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BIDDER BEHAVIOR IN DYNAMIC PRICING MODELS: AN EMPIRICAL STUDY OF CONSUMER GOODS AUCTIONS

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Abstract

The global B2B e-commerce is poised to experience exponential growth in the coming years. The electronic marketplace allows buyers and sellers to engage in commerce using dynamic pricing. These dynamic pricing models result in efficient pricing based on prevailing supply/demand balance. The auction theory models are based on assumptions of bidder behavior. This study presents empirical results of bidder behavior in the context of B2C auctions. Results provide guidance to sellers whose objective is to maximize revenue.

Introduction

The global e-commerce is fast evolving into the business-to-business(B2B) market while the business-to-consumer(B2C), and consumer-to-consumer(C2C) models have suffered recent minor setbacks. The much-publicized demise of dot-coms was inevitable as it often happens in the early stages of all ventures into a new, previously un-chartered territory. Business models of the winners of consumer focused e-commerce are viewed as baseline models for this next phase. Companies that succeed in the B2B space by implementing lessons learned from the consumer e-commerce are destined to realize full potential of the electronic marketplace. These global trends are predicted to continue well into the 21st century. Hardly there is an industry that is not impacted by this emerging business model.

Internet business is dynamic and highly competitive. Competitors that fall behind may never catch up as the first-mover advantage of early entrants may become insurmountable. Therefore the race is on and companies realize that time-to-market for applications must be fast. Businesses that fail to respond adequately to the realities of B2B will find it difficult to compete. The Cambridge, Massachusetts based research firm, Forrester Research estimates that the size of Internet-based electronic markets worldwide will reach $4 trillion by 2004. IDC research of Framingham, Massachusetts projects the figure at $2.8 trillion while a study by the investment firm Goldman Sachs places the figure at $3.8 trillion. The eMarketer(www.emarketer.com) estimates the current share of the B2B sector at 79.2% of the total worldwide e-commerce and forecasts it to reach 87% by 2004.

The B2B marketplaces are online markets that are meeting places designed to facilitate commerce between large pools of buyers and sellers. The Gartner group of Stamford, Connecticut estimates that by 2002 between 7,500 and 10,000 B2B marketplaces will be established. Lessons learned from the surviving e-commerce business models clearly indicate that brick-and-mortar players generally achieve higher degree of success in electronic marketplace and may be positioned to take advantage of the emerging B2B phase by leveraging their existing business relationships on both front and back ends.

The B2B marketplaces are characterized by many-to-many relationship between buyers and sellers. Most B2B business models include dynamic pricing models such as exchanges and online auctions, which by definition are more efficient price discovery mechanisms. Electronic marketplaces offer improved economic efficiency by reducing transaction costs and providing value to both buyers and sellers. All cost savings achieved directly flow to the bottom lines of the participants. The Giga Information Group of Cambridge, Massachusetts and IDC predict that by 2003, companies that engage in commerce through B2B will realize between $180 billion and $480 billion in savings on transaction costs and related expenses alone.

Dynamic Pricing

Dynamic pricing allows buyers and sellers to discover prices in real time. Pricing is determined by what buyers are willing to pay. Price sensitivities of buyers have a direct correlation with the balance between forces of supply and demand. On the other side of the equation, sellers are able to discover prices by what the market will bear at that particular point in time. Compared to the traditional fixed pricing approach, sellers avoid both: charging too much, thus losing out on potential sales; or charging too little which results in money left behind on the table. Parties engaged in dynamic pricing benefit in many ways such as: ability to move outdated inventory, higher returns on inventory; reduced transaction costs; no middlemen, and much wider audience. Dynamic pricing is implemented via traditional Web auctions, reverse auctions, and exchanges. The transparency of Web auctions coupled with their potential to attract geographically dispersed participants can only make the price discovery more efficient.

A Web auction allows buyers and sellers to discover prices through a bidding process. The electronic marketplace enables sellers to put items up for bids and buyers bid for the rights to acquire them. Early literature on auctions mostly focused on the theoretical auction models that were empirically tested for revenue determination and efficiencies in allocation. Field experiments were conducted to test the assumptions of bidder behavior. In other cases, controlled experiments were used for the purpose.

This study presents empirical results of bidder behavior in live Web auctions. Bidders employ different strategies and are assumed to act in a rational manner. Internet is a vast information source and can reduce information asymmetries that may exist among bidders. Results from this study help us understand bidder behavior and may impact how Web auctions are conducted in the electronic marketplace, including the B2B space. The data used in the study were collected from eBay, a widely used B2C and C2C exchange. There are important lessons that can be learned from successful B2C and C2C models. The next section presents a brief background on auctions.

Auctions

An auction is a mechanism of allocating resources on the basis of prices bid by potential buyers. The pioneering work in auction theory was published by Vickrey(1961) who concluded that all four basic auction models(English, Dutch, Sealed first-price, and Sealed second-price) produce the same average expected revenue for the auctioneer. Early literature on auctions focused on theoretical models of revenue determination and efficiencies of models in awarding the item to the highest bidder. Auction models are predicated on one or more assumptions of bidder behavior. Assumptions such as: bids made by bidders are independent (independence assumption); each bidder knows her valuation with certainty but does not know valuations of other bidders (Private Values assumption), and valuations by all bidders are drawn from the same distribution; the Common Values assumption(CV) states that the object offered for sale has some True Value(TV) which is not known to all bidders and each bidder estimates the TV independently.

Wilson(1977) and Milgrom(1979) concluded that optimal bids depend on the number of bidders, and reliability of the value estimates used by the participants. Additionally, higher competition results in the winning bid converging to the unknown TV. Rothkopf(1969) and Wilson(1977) showed that expected payoff to the winner is proportional to 1/N, where N is the number of bidders.

To win an ascending price auction, a bidder must be willing to bid more than the second-highest bidder. In descending price auctions, the prices are reduced until a buyer emerges. In the auction process, all bidders, whether they are unsuccessful low-bidders or successful high-bidders participate in the price discovery mechanism(Cassaday, 1967). Low-bidders force the successful high-bidders to raise the price levels thus causing the price convergence to the TV levels.

In multiple-unit auctions a seller offers Q homogeneous items and bidders bid for both the quantity desired and the bid price. Two formats are commonly used in multiple-unit auctions: discriminatory, where winning bidders pay their own bid price for each unit won; and competitive, where all winners pay the same lowest accepted bid price per unit. In a discriminating auction a bidder faces uncertainty about the acceptance of the bid while facing no price risk, as price equals bid. On the other hand, in a competitive auction, the bidder faces risk of acceptance and price, as the entire quantity is offered at a uniform price that equals the lowest winning bid.

In a recent study, Bapna, Goes, and Gupta(2000) proposed a theoretical framework for Multi-Item online auctions, and support their framework by empirical evidence. Their study classified bidders into three types: Evaluator; Participator, and Opportunist. Evaluators are bidders with a clear understanding of their TV. Participators derive some utility from just being in the game. The Opportunists usually place bids near closing and know the bids made to that point.

In two recent studies of bidder behavior in online auctions at eBay and Amazon, Roth, and Ockenfels(2001, 2001) present models and empirical results of last-minute bidding in single item auctions. The authors conclude that significantly more late bidding occurs in eBay auctions which have a fixed end time as compared to the Amazon auctions which can extend beyond the specified end time if late bids are received. The authors also report that more experienced bidders enter late in some auction to preserve their information advantage. The present study differs in the way that its focuses on "Dutch" auctions on eBay in which bidders may adopt different bidding strategies.

Online Auctions at eBay

EBay is an online auctioneer that connects buyers with sellers by featuring general B2C and C2C auctions. EBay holds no merchandize thus avoids expensive costs of building and maintaining warehouses and earns money by collecting commissions on all completed transactions. The business model used by eBay has proven to be successful. The unmatched success of eBay has invited competition and currently there are about 1,000 retails auction sites operating worldwide. Notable competitors of eBay are Amazon.com and Yahoo.com. Financial community estimates show that among the big players i.e., eBay, Amazon, and Yahoo, eBay receives about 90% of all auction traffic. In a recent quarter, eBay is reported to have completed 68.5 million auctions with the total estimated value of goods exchanged at $1.4 billion.

EBay has a large registered user base, about 3.5 million of which were added in the fourth quarter of 2000, thus bringing the total users to 22.5 million. The user base was 10 million in 1999, as reported by the company. EBay continues to financially benefit from the first-mover advantage.

Consumer-to-Consumer Auctions

The popularity of auctions is evidenced by the current high participation rates and future growth projections. It is estimated that the online auction market will rise from $6.5 billion at year-end 2000 to $18.3 billion by 2004. The Jupiter Media Metrix of New York forecasts the number of participants in online auctions to reach 6 million by 2002 when one out of every nine dollars spent on online shopping will be in the form of auction purchases. A more optimistic picture is painted by the Forrester Research which projects the number of auction bidders to increase by five fold to 14 million by 2003, and auction sales to hit $19 billion.

Bidding in Multiple-Unit Auctions: eBay Model

In a multiple-unit auction on eBay, multiple quantities of the same item are offered for sale. Seller specifies the quantity(Q) offered along with a starting bid called the First Bid(FB). To place a bid, a bidder must specify the quantity desired and the amount bid per item. Bidders are required to bid at least the FB for the first Q items. After bids for the first Q items, future bidders are shown the Current Price(CP), which is the price of lowest successful bid, and must bid a price equal to the CP plus the bid increment. The bid increments are preset by eBay and are scaled to the price level. As bidding progresses, bids are listed in the descending order of price. In case of tied bids, a bid placed earlier is listed first. At the close of bidding, bidders of top Q items are declared winners. All winners receive items at a price equal to the lowest winning bid.

Data Collection

The item that was followed in this study is a novelty household item. Usually such items attract end-users who want to acquire them for personal use. Ten auctions listed by the same seller were tracked from start to finish. Since these auctions were listed by the same seller, factors such as dealer reputation, shipping terms, and acceptable payment methods etc. were uniform. All auctions sold multiple units of an identical item. These auctions took place from mid October 2000 to the middle of February 2001. Each auction listed for exactly 10 days and started with the same FB of $1.00. The quantities offered for sale ranged from 16 to 50 with an average of 36 units. Upon conclusion of each auction, "bid history" and "high bidders" lists were downloaded from eBay site into a spreadsheet.

Method

Ten days the auction was open were divided into ten periods of twenty-four hours each. In each of the ten periods, data on five variables(listed below) were recorded from the bid history. Additionally, bidding activity in the last 24 hours was analyzed. The last day was sliced into six periods, each spanning four hours. The same five variables were tracked over the six periods.

List of Variables

- Total number of bids received;
- Total quantity bid on;
- Average bid price per unit;
- Average bid size;
- Number of winning bids.

EBay does not report average bid size. It was calculated as quantity bid divided by number of bids. Since quantity(Q) was different for some of the auctions, the Number of winning bids variable was normalized for fair comparison.

The following eight hypotheses were specified. These hypotheses test for differences in the bidder behavior over life of the auction. The first four hypotheses, collectively, test for differences in the distribution of bids while the fifth hypothesis tests for location of the winning bids over the ten days. The last three hypotheses test for differences in the bidder behavior as measured by three key variables, on last day of the auction.

1. **Ten-Day Bid Flow Hypothesis** - H0: There is no significant difference in average number of bids received over the ten days.
2. **Ten-Day Quantity bid Hypothesis** - H0: There is no significant difference in the average quantity bid over the ten days.
3. **Ten-Day Bid price Hypothesis** - H0: There is no significant difference in the average bid price over the ten days.
4. **Ten-Day Bid size Hypothesis** -H0: There is no significant difference in the average bid size over the ten days.
5. **Ten-Day Wins Hypothesis** - H0: There is no significant difference in the average number of winning bids over the ten days.
6. **Last Day Bid Flow Hypothesis** - H0: There is no significant difference in the average number of bids over the six periods on last day of the auction.
7. **Last Day Bid price Hypothesis** - H0: There is no significant difference in the average bid price over the six periods on last day of the auction.
8. **Last Day Wins Hypothesis** - H0: There is no significant difference in the average number of winning bids over the six periods on last day of the auction.

Analysis

Single factor ANOVA was performed to test the hypotheses. The results and discussions are presented next. For the variables that show significant differences over the ten periods, further discussions are provided to compare bidder activity on first day(opening), fifth day(middle), and tenth day(closing) of the auction.

Results

The **Ten-Day Bid flow Hypothesis** was rejected ($p<0.0000$). Therefore, the average number of bids received was not uniformly distributed over duration of the auction. Significantly more bids were received in the opening(mean=31.9) and closing(25.9) periods as compared to the middle(5.0) period.

Test shows that the quantity bid(**Ten-Day Quantity bid Hypothesis**) was not equally distributed over the ten days($p<0.0000$). The quantity bid in the opening period(64.1) was the highest. Significantly more quantity was bid in the opening period than the closing (34.9) or the middle(7.3) periods.

Ten-Day Bid Price hypothesis test concludes that the average bid price was not uniformly distributed over the ten days($p<0.0000$). Average bid price increased from the opening period($6.32) to the middle period($20.82) and to the closing period($31.09). The observed price progression is expected as the auctions followed an ascending price, competitive model.

Ten-Day Bid size hypothesis test shows that there was no significant difference in the average bid size as the auction progressed.

Results of **Ten-Day Wins hypothesis** show that winning bids were not equally dispersed over the ten days($p<0.0000$). Significantly more winning bids came from the bids submitted on the last day of auction.

These results confirm that active bidding took place on the last day. These results are consistent with price discovery mechanism expected in an ascending price auction. The last three hypotheses tests reveal strategies used by bidders on last day of the auction.

Results from **Last Day Bid Flow Hypothesis** show that the number of bids received over the six periods, on the last day, were statistically unequal($p<0.0000$) with the last four-hour period receiving the most bids.

The average price bid for the items was statistically not different over the six periods on the last day (**Last Day Bid price Hypothesis**).

The **Last Day Wins Hypothesis** was rejected with $p<0.0000$ meaning that the number of winning bids received on the last day, were not uniformly distributed. Significantly more winning bids were received in the last period of the day.

Conclusions

From these results, it is evident that artificially low FB invites a large number of bidders to the auction as evidenced by the total quantity bid in relation to the number of items offered. Ultimately, most of those bids fail to win. At the same time, those early low-bids are an integral part of the price discovery mechanism. Therefore, it is in the best interest of the seller to list items with artificially low FB. The flow and distribution of bids in the opening period plays a significant role in determining the price progression. If the buyers are informed, and have equal information, then the price discovery mechanism should lead to the prices reaching at or near the TV. Informed bidders appear to have placed their bids in the last four hours of the auction. Bidders entering late can assess the probability of winning the item at prices they are willing to bid. These conclusions support the notion that dynamic price models are efficient ways to discover price at a given point in time. These results may be helpful suggestions for the design of B2B business models. The sellers should list the auctions to attract more buyers as that has a direct impact on the efficiency of the price discovery.

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