MICHIGAN
ROSS SCHOOL OF BUSINESS

Working Paper

Online Auctions and Multichannel Retailing

Jason Kuruzovich
Lally School of Management and Technology
Rensselaer Polytechnic Institute

Hila Etzion
Assistant Professor of Technology and Operations
Stephen M. Ross School of Business
University of Michigan

Ross School of Business Working Paper
Working Paper No. 1176
July 2012

UNIVERSITY OF MICHIGAN

Online Auctions and Multichannel Retailing

Jason Kuruzovich
Lally School of Management and Technology
Rensselaer Polytechnic Institute
Troy, NY 12180
Email: kuruzj@rpi.edu

Hila Etzion
Stephen M. Ross School of Business
University of Michigan
Ann Arbor, MI 48109-1234
Email: etzionh@umich.edu

The Internet enables sellers to offer products through multiple channels simultaneously. In particular, many sellers utilize online auctions in parallel to other online and offline channels. Using an analytical model and data from eBay Motors, we study seller behavior and auction outcomes in the context of multichannel retailing. Our model shows that seller characteristics which affect the distribution and volume of offers in the non-auction channels impact the probability an auction ends in a sale, the probability an item is sold through the auction channel, and the sale price in case of a sale. The impact on the two probabilities can be negative or positive and depends on whether the seller manages the channels jointly or separately. Our empirical analysis examines how the quality of the seller's retail location and her electronic commerce capabilities (i.e., two seller characteristics influencing demand in non-auction channels) impact the auction channel outcomes. The results confirm the joint channel management strategy considered in the analytical model.

Key words: Online auctions, multichannel retailing, electronic commerce, channel management

1. Introduction

In many markets that involve unique items—i.e., used cars, used books, real estate, and antiques—sellers often use several selling channels in parallel. For example, a seller may try to sell an item through her brick and mortar retail location while simultaneously listing it in an online auction site such as eBay, her own website, and other popular third-party websites which facilitate interactions between buyers and sellers (i.e., Cars.com or the Amazon Marketplace). This multichannel strategy is facilitated by the Internet, which decouples the information component of transactions from the logistics component (Van Heck and Ribbers 1997). The Internet enables retailers to reach out to a broader group of customers through a variety of online channels, while offering the product to local customers through a traditional offline location. Given the ease by which even very small retailers can establish online presences utilizing online marketplaces such as Amazon or eBay, it is increasingly important to develop an understanding of sellers' practices in multichannel contexts.

Online auctions have gained enormous popularity. The eBay marketplace alone facilitates over 64 billion dollars in merchandise per year and involves over 95 million active users (eBay 2011). Online auctions like those conducted on eBay attract heterogeneous sellers, and important auction outcomes, such as when sales occur and the sale prices, can be easily observed. Past research has found that seller's rating, the existence of a buy-now price, and the starting bid—i.e., seller and auction characteristics observable by bidders—are associated with both the auction sale price and the likelihood of sale (Ba and Pavlou 2002; Livingston 2005; Ottaway et al. 2003). Recent research has begun to identify ways in which contextual characteristics of the auction channel not directly observed by bidders, such as the existence of concurrent or prior auctions for the same or similar item(s), can influence auction outcomes (Arora et al. 2002; Bapna et al. 2003; Kuruzovich et al. 2010). However, it is yet unknown how auction outcomes might be influenced by the seller's simultaneous use of non-auction selling channels.

To address this gap in the literature, this paper utilizes both analytical and empirical approaches to show that seller characteristics related to the demand in non-auction channels influence the auction channel outcomes. Specifically, we use the theoretical foundation of search theory (Diamond 1985) to analytically model how seller characteristics that affect the volume or the distribution of offers received (i.e., the demand) in non-auction channels influence the probability a given auction ends in a sale (the *auction-sale probability*), the probability a given item the seller lists in the auction channel is sold through the auction channel (the *item-sale probability*), and the expected sale price (*sale price*) when an auction ends in a sale.

Search theory (Ashenfelter et al. 2003; Genesove 1995; Genesove and Mayer 2001) predicts that sellers with better ability to make a sale in the non-auction channels would set higher reserve prices in both the auction channel and the non-auction channels, resulting in two opposing effects on the probability an auction ends in a sale and the probability a given item sells via the auction channel. Specifically, an increase in the non-auction reserve price would increase both probabilities, while an increase in the auction reserve price would decrease them. Thus, the combined effect on the auction channel outcomes is not clear in advance. Our analytical model allows us to derive predictions regarding the nature of the combined effect. We show that the relationship between such seller characteristics and the auction outcomes depends upon whether the seller manages the auction and non-auction channels jointly (i.e., setting reserve prices in the different channels to maximize combined profit) or separately.

We then empirically test our analytical model's predictions with specific seller characteristics related to the quality of the seller's retail location and her electronic commerce capabilities in non-auction online channels. The empirical analyses use outcomes from 43,461 online auctions conducted on eBay Motors by 296 multichannel retailers for 21,630 unique vehicles. The analysis confirms that a seller's retail location and her electronic commerce capabilities significantly impact the above three auction channel outcomes. Specifically, a better retail location or improved electronic capabilities in non-auction channels lead to a lower likelihood of the reserve price being met and a sale occurring in an individual auction (*auction-sale),* a lower likelihood of a vehicle being sold through the online auction channel (*item-sale),* but a higher price in the auction channel when a sale occurs (*sale price*). Overall, our results suggest that sellers engage in the joint channel management strategy examined in the analytical model and may raise their online auction reserve price in response to better sales opportunities in other channels.

This research contributes to the understanding of how sellers use online auctions alongside other channels, an area in which there has been little past research. Consideration of all three channel outcomes (auction-sale, item-sale, and sale price) in the analytical and empirical treatments enables a more complete understanding of sellers' strategies and the cross-channel effects in a multichannel context. While prior work examines consumer behaviors in multichannel contexts (Ariely and Simonson 2003; Etzion et al. 2006; Kumar and Venkatesan 2005; Venkatesan et al. 2007) and seller behaviors in online and offline channels (Brynjolfsson and Smith 2000; Forman et al. 2009; Overby and Jap 2009), this is the first paper to present a theoretically-grounded treatment of how sellers' characteristics related to demand in the non-auction channels affect their online auctions' outcomes. Thus, this research provides insights into how retailers use auctions as part of a multichannel strategy, answering calls for more research on online auctions (Pinker et al. 2003) and multichannel seller strategies (Neslin and Shankar 2009).

The rest of the paper proceeds as follows. We first review how search theory has been used to study outcomes of the auction channel and present the theoretical framework used in the paper. Next, we present the analytical model that explores the relationship between characteristics of the demand in non-auction channels and auction channel outcomes. The predictions from the analytical model are then tested using data from eBay Motors. Finally, implications for theory and practice are discussed.

2. Theory

This section first reviews how search theory has been used to study auction channel outcomes. It then further discusses how seller characteristics related to the demand in non-auction channels are expected to influence the auction channel outcomes of interest.

2.1. Search Theory and Online Auctions

This research utilizes search theory to understand seller behavior in online auctions as part of a multichannel strategy. Search theory specifies that the process of search is influenced by both the potential benefits and the costs of continuing the search (Diamond 1985). When applied to the study of online auctions, search theory can explain a seller's rationale in setting her reserve price (Ashenfelter 1989; Genesove 1995). Setting a high reserve price decreases the chance that the reserve price will be met and the auction will end in a sale, but increases the minimum sale price when a sale occurs. Conversely, lowering the reserve price increases the likelihood of sale, but decreases the minimum sale price. In other words, the seller faces a tradeoff between the sale price and the time required to find a buyer, making search a relevant foundation for understanding the process through which sellers set their reserve price.

Ashenfelter (1989) first suggested that search theory may explain how sellers set and then adjust their reserve price over time. Genesove (1995) empirically tested a model of search in the context of wholesale auto auctions, examining how the mean and variance of market prices for a vehicle influence the search process of sellers in the auctions. Building on this work, Ashenfelter et al. (2003) modeled the sale rate of art as a search process, examining how sellers' reserve prices depend upon market characteristics (i.e., the variance in prices). Genesove and Mayer (2001) found that sellers who originally paid higher prices for condominiums also set higher asking prices when subsequently selling, showing that the reserve price and the time on market are influenced by seller-specific characteristics. Kuruzovich et al. (2010) examined how seller search across sequential online auctions influences the price the seller obtains for an item. Overall, this prior research suggests that search theory can be useful to understanding how sellers set reserve prices when using online auctions alongside other channels. Just as consumers may search for the right product and price across the variety of channels available to them (Ratchford et al. 2003; Ratchford and Srinivasan 1993), sellers of unique items can be conceptualized as searching for a high-valuation buyer across multiple channels, trying to maximize the difference between the price they would obtain and the cost of search (Genesove 1995; Kuruzovich et al. 2010).

On most auctions websites it is not possible to observe sellers' reserve prices, as these prices are private and hidden from bidders. However, by examining the relationship between seller characteristics related to demand in non-auction channels and relevant auction outcomes, we can infer the unobserved relationship between such characteristics and the hidden auction reserve price. For example, Genesove (1995) examined multichannel sales processes in the auto industry prior to the emergence of the Internet (the auction data was from 1951), when dealers alternated between wholesale auctions and their retail location. A wholesale auction would end in a sale if the reserve price was met[1], and when the reserve price was not met the seller had to transport the vehicle back to the retail site. Genesove (1995) found that the expected sale price in the retail channel was negatively related to the likelihood of sale in the wholesale auction channel, indicating that the reserve price in the online auction is influenced by factors driving the price the seller expects to obtain in the other channel (i.e., the retail location). We incorporate this result in our theoretical framework.

2.2. Theoretical Framework

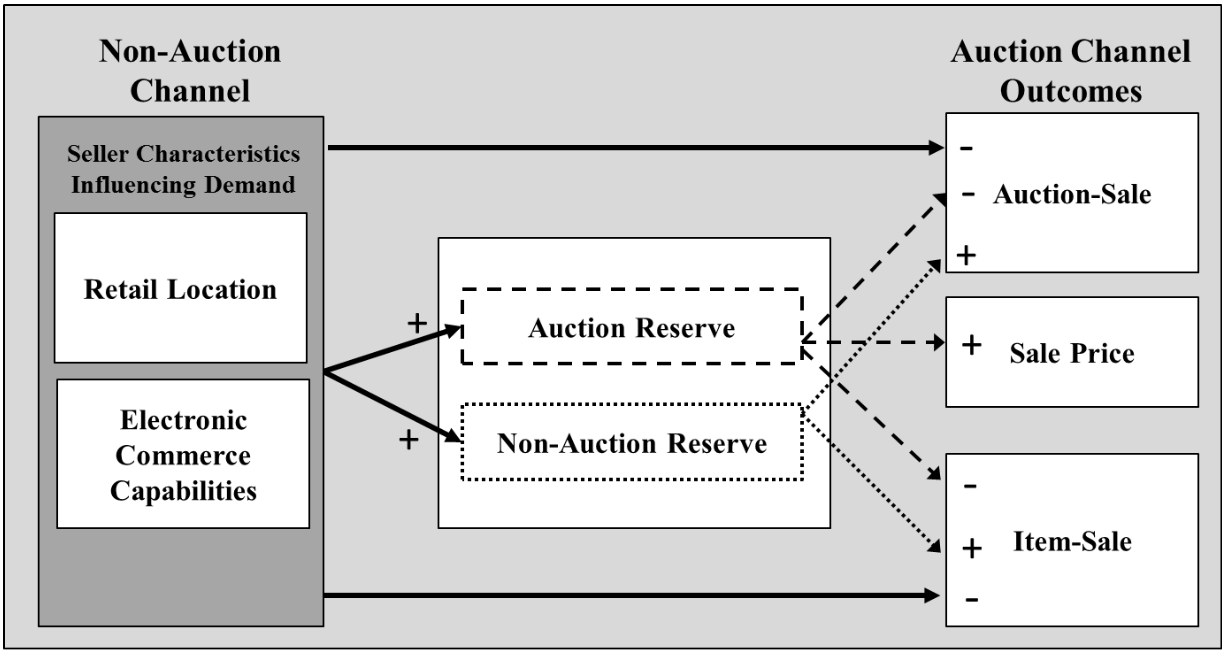
In this paper we consider sellers of unique items who use the online auction channel in parallel to other non-auction channels. In the auction channel, the seller sets a hidden reserve price, which serves as a lower bound on the sale price, and consumers compete for the item by submitting bids. In the non-auction channels, consumers interact directly with the seller by submitting offers (Pennington 1968). Thus, the seller's strategy in the non-auction channels also consists of a secret reserve price, and she accepts the first offer that exceeds the reserve price. Our theoretical framework, presented in Figure 1, demonstrates how seller characteristics that impact the demand in the non-auction channels, and are not apparent to bidders, are expected to affect important auction channel outcomes. As is described next, such effects can be either direct or indirect via strategic changes in the seller's reserve prices.

2.2.1. Auction-Sale Probability. The auction-sale probability is the probability the auction ends in a sale. When considering auctions in isolation, the auction-sale probability is simply the probability that the seller's reserve price is met. In contrast, when sellers use auctions in parallel to other channels, the auction-sale probability is more complex because the seller may terminate the auction early if she receives an attractive offer via another channel, and she may do so whether or not the highest bid received by that time exceeds the reserve price. Thus, the auction-sale probability is affected *directly* by the characteristics of the demand in the non-auction channels. Specifically, better opportunities in non-auction channels increase the probability that an auction would be terminated early, and thus decrease the probability that the auction would end in a sale. However, according to search theory, better sale opportunities in the non-auction channels would lead the seller to use a higher reserve price in these channels. An increase in the non-auction reserve price decreases the probability that the auction would be terminated early. These two opposing effects (the direct effect and the indirect effect via the non-auction reserve price) do not arise when the seller alternates between the channels as in Genesove (1995), but do take place when the seller uses the two channels simultaneously. Finally, previous research utilizing

[1] This is not true when considering the simultaneous use of online auctions and other channels. In this case, even if the reserve is met the seller can terminate the auction early due to an acceptable offer in another channel.

search theory predicts that the auction's reserve price would also increase with seller characteristics that represent better opportunities in non-auction channels (Genesove 1995). An increase in the auction reserve price should have a negative impact on the auction-sale probability.

Figure 1 Conceptual Framework



Note. A plus (minus) sign next to an arrow represents positive (negative) impact—for example, a better retail location is expected to have a negative impact on auction-sale probability, and a positive impact on the non-auction reserve price.

2.2.2 Item-Sale Probability. The seller offers the item in successive auctions until it is sold either in an auction or in a non-auction channel. The item-sale probability is the probability that the item sells via the auction channel, and is a relevant measure of the auction channel performance only in a multi-channel context. Seller characteristics related to demand in non-auction channels can affect the item-sale probability in three ways. First, improved opportunities in non-auction channels have a direct negative effect on the item-sale probability due to the higher likelihood that each auction in which the item is offered would be terminated early. Second, as with the auction-sale probability, this direct affect is mitigated by the strategic increase in the seller's reserve price in the non-auction channels. Third, search theory predicts that better opportunities in non-auction channels would lead to a higher a reserve price in the auction channel (Genesove 1995), which would have a negative effect on the item-sale probability

2.2.3. Sale Price. The auction sale price captures the value obtained by the seller, and it is relevant only for auctions that end in a sale. The sale price in a given auction is not affected directly by seller characteristics related to demand in other channels or by the seller's reserve price in those channels. Such seller characteristics are expected to affect auction sale prices only through their influence on the seller's reserve price in the auction channel. When a seller has better opportunities in other channels, her opportunity cost for accepting a low price in the auction is higher. Thus, better opportunities outside of the auction channel are expected to lead to higher auction reserve prices. While the auction reserve price typically cannot be observed, past findings indicate that the presence of a reserve price is associated with a higher sale price (Lucking-Reiley et al. 2007), and sellers with systematically higher reserve prices are likely to experience higher auction sale prices relative to other sellers in the market.

3. The Model

We model a seller with an item for sale who simultaneously uses several selling channels, one of which is an online auction channel (e.g., eBay marketplace). The non-auction channel(s) may include the seller's local store, her website, and third party websites. We refer to these non-auction channels collectively as "the *direct channel*", because consumers utilizing these channels interact directly with the seller rather than bid against each other. We consider the simultaneous use of the *direct channel* and the *online auction channel* and examine how the characteristics of the demand in the direct channel affect the auction channel outcomes.

The seller lists the item in successive auctions of similar length, while simultaneously offering the item in the direct channel, until the item is sold in one channel or the other. We define the time period in the model as the length of one auction, discount future gains and costs at a rate of ρ per period, and assume a periodic holding cost of c. For simplification, if the seller sells the item in the direct channel during the y^{th} period (i.e., during the y^{th} auction), we assume he still incurs the holding cost for the entire y^{th} period. This assumption should not have a significant effect on the results. In addition, to simplify the treatment of multiple channels, we assume that demands on the two channels originate from two separate groups of consumers. This assumption has been often used in past research on multichannel marketing. For example, Van Ryzin and Vulcano (2004) examine the optimal pricing-replenishment policy when the firm sells in two markets—one fixed-price market and one auction market—and assume demand comes from two different and independent streams of customers. In addition, past research suggests that online auctions are "sticky" channels; buyers engaged in competitive bidding with others frequently ignore comparable offerings in the readily available fixed-price channel, even when such offerings are less expensive than the winning bid of the auction (Ariely and Simonson 2003). It is reasonable, therefore, to assume that the majority of consumers using the online auction channel engage with the seller only through the online auction channel and not across multiple channels. Next we characterize the demand in each of the channels.

The demand in the direct channel consists of λ offers per period. Offers arrive sequentially at random times during the period, and each offer is drawn independently from the common distribution F with support set [βL, βH].[2] The two parameters, β and λ, are seller-specific and represent the ability of the seller to attract offers in this channel. Specifically, β determines the quality of the average offer (in terms of price) as well as the lowest and highest possible offers, and λ determines the volume of offers per period. Both a better support set (higher β) and higher volume (higher λ) can reduce the duration of time it takes the seller to reach a desired reserve price in the direct channel. The seller's strategy in the direct channel is defined by a hidden reserve price, R_D, and she accepts the first offer that exceeds the reserve price. When such an offer arrives, the seller sells the item and terminates the currently going auction.

In the auction channel, the seller expects N bidders to participate in each auction, and each bidder's willingness to pay is drawn independently from the distribution F with support set [L, H]. The seller's strategy is defined by a hidden reserve price, R_A, such that he would sell the item in the auction if the highest bid received in the auction exceeds R_A, and the item was not sold in the direct channel prior to the auction's stated end time. We assume all bidders use proxy bidding (the default bidding strategy in eBay and eBay Motors) and that there is a negligible bid increment. Thus, it is optimal for bidders to submit their true willingness to pay as their proxy bid and let the auction mechanism bid on their behalf the minimum amount needed to win, but only up to their proxy bid (Lucking-Reiley 2000). If only one bidder submits a proxy bid that is higher than R_A then the winning-bid would simply be R_A. If at least two bidders submit proxy bids higher than R_A, then the winning-bid is determined by the expected value of the (N-1) order statistic of N random draws from the distribution F (i.e., the value of the second highest proxy bid). We denote the *CDF* of the second highest draw out of the N draws by G_N( ). Table 1 summarizes the notation used in the model.

In our suggested model, the parameters L and H, as well as the distribution F, are item-specific and are assumed to be the same across channels. In contrast, the parameters β and λ indicate seller characteristics and capabilities that can affect demand in the direct channel but not in the auction channel. In addition, the two channels differ in the mechanism of interaction between seller and consumers. Specifically, in the direct channel the seller will accept the *first* offer that arrives which exceeds R_D, while in the auction channel the price would be determined by the second highest proxy bid that exceeds R_A. Finally, in this paper we analyze a deterministic model in regards to the number of bidders per auction and the number of offers that the seller may receive in the direct channel during an auction. Assuming the number of bidders per auction and the number of offers in the direct channel during an auction are drawn

[2] We do not argue that F is the distribution of valuations, nor do we try to model the relationship between valuations and offers. For the purpose of our model all that matters is that the quality of the offers in the direct channel depends on the parameter β while the quality of bids in the auction channel does not.

from Poisson distributions with the parameters N and λ respectively would not have significant impact on our results, but would significantly complicate the numerical treatments.

Table 1. Notation for Analytical Model

Variable	Description
β	Measure of the quality of the offers in the direct channel
λ	Number of offers in the direct channel per period
N	Number of bidders in each auction
c	Periodic holding cost
ρ	Periodic discounting rate
$F_{(\beta)}$	CDF of offers in the direct channel; support set $[\beta L, \beta H]$
F	CDF of proxy bids in the auction channel; support set $[L, H]$
G_N	CDF of the price in an ascending open-bid auction with N bidders (i.e., CDF of the second highest bid)
R_D	Reserve price in the direct channel
R_A	Reserve price in the auction

3.1. The Expected Profit

The general setup of the model is consistent with a seller search model (Ashenfelter 1989; Genesove 1995; Genesove and Mayer 2001), in which the seller optimizes profit considering the tradeoffs between the time and cost required for finding a buyer, and the resulting price obtained. The expected profit at the beginning of period (auction) t is given by:

$$E\pi_{D\&A(t)} = F_\beta^\lambda(R_D)F^N(R_A)(1+\rho)^{-1}E\pi_{D\&A(t+1)} + \left(1-F_\beta^\lambda(R_D)\right)E[offer|offer > R_D] + F_\beta^\lambda(R_D)NF^{N-1}(R_A)\big(1-F(R_A)\big)R_A + F_\beta^\lambda(R_D)\big(1-G_N(R_A)\big)E[winning\ bid|winning\ bid > R_A] - c\ , \tag{1}$$

where the expected value of an offer in the direct channel conditional on it being larger than the reserve price is given by:

$$E[offer|offer > R_D] = \frac{\int_{R_D}^{\beta H} V f_\beta(v)dv}{\int_{R_D}^{\beta H} f_\beta(v)dv}, \tag{2}$$

and the expected value of the winning bid conditional on it being larger than the auction's reserve price is given by:

$$E[winning\ bid|winning\ bid > R_A] = \frac{\int_{R_A}^{H} x dG_N(x)dx}{\int_{R_A}^{H} dG_N(x)dx}. \tag{3}$$

The first term in Equation 1 is the profit in case there is no sale in period *t*, which equals the discounted profit from period *t*+1. This case happens with probability $F_{\beta}^{\lambda}(R_D)F^N(R_A)$. The second term in Equation 1 is the expected profit when the seller receives an acceptable offer in the direct channel during the *t* auction, and terminates the *t* auction. The third term gives the expected profit in case the seller does not make a sale in the direct channel during the auction and exactly one bidder has a valuation higher than the auction reserve price, R_A. Finally, the last term is the expected profit when the seller does not make a sale in the direct channel during the auction, and at least two bidders have valuation higher than R_A. This last case happens with probability $F_{\beta}^{\lambda}(R_D)\big(1 - G_N(R_A)\big)$. Note that if N=1 (there is only one bidder), then $G_N(R_A) = 1$ and the last term becomes zero.

Finally, we can substitute $E\pi_{D\&A(t)} = E\pi_{D\&A}$ and $\pi_{D\&A(t+1)} = \pi_{D\&A}$ in Equation 1, and solve for $E\pi_{D\&A}$ to get:

$$E\pi_{D\&A} = \frac{(1+\rho)}{\left(1+\rho-F_{\beta}^{\lambda}(R_D)F^N(R_A)\right)} * \tag{4}$$

$$\left(\left(1 - F_{\beta}^{\lambda}(R_D)\right)\frac{\int_{R_D}^{\beta H} Vf(v)dv}{\int_{R_D}^{\beta H} f(v)dv} + F_{\beta}^{\lambda}(R_D)\left(NF^{N-1}(R_A)(1-F(R_A))R_A + \int_{R_A}^{H} VdG_N(v)dv\right) - c\right)$$

The above equation can be used to derive the profit from utilizing only the direct channel or only the online auction channel. When the seller uses only the direct channel, we simply need to substitute $F(R_A) = 1$ in Equation 4, which gives:

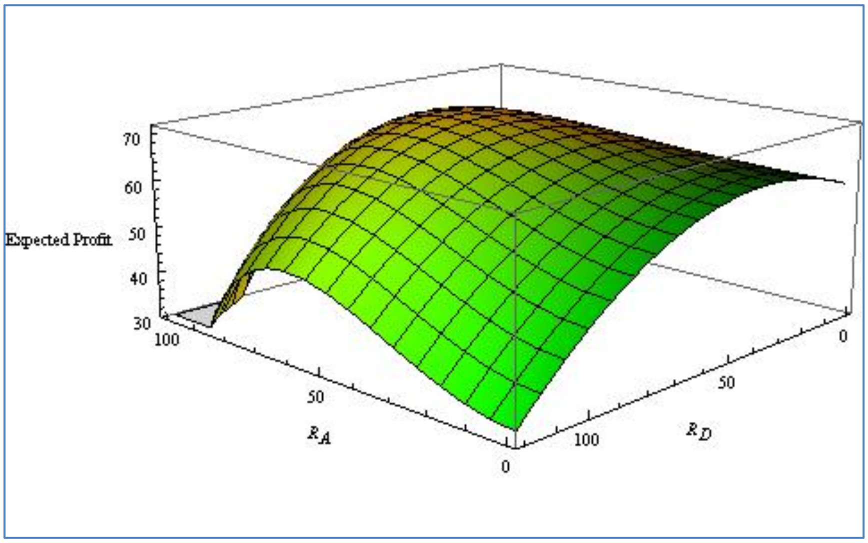
$$E\pi_D = \left(\frac{1+\rho}{1+\rho-F_{\beta}^{\lambda}(R_D)}\right)\left(\left(1 - F_{\beta}^{\lambda}(R_D)\right)\frac{\int_{R_D}^{\beta H} Vf_{\beta}(v)dv}{\int_{R_D}^{\beta H} f_{\beta}(v)dv} - \mathrm{c}\right). \tag{5}$$

When the seller uses only the online auctions we substitute $F_{\beta}(R_D) = 1$ in Equation 4, which gives:

$$E\pi_A = \left(\frac{1+\rho}{1+\rho-F(R_A)^N}\right)\left(NF^{N-1}(R_A)\big(1-F(R_A)\big)R_A + \int_{R_A}^{H} VdG_N(v)dv - c\right). \tag{6}$$

Holding everything else equal, as R_D increases the expected price in the direct channel increases while the probability of sale via the direct channel at any given period decreases. Similarly, holding everything else equal, as R_A increases the expected auction price increases, while the probability of sale via the auction channel at any given auction decreases. The expected number of periods until a sale takes place and the related search costs when considering the simultaneous use of both channels also increase with increases in R_D or R_A. Figure 2 illustrates the seller's expected profit, $E\pi_{D\&A}$, in the R_A-R_D space when F is the uniform distribution. Increasing a reserve price past the optimal value results in a decrease in overall profit because the costs induced from longer search do not adequately make up for the higher resulting sale price. As can be seen from Figure 2, however, the profit is not always a concave function of the auction reserve price. Next, we derive the expressions for the auction-channel outcomes of interest.

Figure 2. The Expected Multichannel Profit in the R_D-R_A Space



Note. L=0, H=100*, β*=1.2, *c*=1, *ρ*=1, *N=2*, *λ*=1 and *F* is the uniform distribution.

3.2. Auction Channel Outcomes

The expected auction price in case of a sale (*EP*) is given in Equation 7. The price equals the second highest proxy bid in case there are at least two proxy bids that exceed the seller's reserve price, and equals the reserve price in case there is one proxy bid that exceeds the reserve. The auction-sale probability (AS) is given in Equation 8. Unlike when considering an auction in isolation, here the auction-sale probability is a decreasing function of the likelihood of a sale in the direct channel. Finally, the item-sale probability (*IS*), as given in Equation 9, is the sum over all periods, $t=1$ to ∞, of the probability that the item is sold in the t online auction. The probability that the item is sold in the t online auction is the product of the probability there is no acceptable offer in the direct channel during the first t auctions, the probability that there is no acceptable bid in the first t-1 auctions, and the probability that at least one bid in the t auction exceeds R_A.

$$EP = \frac{\int_{R_A}^{H} Vg(v)dv + NF^{N-1}(R_A)\left(1-F(R_A)\right)R_A}{1-F^N(R_A)}. \tag{7}$$

$$AS = F_\beta^\lambda(R_D)(1 - F^N(R_A)). \tag{8}$$

$$IS = \sum_{t=1}^{\infty}\left(F_\beta^\lambda(R_D)\right)^t (F^N(R_A))^{t-1}(1 - F^N(R_A)). \tag{9}$$

As can be seen from the above expressions, while the expected auction price does not depend directly on R_D, β, or λ, it is an increasing function of R_A, and under a joint management strategy the optimal value of R_A may depend on β and λ. In contrast, the auction-sale probability and the item-sale probability are functions of R_D and are also direct functions of β and λ (this is consistent with our theoretical framework presented in Section 2). Specifically, an increase in β or λ has a direct negative effect on the *AS* and *IS* probabilities, but is expected to also affect these two outcomes indirectly via the changes it may cause in the values of the optimal reserve prices.

4. Model Analysis

In what follows, we examine how characteristics of the demand in the direct channel (i.e., β and λ) affect the three auction channel outcomes of interest under two management strategies: (1) the independent management strategy, in which reserve price is set for each channel to maximize that channel's profit, and (2) the joint management strategy, in which reserve prices for the two channels are set to maximize the overall multichannel profit. To do so, we assume a specific distribution for *F*, the uniform distribution. When *F* is the uniform distribution, G_N is given by:

$$G_N(y) = \left(\frac{y-L}{H-L}\right)^N \frac{(HN-L-(N-1)Y)}{(y-L)}, \tag{10}$$

and the total multichannel profit is given by:

$$E\pi_{D\&A} = \tag{11}$$

$$\frac{c-\left(2L+H(-1+\mathrm{N})+\left(\frac{-L+\mathrm{R}_A}{H-L}\right)^{\mathrm{N}}\left(H(1+\mathrm{N})-2(L+\mathrm{NR}_A)\right)\right)\left(\frac{\mathrm{R}_D-L\beta}{H\beta-L\beta}\right)^{\lambda}/(1+N)+\frac{1}{2}(\mathrm{R}_D+H\beta)\left(-1+\left(\frac{\mathrm{R}_D-L\beta}{H\beta-L\beta}\right)^{\lambda}\right)}{-1+\frac{(H-L)^{-\mathrm{N}-\lambda}(-L+\mathrm{R}_A)^{\mathrm{N}}\left(-L+\frac{\mathrm{R}_D}{\beta}\right)^{\lambda}}{1+\rho}}.$$

4.1. Channels Managed Separately

In some cases different departments/individuals manage the different selling channels. This management strategy might simplify operation, but often leads to sub-optimal profit. When the seller manages the channels separately, R_D is set to maximize the profit as given in Equation 5, and R_A is set to maximize the profit from Equation 6. Thus, R_D will be a function of β and λ, but R_A would not. As a result, the expected auction sale price, *EP*, does not depend on seller's characteristics related to demand in the direct channel, while the auction-sale and item-sale probabilities do. An increase in β or λ has a direct negative effect on the auction-sale and the item-sale probabilities. However, as explained in Section 2, an increase in β or λ is also expected to lead to a higher R_D, which in turn has a positive effect on both probabilities. Thus, by how much the optimal R_D changes in reaction to changes in β or λ will determine the combined effect on the two probabilities. Finally, it is easy to show that under this management strategy the sign of the derivative of AS with respect to β is the same as the sign of the derivative of IS with respect to β, and thus it is sufficient for us to examine how one of the two probabilities (IS or AS) changes with β[3]. Similarly, it can be shown that either both probabilities increase or both decrease in λ.

[3] This is no longer true when the optimal R_A is a function of β .

Ideally, we would like to obtain closed-form expressions for the optimal values of R_D and R_A as a function of the model parameters (using first order conditions and assuming the profit is concave), then substitute these two expressions in the equation for *AS*, and finally examine derivatives of *AS* with respect to β and λ. However, since it is not feasible to derive closed-form expressions for the optimal reserve prices, (i.e., for the values of R_D and R_A that maximize the expressions from Equation 5 and Equation 6 respectively), we examined numerically a large set of parameter values to determine whether the *AS* probability and the *IS* probability increase or decrease due to an increase in β or λ. We normalized *H* to 100 and considered *L* values between 0 and *H* in increments of 20, *c* values between 0.5% of H and 4% of *H* in increments of 0.5, ρ values between 0% and 4% of *H* in increments of 0.5, *N* values between 1 and 10 in increments of 1, and λ values between 1 and 10[4]. Finally, we consider β values between 0.8 and 1.2 in increments of 0.1, so that the expected offer in the direct channel does not vary by more than 20% from the expected willingness to bid in the auction channel. Above values gave us 180,000 possible combinations of parameter values. Experimenting with different *H* values would only re-scale the problem.

We determined numerically the optimal reserve price in the direct channel, R_D^*, from Equation 5, and the optimal auction reserve price, R_A^*, from Equation 6 for any given combination of parameter values (*H*, *L*, β, *N*, λ, c, and ρ). Then, for every possible combination of parameter values we evaluated the change in the AS probability, and the change in the optimal reserve price R_D^*, when β increases by 0.1, and when λ– the number of offers–increases by 1 (the optimal auction reserve price does not depend on β or λ under the separate channel management strategy). That is, we evaluated the following:

$$\Delta AS(\beta) = AS(\beta + 0.1, R_D^*(\beta + 0.1), R_A^*) - AS(\beta, R_D^*(\beta), R_A^*) \tag{12}$$

$$\Delta AS(\lambda) = AS(\lambda + 1, R_D^*(\lambda + 1), R_A^*) - AS(\lambda, R_D^*(\lambda), R_A^*) \tag{13}$$

$$\Delta R_D^*(\beta) = AR_D^*(\beta + 0.1) - R_D^*(\beta) \tag{14}$$

$$\Delta R_D^*(\lambda) = AR_D^*(\lambda + 1) - R_D^*(\lambda) \tag{15}$$

Note that in the above equations we suppress the dependency of the *AS* probability and the optimal reserve price, R_D^*, on the rest of the parameters.

Our numerical investigation shows that for all parameter combinations the optimal reserve price in the direct channel, R_D^*, went up due to a marginal increase in β or λ (i.e., ΔR_D^* >0). However, only for 119,550 (66.4%) of the parameter combinations considered $\Delta AS(\beta)$ (and thus $\Delta IS(\beta)$) was positive, and for 46,180 (25.6%) of cases it was negative. This shows that in 25.6% of the cases, the direct effect of the higher β dominated the indirect effect of the higher reserve price. Finally, for 154,760 (86%) of the

[4] We note that although the AS probability is a function of R_A and *N*, under the separate management strategy the sign of the change in the AS probability due to a change in β (or in λ) does not depend on *N* or R_A.

parameter combinations $\Delta AS(\lambda)$ (and thus $\Delta IS(\lambda)$) was negative, and for 25,240 combinations (14%) it was positive. Table 2 summarizes the results of the numerical analysis.

Table 2. Results of Numerical Investigation when the Seller Manages Channels Separately

	Positive	Negative	Zero
$\Delta AS(\beta)$ & $\Delta IS(\beta)$	119,550 (**66.4**%)	46, 180 (25.6%)	14,270 (8 %)
$\Delta R_D^*(\beta)$	180,000 (100%)	0	0
$\Delta AS(\lambda)$ & $\Delta IS(\lambda)$	25,240 (14%)	154, 760 **(86%)**	0
$\Delta R_D^*(\lambda)$	180,000 (**100%**)	0	0

Note. The first number in each cell is the number of cases that fall in that category. The second number is the percentage of cases.

Our results demonstrate that when channels are managed separately, not all improvements in seller's capabilities related to the direct channel have the same effect on the auctions performance. While higher offers in the direct channel lead in many cases (66.4%) to higher auction-sale and item-sale probabilities, a higher volume of offers has in most cases (86%) the opposite effect. This implies that the seller increases the reserve price in the direct channel to a higher degree when the improvement is in the level of the offers than when the improvement is in the volume of the offers in the direct channel. Finally, based on our numerical investigation of the model, we derive the following proposition.

PROPOSITION 1. *When managing the two channels separately:*

a) The expected auction sale price in case of a sale (EP) is independent of the quality of the offers in the direct channel (β) and the volume of offers (λ).

b) The optimal reserve price in the non-auction channel increases with both the quality of the offers and the volume of offers.

c) The auction-sale and item-sale probabilities decrease as the volume of offers increases, but are likely to increase as quality of offers increases.

4.2. Channels Managed Jointly

When the seller manages the two channels jointly, he sets the two reserve prices, R_A and R_D, to maximize the total profit as given in Equation 4. When β or λ increases we expect the seller to increase R_D and, as prior research suggests (Genesove 1995), to also increase R_A. While a higher R_D has a positive effect on the auction-sale and item-sale probabilities, a higher R_A would have a negative effect on both. In addition, unlike in the separate management case, here an increase in β or λ may also have an indirect effect on the expected auction price due to its potential effect on the auction reserve price, R_A.

Since it is not possible to derive closed-form expressions for the optimal reserve prices, we determined the optimal prices and the resulting values of the three auction outcomes numerically. Specifically, for any given combination of parameters values, (H, L, β, λ, c, ρ, and N) we searched for the optimal values of (R_A, R_D) by evaluating numerically the profit from Equation 4 at any possible combination of (R_A, R_D), changing R_A from L to H and changing R_D from βL to βH in increments of 1.We could not use the F.O.C numerically because in some cases the profit was not consistently a concave function of a reserve price. Our program identifies the (R_A, R_D) combination that yields the highest profit and then evaluates the three outcomes of interest, according to Equations 7-9, at the optimal reserve prices and given the values of all other parameters. Finally, for each of the 180,000 combinations of parameter values, we evaluated the following 6 expressions as well as the changes in the optimal reserve prices ($\Delta R_D^*(\beta),\ \Delta R_D^*(\lambda),\ \Delta R_A^*(\beta)\ and\ \Delta R_A^*(\lambda)$):

$$\Delta AS(\beta) = AS\big(\beta + 0.1, R_A^*(\beta + 0.1), R_D^*(\beta + 0.1)\big) - AS\big(\beta, R_A^*(\beta), R_D^*(\beta)\big) \quad (16)$$

$$\Delta AS(\lambda) = AS\big(\lambda + 1, R_A^*(\lambda + 1), R_D^*(\lambda + 1)\big) - AS\big(\lambda, R_A^*(\lambda), R_D^*(\lambda)\big) \quad (17)$$

$$\Delta IS(\beta) = IS\big(\beta + 0.1, R_A^*(\beta + 0.1), R_D^*(\beta + 0.1)\big) - IS\big(\beta, R_A^*(\beta), R_D^*(\beta)\big) \quad (18)$$

$$\Delta IS(\lambda) = IS\big(\lambda + 1, R_A^*(\lambda + 1), R_D^*(\lambda + 1)\big) - IS\big(\lambda, R_A^*(\lambda), R_D^*(\lambda)\big) \quad (19)$$

$$\Delta EP(\beta) = EP\big(\beta + 0.1, R_A^*(\beta + 0.1), R_D^*(\beta + 0.1)\big) - EP\big(\beta, R_A^*(\beta), R_D^*(\beta)\big) \quad (20)$$

$$\Delta EP(\lambda) = EP\big(\lambda + 1, R_A^*(\lambda + 1), R_D^*(\lambda + 1)\big) - EP\big(\lambda,\ R_A^*(\lambda),\ R_D^*(\lambda)\big) \quad (21)$$

Note that in above expressions we suppress the dependency of *EP*, *AS*, *IS*, and the optimal reserve prices on all unchanged, parameters. Table 3 displays the results of the numerical investigation.

Table 3. Results of Numerical Investigation when Seller Manages Channels Jointly

	Positive	Negative	Zero
$\Delta AS(\beta)$	10,575 (5.8%)	168,260 (93.47%)	1,165 (0.64 %)
$\Delta IS(\beta)$	11,441 (6.35%)	167,468 (93.04%)	1,091 (0.6%)
$\Delta EP(\beta)$	114,282 (63.49%)	176 (0.09%)	65,542 (36.41%)
$\Delta R_A^*(\beta)$	116,465 (64.7%)	0	63,535 (35.3%)
$\Delta R_D^*(\beta)$	171,170 (95%)	0	8,830 (5%)
$\Delta AS(\lambda)$	13,560 (7.5%)	166,440 (92.46%)	0
$\Delta IS(\lambda)$	12,761 (7%)	167,239 (92.9%)	0
$\Delta EP(\lambda)$	26,854 (14.91%)	1,374 (0.76%)	151,772 (84.3%)
$\Delta R_A^*(\lambda)$	26,854 (14.91%)	1,374 (0.76%)	151,772 (84.3%)
$\Delta R_D^*(\lambda)$	104,377 (57.99%)	0	75,623 (42.01%)

Note. The first number in each cell is the number of cases that fall in that category. The second is the percentage of cases.

From Table 3 we see that expecting higher offers in the direct channel (higher β) has in the majority of cases (for more than 93% of parameter combinations) a negative impact on both probabilities (AS and IS). In contrast, under the separate management strategy, expecting higher offers in the direct channel had in most case (66.4%) a positive impact on both probabilities. One possible cause for this change in the results is that under joint management the seller might increase the auction reserve price in response to better sale opportunities in the direct channel, and a higher auction reserve price reinforce the direct negative impact a higher β has on the two probabilities. Another possible cause is that the reserve price in the direct channel is increased (due to higher β) to a lesser degree under the joint management strategy than under the separate management strategy. Finally, we see that the expected auction sale-price went up only in 63.5% of the cases, which closely corresponds to the percentage of cases in which the optimal auction reserve went up.

A larger number of offers in the direct channel (higher λ) has in majority of cases (for more than 92% of parameter combinations) a negative impact on both the AS and IS probabilities. This is a slight increase from the 86% of the cases for which we saw a negative impact under the separate management strategy. Surprisingly, only for 15% of the cases examined a marginal increase in the number of offers had a positive effect on the optimal auction reserve price and the expected auction sale price. Finally, while under the separate management strategy the optimal reserve price in the direct channel went up in response to a marginal increase in λ for all 180,000 cases examined, under the joint management strategy it went up only in 58% of the cases.

We conclude that, under the joint management strategy, the support set of the distribution of offers and the volume of offers in the direct channel have different impacts on the auction reserve price and the expected auction sale price. While the former (i.e., β) has in most cases a positive impact on the optimal auction reserve price and thus on the auction sale-price in case of a sale, the latter (i.e., λ) does not. In addition, these two demand characteristics clearly impact the reserve price in the non-auction channel more often than they impact the reserve price in the auction channel. Finally, based on our numerical investigation of the model, we derive the following proposition for the joint management strategy.

PROPOSITION 2. *When managing the two channels jointly:*

a) The optimal auction reserve price and the expected auction sale price in case of a sale (EP) are non-decreasing in the quality (β) and the volume (λ) of offers in the non-auction channel.

b) The optimal reserve price in the non-auction channel is non-decreasing in the quality and the volume of offers in the direct channel.

c) *Both the auction-sale and the item-sale probabilities decrease with the quality of offers (β) and with the volume of offers (λ) in the direct channel.*

5. Empirical Context

The analytical model provides us with predictions regarding how seller characteristics associated with demand in the direct channel influence the online auction channel outcomes. To test the insights from the analytical model, we required a context in which sellers of unique items employ an auction channel along with other non-auction channels. The retail market for used cars is a suitable context, as sellers in this market (car dealers) often use online auctions on eBay Motors while simultaneously trying to sell the used vehicles in their lot and through other online channels (i.e., their own website and 3rd party websites like Cars.com or Autotrader.com).

The eBay Motors marketplace is the most popular public auction website serving retail (not wholesale) buyers of vehicles, and has a gross merchandise volume of approximately 8 billion dollars (eBay 2011). While consumers can also sell vehicles on the eBay Motors marketplace, professional dealers conduct a large percentage of the auctions. Retailers post an extensive vehicle description on the auction site—including the make and the model, pictures, vehicle options, and the vehicle identification number (VIN). In addition, all auctions pages indicate general properties of the seller, including feedback provided by previous customers.

Like other auctions on eBay, eBay Motors auctions are 2nd price English auctions. Using a mechanism known as proxy bidding, each bidder enters the highest amount he is willing to bid (referred to as his proxy bid), and the auction mechanism then places bids on his behalf, biding as much as necessary to make sure that the bidder still wins the item, but not more than the proxy bid. As a result, the winner pays a small increment (currently $5 in eBay Motors) over the proxy bid of the second highest bidder. The reserve price of the seller is private, and the item will not sell if the highest bid at the end of the auction is less than the reserve. In addition, sellers can cancel an auction (even if bids were already submitted and reserve was met) if the vehicle sells through another channel. Finally, if the auction does not end in a sale the seller can relist the vehicle in a new auction. In summary, the auction mechanism matches that in our analytical model.

5.1. Measures for Seller Characteristics

In the analytical model we examined how the support of the distribution (represented by β) and the volume (λ) of offers in the direct channel affect the auction outcomes of interest. In reality we cannot observe the distribution or the frequency of offers that originate from non-auction channels used by auto dealers. Thus, in the empirical model we identify two seller characteristics that are likely to impact the distribution and the volume of offers in the non-auction channels: (1) the dealer's retail location and (2) her electronic commerce capabilities in non-auction channels.

5.1.1. Retail Location. A long series of works in the marketing literature have identified location as among the most important aspects of a retail venture (Davies and Harris 1990; Dickinson 1981), influencing both the seller's ability to attract customers and her pricing power. Many consumers prefer to engage in face-to-face discussions with salespeople and select a vehicle by visiting local dealerships. This makes the physical location of the dealership an important factor in overall performance. Location governs how frequently customers will walk through the lot and what the (average) characteristics of those customers will be. Dealers would typically prefer locations providing a high volume of affluent customers.

To measure the ability of a seller to obtain offers through her offline retail location, we used AnySite v8.8 to calculate the average household income (*AHI*) and the total population (*TP*) within a 20-minute drive from the seller's dealership address in year 2007. While we were also able to calculate TP and AHI values based on mileage, drive-time time was more consistent with models of consumer search (e.g., Ratchford and Srinivasan 1993). AnySite is a commercial database that incorporates a variety of public and private datasets to enable assessment of retail location quality, making it a relevant measure consistent with practice. The measure AHI could be considered as a proxy for the quality of offers (β) while the measure TP could be considered as a proxy for the volume of offers (λ), making the location variables from the empirical analysis (AHI and TP) directly relevant to the two parameters from the analytical model (β and λ).

5.1.2. Electronic Commerce Capabilities. Past research has found that electronic commerce capabilities improve retailers' operational performance (Zhu 2004; Zhu and Kraemer 2002). In our context, electronic commerce capabilities capture the ability of the seller to attract customers via electronic channels other than the online auction channel. Car dealers can attract potential buyers by listing their inventory on their own website, and thus the functionality of the dealer's website can affect the volume and quality of the offers received via this channel. In addition, car dealers can use matching services run by 3rd parties to list their vehicles. The number of such websites utilized by the seller may also affect the frequency at which she receives offers. While measuring capabilities of an organization is difficult, measurement of specific IT functionalities (i.e., website features) provides an indicator of the underlying capabilities (Zhu and Kraemer 2002).

We used two measures of the electronic commerce capability of the seller: (1) the functionality of the seller's website and (2) the average number of unique websites (other than the eBay Motors site) used by the seller to list her vehicles. Functionality of the sellers' website is one way to assess her underlying electronic commerce capabilities (Zhu and Kraemer 2002). We refer to this measure as *web electronic commerce capabilities* (ECC_{WEB}). Specifically, to determine the web electronic commerce capabilities of the sellers in our data, two researchers examined the websites of the retailers and noted the presence of eight website characteristics relevant to auto retailing. These characteristics were adapted from a survey created by a leading market research organization specializing in the auto industry and included such things as "lists price on website," and "tool for credit application." A complete list of the characteristics used is found in Appendix A. For each seller (j), the eight website characteristics (c) were summed to calculate an overall web electronic commerce capabilities measure, as given in Equation 22 (where w_{cj}=1 if the characteristic was present on seller j's website and 0 otherwise):

$$ECC_{WEB(j)} = \sum_{c=1}^{8} w_{cj}. \quad (22)$$

The second measure of seller's electronic commerce capabilities captures the extent to which the seller's vehicles have been listed on websites other than the online auction channel. It is common for sellers to list the VIN of the vehicle on each site that they use, enabling potential buyers to obtain a vehicle history report through one of the available online services such as CARFAX. Thus, an online search of the VIN of a vehicle that is being auctioned provides a list of other web pages in which the same vehicle is listed, including dealer websites and 3rd party websites such as Yahoo Autos and Autotrader.com. As this measure indicates the degree to which sellers *searched* (for buyers) on *other websites*, we refer to it as SOW electronic commerce capabilities *(ECC_{SOW})*. Specifically, for each auction in our dataset an automated script used Google to search the VIN shortly after the auction end date, storing the number of filtered pages (i.e., the number of unique domains) on which the VIN had been listed, but excluding websites relating to eBay from the count. The resulting number for auction *i* by seller *j* is SOW_{ij}. Then, SOW_{ij} values for all auctions conducted by the seller (*j*) were averaged (N_j is the number of auctions conducted by seller *j*), as shown in Equation 23:

$$ECC_{SOW(j)} = \frac{\sum_{i=1}^{N_j} SOW_{ij}}{N_j}. \quad (23)$$

The retail location measures of AHI and TP closely correspond to the parameters for the support of the distribution (β) and the volume of offers (λ) from the analytical model. However, the correspondence between our two measures of electronic commerce capabilities and the analytical model is less clear. Past research suggests that website characteristics can influence purchase behavior (Venkatesh and Agarwal 2006), and thus ECC_{WEB} is expected to be positively related to the volume of offers. Similarly, the level of advertising on other websites (ECC_{SOW}) is likely to be positively related to the number of offers, as websites like AutoTrader.com and Cars.com facilitate negotiations between dealers and customers. Finally, it is also possible that ECC_{WEB} and ECC_{SOW} influence the distribution of offers by affecting the types of customers the seller attracts.

5.2. Control Variables.

The analysis incorporated a variety of control variables (car, seller, and auction related) that have previously been identified to influence auction outcomes. In particular, we controlled for vehicle characteristics such as the number of miles, certification, inspection, warranty, vehicle model, vehicle color, model year, and the number of auctions in which the vehicle has been listed by the seller. We also controlled for specific auction characteristics, such as the starting bid, the number of bids, and the auction length. Finally, we included the number of days since the beginning of the data collection, and the number

Table 4. Variables for the Auction Analysis

Variable	Mean	SD	Unit	Description
Seller Characteristics				
AHI	75.34	16.39	\$M	The average household income within a 20-minute drive time from the seller's location, measured in 2007.
TP	825.76	656.22	M	The total population within a 20-minute drive time from the seller's location, measured in 2007.
ECC_{WEB}	5.13	1.94	features	The number of features on the sellers' websites (see Appendix A).
ECC_{SOW}	1.87	0.78	links	The average number of unique links resulting from a Google search of the seller's VINs.
Auction Outcomes				
Auction-Sale	0.12	0.32	0/1	An indicator of whether an auction ends in a sale.
Item-Sale	0.27	0.44	0/1	An indicator of whether a vehicle is sold via the online auction channel.
Sale Price	18.36	12.49	\$M	The sale price for the vehicles sold at auction.
Price Premium	0	3.35	\$M	The auction sale price minus the expected market price based upon values of the controls.
Control Variables				
Miles	43.72	29.18	#	The number of miles listed on the car's odometer.
Certified	0.01	0.08	0/1	Whether the seller lists the car as being certified.
Inspected	0.36	0.48	0/1	Whether the seller lists the car as being inspected
Warranty	0.55	0.50	0/1	Whether the seller lists the car as having a warrant.
Vehicle Model	NA	NA	0/1	The vehicle model, determined from the first 8 digits of the VIN.
Vehicle Color	NA	NA	0/1 x 7	The color of the vehicle, including 7 colors.
Model Year	NA	NA	0/1 x 6	The model year of the vehicle, including 2000-2006.
Time	9.89	5.75	days	The number of weeks since the start of the data collection (accounts for depreciation).
Positive Feedback	485.32	532.31	#	The number of positive feedback messages left on the seller's eBay profile at the time of the auction.
Negative Feedback	3.27	5.80	#	The number of negative feedback messages left on the seller's eBay profile at the time of the auction.
# of Auctions	4.15	3.74	auctions	The number of *total* auctions for the vehicle in the dataset.
# of Bids	11.96	8.38	bids	The number of bids placed in the auction.
Auction Length	7.10	2.25	days	The auction length in days.
Starting Bid	5.55	9.45	\$M	The starting bid set by the seller in the auction
Ended on Weekend	0.21	0.41	0/1	Whether an auction ended on a weekend.
Ended in Buy-it-Now	0.07	0.25	0/1	Whether an auction ended in buy-it-now.

Notes. M = thousand; N=43,461 (auctions) for all except for price analysis where N=5,144.

of positive and negative feedback ratings of the seller. Table 4 presents the variables of interest to the model and the control variables, and provides basic descriptive statistics.

6. Data and Analysis

Using an automated agent we collected data from 1,217,800 auctions on eBay Motors during late 2006 through early 2007, extracting information on the vehicle, the seller, and the auction, as detailed in Table 4. To reduce extremes in price outcomes resulting from product differences, we eliminated from the dataset all vehicles with a model year earlier than 2000, incomplete information on the VIN, unclear titles, or listing outside of the United States. In addition, we further eliminated vehicle models for which there were not at least 3 sales in the dataset. Finally, as the mechanism of influence suggested by our analysis is the sellers' reserve prices, we also eliminated all auctions in which the seller did not set a reserve price. We expect that auctions with no reserve price involved sellers with the specific objective of liquidating vehicles, making the nature of their search process fundamentally different from that of sellers that are maximizing profit.

For practical reasons (i.e., time required for collecting additional information from dealers websites), we selected only the most active sellers — those that sold at least 15 vehicles on eBay Motors during the period of the sample — for additional analysis. We used the information in these sellers' auction pages to locate the website and the physical location of each seller[5], and we eliminated all sellers for which we could not find information regarding other channels. For this subset of selected sellers, we collected additional information regarding the degree to which each seller could attract buyers through non-auction channels (i.e., we determined the values of AHI_j, TP_j, $ECC_{WEB(j)}$, and $ECC_{SOW(j)}$). The final dataset included 296 multichannel retailers, 43,461 auctions, 21,630 unique vehicles, and 5,144 vehicles sales. Prior to empirical analysis, the variables AHI_j, TP_j, $ECC_{WEB(j)}$, and $ECC_{SOW(j)}$, positive feedback, negative feedback, and number of total auctions were logged because an examination of the raw data indicated highly skewed distributions. After being transformed, the variables approximated a normal distribution.

We model the probability an auction ends in a sale (*$AuctionSale_{ij}$*) using logistic regression as given in Equation 24. The vector S_j is the vector of seller characteristics influencing the demand in other channels (i.e., AHI_j, TP_j, $ECC_{WEB(j)}$, and $ECC_{SOW(j)}$), C_{ivj} is the vector of controls (for auction *i* of vehicle *v*, by seller *j*) which are listed in Table 4, and α are the parameters to be estimated.

$$\Pr\left(AuctionSale_{ij} = 1 \middle| S_j, C_{ivj}\right) = \frac{1}{1+e^{-(\alpha_0+\alpha_1 S_j+\alpha_2 C_{ij})}} \qquad (24)$$

The probability a vehicle is sold via the auction channel (*$ItemSale_{vj}$*) is also modeled using logistic regression, and is given in Equation 25. Here, the analyses are at the level of the vehicle, and thus controls

[5] Sellers who are also auto dealers frequently list their website address along with additional identifying information on their auction webpage.

that are at the auction level (*start bid*, *# bids*, etc.) were averaged over all the auctions in which the vehicle was offered, while controls that are at the vehicle or seller level were left as is, resulting in a vector of controls $C_{vj.}$ As before, S_j is the vector of seller characteristics influencing demand in other channels, and λ are parameter estimates.

$$\Pr\left(ItemSale_{vj} = 1 \middle| S_j, C_{vj}\right) = \frac{1}{1+e^{-(\lambda_0+\lambda_1 S_j+\lambda_2 C_{vj})}} \tag{25}$$

The impact of seller characteristics on the auction sale price of vehicles was calculated in two different ways. First, we simply used the auction sale price of the vehicle, SalePrice_{ij}, in an OLS regression including the seller characteristics, S_j, and the controls, C_{ivj}, as given in Equation 26 where γ is the vector of the parameter estimates, and ε is the error terms.

$$\text{SalePrice}_{ij} = \left(\gamma_1 S_j\right) + \left(\gamma_2 C_{ivj}\right) + \varepsilon \tag{26}$$

A limitation of this method, however, is that it includes only vehicles sold by our subset of sellers selected for additional analysis. Because of this, coefficient estimates for vehicle characteristics do not incorporate information from the broader set of vehicles sold. To address this limitation, we first used auction sale prices from all sellers in our data (those with less than 15 sales included) to generate coefficients (θ) for an estimate of the market price based only on the controls and omitting any seller characteristics related to other channels:

$$\text{E}[\text{MarketPrice}_{ij}] = \left(\theta C_{ivj}\right) \tag{27}$$

Then, for each auction sale by a seller from our subset of selected sellers we subtracted the expected market price (θC_{ivj}) from the actual sale price to calculate the price premium for the seller in the auction:

$$\text{Premium}_{ij} = \text{Price}_{ij} - \text{E}[\text{MarketPrice}_{ij}] \tag{28}$$

Finally, we regressed the identified seller characteristics on the price premium, as given in Equation 29, which gave the parameters (Ψ) for the seller characteristics associated with other channels, S_j. In this last step we did not include the controls, as they are incorporated into the calculation of the price premium.

$$\text{Premium}_{ij} = \left(\psi S_j\right) + \varepsilon \tag{29}$$

7. Empirical Results

Descriptive statistics for all the variables are given in Table 4, and correlations between all variables are given in Table 5. Our four measures of the sellers' non-auction channels capabilities (AHI, TP, ECC_{WEB} and ECC_{SOW}) are not highly correlated indicating they are measuring different seller characteristics. In addition, while auction-sale and item-sale are understandably correlated (.61), the correlation is low enough that it justifies examining these dependent variables separately.

The results from the logistic regression analyses and the price analyses are found in Table 6. Before discussing the main results, we discuss some interesting findings for relevant control variables. Several of the controls in our analysis (miles, certified, inspected, warranty) corresponded with the level of quality uncertainty associated with the vehicle. The miles of the vehicle is positively related with auction-sale (p<.001) and item-sale (p<.001), and negatively related to the price (p<.001). A warranty had the opposite effect, being negatively related to auction/item-sale (p<.001), and positively related to the price (p<.001). These findings suggest that having lower quality uncertainty (due to lower miles or a warranty) increased the likelihood the vehicle would be sold through non-auction channels, but at the same time increased the auction price in case of a sale. In addition, the combination of reduced likelihood of sale in the auction channel and increased price in case of a sale suggests that the effect on the seller reserve price exceeded the effect on bidders' willingness to pay[6]. Whether the car was certified or not had no effect on any of the auction channel outcomes. Being inspected influenced positively both the likelihood of auction/item-sale (p<.001) and the price, suggesting that the effect of being certified on bidders' willingness to pay exceeded the effect on sellers' reserve price.

The number of positive feedbacks was, as expected, positively associated with auction-sale (p<.001) and item-sale (p<.001). In addition, while the number of positive feedbacks did not have the expected positive association with the auction sale price, it was positively associated (p<.001) with the expected market price (Equation 27). Thus, when not taking into account seller characteristics related to demand in other channels, the positive feedback had a significant impact on auction sale-price, but once incorporating these characteristics the impact was no longer significant. Negative feedback had the opposite effects, decreasing the probability of auction-sale (p<.001) and item-sale (p<.01) while reducing the auction sale price (p<.01) and the expected market price (p<.001). A higher starting bid was positively associated with auction-sale (p<.001), item-sale (p<.001), and the price when a sale occurred (p<.001). Vehicles were more likely to sell when auctions ended on a weekend (p<.05), and the auctions ending in the buy-it-now option had on average a higher sale price[7]. Finally, the findings for the *number of auctions* control indicate the complex nature of the search process of multichannel retailers. An increase in the number of total auctions for the vehicle reduces the likelihood that the current auction would end in a sale (p<.001). However, an increase in the total number of auctions in which the vehicle is offered increases the likelihood it is sold in the online auction channel (p<.001). In addition, the number of auctions was negatively related to the auction sale price when the price regression included seller characteristics associated to demand in non-auction channels (p<.05), but positively related to the estimated market price (Equation 27) calculated based only on the controls (p<.01).

[6] Buyers are willing to pay more for a car with a warranty. The seller, on the other hand, might set a higher reserve price when the car has a warranty. Both changes (in buyers' valuations and in the seller's reserve) contribute to a higher expected sale price, but while the former increases the likelihood of a sale the latter decreases it.
[7] Because buy-it-now was perfectly associated with auction-sale/item-sale, it was dropped from these analyses.

The main results from the analyses generally support the analytical model outcomes for the joint channel management strategy. We find that higher average household income in the dealer's surrounding reduced the likelihood of auction-sale ($p<.001$) and item-sale ($p<.05$), but increased the selling price ($p<.05$) and the price premium ($p<.05$) when a sale occurred. Similarly, the total population surrounding the dealer location was associated with lower likelihood of item-sale in the auction channel ($p<.01$), but higher sale price ($p<.05$) and price premium ($p<.01$) when a sale occurred. The relationship between total population and auction-sale was in the expected direction but not significant. These findings indicate that retailers with better offline retail location face lower likelihood of selling vehicles in the auction channel, but higher sale price when a sale occurs.

Both measures of electronic commerce capabilities of the dealer were negatively associated with the likelihood of auction-sale ($ECC_{WEB,}$ $p<.001$; $ECC_{SOW,}$ $p<.05$) and the likelihood of item-sale in the online auction channel ($ECC_{WEB,}$ $p<.001$; $ECC_{SOW,}$ $p<.001$), but positively associated with the auction sale price ($ECC_{WEB,}$ $p<.01$; $ECC_{SOW,}$ $p<.001$). Results for the price effects were also significant using the alternate measure of price premium ($ECC_{WEB,}$ $p<.001$; $ECC_{SOW,}$ $p<.05$).

In summary, the results were consistent with the predictions of the analytical model for the joint channel management (Proposition 2). In addition, seller characteristics related to the non-auction channels influenced the auction channel outcomes in a way consistent with search theory—i.e., variables indicating opportunities in non-auction channels were negatively related to the likelihood an auction ends in a sale, but positively related to the sale price, suggesting sellers with better opportunities in other channels set higher auction reserve prices.

Finally, in order to understand the relative impact of changes in the independent variables on outcomes, we used the results from the logistic analyses to calculate the marginal effects across the range of the logged variables. Overall, effect sizes for the outcome variables, shown in Table 7, are in a range where they are meaningful. Effects sizes for item-sale were stronger (4.72% - 10.15%) than for auction sale (n.s. - 3.67%). This suggests that seller characteristics which impact demand in other channels influence the auction-channel outcome more than an individual auction outcome, which may be subject to more variability. Further, the effect sizes for the impact of average household income ($879/$562), total population ($828/$868), and ECC_{WEB} ($856/$1,174) were similar across the calculation of price and price premium, respectively. The effect for ECC_{SOW} was significantly larger for the price calculation ($1,725) than the price premium calculation ($539), but in the same direction. To frame the above effects sizes in terms of the context, we note that on average dealerships reported net profits of approximate $220 per vehicle in 2007 (NADA 2008).

Table 5. Correlation Table

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1 Miles	1																		
2 Certified	-.01	1																	
3 Inspected	-.10	.08	1																
4 Warranty	-.58	.06	.10	1															
5 Time	.03	.00	-.01	-.03	1														
6 Positive Feedback	.02	-.01	-.23	.02	-.01	1													
7 Negative Feedback	.16	-.04	-.16	-.02	-.04	.55	1												
8 # of Auctions	-.12	.05	.05	.14	-.08	.11	-.01	1											
9 Number of Bids	.02	-.01	.06	-.01	.03	.00	.01	.02	1										
10 Auction Length	-.04	-.02	-.08	.01	.05	.21	-.01	.12	.09	1									
11 Starting Bid	-.23	.00	-.05	.14	-.04	-.13	-.14	-.05	-.38	.02	1								
12 Weekend	.01	.00	.05	.00	.00	-.05	.01	.01	.01	.02	.00	1							
13 Buy-It-Now	.02	.00	.01	-.03	-.05	-.01	-.03	-.13	-.09	-.27	.04	.01	1						
14 Household Inc.	-.03	-.02	.08	.02	.01	-.18	-.24	.09	.01	-.08	.01	.00	-.01	1					
15 Total Population	.02	.04	.08	-.04	-.01	.04	-.04	.10	-.01	.03	-.04	-.03	.02	.03	1				
16 ECC$_{WEB}$	-.15	.05	.12	.12	.03	-.17	-.23	.01	.13	-.12	-.14	.05	-.04	.13	-.05	1			
17 ECC$_{SOW}$	-.14	.01	-.10	.13	.00	.11	-.04	.13	-.03	.17	.04	.02	-.05	.10	-.02	.16	1		
18 Auction-sale	.08	-.01	.01	-.08	-.05	-.04	-.01	-.17	-.01	-.22	.02	.01	.74	-.02	.00	-.05	-.08	1	
19 Item-sale	.09	.01	.02	-.08	-.11	-.01	-.01	.05	.03	-.08	-.02	.00	.45	.00	.02	-.09	-.09	.61	1
20 Price	-.45	.00	.06	.32	.00	-.06	-.14	.07	.03	.07	.43	-.01	.09	.08	.01	.02	.17	.07	.03

Table 6. Analyses Results

Variables	Auction-Sale	Item-Sale	Sale Price[1,3]	Market Price[2,3]	Price Premium
ln(AHI)	-0.384***	-0.197*	0.648*		0.414*
	(0.089)	(0.090)	(0.259)		(0.209)
ln(TP)	-0.006	-0.052**	0.126*		0.132**
	(0.020)	(0.020)	(0.057)		(0.045)
ln(ECC_{WEB})	-0.113**	-0.177***	0.390**		0.534***
	(0.035)	(0.037)	(0.118)		(0.091)
ln(ECC_{SOW})	-0.063$^{\Psi}$	-0.166***	0.534***		0.167*
	(0.035)	(0.036)	(0.114)		(0.085)
ln(Miles)	0.067***	0.086***	-1.829***	-0.798***	
	(0.018)	(0.019)	(0.073)	(0.034)	
Certified	-0.225	-0.005	0.675	0.258	
	(0.223)	(0.228)	(0.696)	(0.243)	
Inspected	0.240***	0.255***	0.273**	0.227***	
	(0.034)	(0.036)	(0.100)	(0.069)	
Warranty	-0.158***	-0.172***	0.973***	1.485***	
	(0.042)	(0.043)	(0.125)	(0.089)	
Time	-0.029***	-0.040***	0.006	-0.022***	
	(0.003)	(0.003)	(0.008)	(0.006)	
ln (Positive Feedback)	0.196***	0.192***	-0.028	0.119***	
	(0.015)	(0.016)	(0.048)	(0.025)	
ln (Negative Feedback)	-0.210***	-0.211***	-0.175**	-0.265***	
	(0.019)	(0.019)	(0.057)	(0.047)	
ln(Number of Auctions)	-0.838***	0.247***	-0.155*	0.169**	
	(0.024)	(0.025)	(0.069)	(0.053)	
Number of Bids	0.018***	0.024***	0.023***	0.045***	
	(0.002)	(0.002)	(0.006)	(0.004)	
Auction Length	-0.265***	-0.171***	0.052*	0.059***	
	(0.007)	(0.008)	(0.021)	(0.015)	
Starting Bid	0.017***	0.009***	0.051***	0.108***	
	(0.002)	(0.002)	(0.005)	(0.004)	
Ended on Weekend	0.074$^{\Psi}$	0.084$^{\Psi}$	-0.059	-0.324***	
	(0.039)	(0.046)	(0.110)	(0.076)	
Ended in Buy-It-Now			0.748***	1.065***	
			(0.107)	(0.078)	
Constant	3.510***	1.678$^{\Psi}$	34.355***	33.100***	-7.127**
	(1.003)	(1.016)	(2.980)	(0.407)	(2.303)
Observations	43,461	21,630	5,144	14,601	5,144
Adj R^2/Pseudo R^2	0.138	0.059	0.958	0.945	0.011

Notes: Standard errors in parentheses; *** p<0.001, ** p<0.01, * p<0.05, $^{\Psi}$ p<0.10;
[1] Price from OLS regression including the seller characteristics and the controls. [2] Price calculations based only on the controls and including all multichannel sellers. [3] Dummy variables for vehicle model (1391), vehicle year (6), and color (7) are not shown.

Table 7. Marginal Effects Across Range of Independent Variables

Variable	Min	Max	Auction-Sale	Item-Sale	Price	Price Premium
ln(Average Household Income)	10.80	12.15	-3.67%	-4.72%	$879	$562
ln(Total Population)	9.20	15.78	(N.S.)	-6.40%	$828	$868
ln(ECC_{WEB})	0.00	2.20	-2.01%	-7.47%	$856	$1,174
ln(ECC_{SOW})	-1.64	1.59	-1.59%	-10.15%	$1,725	$539

Note: N.S. =Non significant

7. Discussion

The Internet and online auctions in particular have influenced the way that buyers and sellers interact in a variety of industries. As sales processes are conducted in both online and offline channels, and retailers have many options as to where and at what prices they can list their products, it is necessary to gain a greater understanding of multichannel activities of buyers and sellers (Neslin and Shankar 2009). Our work contributes to this stream of research, offering an analytical and empirical treatment of seller use of online auctions along with other online and offline channels, and demonstrating the interdependency of the channels. The findings provide insights into important auction channel outcomes and the associated revenue for sellers, and thus have implications for both theory and practice, as is further discussed below.

7.1. Implications for Theory

This paper makes several contributions to the theoretical understanding of how sellers operate when using online auctions along with other sales channels and to the study of online auctions in multichannel contexts. First, past research on online auctions has mainly used auction sale price or the likelihood a reserve price will be met (e.g., Bajari and Hortacsu 2003; Lucking-Reiley et al. 2007) as characteristics of the auction channel performance. This research further identifies the combination of sale price, probability an individual auction ends in a sale, and the probability the item sales via the auction channel as an inclusive way of understanding how seller characteristics related to other channels influence auction outcomes. For example, a positive association between seller characteristics and auction price could result from an increase in the bidders' valuations, an increase in the seller's reserve price (also often referred to as the seller's valuation), or both. In the case of retail location and electronic commerce capabilities, the accompanying reduction in the auction-sale likelihood suggests that the cause of the positive association with sale-price was primarily an increase in the seller's reserve price, because an increase in bidders' valuations would have the opposite effect on auction-sale. These two outcomes alone, however, do not characterize whether the increase in the seller valuation is a result of opportunities outside of the auction channel or an increase in her willingness to search within the auction channel. If the identified seller characteristics (AHI, TP, etc.) were associated with better opportunities within the auction channel, then they would be associated with a higher sale-price and lower auction-sale likelihood but not associated (or positively associated) with the item-sale likelihood. The combination of the increase in the auction price and a decrease in the auction-sale and item-sale ratios provides substantive evidence that the effects result from better opportunities in the non-auction channels.

Second, our analytical model further explores the implications of separate and joint channels management. With joint channel management, sellers with better opportunities to attract buyers in the non-auction channels, increase their reserve price not only in the non-auction channel but also in the auction channel. This strategy is likely to result in an increase in auction prices, a reduction in the number of auctions that end in a sale, and a reduction of the number of items that sell via the auction channel. In contrast, if sellers manage each channel separately (maximizing each channels' profit in isolation), then factors that influence the demand in the non-auction channel would have no effect on the auctions reserve prices and the auctions' sale prices.

A third theoretical implication of this work is that it builds upon the stream of research that uses search theory to understand behaviors of sellers utilizing auctions. Search theory has long been used to understand the consumer shopping process as well as the impact of the Internet on commerce (Putrevu and Ratchford 1997; Ratchford and Srinivasan 1993), and on market outcomes (Bakos 1997). Consumers search for products until the benefits of continuing the search no longer outweigh the costs, and by lowering search costs the Internet has lowered prices and increased welfare through increased product variety (Brynjolfsson 1996). In a similar way, sellers that use successive auctions (Bernhardt and Scoones 1994; Cai et al. 2007) or alternate between auctions and other channels (Genesove 1995) can be conceptualized as searching for high-valuation buyers. We add to this stream of literature by showing that search theory can be a useful for understanding the decisions of sellers that utilize auctions in parallel to other channels.

Finally, the empirical findings suggest that researchers must consider biases induced by multichannel sales processes when studying online auctions. We find that sellers are likely to manage channels jointly, and thus their strategies in the online auction channel would take into account opportunities in non-auction channels. When sellers use online auctions in parallel to other channels, studies of any single channel in isolation may be biased, even if each channel targets a separate group of customers.

7.2. Implications for Practice

This work also has several implications for practitioners. First, while operating in a multichannel retail environment is likely to be very complex for organizations, we suggest that conceptualizing the use of multiple channels as a search process can provide a relevant framework for optimizing such business processes. Under this framework it becomes clear that improved opportunities in one channel should in most cases increase the seller's reserve prices across all channels she uses. The optimal strategy in a given channel should be linked to seller's characteristics affecting its demand in other channels.

Second, when sellers evaluate the performance of their auctions, they should consider all three outcomes presented in this paper. For example, a decrease in the auction-sale likelihood (% of auctions that end in a sale) might be perceived badly when considered in isolation, but if it is accompanied by an increase in the sale prices and a decrease in the item-sale likelihood then it might indicate that the seller simply improved her capabilities to attract offers in other channels.

Finally, price sensitive consumers may be able to improve their welfare by searching for sellers who do not have access to other channels. As shown here, sellers with multichannel operations—and especially those with strong alternative channels—are more likely to expect higher sale prices without providing any specific benefit relative to other online sellers.

7.3. Limitations

One key limitation of the empirical work presented here is that it involves only one class of products (i.e., vehicles) and thus the results may be different when considering other types of products. For example, while for vehicles the market on eBay acts as a discount channel when compared to the offline channel, probably due to the fact that it is harder to determine quality of a vehicle when buying online, for other product categories the online auction market might provide a channel in which comparable prices can be obtained. Another limitation is that we cannot examine how direct characteristics of the demand in the other channels (such as the frequency and the distribution of offers) affect auction outcomes. Thus, we have to infer the relationships between observable seller characteristics (such as retail location) and the characteristics of the demand in non-auction channels.

Finally, our analytical results were derived considering a specific distribution of consumers' valuations, the uniform distributions. We acknowledge that analytical models with other distributions might reach somewhat different conclusions. However, we are encouraged by the fact that the empirical results comply with our analytical model predictions.

8. Conclusion

The Internet and electronic commerce provide retailers with tremendous flexibility in the ways they engage and transact with customers. This research shows how the online auction channel outcomes are impacted by seller characteristics that influence her demand in other channels. While prior work examines auction outcomes considering the auction channel in isolation, this is among the first papers to investigate how the auction outcomes relate to a seller's multichannel activities and characteristics.

REFERENCES

Ariely, D., I. Simonson. 2003. Buying, bidding, playing, or competing? Value assessment and decision dynamics in online auctions. *J. Consum. Psychol.* **13**(1&2) 113-123.

Arora, A., H. Xu, R. Padman, W. Vogt 2002. Optimal bidding in sequential online auctions. Working Paper, Carnegie Mellon University, Pittsburgh, PA.

Ashenfelter, O. 1989. How auctions work for wine and art. *J. Econom. Perspect.* **3**(3) 23-36.

Ashenfelter, O., K. Graddy, M. Stevens 2003. A study of sale rates and prices in impressionist and contemporary art auctions. Working Paper, Princeton University, Princeton, NJ.

Ba, S., P. A. Pavlou. 2002. Evidence of the effect of trust building technology in electronic markets: Price premiums and buyer behavior. *MIS Quart.* **26**(3) 243-268.

Bakos, J. Y. 1997. Reducing buyer search costs: Implications for electronic marketplaces. *Management Sci.* **43**(12) 1676-1692.

Bapna, R., P. Goes, A. Gupta. 2003. Replicating online yankee auctions to analyze auctioneers' and bidders' strategies. *Inform. Systems Res.* **14**(3) 244-268.

Bernhardt, D., D. Scoones. 1994. A note on sequential auctions. *Amer. Econom. Rev.* **84**(3) 653-657.

Brynjolfsson, E. 1996. The contribution of information technology to consumer welfare. *Inf. Syst. Res.* **7**(3) 281-300.

Brynjolfsson, E., M. D. Smith. 2000. Frictionless commerce? A comparison of Internet and conventional retailers. *Management Sci.* **46**(4) 536-585.

Cai, G., P. R. Wurman, X. Chao. 2007. The non-existence of equilibrium in sequential auctions when bids are revealed. *J. Elect. Com. Res.* **8**(2) 141-156.

Davies, G., K. Harris. 1990. *Small Business: The Independent Retailer.* MacMillian, London.

Diamond, P. A. 1985. *Search theory.* Massachusetts Institute of Technology, Dept. of Economics, Cambridge, MA.

Dickinson, R. 1981. *Retail Management, with Cases.* Austin Press, Austin, TX.

eBay, I. 2011. Ebay inc. Reports strong second quarter 2011 results. ebay.com.

Etzion, H., E. Pinker, A. Seidmann. 2006. Analyzing the simultaneous use of auctions and posted prices for online selling. *Manuf. & Service Operations Management* **8**(1) 68-91.

Forman, C., A. Ghose, A. Goldfarb. 2009. Competition between local and electronic markets: How the benefit of buying online depends on where you live. *Management Sci.* **55**(1) 47-57.

Genesove, D. 1995. Search at wholesale auto auctions. *Q. J. Econom.* **110**(1) 23-49.

Genesove, D., C. Mayer. 2001. Loss aversion and seller behavior: Evidence from the housing market. *Quart. J. Econom.* **116**(4) 1233-1260.

Kumar, V., R. Venkatesan. 2005. Who are the multichannel shoppers and how do they perform?: Correlates of multichannel shopping behavior. *J. Interact. Mark.* **19**(2) 44-62.

Kuruzovich, J., S. Viswanathan, R. Agarwal. 2010. Seller search and market outcomes in online auctions. *Management Sci.* **56**(10) 1702-1717.

Livingston, J. A. 2005. How valuable as a good reputation? A sample selection model of internet auctions. *Rev. Econ. & Stat.* **87**(3) 453-465.

Lucking-Reiley, D. 2000. Vickrey auctions in practice: From nineteenth-century philately to twenty-first-century e-commerce. *J. Econom. Perspect.* **14**(3) 183-192.

Lucking-Reiley, D., D. Bryan, N. Prasad, D. Reeves. 2007. Pennies from ebay: The determinants of price in online auctions. *J. Ind. Econom.* **55**(2) 223-233.

NADA 2008. Nada data 2008: Economic impact of america's new-car and new-truck dealers. NADA's AutoExec Magazine.

Neslin, S. A., V. Shankar. 2009. Key issues in multichannel customer management: Current knowledge and future directions. *J. Interactive Market.* **23**(1) 70-81.

Ottaway, T. A., C. L. Bruneau, G. E. Evans. 2003. The impact of auction item image and buyer/seller feedback rating on electronic auctions. *J. Computer Information Systems* **43**(3) 56-60.

Overby, E., S. Jap. 2009. Electronic and physical market channels: A multiyear investigation in a market for products of uncertain quality. *Management Sci.* **55**(6) 940-957.

Pennington, A. L. 1968. Customer-salesman bargaining behavior in retail transactions. *J. Market. Res.* **5**(3) 255-262.

Pinker, E. J., A. Seidmann, Y. Vakrat. 2003. Managing online auctions: Current business and research issues. *Management Sci.* **49**(11) 1457-1484.

Putrevu, S., B. T. Ratchford. 1997. A model of search behavior with an application to grocery shopping. *J. Retailing* **73**(4) 463-486.

Ratchford, B. T., M.-S. Lee, D. Talukdar. 2003. The impact of the internet on information search for automobiles. *J. Marketing Res.* **40**(2) 193-209.

Ratchford, B. T., N. Srinivasan. 1993. An empirical investigation of returns to search. *Marketing Sci.* **12**(1) 73-87.

Resnick, P., R. Zeckhauser 2002. Trust among strangers in internet transactions: Empirical analysis of eBay's reputation system. M. R. Baye ed. *Advances in Applied Microeconomics*. 11, Elsevier Science, Amsterdam,

Van Heck, E., P. M. Ribbers. 1997. Experiences with electronic auctions in the Dutch flower industry. *Electronic Markets* **7**(4) 29-34.

Venkatesan, R., V. Kumar, N. Ravishanker. 2007. Multichannel shopping: Causes and consequences. **71**(2) 114-132.

Venkatesh, V., R. Agarwal. 2006. Turning visitors into customers: A usability-centric perspective on purchase behavior in electronic channels. *Management Sci.* **52**(3) 367-382.

Zhu, K. 2004. The complementarity of information technology infrastructure and e-commerce capability: A resource-based assessment of their business value. *J. Management Inform. Syst.* **21**(1) 167-202.

Zhu, K., K. L. Kraemer. 2002. E-commerce metrics for net-enhanced organizations: Assessing the value of e-commerce to firm performance in the manufacturing sector. *Inform. Systems Res.* **13**(3) 275-295.

Appendix A. Dealer's website functionalities used to determine the dealers electronic commerce capabilities (ECC_{WEB})

1. Lists price on website.
2. Lists options on website.
3. Lists all new vehicles on website.
4. Lists photo on website.
5. Links to independent sites.
6. Tool for credit application.
7. Price quotes request form.