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Applying experimental online auctions in marketing research for multi-channel firms

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ABSTRACT

Auction mechanisms allocate consumers' demand revealing incentives. In this study, we highlight field experimental online auctions for their value in new product demand estimation. The immediate question is whether the information from online auctions can be utilized to get the full demand curve across various sales channels, since many firms utilize multi-channel strategies. Each channel may bear different transaction costs for its patrons. Hence, channel selection is the result of consumers' self-selection based on transaction cost economics. Consequently, a consumer's Willingness-To-Pay (WTP) in a selected channel reflects her/his depreciated pure WTP by the mixture of channel specific and individual-related characteristics determining transaction costs. We propose a skeleton model to resolve this self-selection bias, and this projects the partial demand observed in online auction channels to the whole demand curve. We discuss the kind of information that should be required to resolve this problem, and verify our approach using empirical testing. We demonstrate how online auction data, which firms have not yet capitalized on so far, can be a very valuable experimental resource for multi-channel firms' marketing strategies.

1. Introduction

Under an increasingly dynamic and uncertain business environment, the development of new products is a strategic choice for a firm to gain competitive advantage and sustainability (Geng, Stinchcombe, & Whinston, 2001; Hoffman, Menkhaus, Chakravarti, Field, & Whipple, 1993; Ram & Ram, 1988). However, decision-making for launching a new product is fraught with great difficulties and substantial failure rates (Cooper & Kleinschmidt, 1991; Hise, 1989; Kortge, 1989).[1] Inherent difficulty of demand estimation is one of the underlying reasons that accounts for the failure of a new product. Demand estimation is crucial for successful pricing and production arrangements of a new product because profit-maximizing pricing is based on the assessment on how the price will affect the sales of a product (Breath & Ives, 1986; Dean, 1969). Demand estimation is significant not only for deciding general sales and pricing, but also for seeing if the new products enhance consumers' valuation (Menkhaus, Borden, Whipple, Hoffman, & Field, 1992). With no information on demand, firms can neither optimize their production nor prepare marketing strategies.

However, demand has a stochastic nature combined with heterogeneous consumer characteristics (Feng & Xiao, 2000; Zhao & Zheng, 2000). In addition to the statistical fluctuation, the distribution of demands varies over different channels so that limited observation of demands may lead to the positively or negatively biased estimation (Conlon & Mortimer, 2007). Hence, although there have been various approaches for demand estimation, it has been a difficult, unstructured and costly decision-making process for firms (Brockhoff & Rao, 1993; Chen & Hausman, 2000; Jedidi, Kohli, & DeSarbo, 1996; Weiner, 1994). Firms need to seek improved market measurements and analysis methods in order to estimate demands and mitigate the risk of new product failure (Geng et al., 2001; Hoffman et al., 1993).

If we consider new product introduction in high-tech firms, a strong time pressure for demand estimation is amplified because a delay may lead to inappropriate usage of the outcomes (Geng et al., 2001; Gupta & Wilemon, 1990; Liberatore & Stylianou, 1995). In high-tech industries, in which products have relatively short life cycles (Goldstein, 1989; Qualls, Olshavsky, & Michaels, 1981), many winners are not the best products that come later but the first movers into the market (Hutheesing, 1993; Mitchell, 1991; Moore, 2002).[2]

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[1] From one third to a half of all firms reported that they had failed to meet their financial and marketing goals when launching a new product (Cooper & Kleinschmidt, 1991; Kortge, 1989). It was shown again when examining Fortune 1000 firms where nearly half had new product failures (Hise, 1989).

[2] Mitchell (1991) identified entry order effects on market share and a significant "survivor bias" in five technical subfields of the diagnostic imaging industry. When Sega introduced its 16-bit video game player in 1993, its market share leapfrogged from 7% to 50%. Because Sega was the first with new technology, it could defeat Nitendo, which had been the leader of the game market, but a laggard for 16-bit video game players (Hutheesing, 1993).

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The time available for demand estimation is the interval between the debut of the high-tech product and the beginning of mass production and, to get beyond chasm, this time should be as short as possible (Moore, 2002). Time-based competition is a key to reach the majority market in light of the turbulent market environment of high-tech products.

However, traditional marketing approaches often take too long, and consequently are avoided since seriously delayed estimation of demand may harm the introduction of the new product (Geng et al., 2001). Much less guidance is available for demand estimation of high-tech products (Brockhoff & Rao, 1993) and attention is shifting to the electronic markets as an economic information system for resolving this problem (Ozer, 1999; Geng et al., 2001).

In this paper, we pay attention to the real advantage of online auction data for efficient demand estimation in a timely manner. When consumers participate in online auctions, they naturally reveal their reservation price through the bidding process, which means the online auction may offer a rare opportunity to capture WTP (Willingness-To-Pay) easily, not only from actual buyers (winners), but also from potential ones. The demand curve in an online auction is directly constructed by aggregating the last bidding data of every bidder (Menkhaus et al., 1992).[3] Now, the immediate question is whether the information from online auctions can be utilized to get the full demand curve across various sales channels, since many firms utilize multi-channel strategies (Nicholson, Clarke, & Blakemore, 2002; Schoenbachler & Gordon, 2002). Each channel bears different transaction costs for its patrons hence attracts different consumers (Brynjolfsson, Dick, & Smith, 2004; Hann & Terwiesch, 2003; Strader & Shaw, 1997). The realized demand curves are specific to a given choice of channel sets. If a firm knows what segment of consumers are attracted to what channels, and the differences in transaction costs for consumers associated with a certain channel, the firm may extend the partial demand curve obtained from an online auction to other channels so that it may construct the whole demand curve for the entire population. Therefore, in this paper, we

(i) Stress the advantages of using online auction data to estimate the demand curve, which has not been attempted yet, to the best of our knowledge.
(ii) Propose the framework for establishing the full demand curve using a partial one obtained from online auction data. Through this framework, we identify the conditions for demand revealing auctions and additional information the firms should access in order to make use of our approach.
(iii) Test the applicability of our approach through empirical analysis. We collected empirical data on consumer channel choice and demands in the selected channels and compare the demands predicted by our approach with the real demands measured through data collection.

2. Theoretical background

2.1. Auction studies and online auctions

Great attention has been paid to the auction mechanism. One of main the streams of auction research has focused on the optimization of the winners' or the auctioneers' gain. This research examined competitive bidding strategies (Bapna, Goes, Gupta, & Jin, 2004; Brockhoff & Rao, 1993; Milgrom, 1989; Rothkopf & Harstad, 1994a, 1994b) and optimal auction design (Bajari & Hortaçsu, 2004; Bapna et al., 2004; Maskin & Riley, 2000; Riley & Samuelson, 1981). In these studies, the analysis was focused on the winners' behavior and the auctioneers' strategies.

The other stream of research has focused on the demand reveling nature of auctions. Contrary to the former studies, this line of research investigates not only the winners' but also the losers' bids. An auction providing the incentive to bid a price consistent with a true reservation value is defined as a 'demand revealing' or 'incentive compatible' auction (Menkhaus et al., 1992). The nature of these auctions has been adopted as an experimental mechanism for new product demand estimation and called 'lab experimental auctions' (Coppinger, Smith, & Titus. J., 1980; Cox, Roberson, & Smith, 1982; Geng et al., 2001; Hoffman et al., 1993; Menkhaus et al., 1992).

Online auctions show the potential characteristics necessary for being a 'field experiment auctions' for new product demand estimation. First, not only used goods, but also the new products are already traded through online auctions. Some B2C online auctions play the role of retailer by directly selling new products from manufacturers (e.g. uBid, Egghead) and many C2C online auctions (e.g. eBay, Yahoo! Auction) facilitate the transaction of both new and used goods between private sellers and buyers (Bapna, Jank, & Shmueli, 2008; Easley & Tenorio, 2004). Furthermore, online auctions are highly advantageous information sources for demand estimation due to their timely measurability of consumer bids and experimental features for optimization: on many online auction sites, sellers are allowed to tune-up their auctions by experimenting with minimum bid or auction formats (Bapna et al., 2008; Bajari & Hortaçsu, 2004). It shows online auctions' readiness as a medium for randomized field experiments to test the auction theorem (Bajari & Hortaçsu, 2004; Lucking Reiley, 1999).

Many market research tools deal with a large volume of information available but, unfortunately, in an untimely manner (Attaway, 1998; Martinsons, 1994). Even if the abundant market information can be collected promptly, it often fails to capture market demand (Geng et al., 2001; Ram & Ram, 1988). Given theses facts, we suggest that online auctions are very suitable and reliable resources for demand estimation in their capability for attracting a majority of consumers and allowing prompt accessibility to bidding data. However, there is a paucity of studies which illuminate the advantages of online auctions for field experimental potential of demand estimation.

Online auction can employ various auction types and mechanisms so that, in order to provide a demand revealing incentives, these mechanisms need to be controlled. Moreover, compared to the lab experimental auctions, online auctions bear additional dynamics in consumer bidding strategies, which possibly distort true demand revelation. Hence, in the ensuing section, we examine the auction mechanisms and affiliated conditions for developing demand revealing online auctions.

2.2. Online auctions as a demand revealing mechanism

There are various types of auctions and the ways bidders behave are different under idiosyncratic auction types. Hence, the obvious first step to provide an incentive compatible mechanism is to select proper auction types (Coppinger et al., 1980; Cox et al., 1982; Forsythe & Isaac 1982; Menkhaus et al., 1992). Theoretically, it is well known that the optimal bidding in the FPSB (First Price Sealed Bid) auction and Dutch auction is less than the bidder's true value on an item so that they are not demand revealing mechanisms (Cox et al., 1982; Menkhaus et al., 1992). In these

[3] If the price is higher than a bidder's WTP, which is reflected in her last bidding data, she/he would not buy that product, hence the demand for a given price is the number of consumers who have at least the same or higher WTP than the price.