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ESSAYS ON MULTI-ITEM AUCTIONS: THEORETICAL AND EMPIRICAL INVESTIGATIONS

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ESSAYS ON MULTI-ITEM AUCTIONS:
THEORETICAL AND EMPIRICAL INVESTIGATIONS

by

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Dedication

To my parents and my husband

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In this dissertation, I explore bidders' behavior in multiple auctions which are conducted sequentially or simultaneously. The first and the second chapters examine buyers' bidding behaviors in an environment of multiple simultaneous auctions and show that the wildly-used assumption of proxy bidding is inappropriate in the multiple auction setting. The first chapter proposes two models which try to describe online auction platforms. One model has a fixed ending time and the other does not. I show that incremental bidding strategy can arise out of equilibrium and weakly dominate the proxy bidding strategy. Late bidding is also discussed. I use the data I collect from eBay to test these theoretical predictions in the second chapter. The estimation results

basically support the theory part. Incremental bidders who switch among different auctions are more likely to win and have higher payoffs than proxy bidders.

The third essay studies the procurement auctions in the Texas school milk market. I define score functions to map the bids from multiple dimensions to one dimension and analyze the factors that may affect the bids of school milk suppliers. After considering the impacts of these factors including backlogs and cost synergies, I can still find some evidences for existence of collusion among the bidders.

Table of Contents

List of Tables

List of Figures

Chapter 1

A Theoretical Study of Incremental Bidding in Competing Simultaneous Auctions

1.1 Introduction

With the fast development of the internet services in the past decade, online auctions have been established as a convenient and widely-used method for purchasing and selling everyday commodities. Online auctions differ from traditional auctions in that bidders often have to face several overlapping auctions at the same time. Some popular internet auction sites, such as eBay, provide platforms for the sale of a mass amount of identical or very similar goods. When you make a search for some popular product, you can always find several auctions running in parallel. For instance, in early 2008, a search of "Wii console" leads to around 6000 auctions on Ebay. Though the items are almost homogeneous, these auctions can be differentiated in other ways, like the duration of the listing, the shipping methods and sellers' reputation. The sellers of these auctions actually compete with each other for selling their goods. Since it is almost costless for buyers to move from one auction to another, we can expect that a buyer's bidding behavior will be affected by the existence of competing auctions.

The increasing popularity of online auctions has stirred a great amount of economic research. Most existing literature, however, treats auctions as isolated from each other. A consequence of this is that the proxy bidding strategy – submitting only one bid which is your true willingness to pay – is commonly used in theoretical models. In this paper I examine an environment in which several auctions are conducted simultaneously. We will see that proxy bidding cannot be assumed for granted and incremental bidding strategy should not be ignored.

Incremental bidders are players who bid multiple times in one auction. The evidence in the laboratory and the field indicates that this type of bidders widely exists. Ockenfels and Roth (2006) reports that in their data set the average number of bids per bidder is 1.89 and 38 percent of the bidders submit more than one bid.[1] However, the reason for incremental bidding is often explained as the ignorance of the bidders. That is, either these bidders misunderstand the auction rules or they are uncertain about their own valuations. Ockenfels and Roth (2006), Ely and Hossain (2009) describe incremental bidders as inexperienced, naive bidders who mistake eBay's proxy system for an ascending-price auction. Hossain (2008) includes uninformed bidders in his model. He proves that these buyers are unclear about their true willingness to pay and thus bid incrementally to acquire more precise information on their valuation of the object.

In the data set I collected from eBay, the proportion of incremental bidders is even higher. They actually prevail over proxy bidders who submit their values before the last minute. Since so many incremental bidders exist, a question

[1] Other studies, e.g. Wilcox (2000) and Ariely et al. (2005), also mention the phenomenon of incremental bidding.

arises: Is it really the ignorance that leads them to bid multiple times? To answer this question, this chapter develops two connected models of concurrent auctions to provide some theoretical support for the incremental bidding strategy. One model is about auctions with flexible ending times, while the other deals with parallel auctions which have fixed ending times. The two different closing rules allow us to exclude or include another commonly observed bidding behavior – late bidding, sometimes also called sniping. In private-value models, late bidding can be a best response to incremental bidding. Ockenfels and Roth (2006) suggest that late bidding is a bidder's best reply to an incremental bidder, if his value is lower than the value of the incremental bidder. In my models, I will show that compared with the proxy bidding and the late bidding strategy, incremental bidding behavior allows buyers to collect more information about bids received in each auction and therefore other bidders' values. Further, incremental bidding gives buyers much more flexibility than proxy bidding to respond to irrational bidders.

My work draws on the literature that considers the impacts of competing auctions and the incremental bidding behaviors. In recent years, some experimental and empirical works have been done to explore the phenomenon of incremental bidding in online auctions. However, there are few theoretical papers on this topic. Probably the most related research is the study of simultaneous ascending auctions by Peters and Severinov (2006). They build a decentralized dynamic mechanism with multiple simultaneous auctions. The ending rule of this mechanism does not involve any restriction on time and there are no bidding costs. They characterize an equilibrium in which buyers bid incrementally in rounds and move among different auctions. When all the bidders follow this strategy, prices are expected to be uniform across all auctions. Since the setting of the model is in an offline context, only incremental bidding behavior is discussed in this paper. Stryszowska(2005) models simultaneous online auctions as second-price multi-unit auctions. Bidders submit multiple bids to coordinate between auctions. She analyzes the case when there are only two auctions running at the same time.[2] This paper aims to provide some insights of the incremental bidding in the theoretical models that try to describe the online auctions in the real world.

The rest of this chapter is organized as follows. In Section 1.2, the theoretical model with flexible ending times is presented. Section 1.3 extends the model to cases with fixed ending times and introduce the last-minute bidding. Section 1.4 concludes.

1.2 Simultaneous Auctions with Flexible Ending Times

1.2.1 Basic Model

As explained above, the incremental bidding strategy is usually related to the late bidding strategy. To get rid of late bidding and focus on the comparison between proxy bidding behavior and incremental bidding behavior, I first study auctions which have flexible ending times. In this setting, the auctions are automatically extended if some bidder submits a bid right before the scheduled

[2] There are other works , e.g. Hendricks et al. (2008) and Zeithammer (2004) theoretically and empirically study bidding behavior in sequential online auctions. Another theorictial approach of simultaneous auctions focuses on the price dynamics of the auctions, e.g. Hyde et al (2006) used Functional Data Analysis to study the price process of simultaneous auctions.

ending time. This automatic extension rule assures bidders that they will always have an opportunity to respond to the changes of prices. In reality, both Amazon and Yahoo use this soft closing rule. The auctions are designed similar to the model described as below.

Suppose time is discrete, $t = 1, \ldots, T$, where T is the scheduled ending period. If no one places a bid at period T, all auctions close at T. Otherwise, the ending time is extended to the next period. The auctions will end in the first period after T in which no one submits a new bid. Without loss of generality, we assume there are 2 auctions and 3 risk-neutral bidders. The objects sold in these auctions are identical and only one unit of goods is listed in one auction. Each auction has a starting price, or a minimum initial bid, m at $t = 1$. Suppose bidder i arrives in period i. Each of them has an inelastic demand for one unit of the item. Bidder $i's$ true willingness to pay, v_i, is drawn independently from a continuous distribution $F(\cdot)$, with support on $[\underline{v}, \bar{v}]$. Each bidder knows only his valuation and the distribution $F(\cdot)$.

Bidders need to decide whether to place a bid and if he bids, which auctions he should choose and how much he should bid. A new bid placed by a buyer must exceed the current standing bid by at least an increment d. Assume that $T > \dfrac{6\bar{v}}{d}$, so that if all the three bidders would like to raise prices increment by increment in these two auction, they would have enough time to do so.

The following restrictions on buyers' bidding strategies are imposed. First of all, in every period t, each bidder can only bid in one auction. This restriction implies that if a bidder is the current high bidder in some auction, then he will not submit a bid in the other auction. It also implies that if a bidder is not the high bidder in either auction, then she submits only one bid. Secondly, high bidders do not raise their own bid in this soft-ending game. With these two restrictions, we know that the current high bidders will remain inactive until he gets overbid. As a result, each bidder has a decision to make only in periods when he is not a high bidder.

In each period t, the bidders observe the identity of the current high bidder and standing high bid, or say the current price, in each auction. Let i_{st} and w_{st} denote respectively the identity of the high bidder and standing high bid in auction s in period t. If no one has bid in auction s prior to period t, then $i_{st} = \phi$ and $w_{st} = m$, the starting price. If only one bidder has submitted a bid prior to period t, then that bidder is the high bidder and $w_{st} = m + d$, where d is a small increment. Otherwise, w_{st} is equal to the second-highest bid plus an increment.

Define $x_t = (i_{1t}, w_{1t}, i_{2t}, w_{2t})$. A bid history is given by $h_t = (x_1, .., x_t)$. A period-t strategy for a bidder who is not a high bidder in either auction in period t is given by

$$\sigma_{it} : H_t \rightarrow \{0, 1, 2\} \times \Re_+.$$

Here 0 denotes the action in which the bidders does not bid. Otherwise, the strategy maps the history of play into a choice of auction and bid.

At Bayesian Nash equilibrium, the strategy used by each player will maximize his expected payoff given their beliefs about other bidders and the strategies played by other bidders. Now let's see how a proxy bidding strategy and an incremental bidding strategy are defined in this model.

Definition: A proxy bidding strategy, $\widehat{\sigma}_i$, for player i is given by, for $t \geq i$,

$$\widehat{\sigma}_{it}(h_t) = \begin{cases} (s, v_i) \text{ if } w_{st} < w_{s't} \text{ and } v_i > w_{st} \\ \phi \text{ if } v_i \leq \min\{w_{1t}, w_{2t}\} \end{cases} .$$

If $w_{1t} = w_{2t} < v_i$, then bidder i chooses auctions 1 and 2 with equal probability and bids v_i.

This strategy profile means that if a bidder uses the proxy bidding strategy, he will choose to bid in the auction which has the relatively lower standing bid. Further, he always bid his true willingness to pay whenever he is not a high bidder and at least one auction has a standing price lower than his valuation.

Definition: An incremental bidding strategy, σ_i^*, for player i is given by, for $t \geq it$,

$$\sigma_{it}^*(h_t) = \begin{cases} (s, w_{st} + d) \text{ if } w_{st} < w_{s't} \text{ and } v_i > w_{st} \\ \phi \text{ if } v_i \leq \min\{w_{1t}, w_{2t}\} \end{cases} .$$

If $w_{1t} = w_{2t} < v_i$, then bidder i chooses auctions 1 and 2 with equal probability and bids $w_{st} + d$.

For the incremental bidding strategy, the choice of the auctions to participate is the same as the proxy bidding. The only difference is that, with this strategy, bidders always raise the standing price by the smallest increment.

Lemma 1.1 *Any strategy profile in which every bidder submits his value v_i on arrival cannot arise in a Bayesian Nash equilibrium.*

Proof. See the chapter appendix. ■

Note that the strategy profiles stated in lemma 1.1 include the pure proxy bidding strategy defined above. The intuition behind this lemma is that when all the bidders submits his true willingness to pay when he enters the auction, the two bidders with highest values may happen to bid on the same item. Although they made the best decision using the information revealed from the standing bids, they fail to obtain enough information about the high bids. Their payments depend on the existing highest bid in each auction. However, a low standing bid in an auction does not necessarily imply that the high bid in this auction is also low. Some bidder enters an auction which already has a very high bid, thus he and the existing high bidder are involved in a fierce competition against each other. As a result, they are trapped into paying a higher price than necessary. The competition can be avoided if the new comer can learn more about the highest bid in each auction before he places a bid. The incremental bidding strategy is useful in serving this purpose.

Theorem 1.1 *There exists a Bayesian Nash equilibrium in which every bidder plays the incremental strategy* $\sigma^* = (\sigma_1^*, \sigma_2^*, \sigma_3^*)$ *defined above.*

Proof. See the chapter appendix. ■

The definition of σ^* characterizes a completely incremental bidding strategy. Using this strategy, a bidder always participates in the auction which has the lowest price. He moves among auctions and bids the smallest amount possible. This allows him to get more information about the high bid in each auction. When he becomes a high bidder, the standing bid of that auction is at the lowest level he can ever find. During this process, the bidder is competing with some current high bidder who is the most likely to have a low valuation. So the excessive competition among bidders with the highest values no longer exists. If we let $v^{(i)}$ denote the i^{th} order statistic of the bidders' valuation. Under this incremental bidding strategies, equilibrium prices in both auctions are always $v^{(3)}$ (plus d) and the outcome is always efficient. However, as shown in the proof of lemma 1.1, when all bidders use proxy bidding strategy, the price of some auction could be as high as $v^{(2)}$.

It can be shown that if we relax the second restriction stated above and allow the high bidders to raise their own bids, the incremental bidding strategy defined above is still an equilibrium. According to eBay's rule, if a current high bidder raises his bid, the standing bid remains the same and the new bid he submitted becomes the highest bid. As a result, the behavior of other bidders who follow incremental bidding strategy will not be affected. Thus raising his own bid is not a profitable deviation for the high bidder. The restriction that a high bidder cannot raise his bid can be loosen without affecting the equilibrium outcomes.

1.2.2 Discussion

The incremental bidding strategy has two advantages. One advantage as shown above is that it allows the bidders to learn which auction has the lower high bid. The second is that it allows the bidders to respond to some non-equilibrium behavior of rival bidders. Consider the case in which we allow the high bidders to raise their own bids. Then we will have a group of different strategy profiles that can construct the equilibria. These strategy only needs to require bidders to bid incrementally when they are not high bidders. After a bidder finds out the auction with the lowest high bid and becomes a high bidder, the next period he could raise the standing bid by any amount that not exceeds his valuation. As long as everyone uses such a strategy, the outcome of the game would be the same as the case that everyone uses the pure incremental bidding strategy.

However, the strategy that a bidder will remain inactive until he gets outbid weakly dominates any strategy that the bidder submits an additional bid after he becomes a standing high bidder. The reason is that this strategy gives a bidder the flexibility to respond to the non-equilibrium behaviors. For example, suppose a bidder i submits his true willingness to pay v_i when he is the current winner in that auction s. Now if a buyer j comes in and he does not follow the equilibrium strategy. For some reason buyer j bids $v_i - \varepsilon$ in auction s. Even if the high bid of the other auction is much lower than $v_i - \varepsilon$, bidder i cannot switch to it. He has already committed himself to auction s when he submitted his value. If he had stopped bidding as soon as he became the high bidder, he would have been outbid by bidder j and could always move to the other auction.

The fact that the incremental bidding strategy prevails in this model relies on the assumption that it is costless to submit a bid. The proxy bidding strategy certainly has more advantages when the biding cost is involved. This model gives us a taste that incremental buyers may not bid multiple times because they are naive or are off the equilibrium path. The existence of simultaneous auctions can be a reason for submitting multiple bids.

1.3 Simultaneous Auctions with Fixed Ending Times

1.3.1 Basic Model

An important structure of the previous model is the ending rule. Now we impose the fixed ending time to make the model more similar to eBay auctions. The basic set up is the same as before, except that both auctions end at period T. In the auctions with the fixed ending rule, apparently lemma 1.1 still holds. The problem of proxy bidding strategy – high value bidders may participate in the same auction – still exists. Thus, the proxy bidding still cannot construct the equilibrium of the fixed ending auctions. However, the pure incremental bidders also face some challenges now.

Lemma 1.2 *The pure incremental strategy profile* $\sigma^* = (\sigma_1^*, \sigma_2^*, \sigma_3^*)$ *is not a Bayesian Nash equilibrium.*

See the chapter appendix for the proof. The intuition behind this lemma is not complicated. If buyers follow σ_i^*, they still act as there is no fixed ending time and submit bids only when they are outbid. Consider a buyer whose value is relatively high. If he bids incrementally before the auctions end, he makes the competition among buyers fiercer and pushes up the price. If he bids at the last minute, he can win an item for sure at a relative low price.

The incremental bidders are indeed naive if they still use strategy σ^* in this environment. However, they can easily avoid losing at the last minute by submitting their true willingness to pay at T. Consider the revised incremental bidding strategy σ^o as follows.

Define a modified incremental bidding strategy, σ_i^o, for player i as, for $T > t \geq i$, bidder i uses the same incremental bidding strategy as before, i.e.

$$\sigma_{it}^o(h_t) = \sigma_{it}^*(h_t)$$

For $t = T$, player i increases his bid to v_i in auction s if he is the high bidder in that auction s.

Theorem 1.2 *There exists a perfect Bayesian equilibrium in which all bidders use this (revised) incremental bidding strategy* $\sigma^o = (\sigma_1^o, \sigma_2^o, \sigma_3^o)$.

This new strategy will eliminate a bidder's incentive for sniping. If every incremental bidder submits their true value successfully right before auctions end, there is no potential benefits from late bidding. The sniper cannot win an item unless he has a high value. There is simply no reason for a buyer to wait until the last minute to bid. The late bidding strategy, just like the proxy bidding, will probably trap a bidder into a competition with high value bidders. Placing bids at an earlier time, as what incremental bidders do, will enable buyers bid in a cooperative way. They move around and spread in different auctions. Bidders with relatively low valuation will leave the auctions during this process. Therefore, unnecessary excessive competitions among high value bidders are avoided.

1.3.2 Discussion

As explained in the models with flexible ending time, it is weakly dominated for buyers to submit their true valuations too early. Bidding their true values early will make them lose the opportunity to switch to auctions with lower prices if some non-equilibrium behavior occurs. Theorem 1.2 tells that as long as incremental bidders bid their true values at the last minute, there will not be any late bidders at the equilibrium. However, the question is whether incremental bidders really understand this situation and always submit successful bids before ending. In reality it may happen that some people forget to monitor the auction he participates in or fail to submit a last-minute bidding due to problems of the internet service. If some of the incremental bidders are unable to bid their true value before the ending time, it still leaves last-minute bidders the opportunity of obtaining extra surplus.

Now we consider a more general situation, where there are S auctions and $S+1$ bidders. Suppose everyone except the last bidder uses incremental bidding strategy. And some of them are sophisticated bidders who bid up to their value at the last minute, while other are native, then when the last bidder arrives, should he use incremental bidding or wait to snipe?

Theorem 1.3 *Suppose a bidder knows that beside him, a proportion of α incremental bidders follow σ_i^o and the other $1-\alpha$ incremental bidders follow σ_i^*. Whether it is more profitable for him to use the last-minute bidding strategy than to use the incremental bidding depends on the value distribution F, the number of auctions S, the proportion α and the standing price w_{st}. When α is* *fixed, facing the same standing price w_{st}, a buyer is more likely to snipe when S is small.*

This theorem tries to describe the real world more precisely by including both the sophisticated incremental bidders who bid their true value at T and the naive ones who do not. Now the bidder $S+1$ tries to decide whether to start bidding or wait until the last minute. When he bids before T, the bidder $S+1$ can learn about other bidders' valuation gradually. In order to win, he only needs to defeat the current high bidder who has the lowest value. To find out this bidder, he bids incrementally and brings up the price. When bidder $S+1$ bids at the last minute, he needs to defeat the bidder who he selects randomly. But when he wins, there are chances that he participates in an auction with a naive incremental bidder who does not bid his true value at the last minute. Then bidder $S+1$ will pay a relatively low price. If he meets a sophisticated incremental bidder, whether he can win depends on the order of their values. Thus it is more difficult for bidder $S+1$ to win a randomly selected sophisticated bidder at the last minute. In sum, bidder $S+1$ faces a trade-off. If he bids at the last minute, the expected payoff conditional on winning is higher, however the probability of winning may decreases. Which strategy is better is ambiguous.

At some given standing price w_{st}, the bidder's beliefs about a current high bidder's value is set. Since a sniper can only bid in one auction, the winning probability and the expected payoff of sniping is not affected by S. If he plays the incremental bidding strategy, he loses only when his valuation is lower than the valuation of every current high bidder. When S is large, this situation is less likely to happen and the expected payoff of incremental bidding is higher. Therefore, the bidder would rather bid incrementally before T when S is large. Theorem 1.3 demonstrates that even with a fixed ending time and some naive bidders, incremental bidding may still yield higher payoffs than late bidding.

1.4 Conclusions

In summary, this study shows that the existence of simultaneous auctions affects buyers' bidding behavior, and some widely used assumption in single object environment cannot be used for granted. The models constructed in this chapter provide some theoretical support for incremental bidders. Unlike in a single online auction, the proxy bidding strategy may not be the best choice for bidders when multiple concurrent auctions exist. The proxy bidding makes a bidder to commit to one auction, while incremental bidding allows the bidder to acquire information about the high bids and react to irrational bidding behaviors. The incremental bidding is superior in that it allows bidders to coordinate and it gives bidders a lot of flexibility. If a buyer can follow this strategy, he would be more likely to win. And on average, an incremental bidder would pay less than a proxy bidder if they have the same distribution of valuation.

When there is a fixed ending time, if incremental bidders can successfully submit their true willingness to pay at the last minute, there would be no late bidders at the equilibrium. Otherwise, snipers may get benefited from late bidding. The equilibrium outcome depends on factors like the number of concurrent auctions.

I focus on the positive side of incremental bidding in this paper and argue that incremental bidders exist for a reason. However, this does not imply proxy bidding should be discarded. As discussed in Section 1.2, it can construct an equilibrium for each bidder to submit a proxy bid after becoming a standing high bidder, although this strategy is weakly dominated by incremental bidding. Here I assume that there is no cost for submitting a bid and everyone is able to monitor the auctions until the end. In reality, some people may be very busy and value their time a lot. They will not be patient enough to submit numerous bids or wait until the last minute. This type of buyers tend to use proxy bidding anyhow.

1.5 Chapter Appendix

1.5.1 Proof of Lemma 1.1

Consider the following case. Suppose when bidder 3 arrives, bidder 1 and bidder 2 have already submitted their true valuation. I will show that bidder 3 can do better than submitting his valuation on his arrival. To maximize their expected payoffs, bidder 1 and bidder 2 must have bidden on different auctions. To see this, consider these two bidders' choices. For the bidder 1, the two auctions are the same - starting prices are the same and no one has got a bid. The expected payoff from either auction, therefore, is the same. He will choose an auction randomly, say auction 1, and place his bid. The standing bid of auction 1 will become $m + d$, while the standing price of auction 2 remains to be $\dot{m}$. When the second bidder arrives, he will bid in auction 2 which has a lower standing price and thus can give him a higher expected payoff. So he bids his value in auction 2 and the standing bid of auction 2 also becomes $m + d$,

Now the standing bids of the auctions are both $w_{st} = m + d$. Bidder 3 sees the prices and the identities of the current winners. Each bidder's valuation is private information, so he cannot tell the difference between the first two bidders. This means, for bidder 3, the two auctions are identical. So he will bid on either item with the same probability. There is a positive probability that bidders' valuations are ordered as $v_3 > v_1 > v_2 > m$, i.e. the bidder 3 is the highest value. If he submits v_3 on arrival, with 1/2 probability, he would bid in the same auction as bidder 1 and end up paying v_1 for the item he wins. But he could always win an item at the price of v_2 if he follows the incremental bidding.

In general if everyone bids his value when he enters, the bidder with highest value has 50% chance to win an object paying the second order statistic of the bidders' values. While if he follows the incremental bidding, he will always win an object paying the third order statistic which is lower than the second.

Formally,if bidder 3 submits his true value on arrival, his expected payoff is:

$$\begin{aligned} EU_3 &= [v_3 - E(v_i|v_3 > v_i > w_{st})] * \Pr(v_3 > v_i|v_i > w_{st}) + \\ [v_3 - E(v_j|v_3 &> v_j > w_{st})] * \Pr(v_3 > v_j|v_j > w_{st}) * \Pr(v_3 < v_i|v_i > w_{st}). \end{aligned}$$

Let p denote the probability $\Pr(v_3 > v_i|v_i > w_{st})$, then

$$\begin{aligned} EU_3 &= [v_3 - E(v_i|v_3 > v_i > w_{st})] * [p + p(1-p)] \\ &= [v_3 - E(v_i|v_3 > v_i > w_{st})] * (2p - p^2) \end{aligned}$$

Instead, if he uses incremental bidding, his expected payoff would be

$$\begin{aligned} EU_3^o &= [v_3 - E(v_i|\min\{v_3, v_j\} > v_i > w_{st})] * \Pr(v_3 > v_i \text{ or } v_3 > v_2|v_1 > w_{st} \text{ and } v_2 > w_{st}) \\ &= [v_3 - E(v_i|\min\{v_3, v_j\} > v_i > w_{st})] * [1 - \Pr(v_3 < v_1|v_1 > w_{st}) * \Pr(v_3 < v_2|v_2 > w_{st})] \\ &= [v_3 - E(v_i|\min\{v_3, v_j\} > v_i > w_{st})] * [1 - (1-p)^2] \\ &= [v_3 - E(v_i|\min\{v_3, v_j\} > v_i > w_{st})] * (2p - p^2) \\ &\geq [v_3 - E(v_i|v_3 > v_i > m)] * (2p - p^2) = EU_3 \end{aligned}$$

$E(v_i|\min\{v_3, v_j\} > v_i > w_{st})]$ is actually the expected value of the 3rd statistic of bidders valuation given that it is higher than w_{st} and lower than v_3. Therefore, bidder 3 could benefit if he deviates from bidding his true value on arrival. This means that the situation in which everyone bids his true valuation on arrival is not an equilibrium strategy. $\square$

1.5.2 Proof of Theorem 1.1

Bidder $i's$ information set consists of the current standing bids and high bidders' identities in all the auctions. His beliefs are that the valuation of each high bidder is no less than the standing bid of the corresponding auction. To be more specific, at any time t, before bidder i submits a bid, suppose bidder j is the current high bidder in auction s, or say $i_{st} = j$, and the standing bid of auction s is w_{st}. Then bidder $i's$ belief about bidder $j's$ value v_j at this information set is that $v_j \geq w_{st}$. According to σ_i^*, every bidder only submits a bid if his value is higher than the standing bid. So, apparently, this belief rule μ is rational on the equilibrium path where each bidder plays σ_i^*.

Now I will show there is no profit deviation from $\sigma^* = (\sigma_1^*, \sigma_2^*, \sigma_3^*)$ given μ. That is, no buyer can improve his payoff by a deviation from σ_i^* given the specified belief μ. Note that if everyone follows σ_i^*, a bidder always bids on the auction with the lowest standing bid and always raised the price by an increment. The difference between prices of any two auctions is at most as large as the increment d. A bidder quits the auctions if and only if the standing bids of both auctions are higher than his value. Suppose $v^{(k)}$ denotes the k^{th}

highest of buyers' values. So at equilibrium the two bidders who have highest values among all buyers win an item and they pay the price equal to the $v^{(3)}$.

(I) First of all, as defined, player i starts to bid if he is not a current high bidder at period t . Suppose auction s has the lowest standing bid before he submits any bid at t. The standing bid of auction s, as defined above, is w_{st}. If bidder $i's$ value v_i is higher than w_{st}, I will show that he will not improve his payoff if he does not bid at t.

To see this, at period t, as long as $v_i \geq w_{st}$, bidder i would have non-negative expected off if he follows σ_i^*. If bidder i deviates and does not bid at all from t and thereafter he will get 0 for sure, which is weakly dominated by σ_i^*.

Consider other deviations in which he does not bid at t, but bids at some period t', where $t' > t$. At t' he follows some strategy and the last bid he submits before auctions end is $b_i \leq v_i$. This strategy is weakly dominated by submitting b_i at period t. Because the extensive ending rule allows every bidder to respond, the situation he faces at t' would be the same as he submits the bid in period t. Since other bidders still follow σ^*, to win an item, bidder i still need to beat at least one buyers to win an object. And when others follow σ^*, if bidder i wins, his payment would always be $v^{(3)}$. So the probability of winning does not increase and the expected payment does not decrease. Waiting until t' does not improve bidder $i's$ expected surplus. Moreover, bidder i runs the risk that auctions may end before t' if $t' > T$. Therefore it is weakly dominated for bidder i to start bidding until t'.

This implies if bidder i is not a high bidder in any auction and he has a higher value than the standing price of some auction, he will always participate in bidding whenever he gets the chance.

(II) The next step is to show that when a buyer bids, he will always choose the auction with the lower standing bid. Suppose $w_{1t} > w_{2t}$. There is a possibility that the highest bid in auction 2 is below w_{1t} and thus below the highest bid in auction 1. Therefore the expected winning probability of bidding in auction 2 would be higher than bidding in 1, and the expected payment conditional on winning would be lower. Thus the bidder would always choose the auction with the lower standing bid.

(III) The last step is to show that when a buyer bids and he has chosen to bid on the auction with a lower price, he cannot do better than raising the price by more than the increment. As long as other two bidders follow σ^* and bidder i is not the bidder with the lowest value, he will always win an auction and pays $v^{(3)}$. And if he is the bidder with the lowest value, he can never win an auction and will always receive zero payoff. (Or negative payoffs if he bids above his value, which is obviously dominated.) His payment relies on the value of the other two bidders, and bid more cannot increase his winning probability or reduce his payment. However, bid more than the increment can lead to higher payments when other bidders go off the equilibrium path. The reason is similar to lemma 1.1. So bidding more than the increment is weakly dominated by following σ_i^*.

Step (I) - (III) complete the proof there is no profitable deviation from σ^*. So σ^* maximizes bidders' expected payoff given the specified belief μ. $\square$

1.5.3 Proof of Lemma 1.2

Suppose the other two bidders, say bidder 1 and bidder 2, follow σ^*, which means they only raise the standing bid by the increment. Then bidder 3 can infer that the highest bid in the auction bidder 1 or 2 participates would be equal to the second highest plus the increment. In other words, the standing price is actually the highest bid in the auction. When bidder 3 enters in period 3, he will observe that the prices of both auctions would be $m + d$, which is what must occur at period 3 when bidder 1 and 2 play the strategy σ^* in period 1 and 2.

Now, bidder 3 knows that if he does not raise the bid, bidder 1 and 2 will remain in active as defined by σ^*. Thus he can choose any auction at period T and bid $m+2d$. He will win the object for sure at this low price $m+2d$. If he also follows σ^* and start to bid at period 3, the other two bidders will react to his bid. As long as bidder 1 and 2 have valuations higher or equal to $m + 3d$, which is highly possible, bidder 3 can no longer win an object at $m+2d$. Thus if bidder 3 deviates from σ^* and wait till period T to bid, he can increase the winning probability and reduce the expected payment conditional on winning.

Therefore, there is some profitable deviation from σ^* and σ^* is no longer an equilibrium. $\square$

1.5.4 Proof of Theorem 1.2

As in theorem 1.1, bidder $i's$ beliefs are that the valuation of each standing high bidder is at least as high as the standing bid of the corresponding auction. If everyone follows σ_i^o, they will start to bid whenever they arrive. In the proof of theorem 1.1, I show that any deviation that does not involve last-minute bidding is not profitable. Here I only need to check that the last-minute bidding strategy is not a profitable deviation.

When other bidders follow σ_i^o and the price level stays at w_{st}, if bidder i bids before T, he only needs to be one of the two high value bidder in order to win an object. So the expected payoff of bidder i if he bids before T is the same as before, which is

$$EU_i^E = [v_i - E(v_j|\min\{v_{-j}\} > v_j > w_{st})] * [1 - \Pr(v_j > v_i|v_j > w_{st})^2] \ .$$

If he only bids at the last minute, he will randomly choose on one auction to bid in. This is because all auctions have the same price and reveal the same information. His expected payoff from bidding in any auction is the same, which is

$$EU_i^L = [v_i - E(v_j|v_i > v_j > w_{st})] * [1 - \Pr(v_j > v_i|v_j > w_{st}).$$

Since

$$E(v_j|\min\{v_{-j}\} > v_j > w_{st}) \leq E(v_j|v_i > v_j > w_{st}),$$

so

$$EU_i^L \leq EU_i^E \ .$$

The intuition is that when a bidder snipe at the last minute, he needs to defeat the bidder which he randomly chooses and there is a possibility that he chooses the auction in which the standing bidder has the highest value among the three. Therefore, late bidding cannot improve a bidder's payoff and and there is no profitable deviation from σ_i^o. The revised incremental bidding strategy still constructs an equilibrium. $\square$

1.5.5 Proof of Theorem .3

Suppose every buyer except bidder i bid incrementally. If bidder i snipes at T, with probability α, he will meet and a buyer who bids his value and with probability $1-\alpha$, he will meet someone who is inactive at T. When bidder i observes no adjustment in the standing bids and winners' identities, he knows that only S buyers besides him are in the auctions. The price level of auctions is denoted as P. Bidder $i's$ belief about other bidders is, for any bidder j, his valuation $v_j \geq w_{st}$. Based on this belief, he can calculate the probability of his value is lower than a current high bidder. This probability, $\Pr(v_j > v_i | v_j > w_{st})$, is denoted as q.

Then his expected payoff from bids early and bids incrementally is

$$EU_i^E = [v_i - E(v_j | \min\{v_{-j}\} > v_j > w_{st})] * (1 - q^S) \ .$$

His expected payoff from late bidding is

$$EU_i^L = [v_i - E(v_j | v_i > v_j > w_{st})] * (1 - q)(1 - \alpha) + (v_i - w_{st}) * \alpha \ .$$

We know that $[v_i - E(v_j|v_i > v_j > w_{st})](1-q) < [v_i - E(v_j|\min\{v_{-j}\} > v_j > w_{st})](1-q^S) < (v_i - w_{st})$, so the relationship between EU_i^E and EU_i^L is ambiguous. Note that since $E(v_j|\min\{v_{-j}\} > v_j > w_{st})]$ is the expected value of $v^{(S+1)}$ given that $v^{(S+1)}$ is between v_i and w_{st}, it should decrease in S when everything else equal. EU_i^E is increasing in S and q should be the same under the same w_{st}. If we compare two groups of concurrent auctions which have the same standing prices, we know that bidders in the larger group which has more auctions are less likely to snipe. $\square$

Chapter 2

Are Incremental Bidders Really Naive? Evidence from eBay Auctions

2.1 Introduction

The previous chapter provides some theoretical support for the existence of incremental bidders. The basic idea suggested by the model is that incremental bidding is more flexible than proxy bidding and allows bidders to switch to other auctions that are less competitive. In this chapter I will use the data collected from eBay to see if we can find empirical evidences that are consisted with the theory.

Not much empirical work has been conducted on competing online auctions until recent years and the views on incremental bidding are mixed. Anwar et al. (2006) provide one of the first empirical evidences that support incremental bidders. They suggest that eBay bidders do submit multiple bids and bid across competing auctions. They also state that the cross-bidders tend to place bids on the auctions with the lowest standing price. In the study, to overcome complications associated with heterogeneity in item conditions and delivery methods, they focus on competing auctions run by the same sellers. With this restriction, to have enough competing auctions, they have to relax the definition of competing auctions. Though they aim to explore concurrent auctions, the interval between the ending times of the competing auctions in their sample is up to one day.

Haruvy and Popkowski Leszczyc (2008) have some different thoughts on incremental bidding. They ran concurrent eBay auctions in pairs in a controlled experimental design. These pairs involved two identical or very similar auctions. They argue that only a small proportion of bidders ever do cross-bidding and only a little over a half of the switches are moved to the auction with a lower price. Since there are just two auctions in a pair, a random bid will have 50% chances to be placed on the lower priced auction. Thus, there is no strong support to show that incremental bidders switch to auctions that can give them higher payoffs.[3]

In recent years, more individuals start to use online auction platform to buy or sell goods and services. For example, eBay, the most popular online auction site in US, had more than 90 million active users during the year 2009, who contributed to a total trading volume of more than $48 billion. The richness of the data from these online websites allows us to take a closer look of competing auctions. Wii consoles were released in late 2006 and became very popular in US from 2007. This phenomenon provides people a good chance of making profits from reselling the game consoles on auction websites and thus gives us a good opportunity to examine the competing online auctions. In the data set I collected from eBay during mid 2008, I can find enough competing auctions that are almost homogeneous in everything. So unlike what Anwar et al. (2006)

[3]Some other experimental papers have payed attention to the impacts of competing auctions. For example Lin and Jank (2007) further analyze the bidder migration which is similar to the cross-bidding behavior discussed in this paper. They argue that the reasons for the migration is either the bidders were outbid or bargain hunters are looking for a good deal.

did, I am able to ignore the identity of sellers and define competing auctions as auctions which end very closely to each other.

The analysis of the data in this paper shows more evidences in favor of incremental bidding from buyers' perspectives. Incremental bidders are more likely to win than proxy bidders and last-minute bidders. Although the prices they pay are not as low as those paid by last-minute bidders, they do beat proxy bidders when they make use of the flexibility of this strategy. To be more specific, if incremental bidders move back and forth among auctions instead of sticking to one auction, on average they will pay less than proxy bidders on winning.

The rest of this chapter is organized as follows. Section 2.2 describes the data and introduces some important statistics. Section 2.3 presents the major regression results on winning probabilities and winning prices. Different type of bidding strategies, proxy, incremental and late bidding are explored together. More discussions on late bidding and incremental-bidding are contained in Section 2.4. The concluding remarks are in Section 2.5.

2.2 Data Description

2.2.1 Characteristics of Auctions

The data used in this study includes the information of all the Wii console auctions that occurred on eBay between June 04 and June 12, 2008.[4] I select the

[4] The data contains every listing ends in this time period. Auctions with a hidden reserve price are only included if the reserve price is met. I exclude "Dutch Auctions", in which multiple items are listed in one auction, and "Private Auctions", in which bidders' information is not revealed. "Buy-It-Now" auctions are also excluded from the dataset.

Wii console because the auctions of this commodity have some nice characteristics that match closely with the environment of the theoretical models proposed in the second chapter. First of all, new items prevail in these auctions. The retail price of this new product can be found very easily, but bidders' willingness to pay is private information. This is consistent with the private value setting. The online trade of this product provides two ideal features for investigating competing auctions – high frequency and homogeneity.

Due to its limited supply at retail stores and the popularity of this item, the Wii console was one of the hottest commodities on eBay. In 2007, the Wii is the second best-selling game console (behind the Nintendo DS) in the US. However, it is not easy to find a retail store that has a stock. As a result, many buyers turn to eBay to buy it. A high volume of transactions take place on eBay every day.

Table 2.1 gives a description of the frequency of auctions. The dataset consists of 4256 auctions. On average, one item is sold in less than three minutes (162.4 seconds). Since most products are sold during the day time, the intervals between two auctions which end next to each other are very large during the nights. The median of these intervals is much smaller than the average and is only 73 seconds. A large proportion of auctions in the data have parallel peers which end at almost the same time. If two auctions end within five minutes, we say each auction has a 5-minute concurrent auction. 97.5% of auctions have at least one 5-minute concurrent auction and 86.2% have at least one 2-minute concurrent auction. Each auction on average has 5.69 5-minute concurrent auctions and 2.23 2-minute concurrent auctions. In reality it takes time for a bidder to enter an auction or to check whether he wins an item. When an auction ends, losers may not be able to submit a bid in the next auction which will close immediately. Thus, bidders are likely to treat auctions with small difference in ending time as simultaneous auctions.

The frequency of auctions varies from day to night. A figure of the distribution of auctions by ending times is included in the appendix. It shows the average proportion of auctions end in each hour. The percentage is always above 5% between 8 am and 8 pm. I will define this time period as "peak hours". If we compare the auctions conducted during the peak hours and non-peak hours, we can find some differences in the winning price and the crowdedness. The mean of winning prices is a little lower during peak hours, and the average number of bidders is about the same in either period. However, auctions end during peak hours receives more bids.

Table 2.1 Summary Statistics about Auction Frequency

Variables	Mean	Std. Dev.	Min	Max
Median of Intervals b/w Auctions (seconds)	73	-	-	-
Average Interval b/w Auctions (seconds)	162.4	706.29	0	20461
Auctions with 2-min Concurrent Auctions	86.2%	-	-	-
Auctions with 5-min Concurrent Auctions	97.5%	-	-	-
Average Number of 2-min Concurrent Auctions	2.23	1.63	0	9
Average Number of 5-min Concurrent Auctions	5.69	2.94	0	15

Another interesting fact of online Wii console auctions is the homogeneity.

Sellers on eBay are mostly retailers who earn profits from reselling the consoles. They not only sell the identical products, but also collaborate tacitly in other aspects. They tend to use the same descriptions for their items, set the same starting prices and provide the same shipping service. An example of auction listings on eBay is presented in the appendix. From this group of listings, we can see that all the sellers chose the same title and similar descriptions for their auctions, and they all offered free shipping for the items. To present a more complete view on the auctions, Table 2.2 shows the statistics of all the major characteristics of eBay auctions. In general, 93.56% of auctions charge no additional fees for the shipment. In 91.71% auctions, the starting prices are set as 99-cent or lower, which is a very small amount comparing with the retail prices of the Wii console or the winning prices of the auctions. When sellers list items, they can choose the duration of the listing among 1, 3, 5, 7 or 10 days. In our sample, a great majority, 86.72%, of the auctions are 1-day listings.

The eBay allows sellers to promote their items with listing upgrades at some extra charges. One of the most attractive upgrades is called Featured Plus. When a seller chooses this option, his item will appear in the featured item section at the top of the search results page. The auctions without this service will be listed after the featured items. This extra service seems to quite effective especially when there are many auctions going on simultaneously. Since a buyer usually browses a webpage from the top, his attention is more likely to be drawn by featured ones. When a buyer has a time limit to submit a bid, he may not have enough time to look at all the listings on the webpage. Then the ordinary auctions posted on the lower half of a webpage will attract fewer buyers even if they have lower standing prices. Apparently, most sellers value this option and thus 77.91% of listings are featured. Another upgrade option is to make the title bold so that it stands out from other auctions in the list of search results. About 20.16% auctions have bold titles. When the data were collected, other promotion methods were used less often and thus omitted from the dataset.

Table 2.2: Summary Statistics of Auction Characteristics

Characteristic	Percentage
Free Shipping	93.56%
Starting Price $\leq$ \$0.99	91.71%
Duration=1 day	86.72%
Featured Item	77.91%
Bold Title	20.16%

The feedback rating of sellers can be see as a difference among auctions and may potentially affect buyers' bidding decisions. The rating is obtained in the following way. After each transaction is completed, eBay will ask the seller and the buyer to leave a comment and a rating for each other. The feedback score of a seller or a buyer is the sum of the ratings he has received, which can be positive, negative or neutral.[5] A seller's rate is the percentage of the positive feedback scores he has received. In Table 2.3, we see that both the feedback scores of the buyers and of the sellers have large variations. However,

[5]Right after our data were collected, eBay changed the feedback policy to protect buyers. Now sellers can only leave positive ratings for buyers.

the ratings of sellers do not differ much. Most sellers have very high overall rates, the mean of which is 99.15%.

Table 2.3: Summary Statistics of Auction Characteristics (ctd.)

Variables	Mean	Std. Dev.	Min	Max
Sellers' Feedback	966.50	5687.08	-1	177252
Sellers' Rate (%)	99.15	4.05	0	100
Buyers' Feedback	95.28	384.72	-1	8991
Number of Bids	25.63	10.24	1	81
Number of Bidders	12.69	4.34	1	28
Starting Price	17.45	73.44	0.01	589.99
Shipping	1.44	6.06	0	47.98
Winning Bid (No Bundle)	324.14	28.02	210.5	500
Winning Bid (w/ Bundle)	409.85	40.04	255	605

Some sellers bundle two extra remote controllers and a game disk with the Wii console. The extra controllers are must-haves for multi-person games and most buyers need them. However, the supply of controllers in retail store is not as limited as that of consoles, and the prices of controllers are relatively cheap. So the price of a bundle mainly depends on buyers' willingness to pay for the console. The price difference between a console and a bundle is around the retail price for the controllers and the game disk. I do not expect buyers' bidding behaviors to change much when extra controllers are offered. The only change they will make in the auctions of bundles is that buyers add an extra amount to their bids. The amount of money is supposed to be around the retail prices of the extra controllers and the disk. On average, 12.69 bidders participate in each auction. The mean of bids received on each item is 25.63. This infers that there are multiple bidding buyers in the data sets. As stated above, most sellers provide free shipping and choose a nearly-zero starting price. Among those who make different choices, the difference in shipping cost is relatively small while the starting prices vary a lot.

Among these 4256 auctions, in 116 auctions every bidder places only one bid. So only 2.7% of the auctions are not affected by buyers who bid multiple times. This illuminates that incremental biding is the choice of many bidders and cannot simply be ignored as non-equilibrium behavior. Theoretical models suggest that the existence of several competing concurrent auctions affects buyers' strategies. To track their bidding behavior on auctions which overlap the sample auctions, I collected the data of the biding history of every auction that ended as early as May 25, 2008 and as late as June 22, 2008.

2.2.2 Classification of Bidders

In the data set, we observe different bidding behavior. To define the types of bidders in the sample, let me first explain the meanings of the incremental bid and the proxy bid used in this empirical study. The bidding mechanism of eBay allows a buyer to submit any bids that are equal higher than the standing price plus a bidding increment. If a bid is exactly equal to the standing high bid plus an increment, this bid is called the incremental bid. If a bid is higher than the standing price plus the increment, it is treated as a proxy bid. Just like the settings in the theoretical models, the standing price in an eBay auction is the second highest bid plus an increment and the highest bid will not be posted. The bidding history of auctions contains information about the type of each bid, automatic or non-automatic. If a bid is placed by the bidder himself, it is recorded as a non-automatic bid. If eBay adjusts bids on a bidder's behalf, these bids will be shown as automatic bids.

When an incremental bid is placed and becomes the highest bid, the standing high price is actually equal to the highest bid. And the incremental bids are always non-automatic bids. Meanwhile, if a proxy bid is submitted, the true value of this bid is hidden from other bidders and the standing price is still the second highest bid plus an increment. In bidding history, this new standing price is shown a non-automatic bid submitted by the high bidder. When other bidders submit new bids, eBay will adjust the standing prices accordingly. It will raise the price on the bidder's behalf as much as necessary to maintain the bidder's position as the high bidder. The price goes up to the maximum value that the bidder has submitted. These bids posted by eBay will be shown as automatic bids. Thus, in the data of bidding history, a proxy bid will be observed as a non-automatic bid followed by automatic bids.

Note that in the empirical study, the definition of proxy bidding is a little different from the the one in the theoretical part. Since a bidder's value is his private information and the highest bid in an auction is not observed, in practical it is not possible to tell whether a bidder has submitted his true willingness to pay. So here in the study as long as a bidder raises the standing price by more than the increment and allows eBay to bid on his behalf, this bid is considered as a proxy bid. Though this generalized proxy bid may not be a bidder's true willingness to pay, it does have similar properties as the proxy-bidding defined before. For instances, it may let the bidder involve in unnecessary competitions with other high value bidders, and it also allows eBay to adjust the standing bid on the bidder's behalf. Actually the name of proxy-bidding comes from this automatic price-adjusting mechanism of eBay. Therefore, when a bidder submits a bid that exceed the standing price by more than an increment, and uses the proxy bidding mechanism provided by eBay, we will call this bid a proxy bid.

Based on the definition of bids and the bidding history data, I classify bidders as following. If a bidder always places proxy bids, he is called a pure proxy bidder. If a bidder always bid incrementally by himself, we call him a pure incremental bidder. A Proxy-incremental bidder is the bidder who first submits proxy bids and then submits incremental bids, while an incremental-proxy bidder is the bidder who first submits incremental bids and then submits proxy bids. If a winner never gets outbid and only one bid from him appears in the bidding history, it is not possible to distinguish the type of this bid. However, since he wins, this bid is the last bid in the auction and usually placed quite late. Winners who submit these last bids within 10 minutes before the auction ends are treated as last-minute bidders, or say snipers. Other winners who submit the only bid relatively early do not fall in any groups of our interests.

As shown in Table 2.4, 1221 out of the 4256 winners are last-minute bidders. 762 winners are pure proxy bidders, while 773 bidders are incremental. 1449 winners are mixed bidders who have submitted both proxy bids and incremental bids. To be more specific, 314 of them use proxy bidding when they won and the rest 1135 winners bid incrementally when they won. For the other 51 winners, we cannot tell the exact type of them.

Table 2.4: Summary Statistics of Winner's Type

Winner's Type	Numbers	Percentage of All Winners
Last-Minute Bidders	1221	28.69%
Pure Proxy Bidders	762	17.90%
Pure Incremental Bidders	773	18.16%
Incremental-proxy Bidders	314	7.38%
Proxy-Incremental Bidders	1135	26.67%
Unclassified	51	1.20%

The Figure 2.2 in the appendix illuminates the proportion of different types of bidder in winners and losers. From the figure, we can see that the percentages of proxy bidders and incremental-proxy bidders in losers are higher than those in winners. Note that the incremental-proxy bidders are not incremental bidders who submit their maximum willingness to pay at the last minute. Rather, they act more similarly to pure proxy bidders and submit their willingness to pay at a relatively early stage.

Table 2.5: Submitting Time of Last Bids from Each Type of Winners (Units: Seconds before Ending Times)

Winner's Type	Average
Last-Minute Bidders	528.42
Proxy Bidders	3737.19
Incremental Bidders	326.91
Mixed Bidders	
Incremental-proxy Bidders	5284.64
Proxy-Incremental Bidders	779.55

To investigate the mixed bidders more carefully, I examine the timing of last bids placed by each type of winners. The result is reported in Table 2.5. The incremental bidders place their last bids around five and a half minutes (327 seconds) before auctions close. Not surprisingly, the winners who use proxy bids submit their last bids (also their only bids) much earlier, at about one hour (3737 seconds) before ending times. Nevertheless, incremental-proxy bidders place their last bids even earlier (5285 seconds before auctions end). The pure proxy bidders and the incremental-proxy bidders are similar in that both types commit themselves to one auction long before it ends, and are not able to switch to a different auction. Therefore, from here I will treat these two types of bidders as one group. Similarly, incremental bidders and proxy-incremental bidders will be considered as in one group, because both types of buyers are still able to bid on other auctions when they place their last bids. Moreover, on average, the last bids from incremental bidders are placed around the same time as those from last-minute bidders. It shows that most incremental bidders remain active until auctions end.

Table 2.6: Summary Statistics of All Bidders and Proportion of Winners in Each Group

Group	Number of Winners	All Bidders		Serious Bidders	
		Number	% of Winners	Number	% of Winners
1	1221	10943	11.16%	8745	13.96%
2	1076	24438	4.40%	14419	7.46%
3	1908	16000	11.93%	10217	18.67%
4	51	2559	1.99%	437	11.67%

Table 2.6 shows the classification of all bidders and the percentage of winners among each type of bidders.[6] It gives us a general idea of the winning probability of different types of bidders. Serious bidders are are defined as bidders whose last real bid (his bid plus shipping cost) is above $200. Group 1 consists of last-minute bidders. Group 2 contains proxy bidders, including pure proxy bidders and incremental-proxy bidders. Group 3 is composed of incremental bidders, including pure incremental and proxy-incremental bidders. Group 4 are the bidders that do not fit in any definition of the bidder's type.

[6]Here, because of the difficulty of tracking losers in different auctions, I treat every bidder as a different bidder in different auctions. That is, when I calculate these percentages, I assume each bidder participates in only one auction. With this assumption, the winning probability of every group will be underestimated. However, the average number of auctions that each winner participates is approximately the same for all the groups. As long as this is also true for losers, the order of the probability remains the same. This means, compared with the proxy bidders, a larger proportion of incremental bidders have won an item.

11.93% of incremental bidders are winner while only 4.40% of proxy bidders win an auction. The proportion of winners in last-minutes bidders is between the above two groups. To exclude some non-serious bidders, I also look at the percentages among serious bidders whose last bid is above $200. Again, the proportion of winners is the highest in the incremental bidders group, and is the lowest in the proxy bidders group.

2.2.3 Cross Bidding

In chapter 1, the theoretical results from the models of simultaneous auctions imply that a bidder should bid in the auction with the lowest standing bid. If a bidder is aware of the existence of several competing auctions and understands the rules well, he should always switch to the auction with the lowest price whenever possible. Then we will be able to observe buyers bid across competing auctions. In this section, I explore the causes and the effects of this cross-bidding behavior.

Although we do see a large proportion of bidders participate in multiple overlapping auctions, one may argue that this is caused by the re-entry of losers. When a buyer loses in one auction, he will probably bid again in another auction which ends a few minutes later.[7] Since the competing auctions do not end at exactly the same time, this argument is sensible. To distinguish bidding in several auctions simultaneously from bidding sequentially, I define "cross bidding" more strictly. Consider a bidder who at first bids in auction

[7] Hendricks et al. (2008) show this phenomenon and study the effects or re-entry in sequential auctions.

A and then starts to bid in auction B. I say he makes a "switch" if auction A is still open when he places his first bid in auction B. Bidders who ever make a switch are called cross bidders. It is reasonable to believe that these cross bidders understand the multiple auctions environment and do not stick to only one auction at a time. They move to a new auction not because they cannot bid in the old auction anymore, but because they decide not to do so. If a bidder has ever made a switch, he is treated as a cross bidder. Any type of bidders, proxy bidders, incremental bidders or late bidders can be cross bidders.

2.3 Estimation Results

2.3.1 Winning Probability of Different Types of Winners

We know that whether a buyer can win an item largely depends on his valuation, and thus the amount he bids. When we look at the numbers shown in Table 2.6, a question arises naturally - is the higher proportion of winners among incremental bidders caused by higher bids? To answer it, I run a probit regression of the winner dummy on bidders' highest bids[8] and the groups they belong to. The dependent variable is one if a bidder's highest bid is the winning bid of that auction, and is zero otherwise. Table 2.7 reports the maximum likelihood probit coefficient estimates. As expected, the coefficient of highest bid is positive and significant which means that the higher a buyer bids, the more likely he is about to win. Further, we can see that the dummy for late bidders and

[8] Although most sellers offer free shipping, others still charge a fee for the shipment. The bid value used here is the sum of a bidder's highest bid and the shipping cost of the item. Other auction characteristics variables can be added to the regression, but the main results remain the same.

Table 2.7: Probit Regression of Winners on Bidding Values and Bidder Types

Variables	All Bidders	Serious Bidders
Constant	-7.089**	-7.062**
	(0.096)	(0.098)
Highest Bid of the Bidder	0.019**	0.019**
	(0.000)	(0.000)
Dummy for Last-Minute Bidders	0.386**	0.386**
	(0.026)	(0.026)
Dummy for Incremental Bidders	0.452**	0.453**
	(0.025)	(0.025)
Pseudo R^2	0.36	0.26

The dependent variable is the dummy for winners. Standard errors are in parentheses. Variables that are significant at the 5% level are marked with an asterisk. Those that are significant at the 1% level are marked with double asterisks.

incremental bidders are both significantly positive. Thus among buyers whose highest bids are similar, incremental bidders and last-minute bidders win with a higher probability than proxy bidders. The estimate of incremental bidders is larger than late bidders. This is consistent with what we see in Table 2.5, among all buyers, the incremental bidders win with the highest probability. As the theoretical model suggests, proxy bidders may end up with excessive competition among themselves in some of the auctions. They could have won an item if they had switched to a less competitive auction as incremental bidders did. This evidence from data casts doubt on the proxy bidding mechanism.

2.3.2 Impacts of Cross-Bidding on Winning Prices

Among the 4256 winners, I observe 2352 switches across different auctions. Moreover, 85.88% of these moves are from the auction with a higher standing price to the auction with a lower standing price. This finding provides evidence that cross-bidding behavior is related to the difference between the standing bids of competing auctions. From a theoretical perspective, if there are enough bidders who move around and bid across several auctions, the final prices for items in the concurrent auctions should be close to each other. Then, to an individual bidder, whether he switches or not may not make big difference for him. However, in reality there are still many proxy bidders and price dispersion exists most of the time for various reasons. In this situation, a bidder who moves around tends to benefit from this cross-bidding behavior.

The following regression analysis shed light on how the winning price of an auction relates to a bidder's ability of cross-bidding and other auction characteristics. The dependent variable in the regressions reported in Table 2.8 is the real price of each auction, which is the sum of the winning bid and the shipping cost. The regression in the first column does not consider the fixed effects of specific ending times, except that a dummy variable for peak hours is included. The second column report results when dummies for ending days and ending hours are included. The coefficient estimates on cross-bidding are negative and highly significant in these two regressions. The information revealed is that winners who ever bid across different auctions do pay lower prices than those who do not. Note that the cross-bidding winners are not just those bidders who switch to the auctions they win, but also bidders who have ever made switches among other auctions.

This is because I consider the cross-bidding behavior as a bidder's ability, not a one-time result caused by the difference between prices. If a winner never moves between the auction he wins and other auction, the reason could be that the auction he wins always have the lowest price, not that he commits himself to only one auction. Therefore if he had made switches before, we have reasons to believe that the winner understands the situation and we still treat him as a cross-bidder. When facing the price dispersion in competing auctions, these cross- bidders see the difference and switch to auctions with lower standing bids. As a result, they win an item, they tend to win it at a lower price.

In addition, the negative coefficient on the dummy for peak hours may serve as another evidence for the advantage of cross-bidding. As described above in section 2.2, the number of bidders remains the same across the time, while the number of bids is higher during peak hours. The price level, however, has not been driven up. Bidders have more opportunities to bid across items during peak time, because more auctions are open in this period. As a result, a bidder's number of bids and number of switches both increase. The number of bids has a positive effect on prices, but the price level in peak hours decreases. Thus winning prices are probably brought down by bidders' cross-bidding behavior.

The prices of featured items exceed the non-featured items by a large amount. Although eBay charges \$24.95 for this upgrade, the regression results show that this extra service is indeed worth the price. On average the featured items are sold for about \$35 more than the non-featured ones. It is shown above that

Table 2.8: Regression of Winning Bids

Variables	Estimates	
	w/o Fixed Effects	w/ Fixed Effects
Intercept	224.31**	236.92**
	(10.1)	(11.71)
Cross-Bidding	-4.53**	-4.87**
	(1.31)	(1.22)
Buyer's Score	0.00	0.00
	(0.00)	(0.00)
Seller's Rate	0.60**	0.60**
	(0.10)	(0.10)
Duration	0.13	0.2
	(0.34)	(0.34)
Starting Price	0.18**	0.18**
	(0.01)	(0.01)
Dummy for Peak Hours	-3.27**	-
	(1.05)	-
Number of Bids	0.54**	0.55**
	(0.06)	(0.06)
Number of Bidders	0.22	0.08
	(0.16)	(0.16)
Dummy for Bold Titles	0.62	0.31
	(1.06)	(1.06)
Dummy for Featured Items	35.35**	36.70**
	(1.34)	(1.35)
Dummy for Bundles	80.15**	79.84**
	(0.89)	(0.88)
Adjusted R^2	0.733	0.739

The dependent variable is real price, which is the sum of the winning bid and the shipping cost.

most sellers have paid for this option and thus they got a surplus of about $10 per item. On the other hand, the upgrade option of bold titles is not quite effective. Though the charge is low, sellers should not waste money on it. Again, a majority of the sellers have made the right choice.

In general, the number of bids, rather than the number of bidders, affects the winning prices. It implies that bidders who keep placing bids in one auction drive the bidding competition more fiercely and push up the prices. This result seems against the incremental bidding strategy. However, it is only against the naive incremental bidders who do not switch to auctions with lower prices. These bidders usually have limited knowledge of the concurrent auctions, thus limit their attention to one auction at a time. If a bidder does not make use of the flexibility of the incremental bidding strategy, there is no reason for him to do better than a proxy bidder. This can be seen more clearly in the next section.

2.3.3 Winning Prices of Different Types of Winners

It has been shown that incremental bidders are more likely to win than proxy bidders. The next question raised here is whether they win at lower prices. The answer to this question also relates to the cross-bidding behavior. Now, instead of the dummy for cross bidders, I include the dummies for different types of winners in regressions of real prices. The estimates on other auction characteristics variables are similar to the results in Table 2.8 and are omitted here. The coefficients on dummies for last-minute bidders and incremental bidders are reported in the first two columns of Table 2.9. The real price paid

Table 2.9: Regression of Winning Bids on Winner's Type

Variables	Without Fixed Effects	With Fixed Effects	Without Fixed Effects	With Fixed Effects
Last-Minute Bidders	-9.39**	-8.81**	-9.75**	-9.144**
	(0.99)	(0.99)	(1.02)	(1.10)
Proxy Bidders	0.47	0.72	-0.18	0.11
	(1.03)	(1.02)	(1.17)	(1.16)
Last-Minute Bidders	-	-	-4.39*	-4.46*
$\times$Cross-Bidding			(1.99)	(1.98)
Proxy Bidders	-	-	2.14	-2.18
$\times$Cross-Bidding			(1.94)	(1.93)
Incremental Bidders	-	-	-4.72**	-4.62**
$\times$Cross-Bidding			(1.43)	(1.42)
Adjusted R^2	0.739	0.745	0.740	0.745

by last-minute bidders is significantly lower than the other two groups. This is consistent with the prediction of the theoretical models that last-minute bidders enjoy a larger surplus whenever they win. Incremental bidders, however, fail to show any advantage over proxy bidders in winning prices. As explained above, this may be caused by their limited cognition of the coexistence of multiple auctions.

To verify this guess, we need to investigate the difference between winners who bid across auctions and those who do not. Therefore, the cross terms of the dummies for each type and the dummy for cross bidders are added in the regression. The estimation results are displayed in the 3rd and 4th columns in Table 2.9. The cross term for incremental bidders is significantly negative. It confirms the prediction that incremental bidders who understand the competing auctions and switch around get benefited from the cross-bidding behavior. Their winning bids are not only lower than incremental bidders who stick to one auction, but also lower than proxy bidders. Last-minute bidders who have ever made switches also pay lower prices than their peers. The reason is that these cross-bidders examine more than one auction before they place bids and are more likely to bid on items with the lowest standing prices. Nevertheless, proxy bidders are very different from the other two types of winners. Whether they are cross-bidders or not does not seem to affect their winning prices. This is because they commit themselves to one auction too early. Although some of them are aware of concurrent auctions, they cannot switch to other auctions. So this knowledge is useless to them after they submit the proxy bids.

In sum, incremental bidders prevail against proxy bidders, if they really make use of the flexibility of incremental bidding to move across auctions. Otherwise, if they just bid over and over in one auction, they have no advantages over proxy bidders. We can say that keeping bidding in one auction without checking out other auctions is a naive behavior. But as I shown here, not all incremental bidders are naive. Some of them are aware of the situation with multiple concurrent auctions and try to get the best out of it by cross-bidding. They are even more sophisticated than proxy bidders in this sense. As a result, they win with a higher probability and win at a lower price level.

The theoretical model does not show that last-minute bidders will pay less than incremental bidders. Nevertheless, this can be explained by the difference between models and reality. If submitting a bid is costly, "incremental bidders" may raise bids at an amount larger than the increment. If there is a cost to monitor and switch to another auction, incremental bidders are not as flexible as last-minute bidders. These will lead incremental bidders to pay a little higher than last-minute bidders.

2.4 More Discussions on Different Type of Bidding

2.4.1 Impacts of Concurrent Auctions on Late Bidding

As described in the theoretical part, when naive incremental bidders exist, last-minute bidding can be a best response under some circumstances. Lots of factors may influence a bidder's decision of late bidding. Here I focus most attention on the impacts of the competing auctions. To verify theorem 1.3, I run an ordered Probit regression. The dependent variable is the number of snipers who submit bids within 5 minutes before an auction ends.[9] The explanatory variables are the standing bid at that time and the number of parallel auctions which end no more than 2 or 5 minutes apart from the current auction. Results are shown in Table 2.10. When the standing bid is relatively high, fewer bidders snipe this auction. The number of late bidders also decreases in the number of competing auctions, which confirms the prediction. The estimate for the 2-minute concurrent auctions is significant at 1% level, while for the 5-minute ones, the estimate is significant at 10% level. This implies that the late-bidding behavior is more affected by auctions that end really close to each other. Competing auctions weaken a buyer's incentive to bid late.

[9] The regression results remain almost the same if we relax the timing to 10 minutes before the ending.

Table 2.10: Regression of Number of Snipers

Variables	Estimate	P-Value	Estimate	P-Value
Intercept	1.049^{**}	0.000	1.081^{**}	0.000
	(0.199)		(0.199)	
Standing Bid	-0.002^{**}	0.000	-0.003^{**}	0.000
	(0.000)		(0.000)	
Number of 5-Min Concurrent Auctions	-0.011	0.086	-	-
	(0.006)		-	-
Number of 2-Min Concurrent Auctions	-	-	-0.031^{**}	0.007
	-	-	(0.012)	

2.4.2 Impacts of Concurrent Auctions and Past Experience on Bidding

From the other aspect, theorem 1.3 also suggests that bidders are more likely to bid incrementally and switch around when there are more concurrent auctions if they understand the situation well. Also, to see whether the incremental bidders are naive or sophisticated, we can look at their past experience. Do the incremental bidders have lots of shopping experience at eBay? Have they participated in a similar auction before? To see what factors can cause a bidder to use incremental bidding strategy, I run some probit regressions.

Table 2.11: **Probit Regression of Incremental Bidders**

Variables	All Bidders	Serious Bidders	All Bidders	Serious Bidders
Constant	-1.31**	-1.29**	-1.38**	-1.21**
	(0.198)	(0.212)	(0.202)	(0.225)
Log of Buyer's Score	0.021	0.028	0.023	0.030*
	(0.016)	(0.016)	(0.017)	(0.015)
Dummy for Previous Experience	0.133	0.143	0.139	0.146
	(0.151)	(0.138)	(0.129)	(0.132)
Number of 5-Min Concurrent Auctions	0.013	0.016*	-	-
	(0.007)	(0.008)	-	-
Number of 2-Min Concurrent Auctions	-	-	0.021*	0.024**
	-	-	(0.009)	(0.009)

In Table 2.11, the dependent variable is the dummy for incremental bidder, i.e. it equals one if a bidder is an incremental bidder, and zero otherwise. The regressions only examine the effects of a few factors. The buyer's feedback score, which basically depends on how many items they have ever bought or sold at eBay, can reflect their shopping experience. The log of this variable is used here. A buyer's bidding strategy may also be affected by whether he has participated similar auctions in the near past. A dummy for this is also included and equals one if a bidder joined an auction before. Note that most buyers have a single unit demand, so the past experience is usually a losing

Table 2.12: Probit Regression of Incremental Bidders Who Cross-Bid

Variables	All Bidders	Serious Bidders	All Bidders	Serious Bidders
Constant	-1.71**	-1.79**	-1.88**	-1.91**
	(0.218)	(0.322)	(0.219)	(0.325)
Log of Buyer's Score	0.031*	0.038**	0.033	0.040**
	(0.015)	(0.011)	(0.017)	(0.012)
Dummy for Previous Experience	0.183	0.163	0.159	0.176*
	(0.125)	(0.088)	(0.130)	(0.087)
Number of 5-Min Concurrent Auctions	0.011	0.015*	-	-
	(0.006)	(0.007)	-	-
Number of 2-Min Concurrent Auctions	-	-	0.026**	0.028**
	-	-	(0.010)	(0.008)

experience. The first two columns use the number of 5-minute concurrent auctions as an explanatory variable, and the last use the number of 2-minute concurrent auctions. In the first and third columns, the sample includes all the bidders in the data set. The rest two only contains serious bidders whose highest bid (his bid plus shipping cost) is above $200.

The estimation results do show that buyers are more likely to choose incremental bidding when there are more competing auctions, especially in the regressions with serious bidders. However the effects of buyers' experience do not seem to be strong. This phenomenon may be caused that the composition of incremental bidders is quite complicated. The naive ones and the sophisticated ones probably coexist.

Thus I change the dependent variables a little bit and define the dummy to be one when a buyer bids incrementally and switch around, zero otherwise. The purpose is to focus on the relatively sophisticated buyers who use cross-bidding. All other elements of the regressions remain the same as before. T he estimation results are presented in Table 2.12. The coefficients on buyers' feedback score become more significant, which imply that the incremental bidders who cross-bid do have more trading experiences on eBay. The effects of concurrent auctions are similar as before. The incremental bidding is more likely to be observed. However, the dummy for past bidding is still not very significant. A possible explanation is that the past experience, especially the past losing experience may have a mixed impact on a buyer's decision. On one side, after participating a similar auction, the buyer understands the rules, the circumstance and the potential opponents better. This learning effect may cause him to use more complicated strategies like cross-bidding. On the other side, after losing an auction, the buyer may become more desperate, or feel tired in monitoring the auctions frequently, or simply believe there are too many naive incremental bidders. All these changes in his mood may push him away from incremental bidding, therefore he probably just submit a proxy bid or wait to snipe.

These regressions give us some insights on things that may induce incremental bidding. I have run similar regressions on the dummy for cross-bidders and the results are very similar to the ones in Table 2.12. In short, it is more likely for bidders who often buy or sell on eBay to cross-bid and bid incrementally. The reason for choose these bidding behaviors is probably that the bidders understand the auctions well after so many transactions. Or, maybe, they simply have more time to spend on the online auction platform.

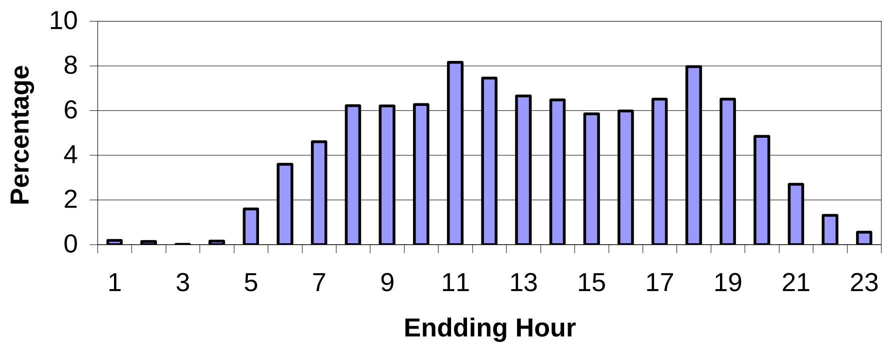
2.5 Conclusions

In sum, the data I gathered from eBay support the theory that incremental bidders will pay less than proxy bidders when they really understand the advantage of this strategy and make use of it. These bidders, contradicting the traditional view, are not naive at all. They move back and forth among auctions to find the best opportunities which allow them to win more and pay less. However, not all the incremental bidders are sophisticated. If they stick to one auction and do not switch around, they cannot do better than the proxy bidders. Further, when some incremental bidders fail to bid their true values before auctions end, last-minute bidders have chances to win an item at a low price.

Moreover, when more auctions are constructed at the same time, bidders are less likely to snipe. This is reflected in the estimation results that the number of last-minute bidders decreases with the number of concurrent auctions. On the other side, buyers are more likely to choose incremental bidding when there are more concurrent auctions. With the prompt development of electronic commerce, I expect to see more and more competing online auctions running in parallel in the real world. Thus the incremental bidding behavior will be observed more frequently. Instead of treating it as some non-equilibrium behavior, we need to examine this bidding behavior more seriously in future studies.

2.6 Chapter Appendix

Figure 2.1 Distribution of Auctions by Ending Times



	Total	N of Bids	N of Bidders	Price
non-peak (20pm-8am)	841	23.96	12.30	326.4
peak (8am-20pm)	3416	26.03	12.79	323.6

Figure 2.2 Distribution of Different Types of Bidders

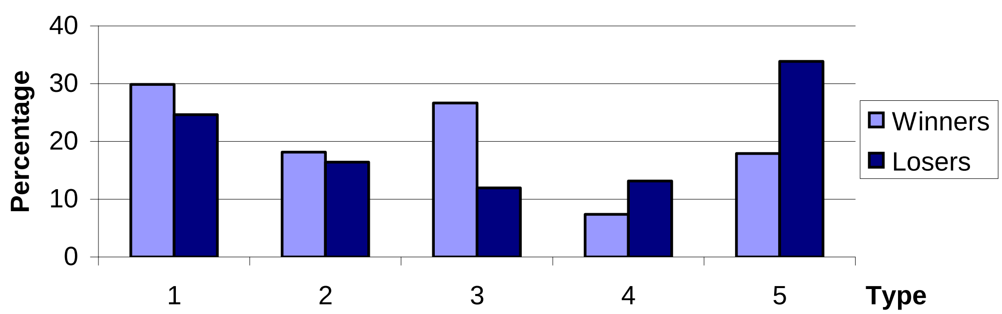
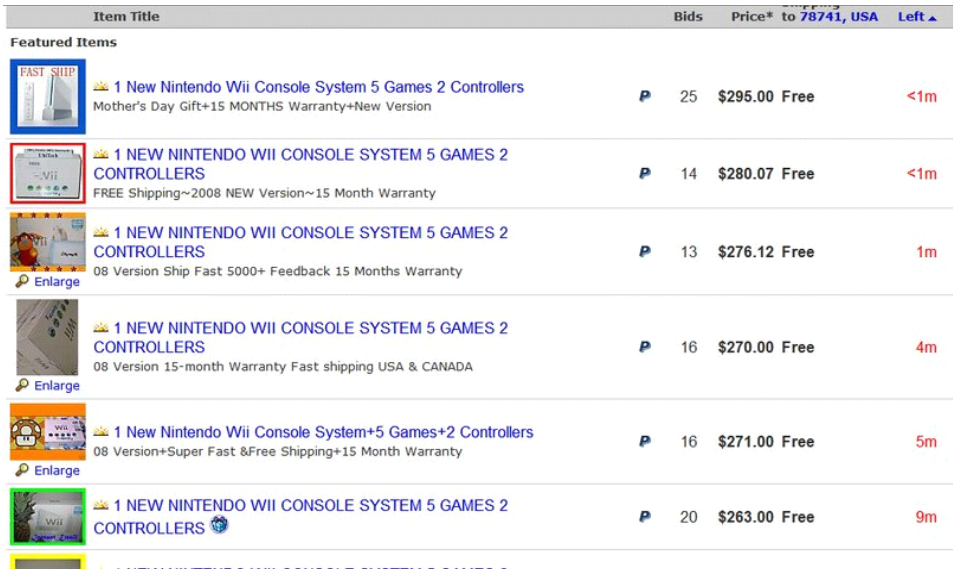


Figure 2.3: An Example of Auction Listings on eBay



Chapter 3

Texas School Milk Market Revisited

3.1 Introduction

Every year school districts around the US conduct procurements on the provision of milk for the next academic year. During the 1990s, there were numerous antitrust cases against the school milk suppliers and evidences of collusion in the procurements were uncovered in more than twenty states. Texas was one of them. In early 90s, the school districts in Dallas-Fort Worth (DFW hereafter) suspect the presence of a bidding ring in the procurement auctions and filed a complaint to the Texas Attorney General's office. The resulting proceedings ended in a damage settlement in which nine companies paid $15.4 million dollars. All of these milk processors pleaded guilty in the criminal trials.

There are several existing papers focus on modeling and detecting the collusions in the school milk markets. Porter and Zona (1999) study the Ohio school milk market. They argue that competitive bids of milk processors should be a monotonically increasing function of the distance between the school district and the processing plant. The reason is that nearby districts are less costly to serve. Porter and Zona find that the defendant's bids are lower on districts further away and they use this as evidence for a collusive agreement among the firms. Hewitt, McClave and Sibley (1993) examine the Texas school milk market and find evidence of a complementary bidding scheme that they believe to be only consistent with collusive behavior.[10]

Some other authors use the data of the procurements to explore other questions. Marshall, Raiff, Richard and Schulenberg (2006) construct a procurement model allowing for cost synergies. They select data from a time period when bidders are believed to act non-cooperatively and their estimation results support the existence of cost synergies. Tichy (2000) examines the data from the aspect of school districts. She tries to find out how a school district official determines the winner and she does an estimation on the scoring function of the districts.

This paper adds to the literature on school milk procurement auctions in following ways. Unlike most papers on collusion, I first construct some simple scoring functions for the bids in order to make use of the data from every type of milk products. Then with the data constructed, I do some regression analysis that is similar to Porter and Zona (1999). However, I also include the impacts of cost synergies and backlogs. This allows me to understand the processor's bidding behavior in a more complete way. As Marshall et al. (2006) suggest, adding in cost synergies sheds doubts on the existing models of collusions.

The paper is organized as follows. In Section 3.2, I describe the background of the school milk procurements in Texas. In Section 3.3 shows the statistics and adjustment of data. The influences of the market characteristics on milk firms' bidding behavior are discussed. The estimation model and results are presented in Section 3.4. A further discussion on collusive behaviors is in

[10] There are more studies on this topic. Pesendorfer (2000) compares the structure of the cartels in the Florida and Texas school milk markets. Lee (1999) focuses on testing Folk Theorem in a repeated game in the Texas market.

Section 3.5. Section 3.6 concludes.

3.2 Texas School Milk Market Background

According to a study conducted by the Department of Agriculture, the school milk procurements are mainly first price sealed bid auctions. Usually an auction starts in spring when the district officials begin to solicit bids on the supply contracts. The auctions are publicly announced and contain detailed information including the quantities and types of milk needed in each district. The milk processors have several weeks to make decisions and submit their bids for each type of milk. Then on the day of letting, bids are opened and made public. The winner, usually the lowest bidder will be selected. The school districts conduct the auctions independently and sequentially. The bidding season usually lasts from May to August.

Originally, the data set on Texas school milk contains information on auctions held between 1980 and 1990. During those years seven large companies Borden, Cabell, Foremost, Oak Farms, Preston, Schepps and Vandervoort, are the major suppliers in the school milk market of the DFW area. They won around 80 percent of the auctions held in 1980s. Besides, six smaller dairy processors also submitted bids to the school districts. The seven large companies were all included in the alleged conspirators which were accused by the school districts in early 90s.

There were some changes in the market structure during the decade. For example, one of the principal processor Preston entered the market and joined the procurement in 1985. The average winning price dropped by about 5% in that year. Although we need further study to draw the conclusion that the entry affected the collaboration and brought down the prices, it is quite possible that the decrease in prices is related to Preston's entry. This paper aims to explore the factors that influence the suppliers' bidding strategy and the collaboration among the bidders rather than the effects of the structural changes. So I will leave this topic for future research and focus on the data between 1986 and 1990. Here I assume that the entry has little effects after 1985. In other words, it is assumed that the processors adjusted their strategies promptly and by the beginning of 1986 they already formed a new cartel the structure of which would not vary much for the following years.[11]

In Texas school milk market, usually four types of fluid milk are sold: whole white, low-fat chocolate, low-fat white and whole chocolate. The production process is quite standardized and is almost the same for all milk suppliers. Basically, to produce fluid milk, the processors pasteurize the raw milk, remove the butterfat and add in flavors, vitamins and other nutritious ingredients. Therefore the major input during the production is the raw milk which is regulated by Federal Milk Marketing Orders (FMO). The FMO price varies regionally and it equals the Minnesota / Wisconsin price plus an increasing that is roughly in proportion to the distance between the region and Minnesota / Wisconsin. The regions are known as "Federal Orders" and each of them has its own market

[11] Another reason for this data selection is that in the sample the numbers of contracts in the earlier years were significantly smaller. This could be caused by data missing in some school districts. For this study it is important to look at the same school districts in different years, because the incumbent information is crucial.

administrator who calculates and posts the raw milk prices. The school milk auctions data sample used in this paper is from the DFW area, which is part of Federal Order No. 126.

The milk processors purchase raw milk from independent farmers or dairy cooperatives. They typically have a long-term agreement, which means a milk processor needs to pay a large amount of penalty if there is a big sudden change in the quantities purchased. To avoid the penalty, for a 10 percent change, the processor plant has to inform the farmers or the dairy cooperatives 6 months in advance. For an increase or decrease of 20 percent, a one year notice is required. Because of this property of the market, it is reasonable to expect that each processor only wants to supply a specific volume of milk at any given time point. Thus they are likely to adjust their bidding strategy based on their backlogs, which depend on the results of auctions that have already ended.

The processed milk is packed individually in paper cartons or plastic bottles and stored in crates. Finally it will be shipped to the destinations by cooling trucks. To each milk processor, the distribution of the milk is the most unique part of the supply process. Besides the schools, the delivery trucks can also supply grocery stores, restaurants and other type of consumers on the routes they drive. To choose the optimal delivery routes for these trucks is a complicated process for a milk supplier. The route assignments are affected by the locations of the milk consumers and, maybe more importantly, the size of the contracts. It is relatively easy to accommodate the needs of a small business on an existed route, but for some large consumers, the milk processors may be required to arrange some specialized shipment. As they win or lose contracts, they are faced with new routing problems.

In sum, the production technologies and input costs in the milk industry are fairly homogeneous and thus common knowledge. But, the milk processors do not know how other processors will solve their routing problems and how the contract of a specific school district can affect their delivery costs. Sometimes winning a district can help the processor to arrange a route and reduce the shipping costs. While aiming at selling the desired volume of milk each year, the processors should also consider which districts' contracts can make them deliver the milk the most efficiently.

The characteristics of Texas school milk market can facilitates the ability of milk processors to collude. As mentioned above, the bidders have similar production costs. When a school district announces a procurement auction, the district official will specify the type and quantities of milk needed. So the milk processors only compete in the prices which simplify the cartel operation. When an auction ends, all the bids are posted and if a cartel member cheats and undercut the bid, other members can find it out very easily. What's more, each year there are hundreds of auctions during the bidding season but they are held at different times. This not only makes it possible for the cartel members to allocate the market, but also allows them to punish a deviating bidder promptly.

3.3 Data Description

As mentioned above, data set used in this paper includes procurement auctions conducted between 1986 and 1990. The number of auctions per year is approximately 130 and the number is roughly constant across years. The total number of auctions is 678 auctions were held in total. For each auction, the data set provides information from many aspects: the name and the location of the school district, the school population in the district, the letting date, the identities and bidding prices of the companies, the identity of the winner, the quantities supplied, number of stops needed, distance, types of bids and whether a cooler is required. Table 3.1 lists and defines variables that are used in the empirical analyses. In what follows, I will discuss the main variables, how they are measured and their relavance to the model.

3.3.1 Scoring Function

I begin with bids. In the milk procurement auctions, when submitting a bid, the bidder does not just submit one price. Instead, he needs to specify the bidding prices for each milk item. To analyze firms' strategies, the first question may be how to compare two bids with different components. The bidding prices, per half pint, for each type of milk are given in the sample. However, the school districts do not explain explicitly how they choose the winner. To undertake the empirical analysis, I need to map these multi-dimensional bidding prices into a single bid. Since the products and services provided by the processors are almost identical, it is reasonable to assume that the school districts are only sensitive to the prices of the products, or say, the total payment to the suppliers. Thus, I use the most straightforward way to map the bids into one dimension: a weighted average is calculated based on the quantities of each kind of milk

Table 3.1: Variable Definitions

Dependent Variables	
PARTICIPATION	One if a firm places a bid in a district, zero otherwise.
BID	The natural log of the deflated scored bids.
Independent Variables - Continuous	
SIZE	The estimated quantity to be supplied in each contract.
SEASON	The percentage of bid season (measured by days) that has passed.
NUMBID	The number of bidders in the auction.
DISTANCE	The approximate distance (in miles) between plant and district.
NUMSTOP	The natural log of the estimated total number of stops per week that are needed to supply the district. The number of stops is calculated by multiplying the number of deliveries per week and the number of schools in the district.
RAWMILK	The natural log of the price of raw milk which is the FMO price for Order 126.
BACKLOG	The up-to-date performance compared with history. Defined as in 3.3.5.
Independent Variables - Dummy	
INCUMBENCY	One if the firm has won the contract of the same district in the previous year, zero otherwise.
ESCALATOR	One if the bid is an escalated price, zero otherwise.
COOLER	One if coolers are provided, zero otherwise.
FAVORABLE	One if the district is located in a favorable area as defined in 3.3.7, zero otherwise.
SMALL	One if the size of the district is less than 160,000, zero otherwise.
PASTLOSER	One if a firm participated but lost in the year before, zero otherwise.
LOST	One if the firm lost an adjacent district in that year, zero otherwise.

listed in the contract.[12]

Besides, the bidding prices are also adjusted for inflation occurred during the sample time period. To capture the effects of inflation on costs and bidding prices, the one-dimension weighted bids are deflated by the CPI of Dallas. Year 1986 is served as the base year.

3.3.2 Fixed Bids versus Escalated Bids

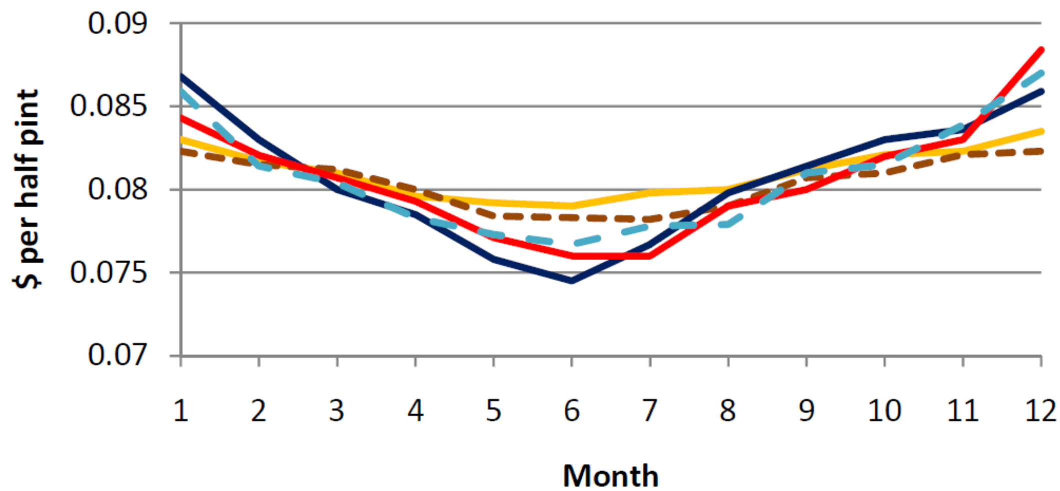
Almost every auction allows the milk companies to submit two types of bids: a fixed bid or an escalated bid. The bid with an escalator clause allows the milk supplier to adjust the prices up or down according to the movement in the price of raw milk, while the fixed bid will not vary during the school year. In the data set, the escalated bids are always lower than the fixed bids. The first possible explanation for this difference is the risks associated with the two types of bids. For a fixed bid, the milk processor will tolerate the risk of unexpected changes in the raw milk price. And the school district will take this risk if an escalated bid is accepted.

However, the pattern of the fluctuation in the raw milk price is another crucial reason for the difference between the two types of bids. Figure 3.1 shows the monthly FMO price of Federal Order 126 between 1986 and 1990.[13] The figure illustrates a seasonal nature, which is consistent throughout the years, of

[12] This weighting is also supported by Tichy (2000) who carefully estimates the scoring function of the school districts. She examines many factors which potentially affect the score and cannot reject the hypothesis that the school districts use the quantities of different milk item as the weight to decide the winner.

[13] The price is deflated by the CPI in Dallas. Year 1986 is the base year.

Figure 3.1: Monthly FMO Price from 1986 to 1990



the raw milk price. The change in the price is simply caused by the demand and supply in the market. The demand for the raw milk is the lowest in late spring and summer when schools are closed and the weather is hot. It peaks in early winter around the holiday season. The production, however, reaches its peak in the spring when the weather is the most favorable and cows start a new lactation cycle. It decreases a little during the hot summer and increases again in the fall. When the weather is cold in winter, the production reaches its valley. As a result, the raw milk price is high during the winter and low in late spring and summer.

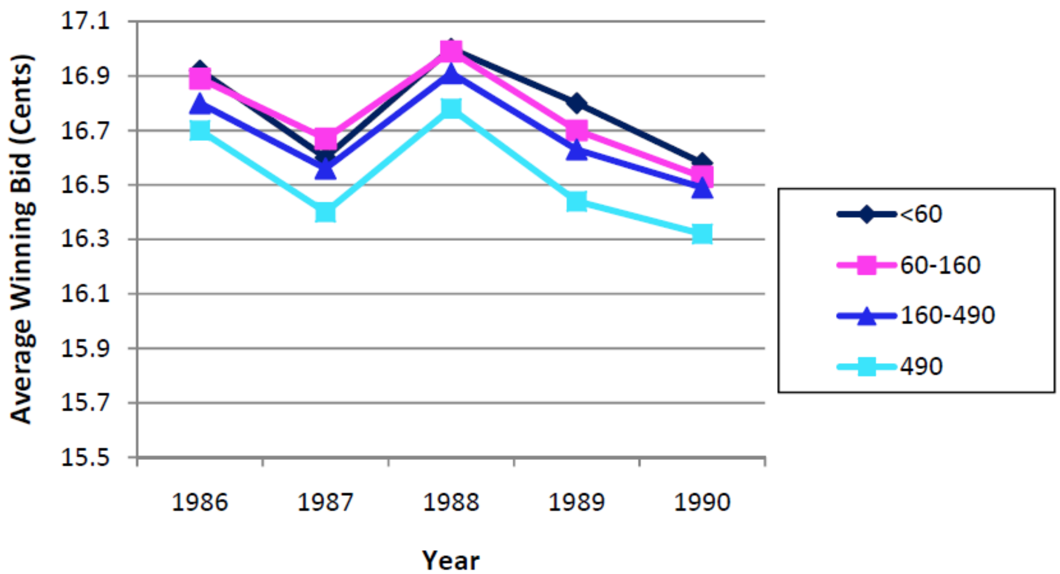
This seasonal variation is well known in the milk industry. The school milk auctions are mostly held between May and August, when the raw milk price is at its bottom. Both the school districts and the milk processors expect the raw milk price to increase as the school year begins. With this expectation, they know that the escalated bidding price will go up later. If a risk-neutral bidder submits a fixed bid and an escalated bid for the same contract, this bid pair should be equivalent. Since the escalated bid will increase and the fixed bid will remain constant, the former one must be lower than the latter on at the starting point which is the letting date.

3.3.3 Contract Size

The size of a procurement can be measured by the total volume of milk demanded by a school district. It can have some potential influences on the underlying costs and thus the bids submitted. First of all, school districts usually have requirements on delivery time and the processors need to unload the milk products during certain time slot. To unload a large quantity of milk may involve some efficiency for the supplier. Also, if the school district has a high demand, it is usually because that the district is highly populated. A populated district typically has more and better paved roads together with more grocery stores and restaurant, which could provide flexibility for a processor to choose the delivery route. However, on the side, winning a large procurement could also make the routing problem more difficult. A large amount of products would require more capacity on a truck. Therefore, it may not be possible to add the school on the existing routes and a milk company may have to arrange a specialized delivery. In sum, the contract size has an ambiguous impact on delivery costs and bids

Besides costs, there is another reason that may make milk processors favor large contracts. Typically a processor has a targeted volume to supply each

Figure 3.2: Average Winning Bid by Contract size



year, because of the long agreement with farmers. Winning large quantities allows the processors to reach their goals more quickly as long as they still have enough capacities. So if a firm still has excess volume at the end of season, large contracts would look attractive and the firm may be willing to bid more aggressively and bring down the prices. The effects of excess volume and backlog will be further discussed later on in Section 3.3.4.

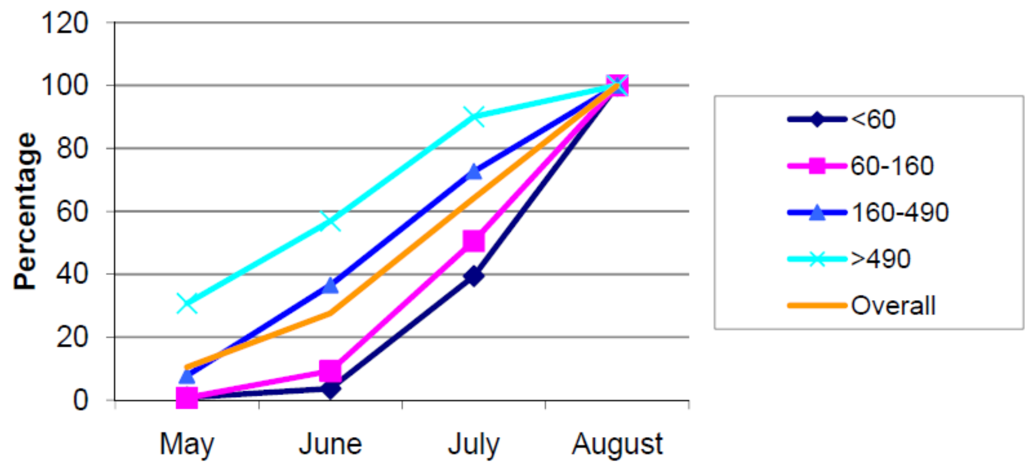
When a procurement is announced, the school district will post the estimated total quantities to supply. Though the actual quantities may deviates from the estimate, the difference is believed to be small. And it is reasonable to assume that processors make bidding decisions based on the estimate if they do not have better knowledge. Based on the estimated quantities in the data, I divide the auctions into four categories, each of which counts for about one quarter of the observations. Figure 3.2 presents the average winning bid of each category by year. It shows the bids of larger contracts tend to be lower and especially, the winning bids of the largest procurements are significantly lower. A similar pattern can be found if losing bids are also included. This provides us a straightforward view of the impacts of contract size on bids and I will control other relevant factors and investigate this impact in a more complete model.

3.3.4 Season

Though the procurement season usually starts in May, most of the auctions are conducted in late summer. Only about 10 percent of the procurements take place in May and the percentage of auctions held in June is most doubled. In July and August, the proportions are both around 35 percent. This trend is shown in Figure 3.3, which shows the cumulative distribution of contracts held in each month. The letting time of different category is also presented in the figure. It seems that larger school districts hold the auctions relatively earlier. Almost all the smaller auctions, which are included in the two categories with quantities below 160,000, occur in July and August. On the other side, 90 percent of the largest auctions are held during the first three months. One fact behind the figure is that each school district tends to conduct its auction at roughly the same time each year. It implies the choice of timing is not likely to be affected by the market.

Figure 3.4 shows the average winning bids in early and late summer. The winning bids of auctions conducted in May and June are generally higher than

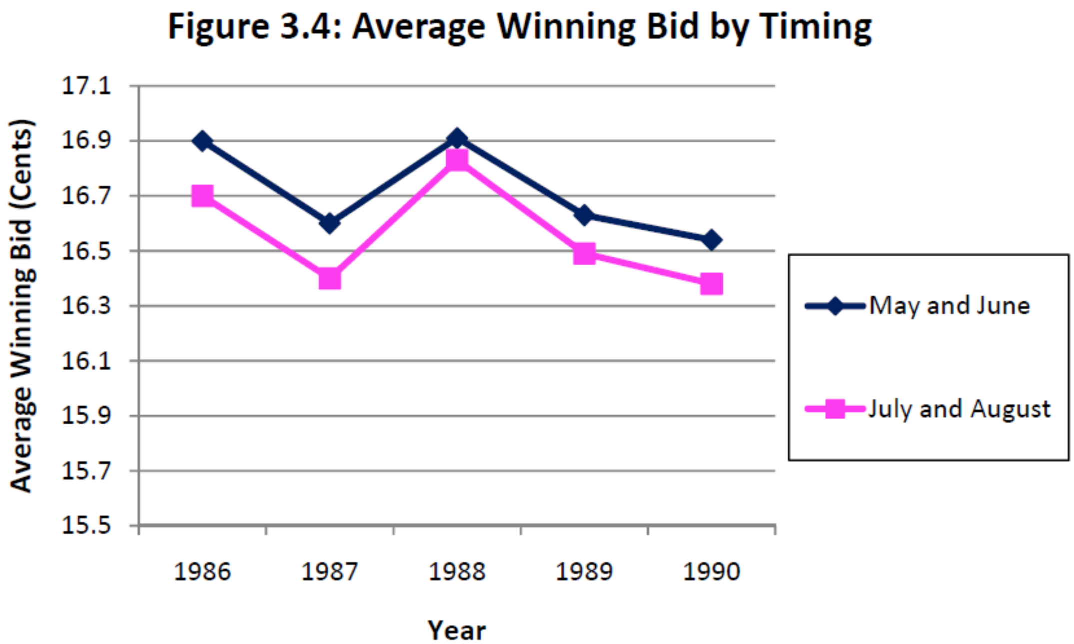
Figure 3.3: Cumulative Distribution of Procurements in Each Month by Contract Size



those in July and August. Since larger procurements occur relatively early, this seems to a conflict with the observations from Figure 3.2 that winning bids are lower in large districts. However, this conflict is a key to study the processors bidding behavior. Besides the contract size, what could be the factors that affect the bids? Is the decrease in bidding prices related with cost synergy or collusion? It will be explored in the regression analysis.

3.3.5 Backlog

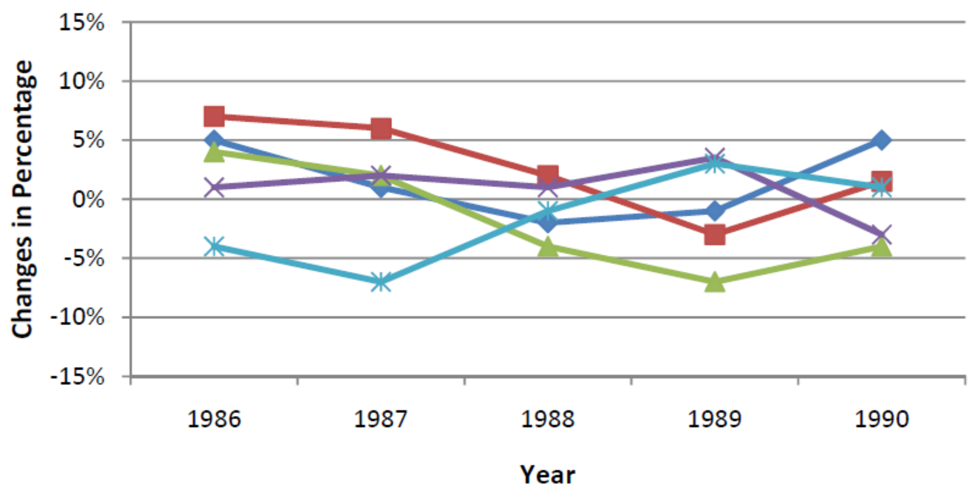
Because of the long-run contract between them and farmers or milk cooperatives, the milk processors have to pay for a nearly fixed volume of raw milk each year in order to avoid large financial penalties. This fixed volume is typically set well before school milk auction season. Thus, it is reasonable to believe



that each milk firm has a targeted total quantity to win every year. They are supposed to make plans forehead and submit bids based according to the plans. If they are rational, at every time point, their bidding strategies should be affected by the whole bidding history, which requires lots of knowledge. Or, they can make things a little simpler by just looking at the progresses they have already made towards their goals. If they fall behind the plans or they have lots of excess volume, they would bid more aggressively and submit lower bids. On the contrary, if a firm has won a large amount of auctions, the incentive to win would be lessened.

A related question for my study would be how to find out their targets given the fact that we cannot tell directly whether they fulfill the goals each year from the data set. However, as you look more closely on the data, you will see that

Figure 3.5: Percentage Change of Total Quantities Won for Five Largest Firms



the quantity which a processor supplies does not vary to a large extent from year to year. For the five largest milk processors, Figure 3.5 tells the percentage changes in the total quantities won by a given firm. Generally, the fluctuations in the quantities between two subsequent years are within 10 percent. We can have a guess on current goals based on their past experience.

When there is a change in the total quantity supplied by a milk firm, we need to take into consideration of two possible reasons: the firm adjusts the goal or the firm fails to meet the goal. I will just assume that each reason counts for half of the change. In other words, I use the average of the actual total quantity supplied by a firm in the year t-1 and in the year t as the targeted quantity for the firm in year t. This would be a close estimate of the actual goal when the fluctuations of quantities are not big, which is satisfied by the data set.

After getting the targets, I construct the variable, which is called the backlog here, to reflect a firm's performance and how close the firm is to its goal. The backlog is built serving this purpose. For each firm, we can get its market share in the previous year by calculating the proportion of the quantities won by that firm. In the long run, when the firms supply relatively constant volume of milk, the market share of each firm tends to be roughly constant. If the firms have no big differences in their preferences, their current market shares can serve as a measure of their performance.

For example, if a firm won 20 percent of the market in the previous year and has won 15 percent of the quantities at some given point of the current bidding season, it implies that this firm need to bid more aggressively and won a larger proportion in the remaining season. The backlog variable is a percentage ratio that illustrates this impact on bidding strategies. The ratio is the difference between a firm's current market share and its previous market share divided by the previous share. As in the example above, the backlog of the firm at that time point would be $(15\% - 20\%)/20\% * 100\% = -25$. A positive number implies that the processor is winning more quantities than before while a negative value may imply that the processor is not doing so well.

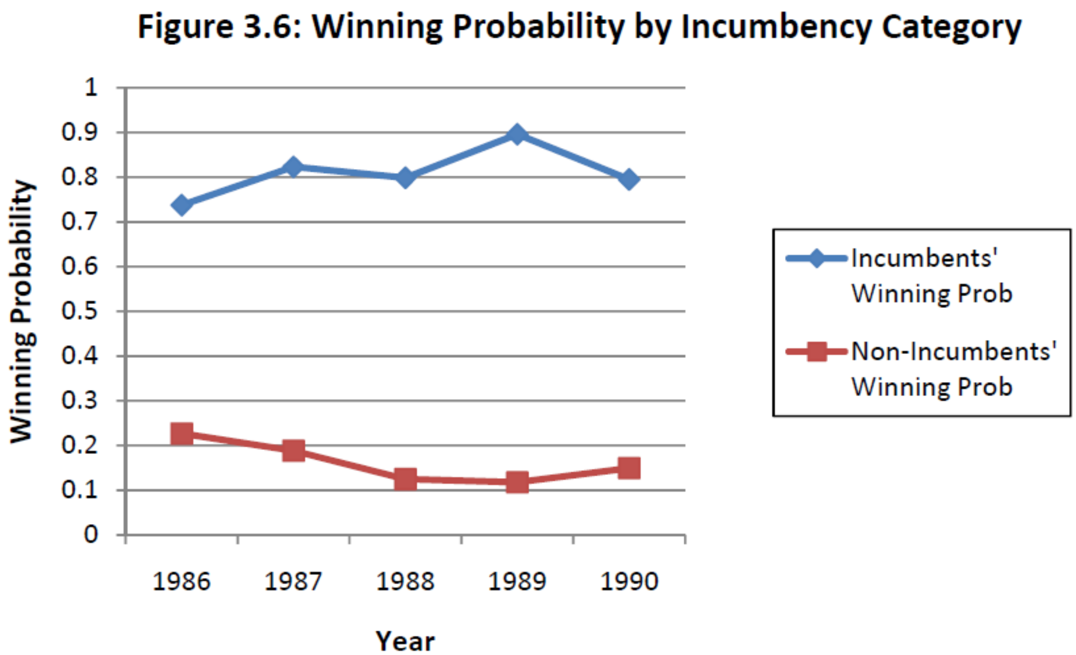
The backlog variable would lost its meaning when the bidding season just starts, because winning or lose a contract would have a huge effect on a firms' market shares. At the extreme, after the first auction, one firm will have the whole market and other have zero shares. However, we do not expect the winning firms to cool down its bidding process or the other firms to bid more actively. It is just too early to tell how they are doing. For this reason, I set the backlog variable to zero for auctions occurred in May which means the backlog has no effects in the early season. Actually, in the data set, no incumbents ever lose an auction in May. This phenomenon is consistent with the scenario when backlogs are zero. Basically they both mean that the firms are doing just as well as they did in the previous year.[14]

3.3.6 Incumbency

Throughout the years, a majority of auctions in the market are won by incumbents. If we look at the probabilities of winning for incumbents and non-incumbents, as illuminated in Figure 3.6, the difference is obvious. Note that, the winning probability of incumbents (non-incumbents) is defined as the percentage of incumbents (non-incumbents) who win, not the percentage of incumbents (non-incumbents) within the winners. Thus, the two probabilities do not add up to one. If a bidder won a contract in the previous year, he is very likely to win it again in the current year. On average, the probability of winning is around 80 percent. However, if a bidder is not an incumbent of that district, the winning probability would be much lower, which is below 20 percent.

If the milk firms only differ in costs and do not collaborate with each other, the high winning probability of incumbent is supposed to be caused by a cost

[14] The fact that large contracts are conducted relatively early provides some convenience for this manipulation. Only a little more than 10 percent observations occur in May, but these auctions count for more than 30 percent of the total quantity. Thus, setting the backlogs of early auctions to zero still leaves us enough sample points to explore the effects of backlogs. Meanwhile, given the large quantities that are already sold by the end of May, winning or losing an auction will no longer influence a firm's market share by a huge amount. Then the constructed backlog variable is able to capture its meaning.



advantage. It is not surprising if incumbents really have lower costs for districts they won. They may know better about the district and have better relationship with the school which could provide them some flexibility for unloading milk products. The truck drivers would be more familiar with the roads. As a result, the delivery costs could be lower.

The cost advantage allows incumbents to submit lower bids and thus they would win more often. If this is the fact, the participation of incumbents will bring down the winning bid even in the cases that the incumbents lose the auction. In other word, if an incumbent does not participate in the auction for some reason, the winning bid is expected to be higher, because other bidders have higher costs. However, a rough compare of winning bids in the two situations, when an incumbent participate or not, does not show significant differences.[15]

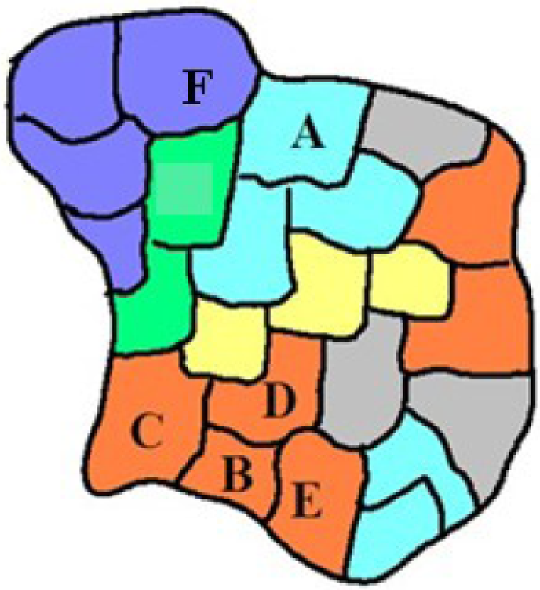
3.3.7 Favorable Area and Cost Synergy

How to measure delivery costs is probably the most challenging questions in the study of school milk auctions. The choice of shipping routes is generally private information. Though economists try to measure the costs using variables like the number of stops, or the distance between milk plants and schools, the estimate may not be accurate. Porter and Zona (1999) find that some milk firms submit lower bids in the districts which are far away from their plants and use it as an evidence of the collusion. However, sometimes distances may not tell the full story.

Suppose there is a small city shown as in Figure 3.7. The black lines are the boundaries of school districts and districts of the same color are supplied by the same milk company. One milk firm, whose markets are painted orange, has only one plant which is located in district A. If there are only two potential consumers, district D and F, the firm would prefer the closer district F with everything else equal. However, if it is similar to the case shown in the figure – all the other districts have already signed contracts with different firms – D and F are the last two conduct procurements, the firm may choose D over F. The reason is obvious that as long as the firm has enough capacity on the truck, it

[15] It is not surprising if the incumbents do not have cost advantages or the advantages have little impacts on bids. It is not difficult for a new delivery driver to get familiar with routes and schools. The studying process would not take a long time and may not cause higher bids from new suppliers.

Figure 3.7: A Simplified Example of Favorable Areas



only need to add a stop at the district D on the way to C/B/E. But supplying F requires the firm to arrange a route especially for it, which could be costly even for a short shipping distance.

This situation is not rare in reality. If we look at the contracts won by milk firms geographically, we can observe that milk processors often won several adjacent districts all together. If winning the procurement of a district can help the firm solve routing problem, the reduction of per unit delivery costs is considered as cost synergy. Since the letting dates spread over four months and auction outcomes are not predictable, it is tricky to find out which districts can generate synergies.

If a firm is not limited by the room on delivery trucks, it would be efficient to supply a cluster of districts that are located closed to each other. It is reasonable to believe that a milk processor prefers districts that are closed to the districts won or those which are likely to be won. Thus when an auction is conduct in a district which satisfies one of the following two conditions, I would say there is potential cost synergy.

Among the districts which share boundaries with the potential district,

(i) the firm has won at least one of them; or

(ii) there is at least one district in which the firm was an incumbent in the previous year and the procurement of the current year has not been held yet.

Basically, it implies that after winning a district, a firm would become more interested in it neighborhood area. Due to the fact that an incumbent is highly likely to win again, I assume firms also prefer to supply places that are close to their incumbency area, as long as the incumbency districts have not switched to a new processor. If a district falls into one of the two categories stated above, it is referred as a “favorable area”. Since the firms’ delivery route could be very complicated, they may not only prefer the adjacent districts. Also the realization cost synergy depends on many factors including the capacity of delivery trucks. It still requires more complete analysis to see whether the defined favorable areas are really preferred by the firms.

3.3.8 Summary Statistics

Table 3.2 presents the summary statistics for some important variables from the data sample. Most of the auctions have relatively few participants. The average number of bidders is 2.39 and auctions with one to three bidders are very common.[16] Since almost all the incumbents participate in the districts they won before, the dummy for incumbency status is about the inverse of the number of bidders, which is 0.41. The table also contains the statistics of all bids, the winning bids and the losing bids. Throughout the paper, the "bids" I use are all standardized and adjusted as described in Section 3.3.1. Since the auctions are procurements, the average winning bids are lower than the mean of all bids.

Table 3.2: Summary Statistics: 1986 – 1990

Variable	Mean	Std.Dev.	Min.	Max.
Number of Bidders	2.39	0.99	1	7
All Bids (cents/half pint)	17.31	1.57	12.14	22.59
Winning Bids (cents/half pint)	16.66	1.51	12.14	22.03
Losing Bids (cents/half pint)	17.80	1.61	12.37	22.59
Raw milk (cents/half pint)	7.98	0.84	7.41	8.81
Distance (miles)	52.31	12.13	0	139
Size (1000 half pint/year)	454.03	92.28	7.20	8,488
Number of Stops	4.18	1.02	1	5
Incumbency	0.41	0.15	0	1

[16] Porter and Zona (1999) observe similar phenomenon in the Ohio school milk auctions: on average very few processors join the bidding. They argue that this is consistent with the scenario that bidders know others' cost. Also it can be caused by the presence of the bidding ring.

3.4 Estimation

3.4.1 Regressions on Participation Decision

To examine the firms' bidding behavior, I first run a Probit regression to examine the participation decisions of the five large firms. The dependent variable is PARTICIPATION as shown in Table 3.1, which equals one if the firm submits a bid in certain district in certain year. The regression results are presented in Table 3.3. I run the regressions in three ways to study how the cost synergy affects the firm's submission decision. In the first regressions, variables that capture the synergy are not included. In the second regression, I use the FAVORABLE variable defined above to capture the synergy effect. And in the last regression, instead of FAVORABLE, I use the LOST variable to see whether losing an adjacent area will affect a bidder's participation. To investigate if the size would affect the synergy, cross terms are also included.

The positively significant coefficients on INCUMBENCY and PASTLOSER tell us that not only the incumbents are more likely to participate, the past losers are also more likely to bid in the same district they bid before. The BACKLOG variable measures the up-to date performance of a bidder. When it is large, it means that the firm has won more than the past. The estimate is negative which means a firm is less likely to participate when it has won more. Or in other way, if a firm lost some districts it won in the previous year, the backlog would be smaller and it is more likely to participate in other districts. Moreover, firms are more likely to bid for larger district, which is consistent as

Table 3.3: **Probit Model of Bidder Submission**

Variables	Regression 1	Regression 2	Regression 3
CONSTANT	1.927**	-1.937**	-2.071**
	(0.151)	(0.135)	(0.116)
INCUMBENCY	0.089**	0.093**	0.081**
	(0.001)	(1.001)	(0.001)
PASTLOSER	0.061**	0.057**	0.060**
	(0.018)	(0.018)	(0.020)
NUMSTOP	-0.006	-0.007	-0.005
	(0.004)	(0.004)	(0.003)
DISTANCE	-0.005	-0.004	-0.007
	(0.003)	(0.003)	(0.006)
SIZE	0.493**	0.453**	0.383**
	(0.112)	(0.121)	(0.142)
SIZE*DISTANCE	-0.022*	0.021*	0.018
	(0.011)	(0.010)	(0.010)
BACKLOG	-0.014**	-0.012**	-0.018**
	(0.005)	(0.004)	(0.005)
COOLER	-0.043	-0.028	-0.030
	(0.038)	(0.031)	(0.019)
SEASON	-0.230	-0.170	-0.092
	(0.139)	(0.141)	(0.090)
FAVORABLE	-	-0.021*	-
	-	(0.009)	-
FAVORABLE*SMALL	-	-0.042**	-
	-	(0.012)	-
LOST	-	-	-0.013
	-	-	(0.010)
LOST*SMALL	-	-	-0.039*
	-	-	(0.020)
Adjusted R^2	0.309	0.310	0.292

Standard errors are in parentheses. The symbols *, ** denote significance at the 5% and 1% levels, respectively.

what I found in the regression on bids.

The firms are more likely to bid in "FAVORABLE" districts where there could be potential cost synergies. And the effect is more significant in small districts. Nevertheless, when I use "LOST" to measure the geographic reason, it is not that significant. I think the reason is that each district has more than one adjacent district. Losing one adjacent district may not be a serious problem as long as the firm has won some other district close by. Unless Porter and Zona found, the DISTANCE variable does not seem to play an important role here. However, the cross term of SIZE and DISTANCE has a negative estimate, which implies the firms are more willing to go further for smaller districts. This is probably because that it is easier to add a stop for smaller districts on the existing routes.

3.4.2 Regressions on Bidding Levels

To explore how bids are affected by the factors discussed above, I construct regressions using the available data. The dependent variable is the natural log of the bids from each auction. The explanatory variables used in the analysis are from the list in Table 3.1. Table 3.4 presents the results of the estimation when I include all the available bids, the losing ones and the winning ones. The left two columns are pooled specifications with common intercepts across all bidders, while right two columns allow separate bidder fixed effects. The first and the third column are the regressions without considering the impacts of the cost synergy. In other words, these models do not pay attention to whether a district is located in a favorable area. And the second and the fourth column contain two more variables to explore the cost synergy.

Some of the coefficients support the analysis in section 3.3. For example, the coefficient of BACKLOG is positive. It means if the firm wins more auctions (a larger backlog), it will bid less aggressively (a higher bid). Or say, they are willing to ask for a smaller payment, when they find out they have small backlogs and need to win more contracts to make full use of the raw milk they already buy. This shows that the firms' bidding behavior is very likely to be affected by the contracts they already win, facing the fact that the volume of the milk they can supply is almost constant.

As discussed above, the size of a contract has an ambiguous influence on the bids. The regression results, especially those from the fixed-effects models, tell that the SIZE variable has a negative sign. That implies the benefits of winning a large procurement – reduction in costs and help for achieving the firms' targeted volume more quickly – overwhelm the problems a large contract generates. Thus the bidding prices in a large procurement tend to be lower. ESCALATOR has a negative coefficient which is consistent with the explanations stated in 3.3.2. The escalated price allows the firm to adjust the bids with the increase of raw milk price, it is on average lower than the fixed bid. The positive coefficient on COOLER reflects the extra costs required for providing coolers with milk.

The variables that interpret delivery costs also yield some reasonable results. First of all, NUMSTOP, by definition is the number of stops a firm has to make in one week. Given the volume of milk, more stops would require more

Table 3.4: Regressions of All Bids

	Basic Model		Bidder Fixed Effects Model	
Variables	w/o synergy	w/ synergy	w/o synergy	w/ synergy
CONSTANT	4.324**	4.353**	4.339**	4.321**
	(0.403)	(0.387)	(0.402)	(0.411)
SIZE	-3.03	-2.57	-3.43**	-2.68**
	(1.98)	(1.58)	(0.49)	(0.34)
SEASON	-0.183**	-0.131*	-0.178**	-0.135*
	(0.030)	(0.062)	(0.038)	(0.562)
NUMBID	0.028	0.023	0.018**	0.017*
	(0.016)	(0.014)	(0.006)	(0.008)
INCUMBENCY	-0.244**	-0.228**	-0.249**	-0.212**
	(0.015)	(0.035)	(0.014)	(0.028)
DISTANCE	0.302	0.343*	0.321	0.417*
	(0.187)	(0.168)	(0.200)	(0.189)
NUMSTOP	0.029	0.030	0.032**	0.034**
	(0.032)	(0.027)	(0.013)	(0.014)
BACKLOG	0.005**	0.006**	0.005*	0.006**
	(0.001)	(0.001)	(0.002)	(0.002)
RAWMILK	0.283	0.249	0.252	0.341
	(0.194)	(0.161)	(0.181)	(0.213)
ESCALATOR	-6.039**	-5.739**	-5.881**	-6.282**
	(1.816)	(1.902)	(1.759)	(2.043)
COOLER	3.842**	3.667**	3.431**	3.782**
	(1.214)	(1.212)	(1.255)	(1.213)
FAVORABLE	-	-0.089	-	-0.085
	-	(0.072)	-	(0.062)
FAVORABLE*SMALL	-	-0.024**	-	-0.019**
	-	(0.009)	-	(0.008)
Adjusted R^2	0.302	0.317	0.364	0.383

Standard errors are in parentheses. The symbols *, ** denote significance at the 5% and 1% levels, respectively.

coordination between truck drivers and schools, more diesel fuel, and more services like unloading products. Therefore the positive sign is consistent with the reality that a larger number of stops asks for a higher delivery cost and, as a result, a higher bid.

In the models without the cost synergy, DISTANCE is not significant. [17] However, after controlling for the potential cost synergy area, the bids do show some negative relationship with the distance. So, I cannot observe any collusion just by looking at the coefficient on DISTANCE. The regressions with FAVORABLE and the product of FAVORABLE*SMALL show how the cost synergy can affect the bids. SMALL is the dummy for districts with smaller need, which counts for almost 50 percent of all the contracts. When this cross-term is included, FAVORABLE is not significant but the product is. This tells us the relatively small contracts do help firms design deliver route and reduce the cost. The larger ones, which would need more capacities, do not generate any synergies.

The difference between bids submitted in early season and late season is also captured by the regression. The coefficient of SEASON is negative and significant even when the impact of cost synergy is considered. Holding everything else constant, from the beginning of the season to the end, the bidding level could on average decrease by more than 10 percent. This phenomenon cannot be explained by other factors and is possibly the result of collusion. More to discussed in Session 3.5.

[17] Porter and Zona (1999) have a similar result and argue that firms sometimes submit lower bids in farther areas. They use it as an important evidence for the existence of bidding-ring.

In a competitive market, a procurement price is expected to decrease as the number of bidders increases. However, here, the estimate of the coefficient on NUMBID is either insignificant (in basic models) or is positive (in fixed –effects models). Meanwhile the INCUMBENCY shows that incumbents do submit lower bids than other bidders. It is still too early to tell whether these results are caused by collusion. The incumbents may have some cost advantages which allow them to bid less. Then when other non-incumbent bidders participate in the auction, they do not only bring in competition, but also bidders with higher costs. And since the average number of bidders is very low, the cost advantage of incumbents can explain the results. Therefore, to see whether the lower bids are caused by cost advantage, we need to do more regression analysis.

Table 3.5 presents the results of regressions with the same group of variables on the winning bids. The models of the four columns are the same and in general, the estimations generate similar results as the previous table. However, the number of bidder is never significant in the regressions on winning bids. What is more important, the coefficient of INCUMBENCY changes into a positive one. It implies that the incumbents can get some premium when they win. Now it is not easy to tell whether incumbents have cost advantages.

On one side, the change in the sign of INCUMBENCY could to be caused by the presence of a bidding-ring. The firms may have agreement with each other and have already divided the market. Their agreement can be very simple, for example, each district is assigned to the incumbent. To make the collusion less detectable to the anti-trust officials, firms also participate in auctions that they are not supposed to win. Thus they would submit some relatively high bids in

Table 3.5: Regressions of Winning Bids

	Basic Model		Bidder Fixed Effects Model	
Variables	w/o synergy	w/ synergy	w/o synergy	w/ synergy
CONSTANT	4.287**	4.441**	5.022**	5.831**
	(0.387)	(0.299)	(0.397)	(0.401)
SIZE	-3.67**	-2.43*	-4.11**	-2.64**
	(1.68)	(1.12)	(0.943)	(0.893)
SEASON	-0.194**	-0.189*	-0.183**	-0.177**
	(0.028)	(0.091)	(0.036)	(0.068)
NUMBID	0.019	0.027	0.018	0.017
	(0.014)	(0.017)	(0.011)	(0.011)
INCUMBENCY	0.207**	0.236**	0.249**	0.242**
	(0.014)	(0.039)	(0.014)	(0.032)
DISTANCE	0.301	0.395*	0.323	0.436*
	(0.232)	(0.201)	(0.242)	(0.212)
NUMSTOP	0.028	0.035	0.034**	0.038**
	(0.017)	(0.029)	(0.011)	(0.011)
BACKLOG	0.005**	0.006**	0.005**	0.006**
	(0.001)	(0.001)	(0.002)	(0.002)
RAWMILK	0.270	0.256	0.239	0.258
	(0.212)	(0.221)	(0.231)	(0.247)
ESCALATOR	-6.017**	-5.823**	-5.839**	-6.034**
	(1.496)	(1.714)	(1.702)	(1.839)
COOLER	3.704**	3.761**	3.779**	3.743**
	(1.361)	(1.325)	(1.375)	(1.285)
FAVORABLE	-	-0.067	-	-0.064
	-	(0.073)	-	(0.058)
FAVORABLE*SMALL	-	-0.019**	-	-0.021**
	-	(0.008)	-	(0.007)
Adjusted R^2	0.313	0.317	0.373	0.384

Standard errors are in parentheses.The symbols *, **denote significance at the 5% and 1% levels, respectively.

these auctions. If this is the case, it would be observed that the incumbents' bids are lower on overage and the winning incumbents can have a premium. However, there may be some firm that cheats or some unexpected bidder that is not a member of the bidding ring. If they offer a lower price than the incumbents, the districts will be supplied by a new processor. So if we look at the districts where the non-incumbents win, the winning bidding price would be lower. That can explain why the INCUMBENCY has a negative coefficient in regressions on all bids, but a positive one in regressions on winning bids.

However, on the other side, a competitive environment may also lead to a similar result. If there is perfect competition and firms' bids are determined by their costs. The high winning probability of incumbents must be caused by the cost advantage and this is consistent with the results in Table 3.4. The non-incumbents win only when they have negative cost shocks or they are willing to accept lower profits. In this situation, the incumbents' winning bids are more likely to be higher than the non-incumbent's winning bids.

The impacts of other factors are almost the same as those in regressions on all bids. The BACKLOG has a positive effect on both the winning bids and losing bids, which suggests the firms do adjust their strategy according to their current performance. After the cost synergy is introduced, the DISTANCE variable becomes significant. The firms do care about the distances. However, they care more about how to win a cluster of district together. Just like the case shown in 3.3.7, compare with winning a closer district, a firm may prefer to win a farther district which can help reduce per unit delivery cost.

Since the cost synergy only can be found in smaller districts and smaller districts typically hole the procurements in late summer, it is reasonable to say that the decrease of bidding prices at the end of the season as observed in 3.3.4 is partly caused by the potential cost synergy. Nevertheless, in all the regressions, the SEASON variable is always significant. There must still be some date-related factors that have not been captured by the models. One possible explanation is the change of the collusive behaviors of the bidders across the season.

3.5 More Discussion on Collusion

Table 3.6: Timing of Changes in Incumbency

(by Percentages of Bidding Seasons)

Year	First Change	Average
1986	45.78	78.92
1987	37.97	76.73
1988	31.61	70.90
1989	48.85	74.61
1990	45.19	89.94

To see why incumbents are much more likely to win than other bidders and whether there is collusion, it may be a good idea to take a look at the cases in which they do not win. Table 3.6 shows the timing of the changes in incumbency. It is measured by the percentage of days that have already passed during the bidding season when the change occurs. In general, a majority of the changes take place in the latter half of the season. Usually there is no switch of incumbents until June when about 30 percent of the bidding season has already passed. And on average, the changes occur at the end of the season when 80 percent of days are gone.

Given that large contracts are conducted at early times, if we calculate the timing by measuring the quantities which have already been assigned, the percentage numbers would be even bigger. This phenomenon does provide some supports of the existence of collusion among the bidders. Recall that one of the market's characteristic that facilitates collusion is that the cartel members can punish the cheaters quite quickly. If some firm cheats at the beginning of a season, the cost of deviating from collusion would be huge. However, at the end of summer, after most auctions are finished, the punishment may not be very effective any more. The firms are not going to meet each others till the next spring and it is not likely that they will still remember to punish a cheater from the previous year. As a result, at the end of a bidding season, the market would become more competitive.

3.6 Conclusion Remarks

This chapter studies procurement data in the Texas school milk market. With a careful analysis of the characteristics of the market, I try to capture most potential factors that can affect the bidding strategies of firms. After constructing a method to score all the bids, I do regression analysis in different settings. Some of the regression results, like the coefficients on the size of contracts, escalated bids, coolers, are similar to the outcomes of previous works. The backlog variable affects the bids in the same direction, which means a bidder who wins more contracts than he used to be would slow down his steps and bid less aggressively.

The introduction of cost synergies provides a new aspect to the study of the collusion. With the data of DFW area, we can no longer use Porter and Zona (1999)'s argument for detecting bid rigging. Therefore I point another two facts that may serve as the evidence for the existence of collusion. The first is the opposite signs of the estimates of incumbency on winning bids and on all types of bids. The second is the significant decrease in the bid level at the end of the bidding season, which could be the result of a collapse down of collusion. Nevertheless, the contribution of this chapter is more modest than detect the collusion in the school milk market. Instead I provide a more complete way to characterize firms bidding behavior which can provide some insights for modeling the collusion.

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