ q_1\ if\ b_{j1}^n < C_H\ and\ the\ preferred\ supplier\ does\ not\ match \\ \\ q_1\ if\ b_{j1}^n \geq C_H \end{cases}$$

(v) The expected <u>total</u> profit over both auctions 1 and 2:

(a) for a low-cost preferred supplier is $q_1(3-q_1)C_H$

(b) for a low-cost nonpreferred supplier is $2q_1C_H$

(c) for a high-cost supplier (preferred or nonpreferred) is 0

(vi) The expected total procurement cost for the buyer is: $q_1[2+(1-q_1)(3-q_1)]C_H$

When $q_1 \geq (1/2)$, the low-cost NPS separates out by bidding q_1C_H $(< C_H)$. Any bid weakly lower than q_1C_H is laced with poison for the low-cost PS: if PS matches, he wins auction 1 at a low profit (equal to NPS's low bid of less than (or equal to) q_1C_H) while making zero profit in the second auction (both suppliers would know that the other has low cost). By not matching, the low-cost PS loses auction 1, but cloaks his true cost. Not matching dominates matching[7] for any bid (weakly) less than q_1C_H.

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[7]The total expected payoff for the low-cost preferred supplier of *not matching* is: $q_1(C_H+C_H)+$

The separating strategy of a low-cost NPS can be sustained when q_1 is relatively large – implying that the bid that deters a low-cost PS from matching allows the NPS to accrue modest profits. The certainty of winning auction 1 at a relatively high bid and the possibility of still earning profit in the second auction renders the separating strategy more profitable for NPS than pooling at C_H.

Nonetheless, the separating strategy comes at a cost to a low-cost NPS and, not surprisingly, he earns a lower expected profit than a low-cost PS. Because the NPS types play a separating equilibrium in auction 1, the PS can detect a high-cost NPS when he sees a bid of C_H (equation 1). The low-type PS milks this information and accrues a winning margin of C_H in *both* auctions against the high-type NPS. In contrast, NPS is locked into a lower bid of $q_1 C_H$ in auction 1 even against a high-cost PS. Furthermore, since both PS types play a pooling strategy (i.e., both high and low types have the same strategy of not matching a bid less than C_H), the NPS cannot distinguish PS's true type going into auction 2; the low-cost NPS bids significantly less than C_H at $T = 2$ (in expectation, as per proposition 2), thus sacrificing margins yet again against a high-cost opponent.

$(1 - q_1)(0 + q_1 C_H)$. The first term is the probability of facing a high-cost nonpreferred supplier multiplied by the winning margin of C_H in each auction. The second term is the probability of facing the low-cost nonpreferred supplier, in which case the low-cost preferred supplier nets 0 in auction 1 and $q_1 C_H$ in auction 2 as per Proposition 2 (the posterior belief of the preferred supplier is 0, while that of the nonpreferred supplier is q_1). In contrast, the expected payoff of *matching* for the low-cost preferred supplier is: $q_1(C_H + C_H) + (1 - q_1)(b_{L1}^n + 0)$ where b_{L1}^n is the low-cost nonpreferred supplier's bid in auction 1. Clearly, the payoff of not matching is (weakly) higher than that of matching for $b_{L1}^n \leq q_1 C_H$.

As q_1 decreases, the separating bid of $q_1 C_H$ decreases, thereby lowering the non-preferred supplier's profit in Proposition 3. So much so, that for sufficiently low q_1 $\left(q_1 < \frac{1}{2}\right)$, the equilibrium breaks down. There is no pure strategy equilibrium for $q_1 < (1/2)$ and, as the next proposition proves, the NPS mixes between bidding at $q_1 C_H$ and bidding at C_H.

Proposition 4 *Under the procurement mechanisms* $(ROFR, 1^{st})$*, the Perfect Bayesian Nash equilibrium of auction 1 when $q_1 < (1/2)$ is as follows:*

(i) The low-cost preferred supplier initially bids at C_H $(b^p_{L1} = C_H)$, and he matches the nonpreferred supplier's bid iff the nonpreferred supplier's bid is greater than $q_1 C_H$. The high-cost preferred supplier bids at C_H $(b^p_{H1} = C_H)$, and he matches the non-preferred supplier's bid iff the nonpreferred supplier's bid equals C_H.

(ii) The low-cost nonpreferred supplier plays a mixed strategy – he bids C_H $(b^n_{L1} = C_H)$ with probability β and he bids $q_1 C_H$ $(b^n_{L1} = q_1 C_H)$ with probability of $(1 - \beta)$, where

$$\beta = \frac{1 - 2q_1}{2(1 - q_1)} \in [0, 1] \,\forall q_1 < \frac{1}{2}$$

Moreover, $d\beta/dq_1 < 0$.

(iii) The posterior belief of the preferred supplier at the end of auction 1, conditional on the nonpreferred supplier's bid b^n_{j1}, is:

$$\Pr\left\{\text{nonpreferred supplier has high cost}\,\middle|\,b^n_{j1}\right\} = q^p_2 = \begin{cases} 0 \text{ if } b^n_{j1} < C_H \\[2mm] \dfrac{q_1}{q_1 + (1 - q_1)\beta} = 2q_1 \text{ otherwise} \end{cases} \tag{3}$$

(iv) The posterior belief of the nonpreferred supplier at the end of auction 1,

134

conditional on the nonpreferred supplier bid b_{j1}^n and the preferred supplier's decision to matched or not, is:

$$\Pr\left\{\text{preferred supplier has high cost}\,\middle|\,b_{j1}^n,\ \text{match or not}\right\} = \tag{4}$$

$$q_2^n = \begin{cases} 0 \ \text{if } b_{j1}^n < C_H \ \text{and the preferred supplier matches} \\[2mm] q_1 \ \text{if } b_{j1}^n < C_H \ \text{and the preferred supplier does not match} \\[2mm] q_1 \ \text{if } b_{j1}^n \geq C_H \end{cases}$$

(v) *The expected <u>total</u> profit over both auctions 1 and 2:*

    (a) *for a low-cost preferred supplier is* $\dfrac{(1 + 3q_1)\,C_H}{2}$

    (b) *for a low-cost non-preferred supplier is* $2q_1 C_H$

    (c) *for a high-cost supplier (preferred or non-preferred) is* 0

(vi) *The expected total procurement cost for the buyer is:* $\dfrac{(1 + q_1\,(7 - 5q_1))\,C_H}{2}$

When $q_1 < (1/2)$, the small total profit earned in auction 1 by a low-cost NPS through the pure strategy of Proposition 3 unglues that equilibrium. Since a pure strategy of bidding higher than $q_1 C_H$ does not work either, the low-cost NPS mixes between bidding at $q_1 C_H$ and C_H. The PS matches the opponent's bid at C_H but not the bid at $q_1 C_H$, i.e., the low-cost PS plays the pooling strategy of Proposition 3. If the NPS bids at $q_1 C_H$ he wins the first auction. If he bids at C_H he loses the first auction, but increases the posterior belief of the PS above q_1 (to $2q_1$ by equation 3), just enough to make the NPS indifferent between bidding at $q_1 C_H$ and C_H.

3.4.2.2 Case (iv): $(1^{st}, 1^{st})$

When the buyer does not offer an ROFR in auction 1, she runs both sequential

auctions as 1st-price where, in each auction, the lowest submitted bid is declared the winner.

Define $q_2^w \in [0, 1]$ to be the winner's belief that his opponent is a high type at the conclusion of auction 1; $q_2^l \in [0, 1]$ to be the loser's belief that the winner is a high type at the conclusion of auction 1, and b_{j1}^s to be bid of bidder $s \in \{w(winner), l(loser)\}$ of cost-type $j \in \{H, L\}$ in auction 1. Note that the characterization of the equilibrium in auction 2 is identical to that identified in Proposition 2, although the notation on beliefs is different (consistent with the present context of winner and loser in auction 1). Hence, we focus our discussion to equilibrium bidding strategies in auction 1 in Proposition 5 below. (Thomas 1996 presents a similar analysis for forward auctions but only with $q_1 = 1/2$.)

Proposition 5 *In a sequential auction where both auctions 1 and 2 are run as standard 1st price, $(1^{st}, 1^{st})$, the Perfect Bayesian Nash equilibrium of auction 1 is as follows:*

1. *(i) A low-cost supplier draws his bid (b_{L1}^s) from a unique and continuous cumulative distribution function $H(.)$ with support $[q_1(1 - \ln(q_1))C_H, C_H)$ and no mass point (atoms) in its domain.*

   (ii) A high-cost supplier bids C_H $(b_{H1}^s = C_H)$.

   (iii) The posterior belief of the winning supplier at the end of the auction 1 conditional on observing the winning bid is:

$$q_2^w \left| b_{j1}^w = \begin{cases} \dfrac{q_1}{q_1 + (1 - q_1)\overline{H}(b_{j1}^w)} & \text{if } b_{j1}^w < C_H \\ 1 \text{ otherwise} \end{cases} \right. \tag{5}$$

(iv) *The posterior belief of the losing supplier at the end of the auction 1 conditional on observing the winning bid is:*

$$q_2^l \left| b_{j1}^w \right. = \begin{cases} 0 \ \textit{if } b_{j1}^w < C_H \\ \\ 1 \ \textit{otherwise} \end{cases} \tag{6}$$

(v) *The expected __total__ profit over both auctions:*

(a) for a low-cost supplier is $q_1(2 - \ln(q_1))C_H$

(b) for a high-cost supplier is 0

(vi) *The expected total procurement cost for the buyer is:* $2q_1[2 - q_1 - (1 - q_1)\ln(q_1)]C_H$

We are unable to find the closed-form solution for the equilibrium bids b_{j1}^w and b_{j1}^l. We are, however, able to characterize the support of the bidding strategies as well as the suppliers' and the buyer's expected profits and costs. Given the symmetry of bidders at the start of auction 1, and in the absence of ROFR (or any such asymmetries), we focus on a symmetric mixed-strategy equilibrium for auction 1 of $(1^{st}, 1^{st})$ – there does not exist an equilibrium in pure strategies.

The low-cost suppliers bid strictly less than C_H, i.e., the suppliers play a separating equilibrium. Because the only information revealed is the winning bid at the end of auction 1, even with two low-cost suppliers competing and playing a separating equilibrium, both posterior beliefs do not precipitate to zero.

Notice also that whereas the upper bound of support for a low-cost supplier's bid is the same as that of a one-shot 1st-price auction of Proposition 2, the lower bound of support, $q_1(1 - \ln(q_1))C_H$, is greater than $q_1 C_H$ of Proposition 2, the implications

137

of which follow. (When beliefs are symmetric at q_1, as in auction 1 above, the lower bound of the support for the mixed strategy equilibrium in Proposition 2 converges to $q_1 C_H$.)

3.5 Information Flows: ROFR vs. 1st price

As noted earlier in Section 3.3, the key to understanding the use of ROFR in sequential auctions is to isolate the information flow ('what' and 'when') and its associated impact on auction 1 strategies.

Recall that in $(1^{st}, 1^{st})$, the information on the identity of the winner and the winning bid is only released at the end of auction 1, after the transactions of auction 1 are complete. In contrast, in $(ROFR, 1^{st})$, the *same* information is released earlier within auction 1 itself.[8] Hence, whereas the 'what' part of information flows are identical across the two settings, the timing and the impact of information differs. We start with the third element of information flows: their impact on the myopic auction 1 strategies.

3.5.1 Impact of Information Flows on Myopic Strategies

An obvious and natural way of teasing the impact of information flows on myopic strategies is to contrast the single auction outcome with the outcome in the first of the two sequential auctions, which is accomplished in Corollaries 1 and 2 below.

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[8]Since the preferred supplier initially bids at C_H, revealing the nonpreferred supplier's bid to the preferred supplier is akin to announcing the current winning bid and the winner. Moreover, note that the information revealed between auctions in $(ROFR, 1^{st})$ is useless since: (i) it can be perfectly anticipated by the suppliers, and (ii) it serves no role in forging beliefs (which are entirely driven by the information released *during* auction 1).

Corollary 1 *Compared to* $(ROFR, \emptyset)$, *a low-cost nonpreferred supplier bids more aggressively, i.e., has a lower (expected) bid in equilibrium, in auction 1 of* $(ROFR, 1^{st})$.

Existing literature (*cf.* Bhikchandani *et al* 2005, Chouiard 2005) highlights nonaggressive bidding by NPS as a key reason for an increase in the buyer's procurement cost in a single ROFR-auction. We corroborate their finding in our single-auction model, while, at the same time, refute this finding in the context of sequential auctions. When compared to a single ROFR-auction, the presence of a future auction induces a low-cost NPS to always bids more aggressively when $q_1 \geq (1/2)$ and sometimes more aggressively, but certainly not less aggressively, when $q_1 < (1/2)$. The genesis of such aggression is the lure of auction 2 profits for both suppliers (for which at least one-sided uncertainty on costs must be preserved when bidding in auction 2), as well as a (relatively more) unfettered strategic interaction between the suppliers that unfolds in a sequential auction.

The NPS knows that the dice is loaded in favor of the PS who can see the NPS's bid and can accordingly revise his own. A one-shot auction snuffs out strategic interactions prematurely – for instance, the strategic implications of matching (or not) by the PS are rendered moot in a one-shot auction – denying the NPS an opportunity to neutralize the advantage enjoyed by the PS. However, in the sequential auction setting, the PS's decision to match or not has strategic implications through beliefs induced for auction 2. In specific, the lure of the second-auction profit weakens the PS's myopic incentive to always win auction 1 by matching the NPS's bid. This weakness is cleverly exploited by the low-cost NPS in a sequential setting, who,

by submitting a low bid at $T = 1$, reveals his type and entrusts the onus of sustaining uncertainty over cost in $T = 2$ onto the PS. In effect, by submitting a low bid the NPS makes it unattractive for PS to match (and reveal his type) thereby blunting his advantage. Such attempts at leveling the playing field comes at a cost for NPS in the form of smaller spoils of winning the first auction due to a low bid, but, nonetheless, is more profitable than simply 'giving up' as in the single auction setting.

It is similarly useful to contrast the first of the sequential auctions, $(1^{st}, 1^{st})$, with the corresponding one-shot auction $(1^{st}, \emptyset)$, whose equilibrium is captured in Proposition 2 when $q_2^p = q_2^n = q_1$. Comparing Proposition 5 with Proposition 2 when $q_2^p = q_2^n = q_1$ we find,

Corollary 2 *Compared to a single auction, $(1^{st}, \emptyset)$, the low-cost suppliers bid <u>less</u> aggressively in the first auction of two sequential $(1^{st}, 1^{st})$ auctions.*

Consider first the single auction $(1^{st}, \emptyset)$ setting. The equilibrium strategy is mixed, which implies that the suppliers are indifferent toward any bid in the support – each such bid nets them the same expected profit. There are two forces that support the mixed strategy equilibrium and hence the indifference. First, the higher the winning bid, the higher the margin, which, ceteris paribus, favors a higher bid. However, a countervailing second force comes in play. The higher the bid, the lower the probability of winning. These two tensions fuse to support the mixed strategy equilibrium.

Now consider the first auction in the sequential $(1^{st}, 1^{st})$ auction setting. The

140

second auction, disturbs the fine balance of the single-auction equilibrium. Since the winning bid is revealed after the first auction (which forges posterior beliefs for both suppliers), a third factor comes into play: the higher the winning bid, the higher the beliefs[9], and hence the higher the profit in the second auction (as before, the profit in the second auction increases in the maximum of the suppliers' beliefs). The third factor upsets the finely-tuned balance of the single auction equilibrium – specifically, whereas a supplier was earlier indifferent between a bid $q_1 C_H + \delta$ and $q_1 C_H$ in the support, he now prefers $q_1 C_H + \delta$ to $q_1 C_H$ due to increased total profits. Since, *ceteris paribus*, bidding less aggressively in auction 1 of $(1^{st}, 1^{st})$ improves total expected profits, the equilibrium bid in auction 1 of $(1^{st}, 1^{st})$ is tweaked to a (relatively) nonaggressive one as compared to the equilibrium bid of a single auction $(1^{st}, \emptyset)$.

3.5.2 The Timing of Information Flows: $(ROFR, 1^{st})$ vs. $(1^{st}, 1^{st})$

A stark contrast emerges when we compare Corollaries 1 and 2. The suppliers bid *more* aggressively in auction 1 of $(ROFR, 1^{st})$ compared to $(ROFR, \emptyset)$ – Corollary 1. In contrast, the suppliers bid *less* aggressively in auction 1 of $(1^{st}, 1^{st})$ compared to $(1^{st}, \emptyset)$ – Corollary 2. Hence, a 1st-price when juxtaposed after a ROFR auction induces aggressive bidding compared to the corresponding one-shot equilibrium; but when juxtaposed after a 1st-price auction weakens the aggression

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[9]For example, if a supplier wins at the lowest bound of the mixed strategy support, the posterior belief that he assigns to the opponent beinng a high cost is just the priors q_1. However, at the extreme, if a supplier wins at a bid of $C_H - \epsilon$, he is convinced with probability 1 that his opponent has a high cost.

in the corresponding one-shot equilibrium. A critical driver of the above differences between $(ROFR, 1^{st})$ and $(1^{st}, 1^{st})$ is the timing of information released: whereas information on the winner and the winning bid is revealed in-between auctions in $(1^{st}, 1^{st})$, the same information is released within auction 1 itself in $(ROFR, 1^{st})$, see footnote 8. Such early release of information exacerbates the strategic interactions between the suppliers implicit in auction 1 with ROFR.

Recall that only with some residual uncertainty over opponents types can either (low-cost) supplier earn a positive expected profit in $T = 2$. This uncertainty 'comes for free' under $(1^{st}, 1^{st})$ – under no circumstances are both posterior beliefs zero (refer to the discussion below Proposition 5). In contrast, the early release of information in ROFR, while conferring an advantage to the preferred supplier who can exploit this information to revise his initial bid, also has the potential to unveil the suppliers' costs possibly precipitating both posterior beliefs to zero. Hence, (at least) one sided uncertainty on costs must be *endogenously generated* in ROFR, as noted in Section 3.5.1 which is costly for the suppliers. the suppliers' cost is the buyer's gain.

Indeed, as Figure 3.1 demonstrates, the buyer enjoys lower procurement cost (for the most part as long as q_1 is not too high or too low) under $(ROFR, 1^{st})$ than under $(1^{st}, 1^{st})$. The figure shows the buyer's total procurement cost on the vertical axis and the prior probability of drawing a high cost, q_1, on the horizontal axis. For most value of q_1, except when q_1 is very small, $(ROFR, 1^{st})$ results in a lower procurement cost for the buyer as compared to $(1^{st}, 1^{st})$. The reason can be attributed to the aggressive bidding by the nonpreferred supplier in the first auction

of $(ROFR, 1^{st})$. (When q_1 is very small, the mixed strategy equilibrium in the first auction of $(ROFR, 1^{st})$ puts increasingly more weight on the nonpreferred supplier bidding at the upperbound of C_H, which raises the buyer's procurement cost. Also, our analysis for ROFR breaks down when $q_1 = 0$.)

In summary, two factors collude together to create the aggression in the ROFR-auction in the sequential $(ROFR, 1^{st})$ setting: (i) the looming second auction; and (ii) the early release of information hardwired into the ROFR mechanism itself. The first factor allows for a more elaborate window of time for the suppliers to strategically exploit the information revealed in auction 1, which differentiates $(ROFR, 1^{st})$ from $(ROFR, \emptyset)$; whereas the second factor fuels a more intense strategic-crossfire between suppliers in the first auction of the sequential ROFR setting – the key differentiator of $(ROFR, 1^{st})$ and $(1^{st}, 1^{st})$.

3.6 Concluding Remarks

The Right-of-First-Refusal is a popular, yet simple, mechanism to decouple price discovery and allocation in auctions. A theoretical understanding of ROFR has been restricted to (single) one-shot auctions, and the prognosis is bleak for the buyer in procurement settings: the consensus, more or less, is that ROFR raises the buyer's (direct) procurement cost in one-shot auctions. Our work in this chapter takes important first steps towards understanding ROFR in the context of sequential (or repeated) auctions, where suppliers' strategies anticipate, exploit and manage information flows within and *across* auctions. (In contrast, such information flows are snuffed out prematurely by a single auction.) We show that the richer strategic interactions in sequential auctions with ROFR, specifically the need to strategically

manage information flows, leads to more aggressive bidding by the nonpreferred supplier, which lowers the buyer's procurement cost.

It is worth noting that the objective of our work in this chapter is not to propose an optimal mechanism for running sequential auctions or, indeed, to even contrast with one if one were known. The leitmotif of the paper is to spotlight the impact of information flows within and across sequential auctions with ROFR, and to show that ROFR can generate lower expected procurement cost for the buyer as compared to other sequential auction settings commonly seen in practice, such as $(1^{st}, 1^{st})$.

Our stylized and parsimonious model of sequential auctions relies on several assumptions but at the very core, our model of sequential auctions with a small pool of suppliers competing over time captures several practical procurement contexts in industries such as automotive, aircraft manufacturing, military and defense, *cf.* Li (2012); or the procurement paradigm of Japanese manufacturers which encourage a small pool of suppliers, *cf.* Dyer (1996). But whether firms actually follow the fairly sophisticated equilibrium predictions remains to be tested empirically. (It is worth noting that Cason *et al.* (2011) experimentally demonstrate that subjects indeed follow the essentials of the Perfect Bayesian Nash Equilibrium, such as deceiving their opponents by strategically manipulating beliefs, in sequential procurement auctions without ROFR; this suggests that some of our results may hold in an experimental setting.) However, there should be little doubt that our work develops and enhances our understanding of the role of ROFR in precipitating an earlier release of information and the possibility of exploiting and managing this information for potential gains, above and beyond the qualitative benefits that are associated with

ROFR. In essence, we show that analyzing information flows and strategies *together* is indispensable for understanding ROFR within the context of sequential auctions.

3.7 Figures and Tables

	# Bidders	Valuations Structure	Information Disclosure	Equilibrium Form
Ortega (1968)	2	continuous &private	all-bid	Separating
Hausch (1986)	2	2 pt. discrete & common	all-bid	Semi - pooling
Thomas (1996)	2	2 pt. discrete & private	all-bid	Semi-pooling
			winning-bid	Separating
Fevrier (2003)	N	continuous & private	winner	Separating
Enkhbayar (2004)	N	continuous & private	all-bid	Mixed
		3 pt. discrete	winning bid	Mixed
Cai (2007)	N	continuous & common	all-bid	Mixed

Tabe 3.1 Summary of literature on sequential auctions
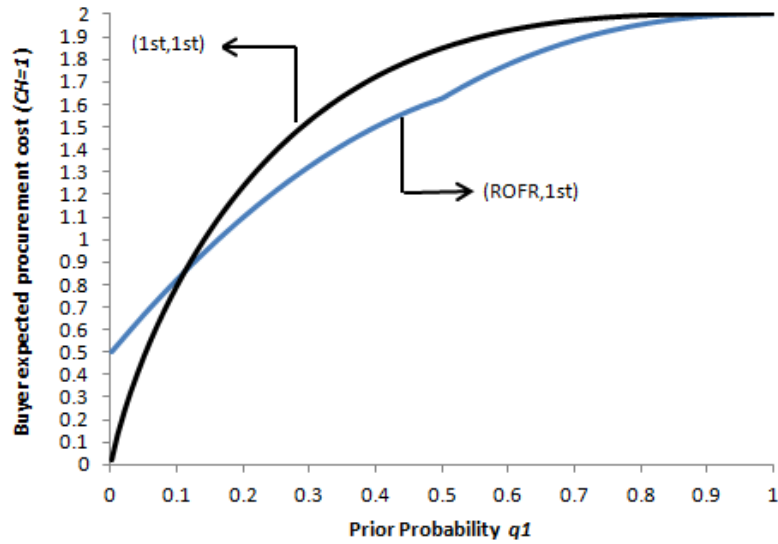
Figure 3.1 Buyers total expected procurement cost across both auctions

3.8 Appendix

In this section, proofs of all the various lemmas, propositions and corollaries in Chapter 3 are presented.

[Although for expositional clarity we dropped ϵ in the main paper (since ϵ is arbitrary small), to validate the robustness of our results we explicitly account for ϵ in our all our proofs in the Appendix. In specific, the lowerbound and upperbound of the support of the mixed strategy profile of the low-cost suppliers in a single-shot 1st-price (or the terminal auction 2 run as 1st-price auction) are respectively $\max\left(q_2^p, q_2^n\right)(C_H - \epsilon)$ and $C_H - \epsilon$. Hence, the equilibrium profit of the low-cost suppliers in auction 2 when it is run as 1st-price is $\max\left(q_2^p, q_2^n\right)(C_H - \epsilon)$.]

Proof of Lemma 1

Proof. Suppose the high-cost supplier bids $b > C_H$ in equilibrium. But the equilibrium breaks down since the opponent can bid ϵ ($\epsilon \to 0$) lower and win the auction for sure. Repetitive application of this argument implies that a high-cost suppliers will bid C_H (equal to their costs) in any auction (with or without ROFR), and this nets them 0 profit in equilibrium. ∎

Proof of Proposition 1

Proof. A low-cost NPS faces two bidding situations: A bid greater than (or equal) to C_H can and will be (profitably) matched by both types of PS, and render the NPS zero profit. Conversely, any bid less than C_H will be matched only by a low-cost PS (since the high-cost PS nets negative profit by doing so). Thus, the low-cost NPS only wins against a high-cost PS by bidding less than C_H. To maximize his profit, the low-cost NPS bids $C_H - \epsilon$ ($\epsilon \to 0$) to secure his most profitable and certain win

against a high-cost PS. The buyer thus incurs a procurement cost of C_H (or $C_H - \epsilon$).

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Proof of Proposition 2

Proof. The proof for this proposition follows the logic of Proposition 1 derived for a forward auction in Thomas (1996), and hence is not restated here. ∎

Proof of Proposition 3

Proof. Consider an equilibrium where a low-cost NPS separates from the high type by bidding strictly lower than C_H ($b_{L1}^n < C_H$) in auction 1 (separating equilibrium). If a low-cost PS matches this bid, the low-cost NPS nets 0 profit in auction 1 as well as 0 profit in auction 2 as per Proposition 2. On the other hand, a low-cost PS who matches the bid of $b_{L1}^n < C_H$ will only gain b_{L1}^n in auction 1 while making 0 profit in auction 2.

In contrast, if a low-cost PS does not match $b_{L1}^n < C_H$, the low-cost NPS will now win and receive his bid (b_{L1}^n) as a payment in auction 1. Moreover, he will net $q_1(C_H - \epsilon)$ in auction 2 from Proposition 2 since the low-cost PS hides his cost by not matching ($q_2^n = q_1$, $q_2^p = 0$). Unlike the previous case, the low-cost NPS will make the total expected profit of $b_{L1}^n + q_1(C_H - \epsilon)$. Note that the low-cost PS who declines to match and "let go" of the auction 1 will only make the profit of $q_1(C_H - \epsilon)$ in auction 2 ($q_2^n = q_1$, $q_2^p = 0$).

Certainly, a low-cost NPS with the bid of $b_{L1}^n < C_H$ prefers the latter case in which the low-cost PS decides to not match. To induce not matching by the PS, the low-cost NPS must bid low enough in auction 1. As the low-cost PS only nets b_{L1}^n in total by matching and $q_1(C_H - \epsilon)$ by not matching, the low-cost NPS can

achieve this by bidding b_{L1}^n in auction 1 which is (weakly) lower than $q_1(C_H - \epsilon)$ to maximize profits. As a result, the low-cost NPS will make the total expected profit of $2q_1(C_H - \epsilon)$: he makes $q_1(C_H - \epsilon)$ auction 1 and $q_1(C_H - \epsilon)$ in auction 2 of $(ROFR, 1^{st})$. The low-cost PS will net 0 in auction 1 and $q_1(C_H - \epsilon)$ in auction 2 when he faces a low-cost NPS.

Since the low-cost NPS play a separating strategy in auction 1, if PS observes the bid of C_H in auction 1, he immediately infers that $q_2^p = 1$. In this situation, the low-cost PS not only earns C_H in auction 1 by matching, he also obtains $C_H - \epsilon$ in auction 2 as per Proposition 2 ($q_2^n = q_1$, $q_2^p = 1$). We summarize the total expected profit each low-cost supplier for this separating equilibrium as following:

$$\pi_{(ROFR,1^{st})}^p = (1 - q_1)[0 + q_1(C_H - \epsilon)] + q_1(C_H + C_H - \epsilon) = (1 - q_1)q_1(C_H - \epsilon) + q_1(2C_H - \epsilon)$$

$$\pi_{(ROFR,1^{st})}^n = 2q_1(C_H - \epsilon)$$

The last step for our proof is to check for deviations. It is straightforward to check that deviations for the low-type PS are not profitable (i.e., matching bids lower than $q_1 (C_H - \epsilon)$ and not matching bids greater than $q_1 (C_H - \epsilon)$). For the low-cost NPS the only (possibly) profitable deviation is to bid C_H in auction 1 and erroneously convince the PS of his high cost. Suppose that a low-cost NPS were to deviate from the proposed strategies and bid C_H in auction 1, behaving as if he were a high-cost NPS. The low-cost PS would update his beliefs to $q_2^p = 1$, assuming that his opponent must have high cost. Thus, he will bid always at $C_H - \epsilon$ in auction 2 from Proposition 2 ($q_2^n = q_1$, $q_2^p = 1$). The low-cost NPS can then win in auction 2 by bidding very close to the bid of low-cost PS which is $C_H - \epsilon$. By

149

comparing the potential profit from deviating $(C_H - \epsilon)$ and the payoff from bidding at $b_{L1}^n = q_1(C_H - \epsilon)$ for low-cost NPS (Equation 7), we conclude that when $q_1 \geq (1/2)$, the proposed equilibrium holds and bidding at $b_{L1}^n = q_1(C_H - \epsilon)$ is optimal.

To calculate the total procurement cost of the buyer in $(ROFR, 1^{st})$, we extract the total expected surplus and the cost of each winner across two auctions under different possibilities of having cost types for the suppliers.

There are four cases (denoted by $k = 1, 2, 3, 4$). For $(k = 1)$ both suppliers are low-cost, for $(k = 2)$ there is a low-cost PS and a high-cost NPS, for $(k = 3)$ there is a high-cost PS and a low-cost NPS and for $(k = 4)$ both suppliers are high-cost. The total expected procurement cost of the buyer over both auctions is given by

$$TC_{(ROFR,1^{st})} = \sum_{k=1}^{4} \Pr(\text{possibility } k) \times [\text{winners' expected profit} + \text{winners' expected cost}]$$

We expressed the expected profit of both low-cost PS and NPS in equation 7. If there exists at least one low-cost supplier in each auction, the winner is the low-cost supplier. The only situation where the winner is a high-cost supplier is when both suppliers are high-cost. Inserting the derived supplier profits expressions, associated probabilities and costs, we find that the buyer's total expected costs (as $\epsilon \to 0$) is given by,

$$TC_{(ROFR,1^{st})} = q_1[2 + (1 - q_1)(3 - q_1)]C_H$$

∎

Proof of Proposition 4

Proof. The proposed separating equilibrium in auction 1 cannot hold when $q_1 < (1/2)$. We find that there does not exist a pure strategy equilibrium of $b_{L1}^n =$

$q_1(C_H - \epsilon)$ in auction 1 so that a low-cost NPS mixes between bidding at $b_{L1}^n < C_H$ and $b_{L1}^n = C_H$. Similar to our discussion in proof for Proposition 3, if a low-cost NPS decides to bid strictly lower than C_H, he should bid at $b_{L1}^n = q_1(C_H - \epsilon)$.

We consider a mixed strategy, where a low-cost NPS bids at C_H with a positive probability of β while he bids at $q_1(C_H - \epsilon)$ with the probability of $(1 - \beta)$. Note that similar to Proposition 3, the low-cost PS never matches the opponent's bid at $q_1(C_H - \epsilon)$. On the other hand, PS (low/high-cost) always matches the bid of C_H in auction 1.

The beliefs are derived from equilibrium strategies and Bayes' Rule. Hence, the posterior belief of the PS upon seeing a bid of C_H by the NPS is $q_2^p = \frac{q_1}{q_1 + (1 - q_1)\beta}$. However, any bid less than C_H by the NPS precipitates the posterior belief of PS to 0. On the other hand, since any PS matches the bid of C_H in auction 1, the posterior belief of NPS when he bids at C_H in auction 1 is $q_2^n = q_1$.

To satisfy the indifference property of a mixing strategy, the low-cost NPS faces a following trade-off. His total expected profit from bidding at $q_1(C_H - \epsilon)$ must equal his total expected profit from bidding at C_H. We know from Proposition 3, the former payoff is $2q_1(C_H - \epsilon)$ (see Equation 7). However, when a low-cost NPS bids at C_H in auction 1, he certainly loses in auction 1 but nets $\max(q_2^p, q_2^n)(C_H - \epsilon)$ in auction 2. When a low-cost NPS bids at C_H, the posterior beliefs are $q_2^p = \frac{q_1}{q_1 + (1 - q_1)\beta}$ and $q_2^n = q_1$. Hence, to sustain this mixed bidding strategy, $2q_1(C_H - \epsilon) = \max\left(\frac{q_1}{q_1 + (1 - q_1)\beta}, q_1\right)(C_H - \epsilon)$. As $0 \leq \beta \leq 1$, it is easy to see in auction 2 that

$\max\left(\frac{q_1}{q_1+(1-q_1)\beta}, q_1\right) = \frac{q_1}{q_1+(1-q_1)\beta}$. Consequently:

$$\pi^n_{(ROFR,1^{st})} = 2q_1(C_H - \epsilon) = \frac{q_1}{q_1 + (1 - q_1)\beta}(C_H - \epsilon) \tag{8}$$

$$\Rightarrow \quad \beta = \frac{1 - 2q_1}{2(1 - q_1)} \tag{9}$$

It is easy to see when $0 < q_1 < (1/2)$, we have $\beta \in [0, 1]$ such that $d\beta/dq_1 < 0$.

The low-cost NPS nets the same payoff as he does in Proposition 3 of $(2q_1(C_H - \epsilon))$.

On the other hand, the profit function of a low-cost PS has two parts. As we demonstrate in Equation 10 (the first term), upon seeing the opponent's bid at $q_1(C_H - \epsilon)$ with the probability of $(1 - q_1)(1 - \beta)$, a low-cost PS only nets $q_1(C_H - \epsilon)$ in auction 2 (since he never matches in auction 1). Moreover, as we see in the second term of Equation 10, if the low-cost PS is leaked the bid of $b^n_{L1} = C_H$ in auction 1 with the probability of $q_1 + (1 - q_1)\beta$, he will make the total profit of $C_H + \max(q^p_2, q^n_2)(C_H - \epsilon)$. From the fact that $\max\left(\frac{q_1}{q_1+(1-q_1)\beta}, q_1\right) = \frac{q_1}{q_1+(1-q_1)\beta}$ in auction 2, we can conclude:

$$\pi^p_{(ROFR,1^{st})} = (1 - q_1)(1 - \beta)q_1(C_H - \epsilon) + [q_1 + (1 - q_1)\beta]\left[C_H + \frac{q_1}{q_1 + (1 - q_1)\beta}(C_H - \epsilon)\right] \tag{10}$$

$$\pi^p_{(ROFR,1^{st})} = \frac{3q_1}{2}(C_H - \epsilon) + \frac{C_H}{2}$$

We derive the total procurement cost of the buyer from the total expected surplus of the winners (from Equation 10 and 8) as well as their costs across two auctions for different possibilities of cost types.

The only difference between calculating the buyer's procurement cost in Proposition 4 and 3 is that due to the mixed strategy of a low-cost NPS in auction 1, the winner of the first auction *may* now become a high-cost PS with the cost of C_H if

there exists a high-cost PS and a low-cost NPS who bids at C_H in auction 1 ($w.p$ of β). In all remaining cases, if there is at least a low-cost supplier, we always have a low-cost winner (PS/NPS) with no cost. This yields to:

$$
\begin{aligned}
TC_{(ROFR,1^{st})} &= (1 - q_1)^2 \times [2q_1(C_H - \epsilon) + \frac{3q_1}{2}(C_H - \epsilon) + \frac{q_1}{2}C_H] + 2q_1^2 C_H \\
&\quad + (1 - q_1)q_1 \times [\frac{3q_1}{2}(C_H - \epsilon) + \frac{q_1}{2}C_H] + q_1(1 - q_1) \times [2q_1(C_H - \epsilon) + \beta C_H]
\end{aligned}
$$

By further simplification and when $\epsilon \to 0$, the final term for $TC_{(ROFR,1^{st})}$ will become:

$$
TC_{(ROFR,1^{st})} = \frac{(1 + q_1\,(7 - 5q_1))\,C_H}{2}
$$

∎

Proof of Proposition 5

Proof. We generalize the proof of Proposition 1 in Thomas (1996) which was stated for $q_1 = 1/2$.

Consistent with Thomas (1996), we focus on a symmetric equilibrium where both the low-cost suppliers in auction 1 follow a strictly continuous mixed bidding strategy. There cannot exist an equilibrium in pure strategy in auction 1 of $(1^{st}, 1^{st})$. Suppose there does. Then for a low-cost supplier (i) who bids at b_{L1}^i, the other low-cost supplier $(-i)$ can bid at $b_{L1}^{-i} = b_{L1}^i - \epsilon$ $(\epsilon \to 0)$ and win the auction with certainty. Thus price competition will precipitate the equilibrium bids in auction 1 to 0 which is not desirable for any low-cost supplier. That necessitates both low-cost suppliers to play mixed strategies in equilibrium of auction 1 of $(1^{st}, 1^{st})$. One can invoke similar argument to rule out atoms in the support of the mixed strategy profile for low-cost suppliers.

Low-cost suppliers always bid strictly lower than C_H in auction 1 of $(1^{st}, 1^{st})$ to avoid ties with high-cost opponents. Moreover, since only the winning bid is announced in auction 1, the low-cost suppliers have no incentive to bid at C_H in auction 1 to hide their cost types. Thus, upperbound support of mixed strategy of the low-cost suppliers in auction 1 of $(1^{st}, 1^{st})$ is $C_H - \epsilon$.

Now suppose that each low-cost supplier (S_1 or S_2) draws his bids ($b_{L1}^i \in [\underline{b}_1^*, C_H - \epsilon]$, $i \in (S_1, S_2)$) in auction 1 from a cumulative density function like $H(.)$. Without loss of generality, we can write down the expected profit of the low-cost supplier S_2 in $(1^{st}, 1^{st})$ as following:

$$\pi_{(1^{st},1^{st})}^{s_2}(b_{L1}^{S_2}) = [q_1 + (1 - q_1) \Pr(b_{L1}^{S_2} < b_{L1}^{S_1})][b_{L1}^{S_2} + \max(q_2^w, q_2^l)(C_H - \epsilon)] \quad (11)$$

$$(1 - q_1) \Pr(b_{L1}^{S_2} > b_{L1}^{S_1})[E(\max(q_2^w, q_2^l))(C_H - \epsilon)]$$

In Equation 11, the first term is the expected profit S_2 nets if he wins auction 1. Upon winning, he is paid his bid of $b_{L1}^{S_2}$ in auction 1 while in auction 2, his payoff is $\max(q_2^w, q_2^l)(C_H - \epsilon)$ or $q_2^w(C_H - \epsilon)$. (The loser of auction 1, who sees a wining bid which is strictly lower than C_H, can infer $q_2^l = 0$.) Note that the formation of q_2^w depends on the winning bid in auction 1. Hence, the low-cost supplier S_2 (winner) will now update his posterior belief according to the Bayes' rule conditional on his winning bid ($b_{L1}^{S_2}$) as following:

$$q_2^w = \frac{q_1}{q_1 + (1 - q_1) \overline{H}(b_{L1}^{S_2})} \quad (12)$$

It is easy to see if $b_{L1}^{S_2}$ turns out to be the winning bid, the winner can infer that the losing opponent has low cost with the probability of $(1 - q_1) \overline{H}(b_{L1}^{S_2})$. On the

154

other hand, the second term in Equation 11 is the expected profit of the low-cost S_2 if he loses in auction 1. While he gains no profit in auction 1, there still exists one-sided asymmetry from the winner's perspective (the low-cost S_1) in auction 2 ($\max(q_2^w, q_2^l) > 0$). This brings a positive expected profit into the auction 2 which is again $q_2^w(C_H - \epsilon)$ with $q_2^w = \frac{q_1}{q_1 + (1-q_1)\overline{H}(b_{L1}^{S_1})}$.

As we can see the expected profit of the low-cost S_2 (loser) in auction 2 will now depend on the winning bid ($b_{L1}^{S_1}$) as well as the mixed strategy of $H(.)$ in auction 1. Since this winning bid is not known prior to the auction 1, in forming his profit function when bids at $b_{L1}^{S_2}$, the low-cost S_2 should take expectations regarding the winning bid to determine his expected future profit in auction 2. This expectation is taken conditional on all possible winning bid which is between the lowerbound ($\underline{b}_1^*$) and the losing bid of $b_{L1}^{S_2}$ in auction 2. Rewriting Equation 11 results in:

$$
\begin{aligned}
\pi_{(1^{st},1^{st})}^{s_2}(b_{L1}^{S_2}) &= [q_1 + (1-q_1)\overline{H}(b_{L1}^{S_2})][b_{L1}^{S_2} + \frac{q_1(C_H - \epsilon)}{q_1 + (1-q_1)\overline{H}(b_{L1}^{S_2})}] + \quad (13)\\
&\quad (1-q_1)H(b_{L1}^{S_2})[E(\frac{q_1}{q_1 + (1-q_1)\overline{H}(b_{L1}^{S_1})})(C_H - \epsilon)]
\end{aligned}
$$

The last step to find out $\pi_{(1^{st},1^{st})}^{s_2}(b_{L1}^{S_2})$ is to calculate $E(\frac{q_1}{q_1 + (1-q_1)\overline{H}(b_{L1}^{S_1})})$. Note that in Equation 13 (the second term), the losing bid is $b_{L1}^{S_2}$. Thus, the probability distribution of the winning bid given the losing bid ($b_{L1}^{S_2}$) simply equals the probability density function of the mixing bidding strategy (dH) given the winning bid is smaller than $b_{L1}^{S_2}$. Thus, the distribution of the winning bid will then become $\frac{dH}{H(b_{L1}^{S_2})}$. This leads to:

$$
E(\frac{q_1}{q_1 + (1-q_1)\overline{H}(b_{L1}^{S_1})}) = \int_{\underline{b}_1^*}^{b_{L1}^{S_2}} \frac{q_1}{q_1 + (1-q_1)\overline{H}(b_{L1}^{S_1})} \cdot \frac{dH}{H(b_{L1}^{S_2})} = -\frac{q_1 \ln(q_1 + (1-q_1)\overline{H}(b_{L1}^{S_2}))}{H(b_{L1}^{S_2})(1-q_1)}
$$

$$(14)$$

155

Equation 13 and 14 yields to:

$$\pi^{s_2}_{(1^{st},1^{st})}(b^{S_2}_{L1}) = [q_1+(1-q_1)\overline{H}(b^{S_2}_{L1})]b^{S_2}_{L1}+q_1(C_H-\epsilon)-q_1\ln(q_1+(1-q_1)\overline{H}(b^{S_2}_{L1}))(C_H-\epsilon)$$

(15)

Due to the nature of the mixed bidding strategy in auction 1, we are not able to find the closed-form solution for the equilibrium bidding strategy from Equation 15. We are, however, able to characterize the support of the bidding strategies which is sufficient to discover the profit function of each low-cost supplier in $(1^{st},1^{st})$. From Equation 15, a low-cost supplier makes the following total expected profit by bidding at the lowerbound $(\underline{b}^*_1)$ in auction 1.

$$\pi^i_{(1^{st},1^{st})}(\underline{b}^*_1) = \underline{b}^*_1 + q_1(C_H - \epsilon)$$

(16)

Furthermore, he also makes the following total expected profit by bidding at the upperbound $(C_H - \epsilon)$ in auction 1.

$$\pi^i_{(1^{st},1^{st})}(C_H - \epsilon) = 2q_1(C_H - \epsilon) - q_1\ln(q_1)(C_H - \epsilon)$$

(17)

Both low-cost suppliers should be indifferent across all strategies they mix over including $\underline{b}^*_1$ and $C_H - \epsilon$. From Equation 16 and 17 we can first conclude $\underline{b}^*_1 = q_1(1 - \ln(q_1))(C_H - \epsilon)$ in auction 1 of $(1^{st},1^{st})$ and the following:

$$\pi^i_{(1^{st},1^{st})}(b^i_{L1}) = q_1(2 - \ln(q_1))(C_H - \epsilon) \quad b^i_{L1} \in [\underline{b}^*_1, C_H - \epsilon]$$

(18)

Similar to how we extracted the total procurement cost of the buyer for different possibilities of cost types for Proposition 3 and 4, we use the expected profit of low-cost suppliers in $(1^{st},1^{st})$. Again, if there exists at least one low-cost supplier in

each auction, the winner is low-cost with a positive expected profit (Equation 18) and zero cost. Finally, only if the buyer faces two high-cost suppliers, the winner is exposed to the cost of C_H in each auction.

$$
\begin{aligned}
TC_{(1^{st},1^{st})} &= (1-q_1)^2 \times [2q_1(2-\ln(q_1))(C_H-\epsilon)] + (1-q_1)q_1 \times [q_1(2-\ln(q_1))(C_H-\epsilon)[\\
&\quad +q_1(1-q_1) \times [q_1(2-\ln(q_1))(C_H-\epsilon)] + 2q_1^2 C_H
\end{aligned}
$$

$$
TC_{(1^{st},1^{st})} = 2q_1(1-q_1)(2-\ln(q_1))(C_H-\epsilon) + 2q_1^2 C_H
$$

By further simplification and when $\epsilon \to 0$, the final term for $TC_{(1^{st},1^{st})}$ becomes:

$$
TC_{(1^{st},1^{st})} = 2q_1[2-q_1-(1-q_1)\ln(q_1)]C_H
$$

■

Proof of Corollary 1

Proof. Consider two cases:

Case (i) $q_1 \geq (1/2)$. The low-cost NPS always bids at $q_1(C_H-\epsilon)$ in auction 1 of $(ROFR, 1^{st})$. This is strictly lower than $C_H - \epsilon$, the equilibrium bid in a one-shot auction.

Case (ii) $q_1 < (1/2)$. The low-cost NPS bids $q_1(C_H-\epsilon)$ with the probability of $(1-\beta) = \frac{1}{2(1-q_1)}$ and bids at C_H with the probability of $\beta = \frac{1-2q_1}{2(1-q_1)}$ in auction 1 of $(ROFR, 1^{st})$. It is easy to show this expected bid is:

$$
= \frac{q_1(C_H-\epsilon)}{2(1-q_1)} + \frac{1-2q_1}{2(1-q_1)}C_H = \frac{C_H}{2} - \frac{q_1\epsilon}{2(1-q_1)} < C_H - \epsilon \tag{19}
$$

■

Proof for Corollary 2

Proof. First of all, it is easy to see the lowerbound support for the mixed strategy profile for low-cost suppliers in $(1^{st}, \phi)$, which is $q_1(C_H - \epsilon)$, is smaller than the lowerbound support in auction 1 of $(1^{st}, 1^{st})$, which is $q_1(1 - \ln(q_1))(C_H - \epsilon)$.

We now prove that the bid distribution $(H(.))$ for a low-cost supplier in auction 1 of $(1^{st}, 1^{st})$ stochastically dominates the bid distribution $(F(.))$ for a low-cost supplier in $(1^{st}, \phi)$. That is, we need to show $H(b^i_{L1}) < F(b^i_{L1})$ when $q_1(1 - \ln(q_1))(C_H - \epsilon) < b^i_{L1} < (C_H - \epsilon)$. (Since the lowerbound support for $F(x)$ is smaller the lowerbound support for $H(x)$, we only check this dominance across the domain of $H(x)$.)

Since in $(1^{st}, \phi)$, Proposition 2, $q_2^n = q_2^p = q_1$ we have $F(b^i_{L1}) = \frac{b^i_{L1} - q_1(C_H - \epsilon)}{(1-q_1)b^i_{L1}}$, with $\epsilon \to 0$. This leads to:

$$\overline{F}(b^i_{L1})(1 - q_1)b^i_{L1} = q_1[(C_H - \epsilon) - b^i_{L1}] \tag{20}$$

In $(1^{st}, 1^{st})$, from the RHS of 15 and from the fact that low-cost suppliers make the expected profit of $q_1(2 - \ln(q_1))(C_H - \epsilon)$ in $(1^{st}, 1^{st})$, we obtain:

$$q_1[\ln(q_1 + (1-q_1)\overline{H}(b^i_{L1})) - \ln(q_1)](C_H - \epsilon) = -q_1[(C_H - \epsilon) - b^i_{L1}] + (1-q_1)\overline{H}(b^i_{L1})b^i_{L1} \tag{21}$$

Since the LHS of Equation 21 is always positive for all $0 < q_1 < 1$, the RHS of this Equation must be positive as well. Thus:

$$(1 - q_1)\overline{H}(b^i_{L1})b^i_{L1} > q_1[(C_H - \epsilon) - b^i_{L1}] \tag{22}$$

∎

Equation 20 and 22 yields:

$$(1 - q_1)\overline{H}(b^i_{L1})b^i_{L1} > \overline{F}(b^i_{L1})(1 - q_1)b^i_{L1} \tag{23}$$

$$\Rightarrow \qquad H(b_{L1}^i) < F(b_{L1}^i)$$

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