EMPIRICAL ANALYSES OF ONLINE PROCUREMENT AUCTIONS: BUSINESS VALUE, BIDDING BEHAVIOR, LEARNING AND INCUMBENT EFFECT

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EMPIRICAL ANALYSES OF ONLINE PROCUREMENT AUCTIONS: BUSINESS VALUE, BIDDING BEHAVIOR, LEARNING AND INCUMBENT EFFECT

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To my parents and all my friends,

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SUMMARY

While there is an ever increasing adoption of e-sourcing, where a buyer auctions off procurement contracts to a small group of pre-qualified suppliers, there is a lack of understanding of the impact of dynamic bidding process on procurement outcomes and bidding behavior. To extend the knowledge of this important issue, in this thesis, we explore empirically the value of online procurement auction on cost reduction, quality management, and winner selection from the buyer's perspective. We also explore how incumbent status affects the procurement outcomes. From suppliers' perspective, we characterize their bidding behavior and examine the effect of incumbent status on bidding. First, we collect detailed auction and contract awarding data for manufacturing goods during 2002-2004 from a large buyer in the high-tech industry. The rich data set enables us to apply statistical model based cluster technique to uncover heterogeneous bidding behavior of industrial participants. The distribution of the bidding patterns varies between incumbent and non-incumbent suppliers. We also find that the buyer bias towards the incumbent suppliers by awarding them procurement contracts more often and with a price premium. Next, focusing on recurring auctions, we find that suppliers bid adaptively. The adaptive bidding is affected by the rank of suppliers' final bids: lower-priced suppliers tend to bid scarcely but actively in repeated auctions. Finally, with field data of procurement auction for legal services, we demonstrate that service prices are on average reduced after dynamic bidding events. Buyer's cost savings are from both incumbent and non-incumbent suppliers. Most interestingly, the cost savings are achieved without the sacrifice of quality. Incumbent winners' quality is higher, on average, than the quality of buyer's supplier base before the auctions, while non-incumbent winner's quality is lower.

These findings imply that the main value of online procurement auctions for business services comes from incumbents in the form of reduced price and enhanced quality. We find that after adjusting for incumbents' higher quality, incumbent bias disappears. Our results also imply that the buyer might possess important information about the incumbents, through past experiences, that cannot be easily included in the buyer's scoring function due to uncodifiability (Levi, Kleindorfer, and Wu 2003). Such information plays a key role in buyer's winner selection decision, and explains why the buyer sometime chooses one supplier over another ignoring the scoring rule. The thesis contributes to the field of procurement and auction literature by enhancing the understanding of the effects of dynamics bidding events and incumbent status, suggesting various important factors that need to be considered in future research.

CHAPTER I

INTRODUCTION

1.1 E-Sourcing and Procurement Auctions

E-sourcing, whereby an industrial buyer procures its direct and indirect inputs through online reverse auctions from a small group of pre-qualified by-invitation only suppliers, has been pushing the boundaries of extant auction theories as well as the "best practices" of service providers ever since their emergence (Elmaghraby 2007; Pinker, Seidmann, and Vakrat 2003). As an integrated part of a firm's e-sourcing strategies, online reverse auction is an effective tool for buyers to repeatedly purchase production materials, to shorten the procurement cycle, and to achieve higher cost savings (Jap 2002).

Despite these benefits, there have been concerns in the adoption and usage of Internet-based enabled procurement auctions due to a lack of understanding of its execution and consequence. One of the criticisms of online reverse auction stems from its bias towards the interest of the buyer. It is reported that long-term buyer-supplier relationship gets damaged when the buyer emphasizes only the final prices and let the auctions determine the winners (Engelbrecht-Wiggans and Katok 2006). The pressure of lowering prices and the feeling of being exploited have created suppliers' resistance to participate (Jap 2002). To respond, software service providers and buyers have been trying to design better auction mechanisms and include buyer-specified non-price attributes, such as quality, delivery and payment term to compare the relative strength of potential suppliers in contract awarding. However, there are a few questions that remain unclear. First, do buyers discriminate against incumbent suppliers or bias toward incumbents as documented in the government procurement literatures? Answers to this question will not only help to mitigate suppliers' resistance in participating, but also help academia better understand the impact of incumbency in online auction markets. Second, whether e-sourcing through online reverse auction can achieve quality management has not been explored in depth due to scarcity of business-to-business (B2B) auctions and contract awarding data. There is also an urgent need to understand the value of online auction in managing supplier quality. This is especially important with the increasing use of online procurement auctions for complex business services, where service quality is a key determinant for buyers to award procurement contracts.

Another key feature of online procurement auctions is their repetition, as they are often conducted yearly or quarterly or even daily (Elmaghraby 2007; Pinker, Seidmann, and Vakrat 2003). Recent analytical work on procurement suggests that suppliers can learn about the market competitiveness by participating in procurement auctions (Fevrier 2003; Jeitschko 1998). However, it is unclear whether supplier learning indeed happens in practice. It also remains unknown whether and how information revealed after the auctions affect suppliers' bidding behavior in subsequent auctions.

Unlike business-to-consumer (B2C) and consumer-to-consumer (C2C) auction markets where auction rules and mechanisms are usually controlled and fixed by market creators, B2B auctions empower industry buyers with the flexibility to specify various auction parameters, such as reserve price, bid decrements and so on. More importantly, online reverse auctions allow the buyers to decide what information to reveal to the bidders before, during and after the auction events. Such information revelation rules, more than any other factors, seem to determine the ultimate success of procurement auctions.[1]

[1]Source: Private communication with Norbert Ore, an industry expert in strategic sourcing.

Together, the aforementioned unique characteristics of procurement auctions: incumbency, repetition of auction events and supplier quality management, create a complex setting that is far different from elegant theoretical underpinnings. With such new challenges, rise new opportunities. Empirical analyses of valuable data sets uniquely available from Internet auctions provide a critical first step towards understanding the effects of online procurement auction design in order to build new auction "theory about facts" and for "putting auction theory to work" as advocated by auction theorists (Milgrom 2004). In the next section, we brief recent advancement of relevant online procurement auction design.

1.2 Online Procurement Auctions Design

Within the last decade, online procurement auctions have quickly evolved from price only auction design to more complicated mechanisms to improve allocation efficiency and to achieve sourcing sustainability (Elmaghraby 2007). Driven by the growing adoption of online procurement auctions, the literature on reverse auctions is also growing. More sophisticated mechanism designs are proposed to facilitate and guide business practice (Elmaghraby and Keskinocak 2003; Vries and Vohra 2003). Cramton and Ausubel (2006) summarize most recent advances in procurement auction design. For the purpose of this thesis, we broadly categorize relevant procurement auction designs into three streams: (1) Price-only auctions; (2) Hybrid mechanisms, for example auction plus post-auction bargaining or negotiation; and (3) Multi-attribute auctions.

In price-only auctions, suppliers are allowed to bid on price alone. This stream of work mainly focuses on mechanism design and characterizing equilibrium bidding behavior. Milgrom (2000b) shows non-strategic bidding leads to competitive market price when goods are substitutes. In a similar setting, Engelbrecht-Wiggans and Kahn (2005) derive low-revenue equilibria that allow bidders obtain goods at prices lower than competitive price. Although the results of these works are discussed within the framework of simultaneous ascending-bid auction, they can be easily applied to reverse auctions with similar rules. When industrial bidders are constrained by capacity, Gallien and Wein (2005) introduce a “smart-market” mechanism that allows bidders to adjust their bids and quantity based on current allocation.

Although theoretically sound, price-only auctions' limitations due to their emphasis on short-term success were quickly realized by both buyers and procurement service providers (Elmaghraby 2007; Jap 2002). To address, academic research proposes varied mechanisms that combine both reverse auctions and post-auction events. The purpose of such design is to maintain the price discovery feature of auctions, but alleviate the price pressure on the suppliers (Engelbrecht-Wiggans and Katok 2006; Salmon and Wilson 2005).

Along the same line, multi-attribute auctions have been gaining more attention due to its ability to enable buyers to evaluate suppliers along diverse dimensions and compare their relative strength. These so-called non-price attributes usually include quality, delivery, payment terms and so on. Buyers are required to specify clearly their preferences for the attributes and reveal them to the suppliers. Therefore, each supplier has an index score on the basis of a buyer's preference. Auction winners are determined by price and suppliers' score for the non-price attributes. Theoretically, multi-attribute auctions would result in competitive bidding and allocation efficiency (Asker and Cantillon 2006; Milgrom 2004; Carr 2003; Snir and Hitt 2003; Milgrom 2000a; Milgrom 2000b). Multi-attribute auctions have been shown to be effective and superior to price-only auctions, by increasing buyer's cost savings and supplier profits in laboratory experiments (Engelbrecht-Wiggans and Katok 2006; Chen-Ritzo, Harrison, Kwasnica, and Thomas 2005). In practice, however, buyers are reluctant to adopt the design due to uncodifiability and unobservability of non-price attributes (Elmaghraby 2007; Dai, Narasimhan, and Wu 2005).

Recently, there is a new stream of studies focusing on the so-called buyer determined auctions (Engelbrecht-Wiggans, Haruvy, and Katok 2006; Chen-Ritzo, Harrison, Kwasnica, and Thomas 2005; Silva, Dunne, and Kosmopoulou 2003). These auctions are similar to the multi-attribute and scoring auctions in the sense that quality is included in evaluating supplier bids. However, instead of submitting both price and the corresponding quality level, bidders submit price only bids given the quality assessment assigned by a buyer prior to the auction. This framework provides more realist models to abstract the prevalent procurement operations through online reverse auctions. In general, the studies presented in this thesis belongs to this framework. We contribute to the field by empirically investigate the effect of online reverse auctions design on bidding behavior and procurement outcomes for both manufacturing goods and complex business services. We also quantify the value of incumbency in various settings. The next section presents the outline of research projects this thesis.

1.3 Research Outline

The purpose of this thesis is to empirically investigate the effects of incumbent status, learning and information revelation pertaining to B2B auctions on suppliers' bidding behavior and auction outcomes. Table 1 summarizes the outline of this dissertation.

The thesis begins with addressing a seeming puzzle in e-souring, that is, the ever-increasing adoption of reverse auctions and related concerns about its potential damage to long-term buyer-supplier relationships. Utilizing e-sourcing data of a major high-tech buyer during 2002-2004, we empirically investigate the relationships among incumbency, bidding behavior and auction outcomes. The unique data set not only captures the entire auction history and bidder type (incumbent or non-incumbent supplier), but also records critical e-sourcing events such as post-auction cost savings calculations and final contract awarding decisions. Bidding patterns exerted in the reverse auctions show that the distribution of bidding strategies is moderated by incumbent status, which, in conjunction with bidding strategies, have significant impacts on the auction outcomes. Specifically, we show that

1. At the contract level, suppliers' final bids depend on incumbent status, bidding strategies, and their interactions.

2. On average, incumbent winners provide lower cost savings for the buyer.

3. On average, incumbent suppliers are three times as likely to win a contract than non-incumbent suppliers.

These findings demonstrate that e-sourcing through reverse auctions does not necessarily damage long-term buyer-supplier relationships.

While auctions are treated as isolated events in Chapter 2, Chapter 3 focuses on recurring procurement auctions where learning is possible. Econometric analyses show that suppliers' final bids at successive auctions are significantly affected by the prior information learned (for example, suppliers' rank orders and the lowest bid price). Moreover, suppliers bid adaptively between auctions, that is, a supplier's bidding dynamics are different in successive auctions; such adaptive bidding behavior is influenced by suppliers' ordinal ranks acquired after auctions. The findings provide initial evidence that by participating in earlier auctions, suppliers can learn important information about the market competitiveness and the efficiency of their bidding strategies.

Chapter 4 aims to quantify the value of incumbency and online reverse auctions in procuring complex business services. To the best of our knowledge, it is the first study that examines the impact of online auctions on both cost savings and quality management. We find that prices are on average reduced after dynamic bidding events. Buyer's cost savings are from both incumbent and non-incumbent suppliers. We do not find, however, that incumbent winners enjoy price premium compared to non-incumbent winners. The cost savings are achieved without sacrificing quality. Specifically, incumbent winners' quality is higher, on average, than the quality of buyer's supplier base before the auctions, while non-incumbent winner's quality is lower. These findings imply that the main value of online procurement auctions for business services come from incumbents in the form of reduced price and enhanced quality.

The rest of the thesis is organized as follows. Chapter 2 describes the methodology and results of the impacts of incumbent status and bidding behavior on auction outcomes in procuring manufacturing goods. Chapter 3 gives the detailed research design and results of supplier learning in repeated auctions. In the context of online reverse auctions for legal services, Chapter 4 investigates the value of online procurement auctions and revisit the issue of incumbent bias. Chapter 5 concludes.

Table 1: An Outline of the Dissertation

Chapter	Setting	Research Questions
2	• Static Auctions • Manufacturing Goods • B2B Bidding Dynamics	• What are the bidding dynamics that characterize the bidding behavior of industrial participants and their impact on auction outcomes? • How does incumbent status affect bidding behavior and auction outcomes?
3	• Repeated Auctions • Manufacturing Goods	• How do suppliers bid in repeated procurement auctions? Do they change bidding strategies between auctions? • If so, how does supplier learning between successive auctions influence their bidding strategies?
4	• Scoring Auctions • Business Services	• What is the value of online procurement auctions in achieving cost reduction and managing supplier quality? • How does incumbent status affect bidding and auction outcomes? Is it different from procuring manufacturing goods?

CHAPTER II

PROCUREMENT OF MANUFACTURING GOODS

Perhaps the most critical question for e-sourcing, whereby an industrial buyer procures its direct and indirect inputs through reverse auctions from a small group of invited suppliers (Dai, Narasimhan, and Wu 2005), is whether this process damages buyer-supplier relationships (Engelbrecht-Wiggans and Katok 2006; Beall et al. 2003; Elmaghraby 2000). Skeptics of e-sourcing sustainability often argue that the price pressures and sense of exploitation create resistance among suppliers (Jap 2002). However, this criticism ignores non-price attributes, such as product attributes, quality, delivery, and buyer and seller types (Milgrom 2000a), that characterize and distinguish business-to-business (B2B) from consumer auctions. These attributes enable a buyer to assess suppliers' relative strength and play decisive roles, according to recent procurement auction theories (Asker and Cantillon 2006; Milgrom 2004; Carr 2003; Milgrom 2000b). Such non-price attributes are often uncodifiable (Levi, Kleindorfer, and Wu 2003) or unobservable, which presents a major obstacle to test them empirically. However, based on previous buyer-supplier relationship, we normally can observe the identity of incumbent suppliers. The incumbent status reflects not only the difference along various non-price dimensions, but also possible difference in the information possessed by different suppliers (Luton and McAfee 1986).

Despite the vast literature pertaining to theoretically sound auction mechanisms, few of these theories are used in business practice (Milgrom 2000b; Rothkopf and Harstad 1994). Empirical investigations therefore provide a critical first step toward building new auction “theory about facts” and “putting auction theory to work” (Milgrom 2004 pp. 26 and pp. 1). In addition to their silence regarding non-price attributes, traditional auction theories focus on the final (or equilibrium) bid but neglect the dynamic bidding process that leads to it. Although research has begun to investigate Internet consumer auctions, specifically the impact of the consumer’s strategic bidding behavior on final bid, seller revenue and auction design (for example, Bapna, Goes, and Gupta 2004; Easley and Tenorio 2004), studies of online procurement auctions remain rare (Elmaghraby 2007; Pinker, Seidmann, and Vakrat 2003), with the exceptions of Snir and Hitt (2003), who examine online service procurement auctions, and Mithas and Jones (2007), who study the impact of auction parameters on buyer surplus. We are not aware of any previous studies that examine the impact of the actual bidding behavior of industrial participants in e-sourcing. Prior to this study, it has remained unknown whether industrial participants employ the same, if any, bidding strategies in B2B auctions as those that appear in consumer auctions.

We collect a unique data set to address buyer-supplier relationships in e-sourcing. We also develop a conceptual model of non-price attributes, bidding behavior, and auction outcomes to apply to this data set. The e-sourcing data from a major buyer in the high-tech industry during 2002-2004 has several advantages. (1) We can observe information about a bidder’s type, that is , whether a bidder is an incumbent or a non-incumbent supplier. This, in conjunction with other constructs such as relationship and previous auction experience, enables us to proxy non-price attributes. (2) The data cover the entire auction history, which enables us to study bidding dynamics through cluster analyses, as well as the impact of bidding behavior on final bids. (3) The post-auction data, showing the cost savings and final contract awarding, enables us to link non-price attributes and bidding behavior to auction outcomes and thereby empirically execute the conceptual model.

This chapter has two key objectives: To study the bidding dynamics that characterize the bidding behavior of industrial participants and their impact on auction outcomes, and to examine the impact of non-price attributes on bidding behavior and auction outcomes.

The institutional analyses shed light on the buyer-supplier relationships puzzle in e-sourcing and supports theoretical arguments about the roles of incumbent status in procurement auctions (Levi, Kleindorfer, and Wu 2003; Milgrom 2000a). The key findings[1] can be best illustrated by Figure 1. First, incumbent suppliers, indicated by closed squares, win the majority (83.1%)[2] of the contracts. Second, most points located above the 45 degree line (for example, point A) with positive cost savings are closed squares, which offers compelling evidence of the impact of incumbent status on final contract awards. A point in this area (shaded light gray) means that the non-incumbent supplier provides potentially higher savings (for example, 80% for point A) than the incumbent supplier (for example, 30% for point A), though the non-incumbent suppliers are not awarded the contract in most cases. Third, there are rare cases such as point B, in which a non-incumbent supplier - indicated by an open circle - wins the contract despite its lower cost savings to the buyer (less than 10% vs. more than 40% from incumbent supplier for point B)[3]. In this area (on or below the 45 degree line with positive cost savings), incumbent suppliers bid equally or lower than their counterpart non-incumbent suppliers. In addition, we observe that the buyer sometimes awards contracts with negative savings (for example, the lower left lined area of Figure 1), and in this specific case, exclusively to incumbent

[1] In the data, for each procurement contract, there is only one incumbent (or preferred) supplier. We use this unique incumbent supplier in our pairwise cost savings comparison with the non-incumbent (or non-preferred) supplier that submitted the lowest final bid. The horizontal x-axis represents the percentage savings from a preferred supplier, and the vertical y-axis is that from the non-preferred supplier that submitted the lowest bid.

[2] The estimated probability from the logit model is 95.9%.

[3] The interviews with the buyer reveal that such scenario is possible, for example, when the quality of the incumbent supplier has dropped prior to the auction event.

suppliers.

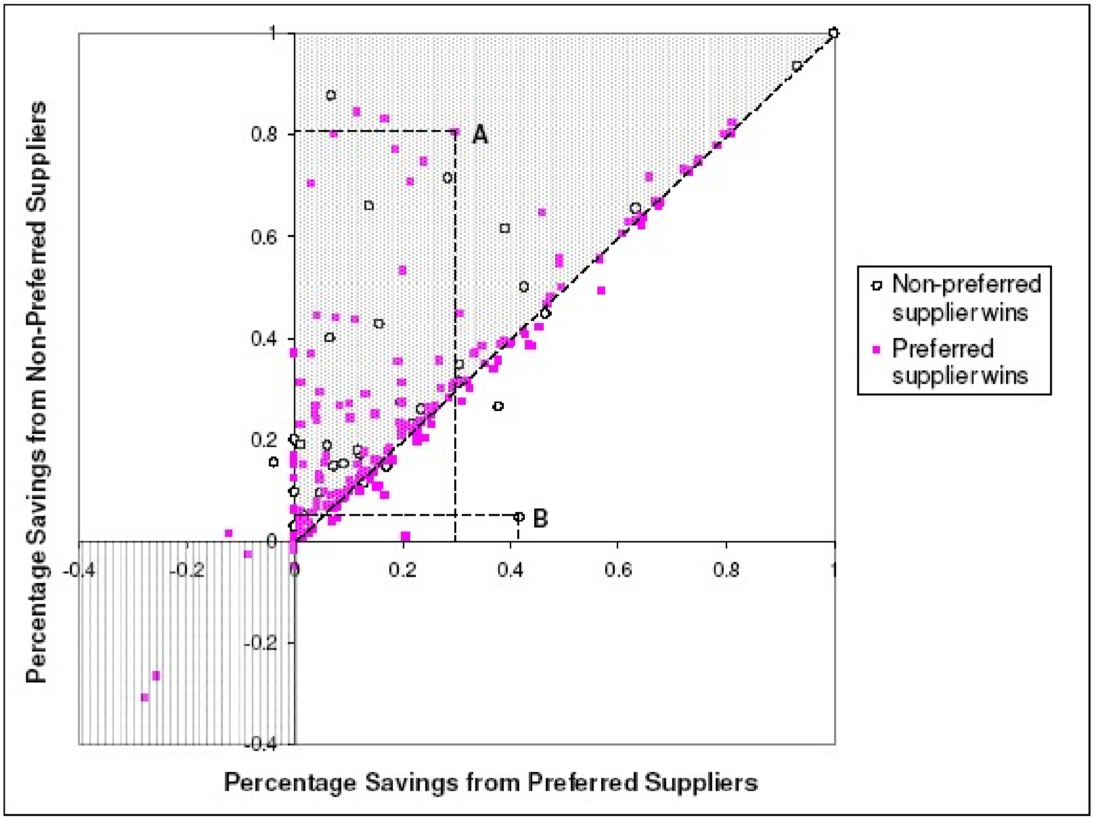

Figure 1: Impact of Incumbent Status (Preferred suppliers are incumbents. Non-preferred suppliers are non-incumbents.)

2.1 E-Sourcing Process and Data

We interviewed and collected data from a major buyer in the high-tech industry that has been using online reverse auctions and other IT tools for sourcing, and has achieved more than $900 million in cost savings, in the past seven years. For example, when the company procures direct materials for its digital video recorder product line, it organizes necessary items such as memory chips and connectors into a single auction event. The company specifies the quantity of each item and awards contracts on an item-by-item basis. Contract awarding is not automatically determined by the auction. Rather, the company manually awards contracts after the auction, taking into account non-price attributes such as quality, delivery, and payment terms. Thus, each item is an independent contract,[4] and the auction event consists of multiple items that are not identical and usually have different values. Next, we describe the key stages in the buyer's sourcing business process as depicted in Figure 2.[5]

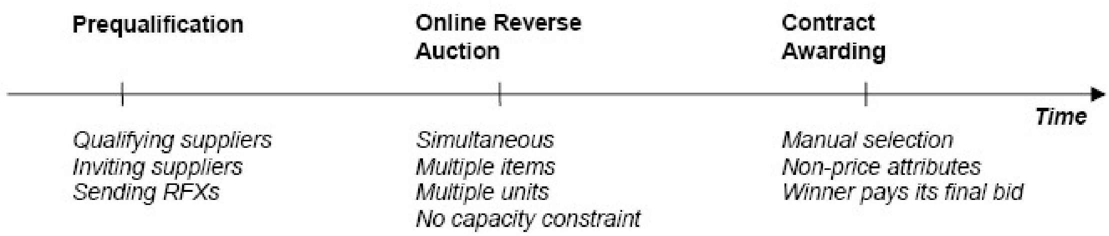

Figure 2: Sequence of Events in Buyer's E-sourcing Process

2.1.1 E-Sourcing Process

2.1.1.1 Prequalification

Prior to an auction event, the buyer calculates a quality score for each supplier on the basis of its past performance. The score is reported privately to each supplier, along with its type (that is, incumbent or non-incumbent); only qualified suppliers are invited to the upcoming auction event. Along with the quality score, suppliers receive specification data for the procured materials, including drawings of the items, material numbers, and performance specifications (for example, RFXs such as request for information/proposal), two weeks prior to the auction event. The procurement contracts usually have a one-year term.[6]

2.1.1.2 Auction

Each auction event consists of purchases of multiple items, though bids are not required for all items. Although the suppliers may bid partial demand, we do not

[4]For this reason, we use the terms "item" and "contract" interchangeably in this chapter.
[5]This e-sourcing process is typical; see the survey paper by Elmaghraby (2007).
[6]Pre-bids are optional for the participating suppliers. When a supplier submits a pre-bid before an auction event, it serves as that supplier's first bid when the auction starts.

observe such behavior in the data set, which suggests supplier capacity does not appear to be an important issue in our data set. A bid decrement is required for each new bid. Normally, the bid decrement is less than 1% of the item value, but it only applies to the supplier's own previous bid, not the current lowest bid.[7] The auction ends when there is no new bid for any item in the auction during a predefined "quiet" period.[8]

2.1.1.3 Information Structure

During the auction, the buyer knows the identities of all suppliers, each and every supplier's submitted bid and the bid ranks for every item. However, a supplier only knows its own rank and the current lowest bid for each item on which it has submitted bids, as dictated by the Web-based procurement auction software. The supplier continues to have access to the information even after it stops bidding, as long as it refreshes the bidding screen from time to time. Suppliers do not know one another's identity or cost structure, nor do they know one another's type (incumbent or non-incumbent).

2.1.1.4 Contract Awarding

Contracts are awarded manually after the auction. Final bids are evaluated item by item rather than for a bundle of items. After earning a procurement contract, suppliers are paid an amount equal to their last bids. The buyer maintains and updates its list of incumbent suppliers after the auction event, so a non-incumbent supplier prior to the auction event may enter this list and become an incumbent supplier; conversely, an incumbent supplier could be dropped from the list due to its unsatisfying performance. The buyer incurs a switching cost if it changes incumbent

[7] For example, if supplier A's last bid is \$10, the current lowest bid is \$8 and the bid decrement requirement is \$1, the supplier can submit \$9 as its next bid, although \$9 is still higher than the lowest bid \$8.

[8] The "quiet" period is usually 5 minutes or less, with unlimited extensions.

suppliers, but this cost is unknown to the suppliers. After an auction event, the buyer provides suppliers feedback, such as why suppliers were not awarded the contract.

We note the gap between auction practice and auction theory, as pointed out in the recent survey of e-sourcing business practices by Elmaghraby (2007). In particular, only partial rank information - namely, current lowest bid and a supplier's own ordinal rank - is revealed to each individual supplier over the course of the auction, provided that the supplier bids. The situation is also complicated by the manual contract awarding decision. The academic literature most similar to this study pertains to multiple-item simultaneous descending auction with rank information - a mix of the several models we review subsequently (Cramton and Ausubel 2006; Engelbrecht-Wiggans and Kahn 2005; Parkes and Kalagnanam 2005; Harstad and Rothkopf 2000; Milgrom 2000b).

2.1.2 Data

We collect two sets of data from the focal buyer: The procurement auction data set and the cost savings analysis data set. These data record the online procurement activities of the buyer during 2002-2004. The procurement data cover the entire bidding history of each auction event, including auction number, supplier number, item number, supplier name, bidding time, unit price, total price, and quantity of each item. This data set includes the bidding details on 64 online procurement auction events pertaining to the purchases of 652 items, in which 149 suppliers submitted 13,036 unique bids. Due to multiple participations by a single supplier, we have data about 8,612 participations.

The cost savings analysis data set includes information about the incumbent suppliers before and after the auction and their corresponding prices. It also contains contract awarding information. Combining these two data sets results in a new data set, such that for each item, we possess the incumbent suppliers' identities and prices

Table 2: Descriptive Statistics of Bidding and Awarding Data Sets

	Bidding Data Set	**Bidding with Awarding**
Number of auctions	64	36
Number of items	652	233
Number of suppliers	149	106
Number of participations	8,612	2,283
Number of unique bids	13,036	8,622

Table 3: Descriptive Statistics of Awarding Data Set

	Mean	**Std. Dev.**	**Min**	**Max**
Contract size (US Dollars)	\$148,097	\$341,777	\$390	\$2,334,150
Number of items per auction	19.38	6.48	1	41
Number of items per supplier per auction	13.54	6.80	1	26
Number of suppliers per auction	9.33	2.74	3	16
Number of suppliers per item	4.21	1.46	2	7
Number of bids per item	17.16	14.78	2	81
Number of bids per supplier	3.76	4.22	1	37

prior to and after the auctions.

To ensure a competitive bidding environment, we remove those items with only one bidding supplier; thus, at least two suppliers compete for a contract. The final combined data set covers the bidding history of 233 items from 36 auction events, in which 106 suppliers submitted a total of 8,622 unique bids in 2,283 participatory events. Tables 2 and 3 summarize these descriptive statistics.

2.2 Conceptual Model

2.2.1 Literature Review

Despite the vast literature on auction theory, few theories have been used in business practice (Elmaghraby 2007; Milgrom 2000b; Rothkopf and Harstad 1994). We briefly review those most relevant for the study.

In a single, indivisible item English auction,[9] in equilibrium, bidders with independent value employ dynamic bidding strategies (Kamecke 1998). When bidding is costless, a ratchet bidding strategy[10] constitutes the equilibrium (Kamecke 1998; Vickery 1961), and this equilibrium outcome is also Pareto efficient.[11]

Ordinal rank information, rather than actual bid price, plays a decisive role in the framework of an affiliated value auction designed by Harstad and Rothkopf (2000), who propose an alternating recognition model of English auctions[12] based on work by Milgrom and Weber (1999, 1982). In equilibrium, the bidders compete for the top two places when they can.

Competitive bidding constitutes the equilibrium strategy for auctioning multiple items simultaneously in ascending order.[13] Such auctions have been used in the Federal Communication Commission (FCC) auctions (Milgrom 2000b). This type of competitive bidding often is described as straightforward or "non-strategic" bidding (Engelbrecht-Wiggans and Kahn 2005; Milgrom 2000b).

Previous auction theory has little to say about the impact of non-price factors

[9] In an English auction, buyers bid openly (open cry) against one another. Each new bid must be higher than the current highest bid by at least a predefined minimum bid increment. The auction ends when no participant is willing to bid further, at which point the highest bidder pays the price it bids.

[10] A ratchet bidder does not bid if it has made the highest offer; otherwise it outbids the current highest offer by small steps up to its private valuation. This bidding strategy is known as myopic or pedestrian bidding.

[11] In the sense that the bidder values the item most wins the auction/item.

[12] The Harstad and Rothkopf (2000) model has the auctioneer call out a price and ask bidders to affirm. One affirming bidder is recognized randomly, and then the auctioneer asks for a higher price to be affirmed by someone else. Having two affirming bidders, the auctioneer proceeds to raise prices in small increments, alternating between the affirming pair. When one of the affirming pair is no longer willing to affirm the current price, the auctioneer seeks a replacement from the rest of the bidder pool. If the auctioneer cannot find a replacement for an existing bidder, the auction ends with the goods awarded to the last affirming bidder at the last price affirmed.

[13] In such competitive equilibrium, a bidder bids straightforwardly: In the first round, it bids on the set of goods for which its demand is greater than zero, it makes new bids in each following round for the goods whose minimum bid price is lower than its valuation, such that the new bid equals the minimum bid price. The minimum bid price is the sum of the highest bid from the previous round and the minimum bid increment.

and incumbency, with the exceptions of a few recent work in multi-attribute auctions (Asker and Cantillon 2006; Parkes and Kalagnanam 2005; Milgrom 2004; Carr 2003; Snir and Hitt 2003; Milgrom 2000b). If the buyer specifies its preferences for these attributes explicitly and accurately, the sellers should bid accordingly, which in theory results in an efficient auction outcome. Although supported to some extent by recent initial experimental evidence (for example, Engelbrecht-Wiggans and Katok 2006; Chen-Ritzo, Harrison, Kwasnica, and Thomas 2005), no previous study uses actual e-sourcing data as we do in this chapter (see the call for empirical research in Elmaghraby (2007)).

A major obstacle for such empirical investigations is that in reality the assumption of specified buyer preferences for non-price attributes often breaks down for several reasons. First, the buyer may not (or not want to) use well-defined scoring rules to weigh various non-price attributes when evaluating bids. This may due to uncodifiability (Dai, Narasimhan, and Wu 2005; Levi, Kleindorfer, and Wu 2003) or strategic ambiguity (Elmaghraby 2007). Second, the non-price attributes of suppliers are not fully available in the buyer's data set (unobservability). We overcome these difficulties by taking advantage of the data, with which we can observe the bidder's type and focusing on the impact of supplier type on bidding and auction outcomes. Third, though theory has postulated the impact of bidder characteristics on final bids, previous literature remains silent about how such characteristics affect bidding dynamics.

2.2.2 Model Description

We develop a conceptual model to address the two research questions and illustrate the conceptual model of incumbency, bidding behavior and auction outcomes in Figure 3.

First, we use a dummy variable *Supplier type* (I) indicates whether a supplier is

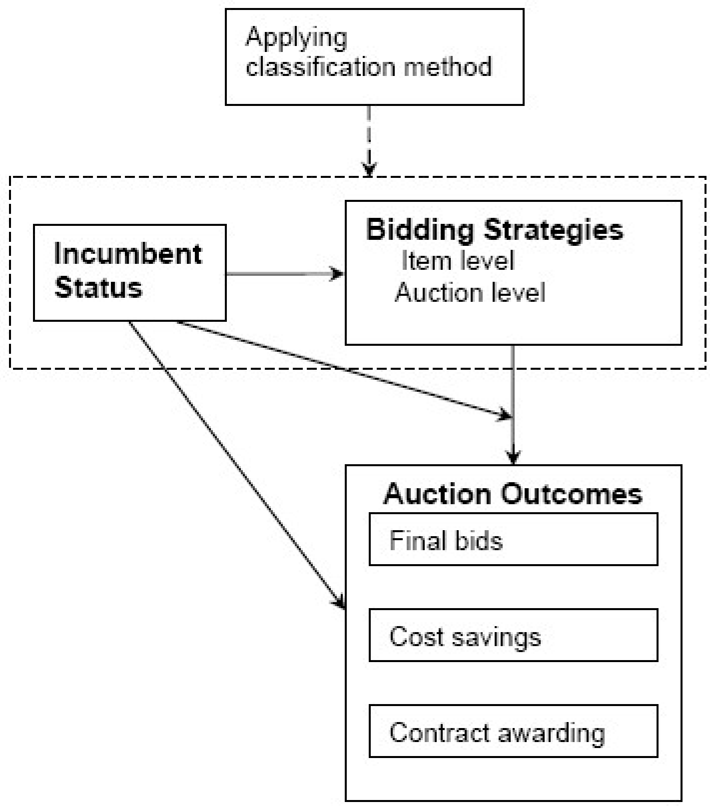

Figure 3: Conceptual Model - Incumbency, Bidding Behavior and Auction Outcomes

an incumbent or not. The variable takes a value of 1 if the supplier is an incumbent and 0 otherwise. Second, we apply a new classification method, latent cluster (LC) analysis to the archived bidding history data, along with the supplier type information. This application enables us to study the actual bidding behavior of industrial participants and classify their bidding strategies. We conjecture that due to information asymmetry between incumbent and non-incumbent suppliers, firms should bid differently. Finally, we measure the auction outcomes using three variables: Suppliers' final bids, buyer's cost savings, and contract award decisions. We examine the impact of incumbent status on auction outcomes directly and, indirectly in conjunction with uncovered bidding patterns.

Because procurement auctions often involve multiple-item auctions, We conduct the analyses at both the item and the auction level. Next, we introduce the strategic variables that we construct to abstract bidding behavior at these two levels.

2.2.3 Constructs

At the item or contract level, we construct the following variables to abstract each supplier's bidding behavior: Time of entry (ET^c), time of exit (XT^c), frequency (FR), average magnitude of bid decrement (DE),[14] and average ordinal rank (RN).[15]

Time of entry and time of exit are the times of a supplier's first and last bids, normalized by the duration of the auction of an item, such that $0 \leq ET^c \leq XT^c \leq 1$. Frequency is the total number of bids a supplier submits for an item during an auction. Bid increment represents an important aspect of bidding strategies, and its magnitude has been used in empirical studies to capture the characteristics of bidding behavior (Easley and Tenorio 2004). For procurement auctions, we construct a similar variable, the average magnitude of bid decrement, to capture the change of

[14] Bid decrement represents the difference between a submitted bid and the current lowest bid.

[15] Only the ranks after a supplier submitted a bid are included in calculating the supplier's average ranks.

each bid compared with the current lowest bid.[16] Finally, competing for ordinal ranks has become increasingly interesting (for example, Varian 2006a). In the setting, each supplier knows its current rank among all competitors during the auctions, and the current lowest bidder has the top rank, that is, rank one. To capture how suppliers respond to the ordinal rank information they obtain over the course of the auction, we construct an average ordinal rank variable, which averages a supplier's ordinal rank across all bids it submits for an item.

To test the robustness of the classified bidding strategies, we organize the constructs into two sets. The first set of constructs includes time of entry, time of exit, frequency and average magnitude of bid decrement, whereas in the second set, we substitute average magnitude of bid decrement with average ordinal rank and retain the rest of the constructs. The findings from both sets are very similar, so we present only the classification with the average ordinal rank.[17]

At the auction level, a supplier's bid is defined as a vector of the bids submitted for a set of items simultaneously per round. We construct time of entry (ET^a) and time of exit (XT^a) at the auction level. Because the suppliers may start bidding for an item as long as the quiet period has not ended, the number of items included in a bid can be increased during an auction. Drawing on Gallien and Wein (2005) and Milgrom (2000b), we construct two variables: Number of items included in the first bid (NI) and number of items added (NA) to the set during the auction to capture changes in the set of items.

[16]Unlike B2C auctions, where the changes are non-negative because of the institution rule, the value of the construct can be either negative or positive. A negative value is caused by the bid decrement rule, set by the buyer, which requires the suppliers to lower their bids against their own bids but not necessarily against the current lowest bid. We calculate the decrement of each supplier's bid, divide it by the predefined minimum bid decrement, and average the amount across the total number of bids the supplier has submitted to get the average magnitude of bid decrement.

[17]The results with average bid decrement are available upon request.

2.3 *Bidding Behavior*

In this section, we describe the latent class analysis method we use for the classification and present the findings.

2.3.1 Methodology

We employ a statistical model-based clustering technique called LC cluster analysis (Vermunt and Magidson 2000) rather than the K-means cluster analysis routinely used in B2C bidding. For the study, LC has several advantages over K-means cluster analysis (Magidson 2002): (1) Variables do not need to be standardized, and the assumption of zero correlations among variables within clusters (local independence) can be relaxed, which not only enables a more realistic model but also decreases the number of clusters; (2) Bayesian information criteria (BIC) and Akaike information criteria statistics can be used to determine the optimal number of clusters; and (3) it can be extended to include covariates to study the impact of external variables on classification. This last feature of LC enables us to estimate the effects of supplier type on bidding clusters.

The LC cluster model takes the following specific form:

$$f(Y_i|\theta) = \sum_{k=1}^{K} \pi_k \prod_{j=1}^{J} f_k(Y_{ij}|\theta_{jk}) \tag{1}$$

where Y_i is firm i's values on a vector of constructs. At the item level, the vector is (ET^c, XT^c, FR, RN) and at the auction level, the vector is (ET^a, XT^a, NI, NA). K is the total number of clusters, and π_k denotes the prior probability of belonging to cluster k. J denotes the total sets of correlated variables, and j is a particular set of correlated variables.[18] Thus, the distribution of Y_i given model parameters θ, is a mixture of class-correlation-specific densities $f_k(U_{ij}|\theta_{jk})$. Drawing on literature on B2C bidding (Bapna, Goes, and Gupta 2004; Easley and Tenorio 2004), at the item

[18] When local independence is assumed, J denotes the number of manifest variables and j a particular variable.

level, we correlate ET^c with XT^c, ET^c with FR, and FR with RN. Similarly, at the auction level, we correlate ET^a with XT^a , ET^a with NI, and NI with NA.

To examine the effects of supplier type, we let Z_i denote the type of supplier i and modify equation (1) as follows:

$$f(Y_i|Z_i, \theta) = \sum_{k=1}^{K} \pi_{k|Z_i} \prod_{j=1}^{J} f_k(Y_{ij}|Z_i, \theta_{jk}) \tag{2}$$

$$\text{where } \pi_{k|Z_i} = \frac{\exp\left(\alpha_k + \beta_k Z_i\right)}{\sum_{k=1}^{K} \exp\left(\alpha_k + \beta_k Z_i\right)} \tag{3}$$

Together, equations (2) and (3) imply two possible effects of supplier type on bidding: On the distribution of K bidding patterns through the modification of the probability of belonging to a certain class $\pi_{k|Z_i}$ (indirect effect) and on the conditional mean of the constructs $f_k(Y_{ij}|Z_i, \theta_{jk})$ (direct effect). For example, without supplier type Z_i, the classification is based solely on the values of the vector of the construct (ET^c, XT^c, FR, RN). This method estimates θ, means and variances of the constructs for each class k. Including Z_i in the model, we regress each construct and each class membership on supplier type. If the impact of Z_i on a construct is significant, we have evidence of a direct effect of supplier type. If any β_k is significant, we have evidence that π_k is affected by supplier type, such that it influences the distribution of bidding behavior. We can compute the distribution of bidding behavior for each supplier type by plugging in the estimated α_k and β_k for each class k in equation (3).

We use the standard Vermunt and Magidson algorithm in the LC analysis software package Mplus, which is essentially the maximum likelihood method to estimate θ, α_k and β_k. We then select the best model on the basis of the log-likelihood (the higher the better) and BIC (the lower the better).

2.3.2 Findings

At the item level, we uncover five bidding patterns that we summarize in Table 4. Column 2 to 5 in Table 4 shows the mean values of the bidding constructs of the five bidding patterns. Non-strategic (labelled as B0) bidders enter an auction of an item early, bid frequently while competing for the current lowest bidder rank, and exit at the end of the auction. Early-evaluator (B1) bidders enter the auction at the beginning and usually bid a couple of times, then quickly exit. Mid-evaluator (B2) bidders enter near the middle of the auction, submit a couple of bids and exit about halfway through. The average ordinal rank of Mid-evaluator bidders is 2.493 (with 1 being the lowest bidder), which suggests they usually do not compete for a top rank. Opportunist (B3) bidders are similar to Early-evaluators in terms of bidding frequency and average ordinal rank but they enter and exit the auction toward the end.[19] Participator (B4) bidders behave similarly to Non-strategic bidders except that they bid less frequently (4.8 times vs. 18.9 times). These uncovered heterogenous bidding patterns indicate a possible rich bidding strategy space that goes beyond the equilibrium competitive bidding strategy. Although not explored in the current study, the findings call for theory building to further investigate the determinants of various bidding patterns. Our focus in this chapter is to present the existence of heterogenous bidding patterns and explore how they are affected by incumbent status empirically.

Splitting the data sample into two sub-samples of incumbent and non-incumbent suppliers, we estimate α_k and β_k from equation 3.[20] We find that the clusters remain unchanged, but the distributions are moderated by incumbent status as we show in Table 5 (Baron and Kenny 1986). Column 2 and 3 show the estimated α_k and β_k

[19] Opportunist (B3) bidders seem to follow something like the last-minute bidding strategy in B2C auctions.

[20] Non-strategic bidding serves as benchmark strategy, where we set $\alpha = 0$ and $\beta = 0$.

as specified in equation 3. All α_k are significant, while β_{B2} and β_{B3} are significant. Therefore, the distribution of the bidding patterns is affected by the incumbent status. The last two columns compute the distribution of the uncovered bidding strategies among the two supplier groups. Furthermore, a two-way Chi-square test confirms the difference in the distribution and demonstrates that except for Non-strategic bidding, the proportion of the rest of the bidding strategies differs significantly between the two supplier types.

Table 4: Classification of Item Level Bidding Behavior

Construct	B0: Non-Strategic	B1: Early-Evaluator	B2: Mid-Evaluator	B3: Opportunist	B4: Participator
Entry	0.116***	0.066***	0.256***	0.804***	0.141***
Exit	0.973***	0.091***	0.488***	0.920***	0.874***
Frequency	18.925***	1.946***	2.556***	2.499***	4.843***
AvgRank	1.297***	1.257***	2.493***	3.020***	1.217***
N	93	537	416	479	754

Notes. *** p <0 .01 ** $p < 0.05$ * $p < 0.10$.

Table 5: Impact of Incumbency on Distributions of Item-Level Bidding Strategies

Bidding Strategy	α_k	β_k	% Among Incumbents	% Among Non-Incumbents
B0: Non-strategic	0	0	4.7	3.9
B1: Early-evaluator	1.817***	-.329	28.7	23.7
B2: Mid-evaluator	1.625***	-.590**	13.1	19.6
B3: Opportunist	1.741***	-.501*	16.1	22.0
B4: Participator	2.080***	.039	37.4	30.9

Notes. *** p <0 .01 ** $p < 0.05$ * $p < 0.10$.

At the auction level, we identify four bidding strategies, which we summarize in Table 6 in the same fashion as in Table 4. Information-seeking (A1) and Wait-and-see (A2) suppliers bid on a small set of items, and rarely change the number of items during the auction. They differ, however, in their entry and exit times: Information-seeking bidders enter and exit early, whereas Wait-and-see suppliers wait until the end of the auctions to enter. Adding-by-bidding (A3) and Non-strategic (A0) suppliers stay longer in the auctions and bid more actively, but Adding-by-bidding suppliers start with a small set of items and gradually increase that number, whereas Non-strategic firms start with a large set of items and seldom add items over the course of the auction. The distribution of these clusters is again mediated by supplier type, as we show in Table 7.

Table 6: Classification of Auction-Level Bidding Strategies

Construct	A0: Non-Strategic	A1: Information-Seeking	A2: Wait-and-See	A3: Adding-by-Bidding
Entry	0.106***	0.111***	0.711***	0.092***
Exit	0.895***	0.240***	0.891***	0.907***
NI	5.957***	5.266***	4.478***	1.856***
NA	1.898***	0.820***	1.563***	17.494***
N	186	85	116	37

Notes. *** p <0 .01 ** p < 0.05 * p < 0.10.

Table 7: Impact of Supplier Type on Distributions of Auction-Level Bidding Strategies

Bidding Strategy	α_k	β_k	% Among Incumbents	% Among Non-Incumbents
A0: Non-strategic	2.468***	-1.316***	48.7	41.6
A1: Information-seeking	1.951***	- 2.078**	13.5	24.8
A2: Wait-and-See	2.144***	- 1.767**	22.4	30.1
A3: Adding-by-bidding	0	0	15.4	3.5

Notes. *** p <0 .01 ** p < 0.05 * p < 0.10.

2.4 Incumbency, Bidding Behavior, and Auction Outcomes

The purpose of this section is to establish the impact of bidding behavior and incumbent status on auction outcomes. We start with describing econometric specifications of the statistical analyses and then proceed to discuss the findings.

2.4.1 Econometric Specification

2.4.1.1 Item Level

We use two dependent variables to measure the auction outcomes: Suppliers' *Final Bids* and buyer's *Cost Savings*. The latter is the buyer's purchasing price prior to an auction less the price after the auction. We standardize both variables by the buyer's previous purchasing price for the same contract/item. We use the following generic equation to estimate the effects of incumbent status (I) and bidding strategies:

$$\begin{aligned}\text{AuctionOutcome} &= \alpha + \beta_1 I + \beta_2 R + \beta_3 E \\ &\quad + \text{BiddingStrategyDummies} + \text{Controls} + \varepsilon. \qquad (4)\end{aligned}$$

By setting the dependant variable *AuctionOutcome* to be *Final Bids* and pooling all suppliers, we estimate the driving factors for suppliers' final bids. By setting the dependant variable *AuctionOutcome* to be buyer's *Cost Savings* and restricting the analyses to winners only, we estimate the driving factors for the buyer's cost savings.

To control for supplier experience and relationship between a particular supplier and the buyer, we include two other variables as the independent variables: *number of additional incumbent items* (R) and *number of previous participated auctions* (E). The number of additional incumbent items is the number of other items in the same auction for which this supplier serves as the incumbent supplier and thereby captures the relationship (R) between the supplier and the buyer. If the supplier is the incumbent supplier for multiple items, it likely has a stronger relationship with the buyer. Finally, the number of previous auctions refers to the total number of previous reverse auctions in which the supplier has participated, which captures the supplier's auction experience (E).

Drawing from previous literature on procurement auctions (for example, Mithas and Jones 2007), we set the controls for both equations as follows: Number of suppliers competing for a particular contract, total number of bids a contract receives, auction length, previous purchasing price (or starting price) of the same contract/item (for which we use the natural log that essentially measures the contract value), and total number of contracts a supplier bids during the same auction (which controls for the suppliers' auction-level strategies).

We use logit models to analyze the relationship of non-price attributes and bidding strategies on contract awarding. We estimate a supplier's probability (p) of winning the contract conditional on the incumbent status (I) and its bidding strategy, as follows:

$$\log \frac{p}{1-p} = \alpha + \beta_1 I + \beta_2 R + \beta_3 E + \text{BiddingStrategyDummies} + \text{Controls} + \varepsilon. \quad (5)$$

The control variables include the achieved cost savings, total number of suppliers bidding for the contract, total number of bids received for a contract, auction duration for a contract, and total number of contracts on which a supplier bid in an auction event.

To shed lights on what is the key factor in buyer's contract awarding decision, incumbent status or low bid, we estimate the effect of incumbent status and lowest bidder status by the following logit model:

$$\log \frac{p}{1-p} = \alpha + \beta_1 I + \beta_2 \text{LowestBidderDummy} + \beta_3 \text{MarkupControls} + \varepsilon. \quad (6)$$

where *LowestBidderDummy* is a dummy variable whose value is 1 if a bidder is the lowest bidder, 0 otherwise. Variable *Markup* captures the difference between a supplier's final bid and the lowest bid. It is normalized by the lowest bid.

2.4.1.2 Auction Level

At the auction level, we obtain several variables as the basis for the econometric model. At the auction-level, we use an aggregated variable to indicate incumbency: TI, the total number of items in an auction event for which a supplier serves as the incumbent supplier. We estimate the aggregated cost savings provided by a supplier as:

$$\begin{aligned}\text{AggregatedCostSavings} &= \alpha + \beta_1 TI + \beta_2 E \\ &\quad + \text{BiddingStrategyDummies} + \text{Controls} + \varepsilon. \qquad (7)\end{aligned}$$

The control variables are the total number of suppliers and auction duration.

Let q denote the probability that a supplier is awarded at least one contract, conditional on its incumbent status and previous auction experience. We estimate:

$$\log \frac{q}{1-q} = \alpha + \beta_1 TI + \beta_2 E + \text{BiddingStrategyDummies} + \text{Controls} + \varepsilon. \qquad (8)$$

The control variables here are total cost savings aggregated at the auction level, auction duration, total number of suppliers, and total number of contracts.

2.4.2 Impact of Incumbency and Bidding Strategy on Final Bids

We regress the final bid of each supplier for each item using equation (4) to estimate the impact of incumbent status and bidding strategies on final bids at the item level. We summarize the findings in Table 8. Due to space limit, we omit the coefficients of control variables. However, as we expected, the coefficents are all in the right directions.

Model I is the baseline model, with the robust ordinary least square (OLS) estimator (Greene 2002) of incumbent status. It shows that, altogether, the three variables I, R, E explain 10.2% of the variance (R^2). Individually, incumbent status (I) has a significant and positive effect on the final bid (0.0375, $p < 0.01$), such that incumbent suppliers' final bids are 3.75% higher than those of non-incumbent suppliers, on average. Albeit with a much smaller magnitude, the relationship variable (R) has the expected positive and significant effects (0.0022, $p < 0.1$). However, previous auction experience (E) has a negative and significant effect on final bids, which may suggest some supplier learning between auctions.[21]

Model II adds the bidding strategy dummies, and its results confirm those of Model I, with an increased goodness of fit (R^2) of 21.9%. Benchmarked against Non-strategic bidders, Mid-evaluator's final bids are the highest on average (0.2796, $p < 0.01$), followed by Early-evaluator (0.1730, $p < 0.01$) and Opportunist (0.1078, $p < 0.05$). The behavior of Participators does not have a significantly different impact on the final bids, which is quite intuitive.[22] Models III and IV verify the robustness of the proxy by testing firm fixed and random effects (Wooldridge 2001), respectively. The results are similar to those in Model II, while the goodness of fit remains almost unchanged. This finding suggests that the proxy already reflects the important difference among suppliers.

To test the interactions between supplier type and bidding strategies, we add Models V (OLS with an interaction term), VI (supplier fixed effect), and VII (supplier random effect). Although the results from Models V, VI, and VII are similar overall,[23] Model VI is best according to a Hausman specification test. Incumbent suppliers' final bids are lower than those of non-incumbent suppliers, when we control for the Early-evaluator (B1) and Mid-evaluator (B2) strategies. Although the coefficient of supplier type increases to 0.1263 ($p < 0.05$), it is not large enough to offset the negative mediating effect (-0.1463 and -0.2228 for B1 and B2). For example: Benchmarked against the final bids of non-incumbent suppliers using B0, the final bids of incumbent

[21] Further treatment of supplier learning behavior is entailed in the next chapter.

[22] Participators differ from the Non-strategic bidders only in their lower bidding frequency, but what drives the final bid is whether the bidders compete for the top place, not how often they bid.

[23] Although a couple of coefficients in Model V are insignificant, they still are in the same directions as those in Models VI and VII.

suppliers using B2 are higher by 19.51% ($p < 0.05$),[24] whereas the final bids of non-incumbent suppliers employing the same bidding strategy B2 are higher by 29.16% ($p < 0.01$). Therefore, the final bids from incumbent suppliers are lower, controlling for B2. In contrast, incumbent suppliers' final bids are higher, controlling for B0, B3, and B4.

[24] This is obtained as follows: $0.1263 + 0.2916 - 0.2228 = 0.1951$.

Table 8: Impact of Incumbency and Bidding Strategy on Final Bids: Item Level

Variable	Full Dataset						
	Model I	**Model II**	**Model III**	**Model IV**	**Model V**	**Model VI**	**Model VII**
I: Incumbent Status	.0375***	.0284**	.0295**	.0290**	.0735	.1263**	.1022*
Supplier Characteristics							
R: Additional incumbent items	.0022*	.0074***	.0154***	.0149***	.0075***	.0157***	.0152***
E: Number of previous auctions	-.0021*	-.0032***	-.0004	-.0003	-.0003	.0002	.0001
Bidding Patterns							
B1: Early-evaluator		.1730***	.1543***	.1596***	.1795***	.1927***	.1914***
B2: Mid-evaluator		.2796***	.2488***	.2545***	.2914***	.2916***	.2921***
B3: Opportunist		.1078**	.0523*	.0730**	.1111***	.0744**	.0906**
B4: Participator		.0413	.0233	.0312	.0385	.0464	.0482
Interaction Term							
Incumbency × B1					-.0438	-.1463**	-.1183*
Incumbency × B2					-.1304*	-.2228***	-.2006***
Incumbency × B3					-.0302	-.0749	-.0555
Incumbency × B4					.0041	-.0776	-.0532
			Supplier FE	Supplier RE		Supplier FE	Supplier RE
F-test	64.98***	61.71***	51.58***		49.23***	39.74***	
Wald Chi^2				616.15***			631.72***
R^2	10.2%	21.9%	22.6%	22.3%	22.1%	23.1%	22.9%
N	2283	2283	2283	2283	2283	2283	2283

In summary, the final bids of Early-evaluator and Mid-evaluator bidders from non-incumbent suppliers are among the highest; those of Non-strategic, Opportunist, and Participator bidders from non-incumbent suppliers are the lowest. Incumbent suppliers' final bids fall somewhere in between. Any full account of suppliers' final bids must consider suppliers' incumbent status, bidding strategies, and their interactions.

2.4.3 Impact of Incumbency and Bidding Strategies on Buyer's Cost Savings

Restricting the investigation to winners, at the item level, we estimate the driving forces behind buyer's cost savings using equation (4) and summarize the findings in Table 9. On average, incumbent suppliers provide less cost savings than non-incumbent suppliers (-0.0592, $p < 0.1$, Model I), a result that is strengthened when we add the bidding strategies dummies (-0.1182, Model II). On average, for each contract, the cost savings from an incumbent supplier is lower than that from a non-incumbent supplier by about 10% of the historical price. As for bidding strategies, both Early-evaluator (-0.1315, $p < 0.01$) and Opportunist (-0.1045, $p < 0.1$) are associated with lower cost savings than is Participator.[25] Supplier fixed and random effect models (Models III and VI) confirm these findings.

At the auction level, we estimate the impact of incumbent status and bidding strategies on the buyer's aggregated cost savings using equation (7). The results, summarized in Table 10, are similar to those at the item level. Winners with more incumbent items on average offer lower cost savings to the buyer. Furthermore, the Adding-by-bidding strategy provides higher cost savings than the benchmark Non-strategic bidding strategy.

[25] Among the winners for the 238 items, only 6 are Mid-evaluator bidders, and 17 are Non-strategic bidders. Due to the small sample size of these two bidding strategies, we limit the item-level bidding strategy space to Early-evaluator, Opportunist and Participator. Because the impacts of Participators and Non-strategic bidders on the final bids are similar, we use Participator as the benchmark for this analysis. Due to high correlation between supplier type (I) and the number of additional items for which the supplier serves as the incumbent supplier (R), we drop the latter in the regressions.

Table 9: Impact of Incumbency and Bidding Strategy on Buyer's Cost Savings: Item Level

Variable	Model I	Model II	Model III	Model IV
I: Incumbent Status	-.0592*	-.1182***	-.1006**	-.1169***
Supplier Experience				
E: Number of previous auctions	-.0048	-.0012	-.0215**	-.0015
Bidding Patterns				
B1: Early-evaluator		-.1315***	-.1202*	-.1311***
B3: Opportunist		-.1045***	-.0805*	-.1033**
Control Variables				
Number of items per supplier		.0074***	.0191**	.0076***
ln(Incumbent price)	.0131**	.0044	.0187*	.0045
Duration		-.0050**	-.0078*	-.0050
Number of bids		.0033**	.0040**	.0033**
Number of suppliers	.0588***	.0401***	.0500***	.0408***
			Supplier FE	Supplier RE
F-test	7.92***	12.88***	10.60***	
Wald Chi^2				92.43***
R^2	16.5%	31.7%	38.4%	33.14%
N	235	235	235	235

Notes. Non-strategic bidding (B0) as benchmark.
*** $p < 0.01$ ** $p < 0.05$ * $p < 0.10$.

Table 10: Impact of Incumbency and Bidding Strategies on Buyer's Aggregated Cost Savings: Auction Level

Variable	Coefficient
TI: Number of Incumbent items	-.0111*
Supplier Experience	
E: Number of previous auctions	-.0024
Bidding Patterns	
A1: Information-seeking	-.0788
A2: Wait-and-see	-.0857*
A3: Adding-by-bidding	.1282*
Control Variables	
Duration	-.0029
Number of suppliers	-.0084
Number of items	-.0005
F-test	3.56***
R^2	14.9%
N	92

Notes. Non-strategic bidding (A0) as benchmark.
*** $p < 0.01$ ** $p < 0.05$ * $p < 0.10$.

2.4.4 Impact of Incumbency and Bidding Strategies on Contract Awarding

We use logit models to analyze the relationship of incumbency and bidding strategies on contract awarding using equation (5) at the item level and equation (8) at the auction level. In Table 11, we summarize the findings at the item level. All three variables (I, R, E) are positive and significant, with incumbent status dominates. The findings at the auction level are consistent, as shown in Table 12. Taken together, incumbent status is the key driver of contract awarding, compared with bidding strategies and cost savings. We calculate the probability of winning a contract conditional on supplier type on the basis of the coefficient of supplier type. At the item level, the probability is 0.92 for incumbent suppliers and 0.27 for non-incumbent suppliers. At the auction level, the probability for incumbent suppliers to win at least one contract is 0.18 but only 0.07 for a non-incumbent supplier. We conclude, on average, that incumbent suppliers are approximately three times as likely to win a contract, ceteris paribus.

Table 11: Logit Model of Contract Awarding at Item Level

Variable	Coefficient
I: Incumbent Status	3.3928***
Supplier Characteristics	
R: Additional incumbent items	.0775**
E: Number of previous auctions	.0592***
Bidding Patterns	
B1: Early-evaluator	-1.4005**
B2: Mid-evaluator	-1.4297**
B3: Opportunist	-.3489
B4: Participator	-.1138
Control Variables	
Savings in percentage	1.0073**
Number of items per supplier	-.0278
Duration	-.0156
Number of bids	-.0129
Number of suppliers	-.2548***
Wald Chi^2	280.65***
R^2	43.6%
N	851

Notes. Non-strategic bidding (B0) as benchmark.
*** $p < 0.01$ ** $p < 0.05$ * $p < 0.10$.

Estimation of the logit model in equation (6) is summarized in Table 13. We omit the coefficients of most control variables and only present the results relevant to the independent variables. As shown in Column 2, both coefficients for incumbent status and lowest bidder status are significantly positive. It is not surprising that these two variables are key factors for the buyer when selecting winners. Interestingly, the coefficient of incumbent status ($\beta_1 = 3.9562$) is much larger than that of lowest bidder status ($\beta_2 = 1.7936$). Surprisingly, variable *Markup* is not significant. When we remove *LowestBidderDummy* from the model, as shown in Column 3, the coefficient of *Markup* is negative and significant. It seems that the effect of lowest bidder status

Table 12: Logit Model of Contract Awarding at Auction Level

Variable	Coefficient
TI: Number of Incumbent items	1.1124***
Supplier Characteristics	
E: Number of previous auctions	.0809**
Bidding Patterns	
A1: Information-seeker	-.5127
A2: Wait-and-see	.1070
A3: Adding-by-bidding	-.3345
Control Variables	
Savings in percentage	-.4019
Duration	-.0144
Number of suppliers	-.0035
Number of items	-.0014
Wald Chi^2	30.54***
R^2	35.5%
N	216

Notes. Non-strategic bidding (A0) as benchmark.
*** $p < 0.01$ ** $p < 0.05$ * $p < 0.10$.

is partially reflected by bidders' markup.

Although these results show that the effect of incumbent status and lowest bidder status are significantly different from zero, it does not give a sense of the economic importance of these variables. The last column of Table 13 presents the marginal impact of incumbent status vs. lowest bidder status. There are three main results here. First, the marginal effects are not trivial. Second, the probability of winning a contract is much higher to an incumbent than (71.4%) a lowest bidder (32.2%). Third, together, incumbent status and lowest bidder status can almost fully justify buyer's contract awarding decision.

Table 13: Logit Model of Identifying Key Factors in Contract Awarding

Variable	Model I	Model II	Marginal Effect
Incumbent Status	3.9562***	3.6268***	71.4%
Lowest Bidder	1.7936***		32.2%
Markup	-.1184	-.2981**	-1.5%
Additional incumbent items	.0785**	.0684**	1.1%
Log-likelihood	-257.51	-279.81	
Pseudo R^2	48.8%	44.4%	
N	856	856	

Note: *** $p < 0.01$ ** $p < 0.05$ * $p < 0.10$.

2.5 Discussion

2.5.1 Bidding Strategies

In this study, we classify B2B bidding patterns and investigate the impact of such bidding behavior on auction outcomes. At the item level, we uncover five strategic bidding strategies, as well as four at the auction level. The findings are robust when we substitute bidding strategy dummies for the original constructs.[26] For example, a supplier's final bid is higher if the supplier enters the auction later but exits the auction earlier; therefore, if a supplier stay active for a shorter period of time, its

[26]Due to space constraint, we report only the detailed statistics of the analysis on final bids. All analyses are available upon request.

final bids tend to be higher. If the supplier bids less frequently and targets a higher rank, its final bids again are higher. We demonstrate in Table 14 that using bidding strategies as dummy variables does not involve any loss of critical information but rather enhances comprehensibility.

Table 14: Impact of Incumbency and Constructs of Bidding Strategies on Final Bid

Variable	Model I	Model II	Model III
I: Incumbent Status	.0286**	.0303**	.0301**
Supplier Characteristics			
R: Additional incumbent items	.0075***	.0138***	.0141***
E: Number of previous auctions	-.0036***	-.0013	-.0010
Bidding Properties			
Entry time	.1198***	.0727***	.0850***
Exit time	-.1253***	-.1277***	-.1203***
Frequency	-.0080***	-.0069***	-.0075***
Average rank	.0365***	.0332***	.0352***
Control Variables			
Number of items per supplier	-.0079***	-.0130***	-.0108***
ln(Incumbent price)	-.0083***	-.0184***	-.0132***
Duration	.0015	.0026***	.0016*
Number of bids	.0010*	.0006	.0006
Number of suppliers	-.0568***	-.0575***	-.0563***
		Supplier FE	Supplier RE
F-test	77.90***	57.48***	
Wald Chi^2			704.33***
R^2	24.60%	24.50%	
N	2283	2283	2283

Notes. *** $p < 0.01$ ** $p < 0.05$ * $p < 0.10$.

At the auction level, B2B bidding strategies are much richer and more complex than those in B2C auctions. For example, the combination of items and their bid sequences are strategic choice variables in B2B but not in B2C auctions. At the item level, though we find similar bidding patterns and use conventional names to benchmark against consumer auctions, we create constructs that can capture the details of industrial bidding. The study is exploratory in nature and the data set is limited to a single industrial buyer. Every supplier in the data set always bids the full required quantity, which implies that the suppliers are constrained neither by capacity nor budget (for example, Gallien and Wein 2005; Jofre-Bonet and Pesendorfer 2003). Therefore, care must be taken in generalizing the findings to other procurement auctions, such as those that entail constraints on supplier capacity.

2.5.2 Incumbent Status

The analyses provide novel evidence regarding the importance of non-price attributes in e-sourcing. An alternative explanation of the difference in the final bids of incumbent and non-incumbent suppliers, however, might refer to the so-called demand reduction phenomena in B2B auctions (for example, Ausubel and Cramton 2002). In multi-unit auctions, demand reduction exists when bidders that demand multiple identical units have lower valuations for latter units. If the auction setting of the study were static multi-unit auctions or if the auctions possessed a uniform price character (for example, FCC auctions), demand reduction may offer an explanation. However, as explained previously, each item in the auction is really an independent contract (which usually has multiple units) and often has distinct values. Therefore, demand reduction does not apply in the auctions we study, because they do not satisfy its required conditions.

2.6 Concluding Remarks

We address a seeming puzzle in e-souring, that is, the ever-increasing adoption of reverse auctions and related concerns about its potential damage to buyer-supplier relationships. The findings suggest that e-sourcing does not necessarily damage buyer-supplier relationships and offer important implications for auction modelers (building new auction theory about facts), practitioners (put auction theory to work), and software service providers (auction platform design).

For auction theorists, we provide novel evidence of firms' bidding behavior and its impact on auction outcomes. We uncover the bidding dynamics in B2B auctions, which previously had remained unknown. Cluster analysis reveals the heterogeneous bidding behavior of the suppliers that compete for a single contract as well as through the entire auction event. The study calls for new auction theories that consider suppliers' bidding strategies for auction design.

We also show empirically that incumbent status plays decisive roles in maintaining buyer-supplier relationships. Incumbency affects the distributions of suppliers' bidding strategies and, in conjunction with bidding strategies, significantly influence auction outcomes, as measured by suppliers' final bids, the buyer's cost savings and suppliers' contract winning probabilities. First, incumbent status influences final bids directly, as well as indirectly through the interactions between bidding strategies and supplier type. Benchmarking against non-incumbent suppliers, at the item level and controlling for bidding strategies, we find that the final bids of incumbent suppliers are higher when they employ three of the five bidding strategies (that is, Non-strategic, Opportunist and Participator) but lower when they use the other two bidding strategies (that is, Early-evaluator and Mid-evaluator). Second, if we restrict the investigation to winners, we find that buyer's cost savings are less from incumbent suppliers on average. Third, we find that incumbent status has a dominant positive effect on contract awarding at both the item and the auction level. On average, incumbent suppliers are three times as likely to win a contract. Furthermore, incumbent status is more important than being the lowest bidder in winning a contract.

This study has some limitations. First, the data come from a single industrial buyer, which uses the same set of rules for all its reverse auctions. Although this data characteristic enables us to examine bidding behavior across auctions, it limits us in examining the impact of various auction and information revelation mechanisms. The latter represents a natural extension of the study that could provide important insights to both practitioners and platform providers. Second, other than supplier type, non-price attributes that are not directly observable in the data might also influence the auction outcomes. This unobservability is a common challenge in studying procurement auctions. However, including supplier experience and measurement of relationship seems able to depict the key differences in non-price attributes among suppliers reasonably well. Overall, we believe this study contributes to a new avenue that aims to develop auction theory about facts, which in turn can be put to use to define tomorrow's best e-sourcing business practices.

CHAPTER III

LEARNING IN REPEATED PROCUREMENT AUCTIONS

3.1 Introduction

Repetition is a key aspect of online procurement auctions as they are often conducted yearly, quarterly or even daily (Elmaghraby 2007). Repetition might alter both buyers' contract awarding decisions and suppliers' bidding behavior, as Pinker, Seidmann and Vakrat (2003) articulate:

> An important element of B2B transactions is their repetition. Buyers value quality and reliability as well as low prices. This means that there might be a preference to send repeat business to suppliers who performed well. Knowing this, suppliers in procurement auctions may bid low to get first-time business with a buyer who will open the door to more lucrative repeat business.

While we examine the impact of incumbent bias and therefore the effect of online auctions on buyer–supplier relationship in the previous chapter, we turn our attention to bidding behavior in repeated online procurement auctions and its determinants in this chapter.

From the perspective of the buyers, auction literature has recognized that one of the effects of repetition on procurement auctions: Buyers can learn about suppliers' cost structures since a supplier's bid reflects its own cost (Pinker, Seidmann, and Vakrat 2003). For example, Beil and Wein (2003) propose a mechanism using inverse optimization with which buyers can learn the suppliers' cost functions by altering a bid scoring function in each round of an auction. From the perspective of the suppliers, industry practice has noticed that online reverse auctions also help suppliers gain market intelligence such as the number of competitors and market price depending on the auction mechanisms (McCrea 2005). Buyers often times use such arguments to encourage suppliers to participate in online procurement auctions.

While procurement auction theorists suggest that, by participating in sequential auctions, suppliers may learn critical competitive information about their environment and react accordingly (for example Fevrier 2003; Jeitschko 1998), their predictions are mixed, however. For example, Fevrier (2003) shows numerically that the winner of the current auction should bid less aggressively than the losers in the subsequent auction, contrary to the prediction of Luton and McAfee (1986). Luton and McAfee (1986) propose an optimal sequential procurement auction design in which the buyer discriminates against the winner of the first stage to induce more aggressive bidding behavior of the winners. In a repeated auction setting, Arora et al. (2007) characterize equilibrium mixed bidding strategies of bidders when facing an unknown number of bidders. They find that, in equilibrium, if only the winner's bid is revealed, the winner of the first period auction bids less aggressively in the subsequent auction due to underestimation of the number of competitors in the auction.

However, which of these predications can be supported empirically has not been explored in depth. By analyzing auction data from an online B2B exchange market, Mithas and Jones (2007) show that revealing bid rank during the auction increases buyer surplus when incumbent supplers are present. Koppius and Van Heck (2003) take an experimental approach to show that revelation of full information induces competitive bidding behavior in the context of single shot auction games. It remains unknown what the suppliers' incentives are for repeatedly participating in reverse auctions, especially for those non-winning suppliers (for example, Jap 2002). On the other hand, although open reverse auctions are prevalent to business practice, auction theory has been silent about the bidding dynamics both within and between auctions (Elmaghraby 2007). It is unclear whether suppliers learn how to bid or they actually have a "short memory".[1] In sum, there is a pressing need of empirical investigations of repeated online procurement auctions, both for theory building and for practical applications.

To shed lights on these important questions, the objectives of this chapter are to empirically investigate: (1) The impact of information learned - rank order and lowest final bid - between successive auctions; (2) Whether suppliers bid adaptively between two successive auctions; and (3) If suppliers alter their bidding strategies conditional on the outcomes of early auctions, what the effect is for the buyer to reveal suppliers' bid rank information.

Via a detailed institutional analysis of a unique set of real-world repeated procurement auction data, we find that, first, lower-bid suppliers tend to reduce their prices less aggressively compared to higher-bid suppliers in the subsequent auctions. Second, the cost disadvantage of the higher-bid bidders cause their final bids to remain higher in the subsequent auctions. Third, suppliers bid adaptively between two successive auctions. Finally, suppliers' adaptive bidding behavior is conditional on their bid ranks revealed after the early auctions.

3.2 Background and Hypotheses

3.2.1 Price Formation

There is a rich and growing theoretical literature on sequential auctions. Specifically, there has been an increasing attention on the information transmission and learning in recurring auctions (for example, Fehr and Riis 2003; Fevrier 2003; Jeitschko 1998). The models studied in Von der Fehr and Riis (2003) and Fevrier (2003) are closer to the sourcing and procurement process of this study. This process can be illustrated

[1]Source: Private communication with Norbert Ore, an industry expert in strategic sourcing.

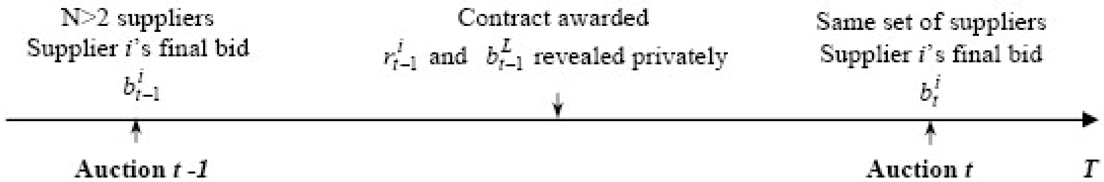

Figure 4: Sequential Procurement Auctions

in Figure 4. A buyer wants to procure Q units of a good in each of two periods. The same set of $N > 2$ suppliers compete for the purchasing contract in both periods. Let b^i_{t-1} and b^i_t denote supplier i's final bids in the two periods respectively. Assuming there is no capacity or budget constraint in either period, we normalize $Q = 1$. At the end of the first auction, suppliers know about their own rank orders r^i_{t-1}[2] and the lowest bid price b^L_{t-1}.

Drawing from the aforementioned analytical analysis (Fevrier 2003; Fehr and Riis 2003), we make the following conjectures regarding suppliers' final bids in the sequential auction setting:

Hypothesis 1 *Compared to the lower-bid suppliers of the first period, the higher-bid suppliers reduce their prices more aggressively in the second period.*

However, theoretical work in procurement literature has suggested that incumbent suppliers can achieve cost reduction through either strategic investment (for example, Stole 1994; Farrel and Shapiro 1989; Riordan and Sappington 1989; Demski, Sappington, and Spiller 1987; Rob 1986) or learning-by-doing (for example, Elmaghraby and Oh 2006; Laffont and Tirole 1988; Anton and Yao 1987). Therefore incumbent suppliers are more cost efficient and can afford to bid less aggressively. On the contrary, higher bidders of the first period miss out the chance of further reduce cost. The bids of these suppliers should reflect this cost disadvantage. Our next hypothesis summarize this conjecture:

[2] $r^i_{t-1} = 1, 2, 3, 4, N$ with $r^i_{t-1} = 1$ represents the lowest bidder, that is, the highest rank.

Hypothesis 2 *Compared to the lower-bid suppliers in the first period, the higher-bid suppliers' final bids remain higher in the second period.*

To test Hypotheses 1 and 2, we estimate the following econometric model:

$$\log{(b_t^i/b_{t-1}^L)} = \alpha + \beta_1 r_{t-1}^i + \beta_2 \log{(b_{t-1}^i/b_{t-1}^L)} + \beta_3 \text{Controls} + \varepsilon_i. \tag{9}$$

where $\log{(\frac{b_{t-1}^i}{b_{t-1}^L})}$ is used to measure the difference between supplier i's bid at auction $t-1$ and the market price so as to overcome the issue that the purchasing contracts in my data set are non-identical. If $\beta_1 < 0$ is significant, we can conclude that supplier i's final bid b_t^i in auction t decreases as r_{t-1}^i increases, therefore, Hypothesis 1 would be supported. If $\beta_2 > 0$ is significant, suggesting that supplier i's final bid b_t^i in auction t increases as its bid b_{t-1}^i in auction $t-1$ increases, Hypothesis 2 would be supported.

3.2.2 Bidding Dynamics

To the best of our knowledge, there has not been any study on the changes in suppliers' bidding dynamics in repeated procurement auctions. However, a few studies on B2C auctions have shown the difference in bidding behavior between experienced and inexperienced bidders. Roth and Ockenfels (2006) attribute the discrepancy to bidders' learning of better bidding strategies that are associated with higher winning probability and consumer surplus. Bapna et al. (2005, 2004) find that the distribution of various bidding strategies observed at eBay auction site alters from 1999 data to 2000 data. Since the stake of B2B auctions is much higher than that of B2C auctions, suppliers might have more incentives to learn about how to bid, and adapt their behavior according to the enviornment. Therefore, we conjecture that:

Hypothesis 3 *Suppliers bid adaptively between two successive auctions.*

Hypothesis 4 *Suppliers' adaptive bidding behaviors are conditional on bid rank information (r_{t-1}^i).*

We take a two-step approach to test these hypotheses. First, following the method detailed in the previous chapter, we use four constructs to abstract bidding behavior for the auctioning of a procurement contract: time of entry, time of exit, number of bids and average rank order. We then apply LC cluster analysis to classify bidding behavior.[3] In the second step, we estimate a Latent Markov (LM) model to correct measurement errors in the first step and more importantly, to estimate the transition probabilities of bidding strategies in two successive auctions. The LM has the form as shown in Figure 5. Let B_{t-1} and B_t denote the vectors of the bidding strategies in auctions $t-1$ and t respectively. Let R_{t-1} denote a dummy variable indicating whether a supplier is among the top two bidders at the end of auction $t-1$. The joint distribution of the three variables $\pi_{b_t b_{t-1} r_{t-1}}$ can be decomposed into a set of conditional probabilities:

$$\pi_{b_t b_{t-1} r_{t-1}} = \pi_{b_{t-1}} \pi_{r_{t-1}|b_{t-1}} \pi_{b_t|b_{t-1} r_{t-1}}. \tag{10}$$

Therefore $\pi_{b_t b_{t-1} r_{t-1}}$ can be estimated by specifying a set of logit models for the conditional probabilities. Our focus is estimating the conditional probability $\pi_{b_t|b_{t-1} r_{t-1}}$, which is the probability of bidding b_t at auction t, given the supplier's bidding strategy b_{t-1} in the previous auction and the corresponding outcome r_{t-1}. Using a logit formulation, $\pi_{b_t|b_{t-1} r_{t-1}}$ can be expressed as:

$$\log\left(\frac{\pi_{b_t|b_{t-1} r_{t-1}}}{1-\pi_{b_t|b_{t-1} r_{t-1}}}\right) = \beta_1 X_{B_t} + \beta_2 X_{B_t B_{t-1}} + \beta_3 X_{B_t R_{t-1}} + \varepsilon. \tag{11}$$

where X_{B_t} is a vector of the bidding strategies in auction t; X_{IJ} are vectors of the combination of variable I and J. For example, $X_{B_t B_{t-1}}$ is a vector of the combination of bidding strategies at both auctions $t-1$ and t. With this a model, we can estimate the changes in bidding behavior, and more importantly, the impact of the outcomes of the first period on suppliers' bidding behavior at the second period.

[3] The small sample size prevents us from using the strategic variables directly to form the dynamic model, which is the main reason why we adopt a two-step method.

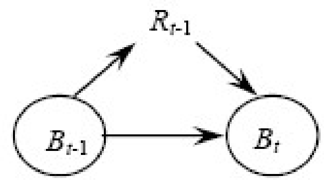

Figure 5: Latent Markov Model with Rank Order Information

3.3 Data

The data set we used for this chapter is obtained from the same buyer in the high-tech industry described in the previous chapter. These data record the procurement activities of the buyer from year 2001 to 2004. There are 316 auctions in year 2001, 459 auctions in 2002, 487 auctions in 2003, and 189 auctions in 2004. The data set covers the entire bidding history of each auction, including auction number, supplier number, item number, supplier name, bidding time, unit price, total price and quantity for each supply item, among others. From the data set, we select 227 purchasing contract auctions with each one of them has been repeated for at least once. The average time lag between two auctions is about 10 months, with a standard deviation of 7 months. The longest time lag between two auctions is almost 3 years, while the shortest time lag is a couple of days. Moreover, we remove the auctions that have less than 3 suppliers to fulfill the assumption of theoretical studies in the literature. In total, 69 suppliers bid repeatedly for a subset of these contracts. If a supplier bids in two successive auctions, its bids from both auctions form one single data point. This selection method results a sample of 693 data points for our empirical analyses.

3.4 Results

3.4.1 Rank Order and Lowest Bid

When testing Hypotheses 1 and 2, we control for the number of repeating suppliers and other suppliers, as well as the year dummies. The results are presented in Table 15. Model I uses robust OLS estimator and excludes year dummy variables. The coefficients support both hypotheses 1 and 2. First, the negative coefficient for r^i_{t-1} $(-0.0918, p < 0.01)$ indicates that when supplier i is one of the lower bidders, $\log \frac{b^i_t}{b^L_{t-1}}$ increases. In other words, supplier i's price reduction in auction t is lower than that of higher-bid suppliers. Furthermore, the positive coefficient for $\log(b^i_{t-1}/b^L_{t-1})$ $(0.0495, p < 0.1)$ implies that when supplier i is not cost efficient, that is, its bid is much higher than the market price as signaled by b^L_{t-1}, the bids of the supplier remain to be higher in the subsequent auction t.

When we add year dummy variables (Model II), the coefficients of year 2002 and 2003 are significant but have opposite signs. At the same time, coefficient of $\log(b^i_{t-1}/b^L_{t-1})$ is not significant anymore. It seems to suggest that the changes in the industry have a stronger impact. Furthermore, the number of repeating suppliers is not significant. On the other hand, an increase in the number of other suppliers drives down suppliers' bids. To test the robustness of the results of Model I and II, we estimate the unconstrained version of the two models in Model III and IV. Results of these models are consistent. In sum, the results support the two hypotheses on the final bids in repeated auctions.

Table 15: Regression of Price Ratio on Rank Order and Lowest Bid

	Model I $\log(b^i_t / b^i_{t-1})$	Model II $\log(b^i_t / b^i_{t-1})$	Model III $\log(b^i_t)$	Model IV $\log(b^i_t)$
r^i_{t-1}	-0.0918***	-0.0868***	-0.0819***	-0.0744***
$\log(b^i_{t-1} / b^L_{t-1})$	0.0495*	0.0284	0.0751**	0.0526**
$\log(b^i_{t-1})$			0.9235***	0.9145***
Number of repeating suppliers	0.0240	0.0051	-0.0023	-0.0280
Number of other suppliers	-0.0613**	-0.1034***	-0.0727***	-0.1268***
year2002		-0.0850*		-0.1992***
year2003		0.1991***		0.1670**
year2004		-0.0518		-0.1363
Constant	0.1309	0.1994**	0.3599***	0.5479***
Observations	693	693	693	693
R^2	2.6%	4.1%	86.5%	86.9%

Notes: * $p<0.1$ ** $p<0.05$ *** $p< 0.01$.

3.4.2 Adaptive Bidding Behavior

The first step reveals five bidding strategies that are consistent with the findings in the previous chapter, namely, Non-strategic bidding, Participator, Early-evaluator, Mid-evaluator and Opportunist. The discovered strategies formed the set of bidding patterns for B_t and B_{t-1}.[4]

Utilizing the results from the first step, we next estimate the LM model following the method in Vermunt et al. (1999). Figure 6 shows the estimated transition probabilities without the effect of auction outcome R_{t-1} from the LM analysis. Each arrow in Figure 6 indicate the probability of suppliers switching from one bidding pattern in auction $t-1$ to another in auction t. The most interesting finding of this analysis is the behavior of a Participator. The probability of a Participator in auction $t-1$ to retain the same bidding behavior in auction t is approximately 44% ($p < 0.05$). Compared to the probabilities to switch to other bidding patterns, a Participator is most likely to retain the same bidding strategy in the second auction event. We show in the previous chapter that a Participator is more likely to win a contract compared to other bidding strategies. Therefore, the high probability transition we obtained is reasonable given the high probability of earning the contracts. By the same token, Early-evaluator, Mid-evaluator, and Opportunist bidders, when they are the non-winning bidder of the current auction, tend to switch to be a Participator in the next auction event, to increase the probability of winning the deal.

So far, the LM analysis reveals initial evidence of changes in bidding behavior in sequential procurement auctions. However, it is silent in terms of whether the adaptive bidding behavior is driven by the information suppliers learned from the first auction. Next, we restrict our attention to this by including the coefficients of $X_{B_t R_{t-1}}$. Specifically, we compute the transition probability conditional on the auction

[4]Due to their sparseness, Non-strategic bidding is dropped in the second step.

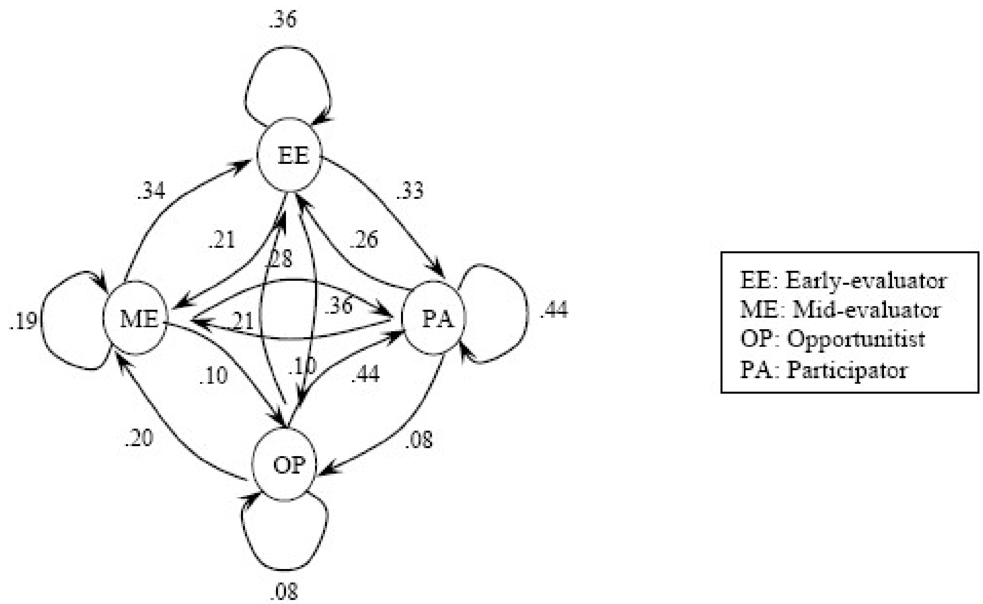

Figure 6: LM Model Analyses Reveal Evidence of Adaptive Bidding Behavior

outcome R_{t-1}, as shown in Table 16. Each row represents the bidding strategy at auction $t-1$ and two possible outcomes: being a high ranked supplier (lowest two bidders) vs. a low ranked supplier (higher-bid bidders). Each column represents a bidding strategy at auction t. All the transition probabilities presented in Table 16 are statistically significant, suggesting that whether being a high or low ranked supplier after auction $t-1$ drives suppliers' adaptive bidding behavior between auctions.

Table 16: Transition Probability Mediated by Rank Order

			Auction *t*			
			Early-evaluator	Mid-evaluator	Participator	Opportunist
Auction *t-1*	Early-evaluator	Low rank	0.3925	0.1869	0.3178	0.1028
		High rank	0.2143	0.2857	0.3929	0.1071
	Mid-evaluator	Low rank	0.3525	0.1721	0.3607	0.1148
		High rank	0.3125	0.2813	0.3438	0.0625
	Participator	Low rank	0.3011	0.1935	0.3656	0.1398
		High rank	0.2474	0.2216	0.4742	0.0567
	Opportunist	Low rank	0.5000	0.1667	0.2778	0.0556
		High rank	0.2075	0.2075	0.4906	0.0943

We depict these transition probabilities graphically in Figure 7 and 8 respectively. Figure 7 presents the transition probabilities when the suppliers are the lowest two bidders of an auction. Figure 7 demonstrates the probabilities of changing bidding patterns when the suppliers are not the lowest two bidders. There are two main results from these estimations. First, when suppliers are the lowest bidders of an auction,[5] they tend to become a Participator in the second period. For example, an Early-Evaluator from the first period has a probability of 39% to be a Participator, which is the highest transition probability for an Early-Evaluator. An Opportunist from the first period has a probability of 49% to be a Participator. This is somewhat surprising comparing to B2C auctions. Roth and Ockenfels (2006) show that more experienced bidder at auction website such as eBay tends to bid at the last minute, rather than increasing bids gradually throughout the duration of the auctions. Bapna et al. (2004) provide additional support for this finding in their study. One of the reasons that we observe different results in the B2B auctions could be the high stake of procurement contracts. When the stake is high, winning the auction and secure a long-term contract could be more important than short-term gains. Once a supplier learns that its cost structure is competitive in the market place given the results of the first period auction, he might have more confidence to compete and bid in subsequent auctions.

The second result is that we do not observe a strong tendency to become Participators for non-winning suppliers. It could be that these suppliers are still searching for their optimal bidding strategies. Taking together, we conclude that the LM model provide evidence of suppliers' adaptive bidding behavior in successive auctions. Overall, it seems that winning suppliers tend to become Participators.

[5] According to our interview with industry experts, the two lowest bidders have the highest probability of winning a contract. Therefore, resulting in the lowest two ranks can be seen as a proxy of winning a contract.

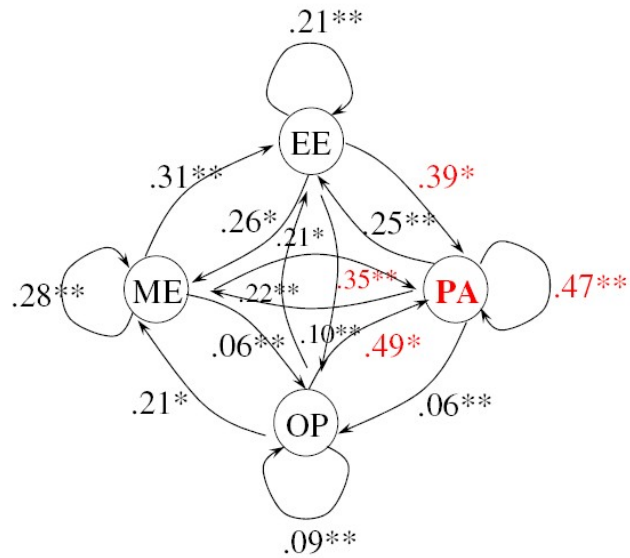

Figure 7: Transition Probability of Lower Bidders

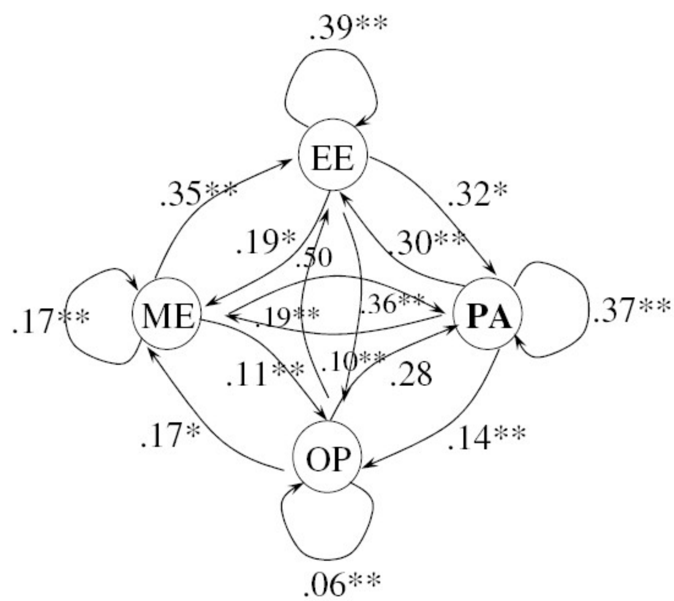

Figure 8: Transition Probability of High Bidders

3.5 Discussion

An important feature of online reverse auction is that the buyers determine what information suppliers can access before, during and after auctions (Elmaghraby 2007). In other words, buyers control what information can be revealed to the suppliers. The more information about the market a buyer reveals to the suppliers, the more suppliers can learn about their competitive environment through participating in the online reverse auctions. Although academic research has shown that full disclosure of information encourages more competitive bidding behavior (Arora et al. 2007; Koppius and Van Heck 2003), buyers are often times very hesitate to reveal crucial information such as supplier identity or final bids of all suppliers in practice. The hesitation might be driven by avoiding potential collusion behavior of the suppliers. Instead, buyers usually reveal partial information such as the lowest bid and/or the rank order of a supplier's bid, during and after the auctions. Anticipating partially revealed information, supplier should update their bidding strategy upon receiving new information about the market in repeated procurement auctions (Arora et al. 2007; Pinker et al. 2003). Our purpose in this study is to empirically investigate how partially revealed information affect price formation of the auctions, as well as suppliers bidding behavior in repeated auctions.

With a unique set of repeated procurement auction data, this chapter verifies that suppliers can learn market information by participating. Specifically, we find that suppliers adjust their bids in subsequent auctions after the buyer reveals the lowest bid and suppliers' own bid ranks. Learning has two effects. First, upon knowing it as a cost efficient supplier compared to the competitors, the supplier would reduce its bid less aggressively in the successive auction. Second, higher-bid supplier are unable to bid as competitively as the cost efficient suppliers in the second period. We also contribute to the field by examining the adaptive bidding behavior of suppliers, which has not been explored in depth in the literature. Our LM model provides evidence that suppliers modify their bidding dynamics conditional on their bid ranks. In general, winners of the first period have a high probability to exert Participator bidding behavior in the second period. We attribute this result to suppliers' newly gained confidence in their cost structure through the feedback of the market.

The study has unavoidable limitations. First, due to the small sample size, we cannot include more information revealed by the buyer in the LM model to separate and compare the driving factors of suppliers' adaptive bidding behavior. Second, we do not possess contract awarding data for all the auctions in the data set. To resolve this issue, we use whether a supplier is one of the two lowest bidders to approximate contract awarding. A more complete data set would allow us to examine directly how suppliers respond upon winning a contract. At its current stage, the focus of this study includes only suppliers who have participated in repeated auctions. We do not know how the existence of short-term suppliers would influence learning. A natural extension is to compare the behavior of short-term suppliers with returning suppliers to investigate whether learning by participating yields any advantages for, and how, if at all, the number of short-term suppliers influences the effects of learning (Elmaghraby 2005).

CHAPTER IV

PROCUREMENT OF COMPLEX BUSINESS SERVICES

4.1 Introduction

According to a recent CAPS research study (Beall et al. 2003), more than 35% of firms with a spend of over $100 million now use online reverse auctions for their procurement operations. Initially, online procurement auctions find most applications in purchasing manufacturing goods. Dynamic auctions have been reported to provide double-digit savings totaling to more than $300 Million annually (Hannon 2004). Upon gaining experience and success, firms are seeking to apply online reverse auctions to many other areas such as complex business services and capital goods. For example, a survey conducted by A.T. Kearney (2006) shows that 16.1% of the expense of large financial institutions falls into the indirect spend category. Cost of professional services takes the greatest portion, 4.6%, within the indirect category.

Professional services is a vast category with many subcategories such as marketing consulting, insurance, legal services and so on. Its unstructured cost function and information put challenges to sourcing professional services through online auctions. However, when conducted appropriately, firms can achieve an average annual savings of 9.8% (A.T. Kearney 2006). Perhaps the best case of procuring professional services through online reverse auctions is General Electric's (GE) sourcing for legal services practice.[1] GE Commercial Finance (CF) division uses law firms for over $300 million business annually. Initiated in 2003, the CF division started to focused on increasing

[1]We are extremely grateful to Charles Kirol from General Electric (GE) Commercial Finance, the key originator behind GE's *Competitive Bidding Process*. We are thankful for his time, enthusiasm, and insightful discussion. This study would not have been possible without his support and generous provision of the thoroughly documented data.

the value of legal services by reducing service costs and strengthening its strategic relationship with a smaller number of law firms through a “Competitive Bidding Process”. According to GE,

> “The Competitive Bidding Process is designed to facilitate selection of pre-qualified legal service providers for specific types of legal services ranging from litigation to transactional matters.”

GE’s bidding process is unique and innovative. First, GE’s internal lawyers who represent all of the CF business units identified 34 areas of legal services that will be included in the bidding process. A bidding event, identified as a “Competitive Bidding Room”[2] , is designed for each area of legal services. GE next proceeded to invite qualified law firms to participate in each bidding room to compete in a dynamic bidding event for a two-year period contract. The most eminent strategy of GE’s bidding process is its winner selection procedure. Law firms are informed that the selection will be based upon quality considerations such as specific personnel, relevant experience, and availability, as well as economic considerations such as suppliers’ bid price and capability to comply with GE’s transaction related policies.

Following the pioneering strategy of GE, many other large firms have started to apply online bidding events to complex business services sourcing. For example, SUN Microsystems used dynamic bidding events for sourcing for legal service, business process outsourcing and so on, with an annual total contract value over $1.4 billion (Serrato 2006). Given the large contract value of business services and the increasing trend of applying dynamic auctions for sourcing, it is crucial for firms to understand the effect of the dynamic bidding process on both cost reduction and supplier/service quality management.

[2]In this study, we use auctions and bidding rooms interchangeably to refer to one dynamic bidding event.

Another unique feature of procuring business services is the concern of incumbent effect. In government procurement, there is strong evidence in the literature suggesting buyer's bias towards the incumbent suppliers (Silva, Dunne, and Kosmopoulou 2003; Greenstein 1993). Incumbents are awarded production contracts more often and receive a premium compared to non-incumbent winners. However, incumbent bias presented in online procurement auctions does not seems to be as strong as documented in the traditional government procurement literature. On the contrary, incumbent suppliers are found to be reluctant to participate in the auctions, citing a fear of price pressures and sense of exploitation (Beall et al. 2003; Jap 2002). With a data set of procurement auctions for manufacturing goods, Zhong and Wu (2006) show that although incumbent firms are awarded production contract three times as non-incumbent firms, the price premium incumbent firms receive is not as large as in the government procurement. The source of the observed incumbent bias comes mainly from the non-trivial switching cost incurred by the buyers when switching suppliers (Zhong and Wu 2006; Silva, Dunne, and Kosmopoulou 2003; Greenstein 1995; Greenstein 1993) and the cost advantage that incumbents can obtain from learning-by-doing (Elmaghraby and Oh 2006). In manufacturing and product development, switching cost can be affected by factors like system compatibility, relationship specific investment in technology, and buyer's cost to evaluate new suppliers. In the procurement of business services, however, many of these factors are absent. Therefore, whether incumbent bias is still prevalent remains unclear. In this study, we utilize the data from GE's bidding events for legal services to address the issue of incumbent bias and the value of online reverse auctions. Specifically, we probe the impact of incumbent effect and provide a novel explanation. The value of online auctions is evaluated through measuring achieved cost savings and supplier quality. To summarize, in this chapter, we attempt to shed lights on the following research questions:

- Do reverse auctions drive firms' cost savings in the category of business services?
- Can the cost savings be achieved without sacrificing quality?
- What is the impact of the incumbent status?

The rest of the chapter is organized as follows. Section 2 reviews relevant literature. Section 3 describes GE's dynamic bidding process and data in detail. Section 4 develops hypotheses and methodology. Section 5 presents statistical results. Discussion is offered in Section 6.

4.2 Literature Review

In recent years, an increasing body of research has been developed to provide better understanding of procurement operations through online dynamic auctions. Elmaghraby (2007) offers an overview of current practices in industry. Rothkopf and Whinston (2007) provides a summary of the current landscape and future research opportunities on e-Auctions for procurement. In the following, we review related studies in procurement auction literature that consider the sources of incumbent bias and impact of such bias on procurement decisions and outcomes.

The vast amount of theoretical work in the procurement literature has suggested that incumbent advantage can exist because of strategic investment or learning-by-doing. Therefore, buyers incur non-trivial switching cost if they select the non-incumbent suppliers. Essentially, switching cost is the main factor that buyers award incumbents contracts more frequently and with higher contract prices. For example, Riordan and Sappington (1989) show that second production source has limited value when the incumbent investment improves the project value to the buyer in the future. On the contrary, Demski et al. (1987) examine the potential gains from a second supply source when the costs of the incumbent and the second source are correlated. They find that it maybe optimal to select the second source if its cost disadvantage is not excessive. Explicitly considering switching cost, Cabral and Greenstein (1990) and Li and Debo (2005) study the impact of switching cost on buyer's supplier selection decisions. Elmaghraby and Oh (2006) include the effect of learning-by-doing in their two-stage model to compare the trade-off between staying with the incumbent and second sourcing. They show that the expectation of cost reduction through learning as an incumbent induces suppliers to shade their bids in the first period, while the opportunity to participate in the second period give suppliers the incentive to inflate their bids. Literature in auction theory provides a framework of optimal mechanism design and bidding in the presence of incumbent and non-incumbent bidders.[3] For example, Maskin and Riley (2000) characterize bidding strategies in asymmetric auctions where some firms are systematically more efficient than others. Luton and McAfee (1986) propose a two-stage sequential auction model with possible learning between the two stages. The optimal auction design induces the buyer to discriminate against the winner of the first auction in the latter stage. Therefore, the winner of previous auctions have to bid more aggressively in order to win the second auction. To incorporate quality consideration which is prevalent in procurement auctions, Che (1993) proposes a multidimensional auction model where bidders are evaluated by both submitted bid price and quality level.

Although theoretical work in incumbency has been prolific, empirical investigation of incumbent bias in depth has been very scarce. Exceptions include Greenstein (1993), De Silva, Dunne and Kismopoulou (2003), and Bajari, Houghton and Tadelis (2007). Utilizing the data from federal computer procurement, Greenstein (1993) finds that incumbent is, not surprisingly, more likely to be selected as the winner of the supply contract. However, this probability is affected by the compatibility of a buyer's

[3] For a thorough review of the relevant theoretical literature, see Klemperer (2000, 1993), Milgrom and Weber (1999, 1982), McAfee and McMillan (1987). For a review of structural empirical models of auctions, see Athey and Haile (2006).

installed base and the future system. De Silva, Dunne and Kismopoulou (2003) compares the bidding behavior of incumbent and new entrant firms in government road construction auctions. Following the framework of asymmetric model of auctions, they find that new entrant firms bid more aggressively and win with lower bids. Bajari, Houghton and Tadelis (2007) examine the bidding behavior of suppliers in procurement auctions of highway construction contracts. They point out that adaptation cost - the cost related to contract renegotiation, dispute resolution and disruption of planned production - is significant in highway construction projects. In anticipating adaptation costs, bidders raise their bids by \$6.36 beyond each expected loss of \$1. Their work implies that adaption cost plays a key role in choosing between renegotiating with incumbent suppliers or using competitive bidding mechanisms. Most of existing empirical study focus merely on price formation in procurement auctions, ignoring the importance and existence of quality consideration in both theory[4] and industry practice (Elmaghraby 2007). Using an experimental approach, Jap (2003) demonstrates the existence of incumbent bias in online auction markets. To our best knowledge, Lalive and Schmulzler (2007) is the only empirical paper using field data to explore the impact of procurement auctions on *ex post* quality. They find that, comparing with traditional negotiation mechanisms, the frequency of service on passenger railway lines in Germany is significantly improved when the service providers are selected through competitive bidding.

In the Information Systems literature, a few studies address the issue of incumbent bias. Snir and Hitt (2003) note significant portion of non-awarding auctions in an exchange market. They suggest that many buyers might use auctions to gather price information in order to negotiate with their incumbent suppliers. Utilizing real-world procurement auction data and contract awarding record, Zhong and Wu (2006) find

[4]Asker and Cantillon (2006), Milgrom (2004), Che (1993), Dasgupta and Spulber (1990), and Anton and Yao (1987) all propose auction models where both price and quality are considered in winner selection and bidding

that incumbents are three time as likely to win a manufacturing contract as the non-incumbent suppliers, while enjoying a small amount of price premium compared to non-incumbents. These studies seem to suggest that, often times, incumbent is the winner in online auctions (Elmaghraby 2007). In a repeated auction setting, Arora et al. (2007) characterize mixed bidding strategies in equilibrum while bidders face an uncertain number of competitors. They find that, in equilibrium, if the winner's bid is the only revealed bid, the winner of the first period auction bids less aggressively in the subsequent auction due to underestimation of the number of competitors in the market. In the spirit of Greenstein (1993), Chen and Forman (2006) identify and measure buyer's switching cost in procuring local area network equipment.

Several gaps in the existing literature are noticeable. First, in general, empirical studies that quantify the incumbent advantage in the context of online procurement auctions is scarce. Second, within the limited empirical work on procurement auctions, government procurement and procurement of manufacturing goods are the main focuses. With the increasing use of online auctions for procuring business services in the private sector, how they are, if at all, different from previously studied environment and product categories is unclear. Finally, majority of the literature only focus on price competition in the procurement operation. In practice, quality assessment is believed to be a crucial dimension in online procurement auctions (Elmaghraby 2007). However, how switching suppliers will affect quality or how concerns of quality will affect buyer's supplier selection decision is rarely investigated. We complement recent theoretical and experimental work on characterizing bidding behavior in online procurement auctions where a buyer's utility is determined by both price and supplier quality (Engelbrecht-Wiggans et al. 2006; Kostamis et al. 2006; Chen-Ritzo et al. 2005). While bidders are treated as identical in the absence of incumbent status to stylize the auction design, it is important to provide empirical evidence of incumbent bias in order to build more realistic and generic models. From the point view of online procurement auctions for business services, in this chapter, we explore the existence of incumbent bias and quantify the value of online reverse auctions in cost reduction and quality management.

4.3 Dynamic Bidding for Legal Services

The buyer's in this study has an aggressive goal to conduct competitive bidding for legal services where appropriate. The ultimate goal is to create a "short list" of approved law firms for various service categories and geographic regions that must be considered for all service work for the contracted period of time.

GE has a unique e-Procurement process that can be described as follows. The procurement team and the lead internal lawyers first specify the expertise levels for each legal service category, for example real estate and bankruptcy. An auction is organized for each category. Only pre-qualified suppliers are invited to the auctions and are informed in advance that they will be evaluated based on both economic and quality considerations. Therefore, being the lowest bidder does not ensure being selected into the "short list". The suppliers are also informed that multiple winners will be selected, or to be on GE's "short list" of suppliers. However, selected suppliers do not know how many billable hours they will get for their services. The winners do know that they have the probability to get actual contracts from GE at certain future time during the contract years.

GE uses a dynamic reverse auction mechanism to induce competitive bidding for their legal services. Suppliers are required to bid the hourly rate for the pre-defined expertise levels. The total bid, or the "blended rate" as referred by GE, of a supplier is the sum of the hourly rate for different expertise levels the supplier submits. The final total bid is used to compare and rank suppliers' prices. If a supplier is selected and used, it will be paid the amount equal to its final bid. During an auction, GE conceals suppliers' identity, and only makes a supplier's current bid rank and the lowest bid visible to the suppliers. Each auction starts with a short initial period of about fifteen minutes with unlimited extension periods. This period is automatically extended when there are new bids submitted in the last five minutes. The auctions ends when there are no new bids arriving for any expertise level. The lowest bid of the auction is revealed to all suppliers, though the identity of the lowest bidder is not. Suppliers also know their final standing of the bidding process.

4.3.1 Scoring Rules and Stated Preference

The most distinct and innovative element of GE's procurement strategy for legal services is its consideration of both economic and quality factors. Economic consideration reflects that each law firm will be assigned an economic score based on financial considerations with respect to the relevant legal service category. Quality considerations, on the other had, refer to the fact that GE also assigns a legal score to each supplier assessing their non-economic performance. The economic score and the legal score are weighted equally in obtaining a supplier's final composite score. In this section, we describe in detail, the component of these scores and how they are used by GE to select winning suppliers.

The economic score has two components: bid rank and sourcing rate. Bid rank is merely the rank of each supplier's final bid. Sourcing rate is the scoring established during the Request for Information (RFI) stage prior to an auction. The rating is based on suppliers' self-reported answers to a set of GE's questions regarding payment terms, pricing policy and invoice policy. It essentially captures various transaction related issues. Lastly, the economic score is the weighted average of Bid Rank (95%) and sourcing rate (5%).

The legal score also consists of two elements: Expertise, Efficiency and Capacity (EEC) score and legal rating. EEC score captures the following quality measurements:

- Experience, market knowledge, expertise and efficiency of specific personnel

- Law firm's depth and support resources with respect to such personnel
- Law firm's capacity to handle volume of work for the relevant business units
- Law firm's ability to interface well with customers and GE

GE's internal lawyers are responsible for assigning EEC score to the suppliers based mainly on GE's past experience with the law firm such as firm reputation, historical performance, internal stakeholder recommendation and experience, transaction experience and firm resume. Legal rating captures considerations such as law firm's ability to represent GE without numerous potential conflict situations and their full compliance with the GE Company Outside Counsel Policy. Although the score is also assessed by GE's internal lawyers, it is mainly based on law firms' self-submitted documentation and firm resume. Therefore, comparing to EEC score, legal rating is a more subjective measure of quality. Similar to the computation of economic score, the legal score is the weighted average of EEC score (85%) and legal rating (15%). The final composite score is the sum of the economic score and the legal score. Table 17 summarizes the description of all four components of the composite score.

Table 17: Components of Composite Score

	Name	Description
Economic Score	Bid Rank	Suppliers' final bid ranks.
	Sourcing Rate	A score established through RFI, capturing transaction related policies such as payment term, pricing and invoice policy.
Legal Score	Expertise, Efficiency and Capacity	GE internal lawyer's efficiency assessment established before auctions based on the suppliers' reputation, past performance, transaction experience, and so on.
	Legal Rating	A score assigned by GE internal lawyer, measuring legal aspect such as full compliance with the GE Company Outside Counsel Policy.

All four scores are designed in a way such that a lower score indicates a superior supplier. For example, if there are two suppliers, A and B. Supplier A's Bid Rank is

5, Sourcing Rate is 1, EEC score is 1 and Legal Rating is 10. Therefore, according to the scoring function, supplier A's economic score is 4.8 ($5 \times 0.95 + 1 \times 0.05$) and its legal score is 2.35 ($1 \times 0.85 + 10 \times 0.15$). Unlike supplier A, supplier B's Bid Rank is 1, Sourcing Rate is 5, EEC score is 10 and Legal Rating is 1. Thus, supplier B's economic score is 1.2 ($1 \times 0.95 + 5 \times 0.05$) and its legal score is 8.65 ($10 \times 0.85 + 1 \times 0.15$). We can conclude that based on GE's assessment, supplier B's final bid is lower than supplier A's. Supplier B's overall economic consideration is also better than supplier A. However, supplier A's quality of service exceed supplier B given supplier A's lower legal score. Adding the economic score and legal score together, firm A's composite score is 7.15, which is lower than that of firm B, 9.85. According to GE's scoring rule, firm A is a better supplier comparing to firm B. When selecting winners, firm A should be preferred over firm B.

The suppliers are fully aware of the design and the purpose of these scores. They know that all the aforementioned factors will be considered by the buyer when selecting winners. However, they do not know their individual scores or the scores of their competitors at any moment during the entire procurement process. Although suppliers' score is the main point of discussion during winner selection process, it is not necessary that suppliers with lower composite scores are guaranteed to be awarded the contract.

4.3.2 Data

We use online bidding data of 34 auction events for legal services conducted by GE at the end of year 2003. The selected suppliers will collectively handle all of GE's legal work for a two-year period starting in January 2004. This contract term has been further extended to 2007. In total, these contracts cover 95% of GE CF's legal services needs during the three year period.

Before the application of dynamic bidding process, suppliers offer hourly rates for each of their expertise levels. The hourly rate was applied to all legal services categories defined by GE. The data set includes the before-auction rates and actual billable hours each incumbent supplier received in year 2003. Since suppliers are requested to submit bids for the required expertise levels in different auctions, their hourly rates for the same expertise could vary for different auctions.[5] The data set includes the new hourly rates after the auctions. However, the actual billable hours to the selected suppliers are unavailable. We also have the access to the detailed scoring result of each invited supplier, including the individual value of their Bid Rank, sourcing rate, EEC score, legal rate, as well as the economic score, legal score, and the final composite score calculated given GE's scoring rule. The data set also includes the identity of the winners in each bidding room. Table 18 shows a brief descriptive statistics of these auctions.

Table 18: Descriptive Statistics

	Mean	Std. Dev.	Min.	Max
Number of Suppliers	14.00	7.10	7	37
Number of Winners	4.17	1.34	1	7
Number of Bids	67.73	44.20	10	235
Duration (in minutes)	49.93	13.94	24	92
Final Bids (hourly rate)	\$316.33	\$104.78	\$120.00	\$695.00

4.4 Hypotheses and Methodology

4.4.1 Hypotheses Development

Surveys based on industry practice has consistently reported firms' cost reduction from around 5% to 25% after applying dynamic bidding events to sourcing process (Elmaghraby 2007; Beall et al. 2003; Jap 2002). The estimation of existent empirical investigation on online procurement auction markets concur with the outcomes of the survey (Mithas and Jones 2007; Zhong and Wu 2006). Our first hypothesis extend

[5]If the discrepancy between the hourly rates is too significant, GE will discuss it with the suppliers after the auctions.

the existing findings to the context of procurement of business service.

Hypothesis 5 *Legal service hourly rates, on average, are reduced after the dynamic bidding process.*

Empirical studies on government procurement shows that buyer often times bias towards incumbent suppliers due to significant switching cost. When incumbents are awarded procurement contracts, they also receive a price premium compared to the non-incumbent winners (Silva, Dunne, and Kosmopoulou 2003; Greenstein 1993). Although incumbent suppliers are cited to be very skeptical about participating in online reverse auctions (Beall et al. 2003; Jap 2002), empirical study on procurement auctions for manufacturing goods provides evidence of incumbent bias (Zhong and Wu 2006). Our next hypothesis postulate that similar incumbent effect can be found in procurement auctions for business services.

Hypothesis 6 *Cost savings from non-incumbent winners are higher than that from incumbent winners.*

As we described in detail in Section 3, GE utilizes a sophisticated scoring function to assess both the economic and quality performance of the suppliers. One main purpose of designing a scoring rule is to have a standardized approach to compare suppliers' quality of service. Although limited empirical study shows that service quality is higher when suppliers are selected through bidding process comparing with traditional negotiation mechanisms (Lalive and Schmutzler 2007), according to an industry survey (Beall et al. 2003), many firms suspect that cost savings through online auctions can be achieved without sacrificing product or service quality. In this study, we conjecture that:

Hypothesis 7 *Quality of the supplier base decreases after the dynamic bidding process.*

Separating incumbent suppliers from non-incumbent suppliers, literature is not clear about which type of suppliers have higher quality. On one hand, through working closely with a buyer, incumbent suppliers have the opportunity to improve their operational efficiency, and thus achieve better performance (Laffont and Tirole 1988; Luton and McAfee 1986). On the other hand, new entrants may possess new technology or innovative business process that enable them to potentially outperform incumbent suppliers. Which of the two predictions can be supported by empirical data is unknown. Our next hypothesis postulates that:

Hypothesis 8 *On average, the quality of incumbent winners is higher than the quality of non-incumbent winners.*

A third dimension in evaluating the incumbent effect is buyer's winner selection decision. Our data show that among the 142 winners across the 34 auctions, 97 are incumbent firms (68.3%). Existing literature on procurement auctions provides strong evidence that buyers award contracts more often to the incumbent due to the so-called "lock-in" effect of incumbency (Elmaghraby and Oh 2006; Zhong and Wu 2006; Greenstein 1995; Greenstein 1993). The phenomenon is mainly attributed to non-trivial switching cost that the buyers might incur when contract with new suppliers. However, many of the sources of switching cost in manufacturing and product development, such as compatibility of the future system with the existing establishment (Chen and Forman 2006; Greenstein 1993) and strategic investment in capacity and technology of incumbent firms (Farrel and Shapiro 1989; Riordan and Sappington 1989; Farrel and Gallini 1988), do not apply to the application of procurement auctions for business services. Whether the incumbent effect that has been studied previously can be extended to the current setting is unclear. To shed light on this question, our last hypothesis aims to test incumbent effect on contract awarding.

Hypothesis 9 *The buyer is more likely to reverse its stated preference in order to select incumbent firms as winners.*

In other words, we conjecture that GE favors the incumbent suppliers by awarding them contracts more often even if an incumbent's composite score is higher than the suppliers who are not selected.

4.4.2 Methodology

A challenge imposed by the data set is the unavailability of the actual billable hours after the bidding events. In absence of this information, we are not able to compute the exact cost savings after the auctions. Instead, assuming the billable hours in year 2003 are acceptable approximations of the service hours billed to the winners after auctions, we compare the hourly rate before and after the bidding events in order to estimate the cost savings. We also assume that the hourly rates incur an annual inflation rate of 5%.[6] Lastly, the small sample size of the data set limits the possibility of econometric analysis. Non-parametric estimation is used for our hypothesis testing and statistical inference when the sample size is small (Wooldridge 2001).

4.4.2.1 Measuring Cost Savings

To test Hypothesis 5, we first calculate the average hourly rates across all expertise levels before and after the auctions for each bidding room. We apply the assumed 5% inflation rate to the average hourly rate in order to obtain the three-year average cost savings. Two sample t-test is applied to the three-year average hourly rate and the auction rate to evaluate whether the difference between before and after auction hourly rates is significant or not. If the difference is significant, we have evidence to support Hypothesis 5. Next, in order to test Hypothesis 6, we separately calculated the average hourly rates of the incumbent winners and the non-incumbent winners and apply t-test to assess whether the two types of suppliers provide significantly different cost savings.

4.4.2.2 Measuring Quality

We test Hypothesis 7 by comparing four measures before and after the auctions: average sourcing rate, average economic score, average legal score and average overall

[6]The industry estimation of the inflation rate is usually between 6% to 14%. Our assumption is therefore conservative.

score. Bid Rank is excluded since it is not a measure of quality. The averaged scores reflect the overall quality of the supplier base before and after the auctions instead of the performance of any individual supplier. To test Hypothesis 8, we separately calculate the average scores of the incumbent winners and the non-incumbent winners in order to analyze whether the change in the quality of the suppliers is consistent between the two types of suppliers.

4.4.2.3 Measuring Incumbent Effect

Our rational to test Hypothesis 9 can be described as follows. First, assuming that the scores are objective assessments of suppliers' performances, if the buyer does not favor either incumbent suppliers or non-incumbent suppliers, it should strictly follow its *stated preference* when selecting auction winners. In other words, we should observe that given any pair of suppliers with only one of them being the winner, the winning supplier should have a lower composite score (reflecting better overall performance). It should not matter whether the pair of suppliers are both non-incumbents, both incumbents, or a mixed pair of non-incumbent and incumbent. If the buyer does not follow the stated preference strictly, we can derive its *revealed preference* (Varian 2006b; Samulson 1938) based on the final contract awarding choices. If the buyer treats the incumbents and the non-incumbents equally, the buyer's revealed preference over economic score and legal score should be consistent given any pair of suppliers. If the buyer's winner selection decision deviates from the speculated behavior, we have evidence to support Hypothesis 9.

Next, focusing only on the cases where the stated preference is not followed, we evaluate whether the preference is reversed due to quality or due to price consideration. And whether such consideration is affected by incumbent status.

We start our analysis by forming four groups of suppliers. Each group consists of paired suppliers with only one of them being the winner. However the Bid Rank of the winner is higher than that of the other supplier. Putting it in other words, the final bid of the winner is higher between the two suppliers. The four groups differ in the types of suppliers included in each pair. We define group A as the group with paired non-incumbent suppliers; group B with paired incumbent suppliers; group C with one incumbent and one non-incumbent supplier in the pair when the incumbent is the winner; group D with one incumbent and one non-incumbent supplier in the pair when the non-incumbent is the winner. The grouping of suppliers is summarized in Table 19. This step sets the foundation for us to examine the difference in buyer's revealed preference and winner selection decisions when facing non-incumbent versus incumbent suppliers.

Table 19: Groups of Paired Suppliers

Group ID	Types of Suppliers Included in Each Pair
A	Non-incumbent only
B	Incumbent only
C	One non-incumbent, one incumbent (Incumbent is the winner)
D	One non-incumbent, one incumbent (Non-incumbent is the winner)

Given the four groups, we examine the following questions to test Hypothesis 9.

1. Does buyer's revealed preference match its stated preference as expressed in its scoring rule?

2. If the revealed preference does not match the stated preference, how often are the stated preference reversed? Does the frequency of preference reversal differ significantly among the four groups of paired suppliers?

3. Do the revealed preferences imply an emphasis on quality or price?

4. Does the revealed preference differ significantly different among the four groups of paired suppliers?

4.5 Results

4.5.1 Price

For each auction, we calculate the average hourly rate across all suppliers and all expertise levels specified for the auction. Before the auctions, we calculate the average hourly rate of incumbent suppliers; after the auctions, we calculated the average hourly rate of the newly selected suppliers. These two measures are listed in column 2 and 3 in Table 20. Column 4 of Table 20 is the percentage savings given the average auction hourly rate before and after the auctions. T-test indicates that the difference between the average hourly rate before and after auction is not significant ($p = .1553$).

Assuming a fixed 5% inflation rate for three years, the last column of Table 20 shows the three-year average savings in percentage. On average, legal service procurement through auctions achieved 12% cost reduction per year. T-test shows that the cost savings is significant ($p = .0000$). Therefore, Hypothesis 5 is supported.

There are auctions in our data set that only award incumbents, while the rest award both incumbent and non-incumbent suppliers. On average, the three-year average savings is 10.4% for auctions that award the incumbents only; and it is 13.3% for auctions that award the both types of suppliers. However, the difference in the savings is not significant ($p = .5165$). Next, we focus on the auctions that awarded to both incumbent and non-incumbent suppliers. A comparison of the average auction hourly rate from incumbent winners and non-incumbent winners shows no significant difference, with a 11.3% cost savings from incumbents and 12.3% cost savings from non-incumbents. These results do not support Hypothesis 6.

4.5.2 Quality

To test Hypothesis 7, we compare the average sourcing rate, average economic score, average legal score and average composite score of the supplier base before and after auctions. These scores, according to their definition, measure firms' performance

Table 20: Cost Savings after Auctions

Auctions	Rate before Auctions	Rate after Auctions	Savings	3-year Average Savings*
Aviation Equipment	$390.11	$344.28	11.7%	19.9%
Bankruptcy Midwest	$261.39	$239.44	8.4%	16.8%
Bankruptcy National	$457.30	$437.43	4.3%	13.2%
Bankruptcy NE	$278.42	$243.31	12.6%	20.7%
Bankruptcy SE	$285.70	$237.87	16.7%	24.4%
Bankruptcy SW	$284.27	$228.94	19.5%	26.9%
Core Loans - Central	$287.45	$354.43	-23.3%	-11.9%
Core Loans - East	$358.03	$345.45	3.5%	12.4%
Core Loans - National	$380.87	$407.45	-7.0%	2.9%
Core Loans - West	$355.37	$421.28	-18.5%	-7.6%
Energy M&A	$463.36	$393.22	15.1%	23.0%
Energy Pro Fin	$443.65	$328.79	25.9%	32.7%
Equipment Mid West	$227.99	$224.46	1.5%	10.6%
Equipment National	$341.81	$407.35	-19.2%	-8.2%
Equipment NE	$265.88	$264.09	0.7%	9.8%
Equipment SE	$275.02	$246.59	10.3%	18.6%
Equipment SW	$257.30	$227.14	11.7%	19.9%
Equipment West	$268.30	$249.13	7.1%	15.7%
Industrial	$404.53	$347.12	14.2%	22.1%
M&A Asset Stock Acq.	$449.98	$379.91	15.6%	23.4%
M&A Portfolio Purchase	$307.69	$339.05	-10.2%	0.0%
New Money DIP	$393.08	$438.30	-11.5%	-1.2%
Real Estate Mid West	$296.78	$265.35	10.6%	18.8%
Real Estate NE	$330.73	$270.47	18.2%	25.8%
Real Estate SE	$312.58	$268.39	14.1%	22.1%
Real Estate SW	$321.78	$266.56	17.2%	24.8%
Real Estate West	$344.51	$321.00	6.8%	15.4%
Receivable Financing	$289.23	$350.06	-21.0%	-9.9%
SIL	$373.50	$315.07	15.6%	23.4%
Sponsor Finance	$354.46	$413.02	-16.5%	-5.8%
Tax Credit Deals	$322.43	$325.19	-0.9%	8.4%
Tax Exempt	$280.91	$267.86	4.6%	13.4%
Telecom	$302.01	$338.84	-12.2%	-1.8%
Trade Receivable	$308.14	$371.25	-20.5%	-9.4%
Average	$331.60	$319.94	3.1%	12.0%
p-value			0.1553	0.0000

* Assuming 5% Inflation Rate

along the quality dimension.

As shown in Table 21, Column 2 is the average scores of the incumbent firms before the auctions. Column 3 shows the average scores of the selected winners after auctions. Comparing these scores before and after auctions, we find that all the average scores decrease after auctions, suggesting improvement in supplier quality. However, only the reduction in economic score (from 6.29 to 4.70), which largely reflects the ranking of the final bids, is significant. Therefore, it is not surprising that the decrease in composite score is also significant since it is merely the sum of economic score and legal score. This finding further confirms Hypothesis 5, which states that the prices are reduced after auctions.

Next, we separate non-incumbent winners from incumbent winners. Column 4 in Table 21 lists the average scores of incumbent winners, while Column 5 has the average scores of non-incumbent winners. Comparing with the average scores before auctions in Column 2, the changes in average sourcing rate in Column 4 and 5 are not significant. Similar to the value in Column 3, the average economic score of incumbent winners (in Column 4) and that of non-incumbent winners (in Column 5) are significantly lower that the average economic score before auctions.

Interestingly, unlike pooling incumbent winners and non-incumbent winners together, the average legal score of incumbent winners is significantly lower than that before auctions (2.83 compared to 3.32, $p < .1$). On the other hand, the average legal score of non-incumbent winners is significantly higher than that before auctions (4.24 compared to 3.32, $p < .1$). Moreover, we find that incumbent winners' composite scores is significantly lower than the average composite scores before the auctions (7.75 compared to 9.46, $p < .01$). However, there is no significant difference between the average composite score of non-incumbent winners and that of before the auctions (8.85 compared to 9.46). These results imply that the majority gain of procuring legal services through auctions is from the incumbent firms. On one hand, the quality of selected incumbent firms is on average higher than the quality of the firms before auctions. On the other hand, the prices of the incumbent winners are significantly lower than the price before auctions. Including non-incumbent firms seem to have created a competitive environment that induces incumbent firms to lower their prices. Although the quality of non-incumbent winners is not as high as incumbent firms, their low prices ensure that their overall performance measured by the composite score is comparable to the incumbent firms before the auctions. Therefore, Hypothesis 8 is supported.

Table 21: Quality Measures of the Supplier Base Before and After Auctions

Average Scores	Before Auctions	After Auctions	Incumbent Winners	Non-Incumbent Winners
Sourcing Rate	3.78	3.68	3.84	3.52
Economic Score	6.29	4.70***	4.92***	4.61***
Legal Score	3.32	3.30	2.83*	4.24 *
Composite Score	9.46	8.01***	7.75***	8.85
N		34		

Note: * $p < .1$ ** $p < .05$ *** $p < .01$

4.5.3 Winner Selection

We find 62 pairs of firms for group A, 32 pairs of firms for group B, 86 pairs of firms for group C and 13 pairs of firms for group D. Figure 9 and 10 plots the composite scores of the lower bidder (x-axis) vs. the composite score of the winner (y-axis) of the paired suppliers for the four groups. On the plots, the dots marked by "*" indicate the cases where the buyer follows its stated preference by awarding the contract to the supplier with lower composite score. On the contrary, the dots marked by "+" are the cases where the winner's composite score is higher than the lower-bidder's composite score, indicating that the buyer's revealed preference does not match its stated preference.

Table 22 summarizes the percentage of cases where the buyer's revealed preference does not match its stated preference. We notice that group A has the lowest

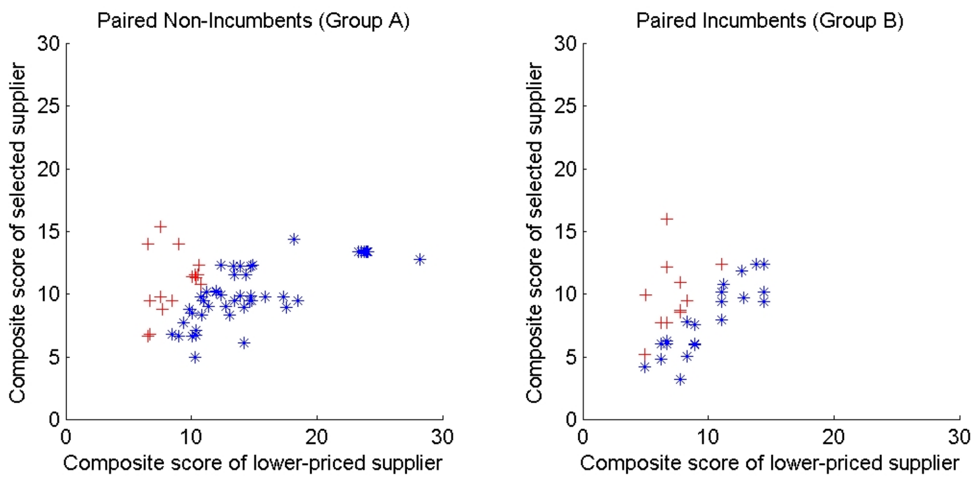

Figure 9: Comparison of Composite Scores of Paired Suppliers in Group A and Group B. ("+" indicates stated preference is not followed; "*" indicates stated preference is followed.)

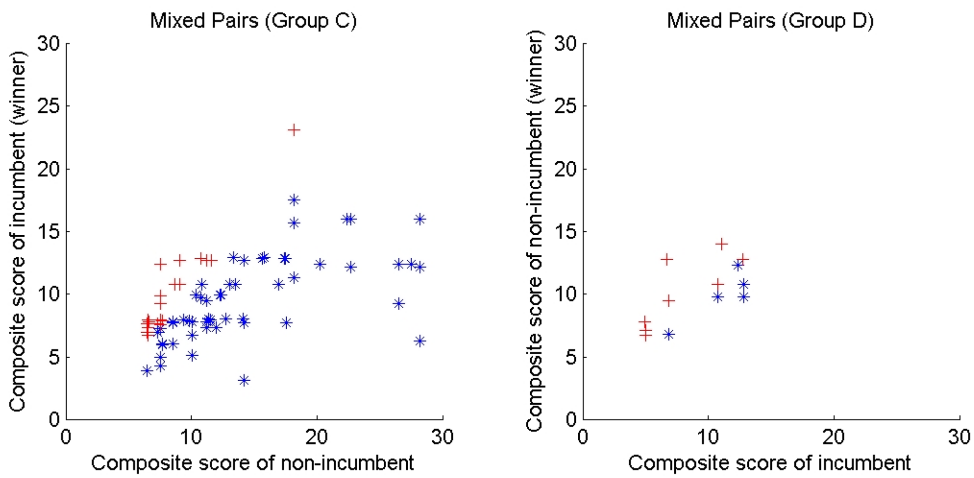

Figure 10: Comparison of Composite Scores of Paired Suppliers in Group C and Group D. ("+" indicates stated preference is not followed; "*" indicates stated preference is followed.)

Table 22: Buyer's Stated Preference vs. Revealed Preference

	Group A: Non-Incumbent	Group B: Incumbent	Group C: Mixed Pairs (Incumbent Wins)	Group D: Mixed Pairs (Non-incumbent Wins)
Number of Pairs	62	32	86	13
Number of Violations	15	11	25	8
Percentage	24.2%	34.4%	29.1%	61.5%

percentage (24.2%), followed by group C (29.1%), group B (34.4%). Interestingly, when a non-incumbent is selected over an incumbent supplier, the buyer ignores the scoring rule even more frequently (with a high percentage of 61.5%).

Next, we conduct chi-square test for proportions to investigate whether the percentages presented in Table 22 are significantly different between any two groups. The p-values of the test are listed in Table 23. Row 2 and row 3 of Table 23 suggests that there is no significant difference between group A and B, group A and C, or group B and C. In other words, we do not find the evidence that the buyer would violate the scoring rule more often in order to select incumbent firms over non-incumbent firms.

Table 23: Chi-Square Test for Proportions

	A: Non-Incumbent	B: Incumbent	C: Mixed Pairs (Incumbent Wins)
B: Incumbent	0.2957		
C: Mixed Pairs (Incumbent Wins)	0.3299	0.6096	
D: Mixed Pairs (Non-Incumbent Wins)	0.0079	0.0945	0.0373

In order to further explain why the revealed preference does not follow the scoring rule and, when it happens, whether the buyer evaluates incumbent firms and non-incumbent firms differently, we concentrate only on the cases where the scoring rule is not enforced. Specifically, we compare the economic score and legal score of the paired suppliers to investigate which attribute is more important, price or quality. Figure 11 plots the economic score (in x axis) and the legal score (in y axis) of the paired suppliers for the non-incumbent only (group A) and the incumbent only (group

B). Figure 12 plots the scores for the paired suppliers in group C and D. The two ends of the curve indicate the paired suppliers, with the end marked by "+" as the winner. The lines travel from upper left to bottom right indicate that the winner is selected due to better quality, that is lower legal score but higher economic score. We refer to these cases as "quality over price" choices. In contrast, the lines travel from bottom left to upper right indicates that the winner is selected due to better price, that is, lower economic score but higher legal score. We refer to these lines as "price over quality" choices.

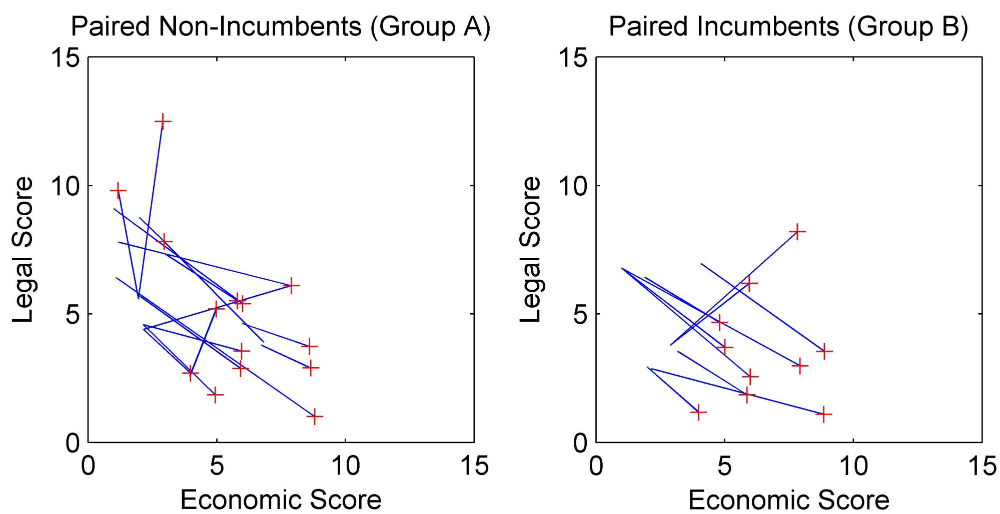

Figure 11: Revealed Preferences of Group A and Group B. ("+" indicates a winner.)

It is apparent that "quality over price" choices are dominant among all four groups. We apply binomial test to the proportion of "quality over price" cases for group A,

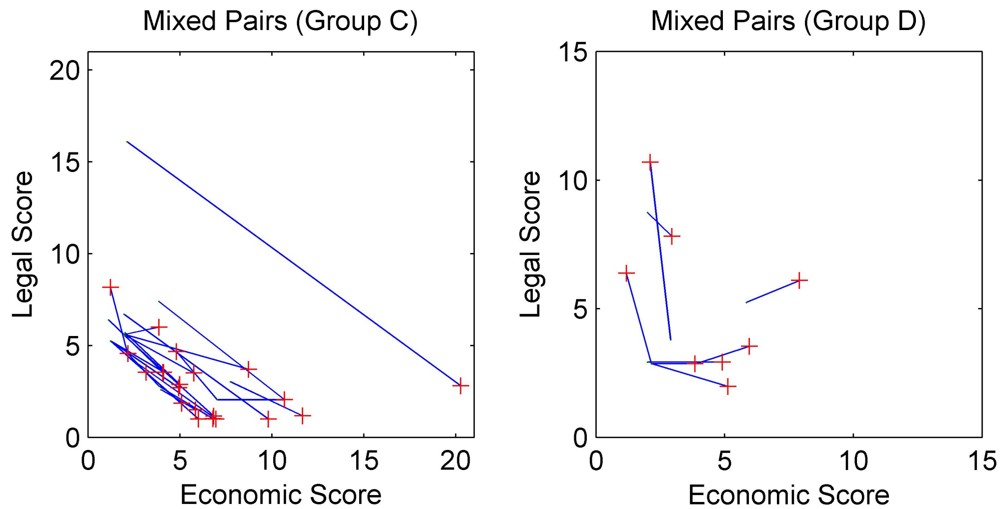

Figure 12: Revealed Preferences of Group C and Group D. ("+" indicates a winner.)

B and C.[7] The results are shown in Table 24. Column 2 summarizes the observed proportion of "quality over price" choices. Column 3 states the hypothesized proportion. The last column shows the p-value of the test results. We cannot reject that the proportion of "quality over price" cases is no less than 95% for group A and B, nor the proportion is no less than 90% for group C. Therefore, we have strong confidence to conclude that when the buyer selects a winner against the scoring rule, the buyer is putting more emphasis on quality over price.

However, it is still yet to be tested whether incumbent status affect how the buyer balances between quality and economic consideration. Restricting to only the "quality over price" cases, we summarize the descriptive statistics of the slopes of the

[7]Group D is excluded due to insufficient sample size.

indifference curves in group A, B and C[8] in Table 25. There are a couple of main findings. First, the mean slopes are all between (-1, 0) and significant, which further confirms the conclusion that a winner is selected due to superior quality when the buyer's revealed preference does not match its stated preference. Second, we conduct Mann-Whitney test and find no significant difference in the mean slope between any two groups.[9]

To summarize, the series of analyses described in this section do not yield strong evidence of incumbent effect in buyer's winner selection process. Instead, we find that quality consideration is crucial in selecting winners and incumbent status indicates better quality compared to non-incumbents among the winners.

Table 24: Binomial Test for the Proportion of "Quality over Price" Choices

Group	Observed Proportion	Test Proportion	p-value
A	85%	$\geq$ 95%	.135
B	89%	$\geq$ 95%	.370
C	85%	$\geq$ 90%	.323

Table 25: Slopes of Revealed Preference Curves for the "Quality over Price" Choices

	Mean	Std. Dev.	Min	Max	N
A: Non-Incumbents	-0.64***	0.27	-0.98	-0.25	11
B: Incumbents	-0.66***	0.20	-0.88	-0.26	8
C: Mixed Pair (Incumbent Wins)	-0.71***	0.19	-0.96	-0.28	17

Note: * $p < .10$ ** $p < .05$ *** $p < .01$

4.6 Discussion

In this study, we attempt to shed lights on the value of online reverse auctions and incumbent effect in the context of business services procurement. We specifically study the impact of online procurement auctions on cost reduction and quality management

[8] Group D is excluded due to insufficient sample size

[9] All p-values are larger than .5, which gives us confidence to conclude that the test result is not significant given the small sample sizes.

from the buyer's perspective. We explore in detail the existence and possible source of incumbent bias. By comparing the hourly service rate before and after auctions, we find that, on average, hourly rates across all legal service categories are reduced by 12.1% after auctions, assuming a 5% inflation rate for three years. Separating incumbent winners from non-incumbent winners, we find that cost savings are from both incumbent and non-incumbent firms. Although, on average, the savings from incumbents (11.3%) are lower that those from non-incumbents (12.3%), the difference in the savings is not significant. Overall, auctions that award only incumbents achieve less savings on average (10.4%) compared to the rooms award both incumbent and non-incumbents (13.3%). Again, the difference in the savings is not significant.

To the best of our knowledge, this study is the first attempt to empirically quantify the effect of online reverse auctions on suppliers' quality management. Our non-parametric analysis shows that, in general, various scores (sourcing rate, economic score, legal score, and overall score) decrease after auctions. However, only the decrease in economic score, which largely reflects the ranking of suppliers' final bids is significant. Separating incumbents from non-incumbents, we find that the legal score of incumbent winners is significantly lower ($p = .0699$) than that of the incumbents before auctions. The economic score and the overall score of the incumbents winners continue to be significantly lower that those of the incumbents before auctions. Finally, the legal score of non-incumbent winners are significantly higher ($p = .0644$) than that of the suppliers before auctions. While the economic score of the non-incumbents winners continue to be significantly lower that that of the suppliers before auctions, their composite score is not significantly different. The findings imply that the value of online procurement auctions for legal services comes from incumbent suppliers. Selected incumbents provide reduced price and increased quality measurement. Non-incumbents are included in the auctions to induce price competition. Although their quality is higher than incumbent suppliers, the overall performance of selected non-incumbents can match up the overall performance of the suppliers before the auctions. Therefore, the cost savings are achieved through online auctions without sacrificing quality.

We do not find incumbent bias in procuring of legal services, which suggests new explanations of incumbent effect. First, we find that although the buyer uses well-defined scoring rule to assess the performances of the suppliers, winner selection does not always follow this rule. However, the buyer does not forego the rule more often in favor of incumbent suppliers. Second, when the buyer selects a winner against the scoring rule, the winning supplier is chosen due to superior quality as measured by its legal score. There is no significant difference between incumbent and non-incumbents in terms of buyer's revealed preferences over price and quality. These findings suggest that the previously supported incumbent effect in government procurement (Silva, Dunne, and Kosmopoulou 2003; Greenstein 1995; Greenstein 1993) and online procurement of manufacturing goods (Zhong and Wu 2006) that mostly caused by non-trivial switching cost cannot be extended to online procurement of business services. Alternatively, our results imply that the incumbent status, on one hand, reflects higher quality. Incumbent bias disappears when adjusting for their higher quality. Our results also imply that the buyer might possess important information about the incumbents, through past experiences, that cannot be easily included in the buyer's scoring function due to uncodifiability (Levi, Kleindorfer, and Wu 2003).

CHAPTER V

CONCLUSION

E-sourcing, whereby an industrial buyer procures its direct and indirect inputs through reverse auctions from a small group of invited suppliers, has been pushing the boundaries of extant auction theories as well as the "best practice" of service providers and traditional auction houses ever since their emergence. Careful econometric analyses of valuable data sets of Internet-based procurement auctions provide a critical first step towards building new auction "theory about facts" and for "putting auction theory to work" as advocated by auction theorists. In this dissertation, several unique data sets are collected that allow detailed institutional analysis of actual bidding behavior in real-life B2B auctions. Three related projects are conducted to empirically investigate the impacts of incumbent status, learning, and information revelation.

The thesis begins with addressing the question of whether e-sourcing damages long-term buyer-supplier relationships. The research question is explored by analyzing the relationships among incumbency, bidding behavior and auction outcomes in the context of a unique data set from a major high-tech buyer during 2002-2004. The analyses reveal heterogeneous bidding behaviors whose distribution is affected by incumbent status. More importantly, incumbency, in conjunction with bidding strategies, has significant impacts on the auction outcomes as measured by suppliers' final bids, buyer's cost savings and suppliers' contract winning probabilities. These findings reveal that e-sourcing via reverse auctions does not necessarily damage existing buyer–supplier relations.

While auctions are treated as isolated events in the first study, the second study focuses on recurring procurement auctions where learning is possible. It is shown that suppliers' final bids at successive auctions are significantly affected by the prior information learned (for example, suppliers' rank orders and lowest bid price). Moreover, suppliers bid adaptively across auctions, that is, a supplier's bidding dynamics are different in successive auctions. Such adaptive bidding behavior is influenced by suppliers' ordinal ranks acquired between auctions. The findings provide initial evidence that by participating in online auctions, suppliers can learn important information about the competitive market and the efficiency of their bidding strategies.

The novelty of the third study in the thesis are three-fold. First, to the best of our knowledge, this is the first study exploring the business value of online procurement auctions for complex business services. Second, it is the first study that examines the impact of online auctions on both cost savings and quality management. We find that prices are, on average, reduced after dynamic bidding events. Buyer's cost savings are from both incumbent and non-incumbent suppliers. We do not find, however, that incumbents have price premium compared to non-incumbent suppliers. The cost savings are achieved without the sacrifice of quality. Interestingly, incumbent winners' quality is higher, on average, than the quality of buyer's supplier base before the auctions, while non-incumbent winner's quality is lower. Together, these findings imply that the main value of online procurement auctions for business services comes from incumbents in the form of reduced price and enhanced quality. Finally, we offer new explanations of incumbent effect in procuring business services. Our results show that incumbent status reflects higher quality. When adjusting for their higher quality, incumbent bias disappears. Our results also imply that the buyer might possess important information about the incumbents, through past experiences, that cannot be easily included in the buyer's scoring function due to uncodifiability (Levi, Kleindorfer, and Wu 2003). Such information plays a key role in buyer's winner selection decision, and explains why the buyer sometime chooses one supplier over another ignoring the scoring rule.

The thesis contributes to the field of procurement and auction literature by enhancing the understanding of the effects of dynamics bidding events and incumbent status, suggesting various important factors that need to be considered in the further advancement of the literature. Taken together, the empirical evidence presented in this dissertation provide stepping-stones for new procurement auction theory building and practical design of electronic markets.

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