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Auctions versus Posted Price Internet Channels: A Seller's Perspective on When to Make and When to Take

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Report Summary

In today's marketplace, firms face a dizzying array of routes to market. Sellers in multi-generational, heterogeneous product markets must choose the appropriate channel or sequence of multiple channels to maximize their margins and probabilities of sale. Such markets might include, but are not limited to, goods such as used products, collectibles, homes, and even dating partners.

Here, Ernan Haruvy, Sandy Jap, and Robert Zeithammer develop a model to explain how firms should choose between auction- versus Internet-based channel formats. Based on data from the wholesale used car market, they propose a theoretical model by which sellers can maximize their profits by managing their product placement choices between an auction channel (which yields higher probability of sale with lower margins) versus an Internet channel (which yields lower probability of sale but significantly higher margins against a high cost of delay).

This multichannel context raises a number of intriguing issues. How should the seller choose among these channel options and what are the circumstances under which the choice of each channel dominates? In other words, how can the seller optimally manage the tradeoffs between the probability of sale and expected margins against a high cost of delay? Does it make sense for the seller to use a combination or sequence of channels in its market approach?

The authors advance a structural model to inform how the seller must trade-off the costs and benefits of one channel over another and identifies their options within the context of a three-period game. The model predicts the impact of changing channel listing fees and ascertains the period in which the seller will switch its selling strategies across the channel options as well as the timing and duration that is optimal for each offering. The model also improves the seller's price premium and sales probabilities across these channels by identifying and incorporating systematic channel and product characteristics (such as car condition, seasonality, and the role of past sale failures).

Finally, the authors use a proprietary dataset to show that the theoretical model resonates with the real institutional context and offers empirical support for its various assumptions. Their investigation suggests that such models will allow sellers to develop selling strategies based on channel selling costs, derive implications for market and channel design, prescribe and identify key switching points in a go-to-market strategy, and connect channel costs to the selling price across channels. It offers a starting point for further investigations into optimal channel strategies for forward-looking, profit-maximizing sellers faced with multiple routes to market.

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Introduction

A fundamental problem of the firm is how to get their goods to customers. As a result, channel intermediaries play a key role in offering routes to market. How can sellers in multigenerational, heterogeneous product markets choose the appropriate channel or sequence of multiple channels to maximize their margins and probabilities of sale? This is the central task faced by many sellers in general. We will investigate this question specifically in markets where quality differences exist. Such markets might include but are not limited to goods such as used products, collectibles, homes, and even dating partners. This context is particularly challenging because quality differences should also map to price differences; in other words, products in better condition or of higher quality ought also to fetch higher prices. For this reason, dynamic pricing mechanisms such as auctions can be particularly effective and efficient channel formats (versus posted price channels such as retail outlets) particularly when the buyers and sellers are knowledgeable and regular participants.

These characteristics are vividly illustrated in the wholesale used car market, which also serves as the context for this work. There are 24 times as many used cars on the road than new cars. The wholesale used car market is three times greater than the new car market, representing over $301 billion in annual exchange, involving over 240 million cars and over 80,000 businesses including dealers, rental car firms, banks, car manufacturers, financing companies, fleets, and many others. The customers in this market are organizational buyers who repeatedly purchase multiple units and are knowledgeable about product quality and industry trends.

Sellers have the choice to sell their cars in a weekly auction, held at thousands of facilities across the world (hereafter referred to as the *physical* channel) or in an online 24/7 channel (hereafter the *Internet* channel). These channels possess key tradeoffs in terms of their timing, pricing structure, and assortments. For example, the physical channel involves collocated products and real-time auctions, which suggests that sellers must move cars to auction sites and take the market price for their goods, making them *price takers*[1]. This channel moves large volumes of cars from sellers to buyers very quickly; the competitive auction mechanism makes it unlikely that sellers will earn substantial premiums with this approach. In contrast, the

[1] Sellers are allowed to reject an unacceptable winning price, which is presumably some price lower than the market value of the car minus the cost involved in selling the car later or elsewhere. However, failures to sell in the physical channel are relatively rare.

Internet channel allows purchases of cars from any location and at any time, thus sellers are typically *price makers* – i.e., they set the posted prices for their goods. Sellers in this channel face a clear tradeoff between the probability of sale (typically lower than the physical channel) with a high cost of delay, but the opportunity to capture a price premium is much more likely.

The juxtaposition of choices in this multichannel context raises a number of intriguing issues, such as how should the seller choose among these channel options and what are the circumstances under which the choice of each channel dominates? In other words, how can the seller optimally manage the tradeoffs between the probability of sale and expected margins against a high cost of delay? Does it make sense for the seller to use a combination or sequence of channels in its market approach? In this research, we advance a structural model to inform the seller‘s optimal channel choice and sequence. We also improve the seller‘s price premium and sales probabilities across these channels by identifying and incorporating systematic channel and product characteristics (such as car condition, seasonality, and the role of past sale failures).

Contribution

From a theoretical standpoint, we inform the multichannel literature in marketing and information technology. We advance a structural model that identifies optimal seller channel choice and sequence strategy as a function of the seller‘s channel costs and car characteristics. The model provides a framework for understanding how the seller must tradeoff the costs and benefits of one channel over another and illuminates their options within the context of a three period game. The model identifies the period in which the seller will switch its selling strategies across the channel options as a function of its selling costs across the channels and allows us to predict the impact of changing channel listing fees, capture the key tradeoffs that sellers face, and account well for subsequent observed data.

We use a proprietary dataset to establish some external validity for the structural model. Collectively, our intent is to provide a starting point for stimulating additional investigations into optimal channel strategies for forward looking, profit maximizing sellers faced with multiple routes to market.

This work allows for several important insights. First, we can inform the sellers‘ channel choices and decision-making process by estimating the sale probabilities and likely premiums associated with their choice of the physical or Internet channel. Second, we provide important managerial implications for the market maker. Specifically, we develop a selling strategy based on channel selling costs, derive implications for market and channel design, prescribe and identify key switching points in a seller‘s go-to-market strategy, and connect channel costs to the selling price across channels. Finally, we consider the external validity of our theoretical model.

Organization of this report. From here, we briefly review relevant past research on multichannel management and the effects of adding an Internet channel to a legacy channel. The bulk of this work has taken the perspective of the buyer; we are one of few that explicitly examine the seller‘s perspective. This is followed by a description of the wholesale auto market, and the development of a structural model of dynamic channel choice that allows us to better understand how the seller trades off the benefits and costs of one channel over another and predicts the period in which sellers will switch their go to market strategy among the channel possibilities. We then offer data in support of the model assumptions and to provide external validity and conclude.

Background

The research is positioned within the growing literature on multichannel usage and choice in the marketing and information technology literatures. We are particularly focused on issues involving the choice between online and offline channels. The bulk of the extant literature examines the issues from the perspective of the buyer, while considerably less speaks to the seller‘s task.

Buying in a multichannel context. The buyer‘s channel choice between a direct online market and conventional (in our case, wholesale) channel can be modeled as a tradeoff between two payoff components. For example, Balasubramanian (1998) modeled this choice as a tradeoff between fixed disutility costs in the conventional channel and the lowered search and transportation costs online. Overby and Forman (2009) view channel choice as a mechanism for shifting purchases across a wider geographic area as well as shifting their purchases from high-price to low-price locations. In the present research we focus on the tradeoff between the car‘s premium conditional on sale and the probability of sale.

Another stream of literature has evolved to focus on the antecedents of the customer‘s channel choice and organizational performance. Researchers have found that channel choice is driven by buyer characteristics (Hitt and Frei 2002; Xue, Hitt and Harker 2007) including price expectations (Brynjolfsson and Smith 2000), price sensitivities (Chu, Chintagunta and Cebollada 2008), basket size and cross-buying behaviors (Venkatesan, Kumar, and Ravishanker 2007) and firm variables such as marketing communications (Thomas and Sullivan 2005) and product assortment variety (Brynjolfsson, Hu and Smith 2003). This stream has found that multichannel buyers are generally profitable (Sullivan and Thomas 2004, Venkatesan, Kumar, and Ravishanker 2007) and that buyers who shop online have lower price sensitivities (Chu, Chintagunta and Cebollada 2008) and their surplus gains through increased product variety is substantially greater than the gains received from increased competition among sellers (Brynjolfsson, Hu, and Smith 2003).

The use of multiple channels has also focused on how the addition of an Internet channel impacts the organizational performance of a firm with offline channels. This stream of work shows that the addition of an Internet channel generally impacts overall firm performance in a positive manner (Geyskens, Gielens, and Dekimpe 2002; Deleersnyder et al 2002, Yoo and Lee 2011), although it can also lead to an increase in costly product returns and physical channel investments that decrease profits (Ofek, Katona and Sarvary, 2011).

More broadly, research has focused on the sale of homogeneous goods through online and offline channels. One important finding is that Internet channels facilitate price competition with offline channels (although not without some friction), branding, awareness, and trust remains important differentiators among Internet retailers (Brynjolfsson and Smith 2000); this is consistent with the predictions of Alba et al (1997).

Adding an Internet channel. Research considers how the addition of the Internet channel impacts the physical channel. For example, Biyalogorsky and Naik (2003) show that the Internet channel minimally cannibalizes offline channel sales and can enhance overall brand equity, while others examine customer migration across the channels in response to marketing communications (Ansari, Mela and Neslin 2008), channel inertia and dynamic pricing mechanisms (Langer et al 2008). Forman, Ghose and Goldfarb (2009) consider the effect of the physical channel on online sales. They find that when a store opens locally, people substitute away from online purchasing, suggesting that the disutility costs of purchasing online are substantial and offline transportation costs matter. Offline entry also decreases consumer sensitivity to online price discounts.

Our research departs from these trends in important ways. First, our focus is on the *seller's choice* of channel, as opposed to the buyer‘s channel choice. Historically, research on the seller‘s use of multiple channels has examined the seller‘s choice between a vertically integrated (i.e., direct) channel and an independent (or indirect) channel form (e.g., Dutta et al 1995; Moriarty and Moran 1990; Purohit 1997; Sa Vinhas and Anderson 2005). We focus on the seller‘s choice among two independent channel forms – a physical and internet channel – through one intermediary (i.e., the market maker). We are particularly interested in the implications of this channel choice for the market maker, who must manage a *two-sided market* of both downstream retail buyers and wholesalers and upstream fleet and manufacturer sellers. The perspective of prior research has been on intermediaries who need only focus on their downstream customer.

From a product perspective, we are starkly different. The products in our research are *used, heterogeneous, multi-generational products*, whereas much of the past work has examined the sale of new, homogenous units of commodity goods such as books, movies, and packaged goods. Finally, past research has mostly examined channels with posted prices. In contrast, our research examines channels in which *sellers can be both price makers* (i.e., via posted prices) *and price takers* (i.e., via a dynamic auction mechanism).

The Setting

The North American wholesale car market has been described by Genesove (1995), Grether and Plott (2009), and Overby and Jap (2009). Sellers are fleet organizations (e.g., car rental companies), manufacturers (e.g., BMW leasing), and retailers (e.g., independent and franchise dealers). Buyers are primarily retailers and wholesalers; consumers are not allowed in the market events. The market maker offers approximately 100 auction locations where weekly sales facilitate more than 10 million transactions representing over $50 billion in value. Sellers can choose to sell their cars through these physical locations or via an online marketplace where cars are available on a 24/7 basis. Buyers are given identical information about the car for sale in both channels. Specifically, they can view the car and are given a complete list of its attributes, location, the market maker‘s price expectation, the car condition, and whether the car has been recently offered (i.e., it failed to sell at the last offering).

An expected market price for each vehicle is determined based on “hard” observable data such as the car body, year, mileage, and the selling price of cars with those attributes over the past 30 days. Each car is given a condition code, an integer ranging from 0 to 5 with 0 representing salvage parts, 1=extra rough, 2=rough, 3=average, 4=clean and 5 represents an extra clean condition. In order to receive a grade 5, the car can only have minor defects and require no paint or body work, while a grade 0 car is one that is inoperable and suitable only for scrap. The condition code is assigned by the market maker, who examines the car along nine dimensions: body defects (ranging from scrap-substantial-minor), previous repairs (poor to acceptable to high quality), parts (missing broken, minor missing, ok), interior (severe damage, normal wear, no damage), frame (bent, possible previous substandard repair or probable damage, ok), powertrain (inoperable, operable poor condition, ok), accessories (inoperable, minor repairs, ok), fluids (low/dirty, may need service, full/clean), and tires (flat, worn, good, near new).

In the physical channel, buyers are notified in advance of the sale event which cars will be offered and in which lane. On the day of the sale, buyers can walk the lots to “kick the tires” and physically inspect the cars. During the sale, buyers can either be physically located at the site or can participate via an Internet browser; regardless, all buyers can observe the bidding activity and competitive bids. A sales event can span 2-3 hours, with hundreds of cars being offered sequentially across 15-20 plus sale lanes simultaneously. Buyers are free to migrate across the lanes and bid on any car. An auctioneer who determines the maximum price in the group and looks to the seller for approval conducts the bidding process. The seller representative can either accept the price or refuse to sell at that point. Hence, the seller acts only after the buyers have bid and the entire offer distribution is observed.

In contrast, the Internet channel is not limited by time or space. The cars may be located at the market maker facilities or customer lots; the market runs 24/7 and is accessible to organizational buyers all over the world. Cars in the Internet channel may be offered for bidding, which would seem a viable tactic in situations where the markets are thin and sellers are short on information. However, we observe that a large majority (61%) is offered at a fixed (i.e., buy now) price. A buy now price is the price at which the seller stipulates *ex ante* the price at which she is willing to end the auction immediately. For early sellers, there is an incentive to use the buy now option, particularly if a similar car will be offered later by a competitive seller and bidders desire multiple cars (Kirkegaard and Overgaard 2008). Thus, there is little bidding competition in the Internet channel; perhaps this channel is used for spot purchases, although as will be subsequently described in the Data section, the channel is not solely used for long-tail purchases of rare cars.

A Model of Dynamic Channel Choice

We begin by developing some key assumptions and establishing the scope of the model. The world evolves in discrete time, with one period equivalent to a week. Each car *i* is described by its ex-ante expected selling price m_i, condition Z_i, and a scalar state variable x_i that counts how many times the car has been offered for sale recently without success. The ex-ante selling price is based on a moving average of similar cars sold recently, and it accounts for all other vehicle characteristics, such as mileage or year, other than Z_i.

In each period, the seller decides between two channels for selling the car: j=0 is the physical channel and j=1 is the online channel. Seller s faces a cost $c_{s,j}$ of offering the car for sale in channel j. This cost is incurred whether or not the car sells, and corresponds to transportation, opportunity cost of time, and marketing costs related to creating and monitoring the online listing.

Each channel yields a probability of sale p_j and an expected margin above m_i of $r_{i,j} = E\left(price_{i,j} - m_i\right)$. The physical channel sells the car by auction, and as in the marketplace context, the seller has an opportunity to reject all the bids in the end of the auction. We do not accurately observe the rejected high bids, so we summarize the payoffs with a contingent probability function $p_0\left(x_i, Z_i\right)$ and $r_0\left(x_i, Z_i\right)$. Note that $r_{i,j}$ depends on i only through the two attributes Z_i, and x_i that do not enter the pre-computed m_i. All other vehicle characteristics, such as mileage or year, are already accounted for by m_i. Offering the car in the physical channel thus yields a current-period payoff of: $\pi_{s,0} = p_0\left(x_i, Z_i\right) r_0\left(x_i, Z_i\right) - c_{s,0}$.

The online channel sells the cars through posted price offers, and sellers face a demand curve $p_1\left(x_i, Z_i; r_1\right)$. When the seller charges a "price" (really a margin above expectation) of r_1, he collects a payoff of: $\pi_{s,1}\left(r_1\right) = p_1\left(x_i, Z_i; r_1\right) r_1 - c_{s,1}$.

After any unsuccessful listing, the seller can exit the market indefinitely and collect some outside payoff $\Pi_{s,2}$ by selling the car directly to consumers from his lot or through a different intermediary. The seller is forward-looking, discounts future payoffs with factor $\beta<1$ per period, and wants to maximize his expected profit.

When $p_0(x_i, Z_i)$ is close to one (as is the case in our market context), this model is an optimal stopping problem with both the physical channel and the outside option equivalent to ―stopping" and the Internet channel equivalent to ―searching". In the spirit of Rust (1987), we start by solving a simple example of the seller's problem with a simple linear demand function and no econometric error terms.

In our empirical investigation, we focus on a single seller and a single car, suppress the seller and car subscripts throughout, and set the key properties of the model as follows: First, we let $p_0(x)=1, r_0(x)=0$. That is, the physical channel sells immediately, has no memory of unsuccessful selling attempts, and yields average returns. Second, $p_1(x \mid r_1)=\max\left\{0, \frac{T-x}{T}(1-r_1)\right\}$ where $r_1 \in [0,1]$: the Internet demand gradually disappears after T unsuccessful Internet listings. The scaling of r is just a change of currency to make 1 the maximum possible margin. Third, $\Pi_2 < -c_0$: the outside option is always dominated by the physical channel. Fourth, $0 \le c_0 < \frac{c_1}{1-\beta}$: the seller will eventually stop – this is a technical assumption that would not be necessary with a robust outside option. Given the above assumptions, the seller's problem simplifies to $V(x)=\max\{-c_0, R_1(x)-c_1\}$, where R_1 is the forward-looking state-dependent payoff from the Internet channel net of everything other than the cost of selling. The simple linear demand curve means the optimal myopic internet price would be ½ regardless of state. The optimal dynamic price is different because of the option value of waiting:

$$\arg\max_{r_1}\left[\frac{T-x}{T}(1-r_1)r_1+\beta\left(1-\frac{T-x}{T}(1-r_1)\right)V(x+1)\right]=\frac{1+\beta V(x+1)}{2} \tag{1}$$

and so $R_1(x)=\frac{T\left[1+\beta V(x+1)\right]^2-x\left[1-\beta V(x+1)\right]^2}{4T}$. It helps to parameterize R_1 in terms of the number k of selling attempts left before T, i.e.,

$$R_1(T-k)=\beta V(T-k+1)+\frac{k\left[1-\beta V(T-k+1)\right]^2}{4T} \tag{2}$$

where the first term is exactly the payoff from waiting one more period, and the second term is the net ―gambling benefit" from trying the Internet channel in the current period. By optimality, V must be non-decreasing in k, so it is immediate that the gambling benefit increases in k and so the entire $R_1(T-k)$ increases in k.

We now solve the game backward from $x=T$. There is no more Internet demand above $r_1=0$ from this point on, so the channel choice is driven by costs. The seller thus chooses the physical channel in the $x=T$ state because $c_0 < \frac{c_1}{1-\beta}$, so it is cheaper to stop rather than to continue offering in the Internet channel ad infinitum. This behavior implies $V_s(T) = -c_0$, and we can induct backward to state T-1.

At T-1, the Internet revenue is simple: $R_1(T-1) = -\beta c_0 + \frac{(1+\beta c_0)^2}{4T}$, so the seller chooses the Internet channel whenever $c_1 < c_0 + R_1(T-1) \Leftrightarrow c_1 < (1-\beta)c_0 + \frac{(1+\beta c_0)^2}{4T}$, i.e. when the Internet cost is small relative to the physical cost.

Suppose the seller chooses the Internet channel at T-1, i.e. $c_1 < c_0 + R_1(T-1)$. Then, $c_1 < c_0 + R_1(T-k)$ because $R_1(T-k)$ increases in k, and so we immediately see that the seller would also choose the Internet channel in every state 0,1,…,T-2. Intuitively, the payoff from the Internet channel can only increase with more attempts left before T because the product either sells for an even higher price or the seller can try to sell it again. The value function is the maximum of the two channels, so it must increase as well. So if a seller is willing to try the Internet channel in period T-k+1, he will try the Internet channel in every period 0,1,…,T-k.

Suppose instead that the seller chooses the physical channel in T-1, so $V(T-1) = -c_0 > R_1(T-1) - c_1$. Plugging this V into equation 2 yields $R_1(T-2) = -\beta c_0 + \frac{(1+\beta c_0)^2}{2T} > R_1(T-1)$. Therefore, sellers with $c_1 \in [c_0 + R_1(T-2), c_0 + R_1(T-1)]$ try the Internet channel up to time T-2 but switch to the physical channel at time T-1.

The recursion pattern is now clear: a seller who plans to switch to the physical lane after T-k +1 unsuccessful Internet attempts faces the following Internet payoff in state T-k

$$R_1\left(T-k \mid \text{PHY in } T-k+1\right)=-\beta c_0+\frac{k\left(1+\beta c_0\right)^2}{4T} \tag{3}$$

and some even higher Internet channel payoffs in earlier states 0,1,…,T-k-1. Since the RHS of equation 3 is increasing in k, the optimal strategy is simple: for a fixed pair of costs (c_1,c_0), there will be a cutoff value of k* such that the seller keeps trying the Internet channel until k* and then switches to the physical channel to sell right away.

In the initial state x=0, equation 3 simplifies to $R_1\left(0 \mid \text{PHY in } 1\right)=\frac{\left(1-\beta c_0\right)^2}{4}$ which does not depend on T because the Internet demand is just 1-r_1 in the first period. Therefore, we have derived the solution to the optimal stopping problem:

Proposition: The seller with costs $c_1 > c_0+\frac{\left(1-\beta c_0\right)^2}{4}$ sells the car immediately in the physical lane.

No sellers try the Internet channel unsuccessfully more than T-1 times.

For every $k=0,1,2,\ldots,T-1$, the optimal strategy of a seller with costs $c_1 \in\left[(1-\beta)c_0+\frac{k\left(1+\beta c_0\right)^2}{4T},(1-\beta)c_0+\frac{(k+1)\left(1+\beta c_0\right)^2}{4T}\right]$ is to try the Internet channel T-k times and then switch to the physical channel if the car does not sell. The cost regions are illustrated in Figure 1 for a specific case.

Knowing the seller strategy identifies a band in (c_1,c_0) space. Knowing prices charged on the Internet in the last period before switching to the physical channel identifies c_0. Therefore, we should be able to estimate both costs by observing # of attempts and posted prices. It is also likely that additional identification will be available from a non-degenerate outside option.

In practice, the market maker is unable to observe the true costs of sellers, only the prices at which the cars are listed and sold. However, examining a market context can give us directional evidence of sellers‘ forward-looking channel choices and their impact on price and sale probability outcomes. We now turn to these possibilities.

Empirical Investigation

The data

Our data includes sellers who participate in *both* the physical and Internet channel in 2008. The car models are all 2006 and newer and include models such as the 300, Corolla, Escape, Explorer, Focus, G6, Highlander, Impala, Malibu, Mazda6, Mustang, Sienna, Sonata, Taurus and Towncar.

The data consist of 299,441 individual listings, representing 193,845 unique cars. These are the observations that are usable (we did not consider observations with predicted market price missing or recorded at 0 or with a condition of salvage value). Of these, 31,162 are Internet listings (representing 5,557 cars) and the remaining are physical listings. 187,373 physical channel sales were recorded. 7663 Internet sales were recorded. This is slightly more than the number of unique car IDs because a few cars were sold multiple times in the sample. In the sections below, we consider the empirical evidence for some of the model assumptions and implications.

Channel characteristics

Probability of sale. In the model development, we asserted that sellers can sell a car in the physical channel with near certainty. Consistent with this, we find that a larger proportion of the cars first listed in the physical channel are sold in that listing (69.8%) relative to the Internet channel (24.5%). This high proportion of sales in the physical channel is the bases for a key assertion we made in the model development—namely, that sellers can sell a car in the physical channel with near certainty. In fact, of the unsold cars in the physical channel, 84% had recorded high bids that were generally in the neighborhood of the expected price as reported by the market maker. Thus, in nearly all physical listings, sellers could have sold the car for a reasonable price. In the Internet channel, the picture is very different with a much smaller probability of sale, and so a seller takes a risk of delayed sale by listing on the Internet.

Price premiums. The model also asserts that price premiums would be higher and sales probabilities lower in the Internet than physical channel. The price premium is the difference between the final selling price and the market maker‘s price expectation. The average price premium for the 15 top selling models we considered is M = -$98.2 (SE $2.3 with 187,373 sales) in the physical channel and M = $126.3 (SE of $8.8 with 7633 sales) in the Internet channel. This difference is significant at $p<0.0001$. Note that the premium in the physical channel is negative, meaning a discount. Thus, sellers face on average lower prices in the physical channel than in the Internet channel and should factor these differences into their price expectations.

Differences across product condition (i.e., quality). Over all 15 models, we observe that cars in condition 1 and 2 have a significantly lower probability of sale on the Internet channel (0.10 in Internet; 0.67 in physical, $p<0.0001$), but this is somewhat offset by a higher expected premium on the Internet channel (lower expected discount): M = -$461 in internet vs. M = -$994 in physical ($p<.0001$). For cars in condition 3 and 4, the difference in sales probabilities and expected premium shrink but are still highly significant. These cars have a significantly lower probability of sale on the Internet channel (M = 0.26 in Internet; M = 0.70 in physical, $p<0.0001$), but a higher expected premium on the Internet channel: M = $145 in internet vs. M = -$29 in physical ($p<.0001$). Thus, cards in all conditions face a tradeoff between premium and sale probabilities.

Seller strategies

Are some sellers more effective at generating channel premiums than others? Absolutely. In Figure 2, we split the sellers based on their earned overall premiums above the market maker‘s price expectation across the channels and find that in fact sellers in the fourth and fifth quintiles are able to beat the market maker‘s price expectations in both the Internet and physical channel. This suggests that as much as 40% of the sellers are quite effective at managing their channel choices – i.e., these sellers know when to make versus when to take their car prices. As one can see from Figure 3, the more successful sellers are typically higher volume sellers, perhaps suggesting that more experienced sellers or sellers with scalable quantities are better at obtaining premiums across the channel forms.

Are successful sellers more tech savvy? We inform this possibility by examining the ratio of Internet listings over physical listings across the seller success quintiles and we see no evidence to this effect; successful channel sellers do not appear to possess a technology advantage (although it is possible the non-tech savvy sellers might overlist on the Internet simply because they do not fully understand the advantages and disadvantages of that channel). Simply put, there is no discernable pattern in terms of ratio of Internet to physical listings.

Are there geographical differences? Not really. We tested for geographical effects, finding only that the western United States (dominated by several California markets and Seattle) lists on the Internet a bit more often than other regions (M = 9.5% Internet listings, compared to M = 6.5% to 7.7% for all other regions), resulting in lower probability of sale.

Why are sellers able to obtain such price premiums in the Internet channel? It may be that buyers are less price-sensitive online than offline. This would be consistent with what Chu, Chintagunta and Cebollada (2008) found in their study of products across twelve vastly different product categories and types. As in their context, it may be the case that buyers have time sensitivities, are able to easily compare and search for options, and because the online channel is a virtual monopoly in online shopping options. It might also be that sellers know when to switch (or migrate) across the channel formats.

What channel migration is observed? The model specifies that after any unsuccessful listing, the seller can either exit the market indefinitely or pursue a path with an outside payoff. We consider the possibility that the seller might migrate to the alternative channel format. For the most part, cars listed in the physical channel sell on the first listing (M = 77% of cars in the physical channel sold on the first listing). Even cars unsold on the first physical channel listing will eventually sell in that channel (e.g., at a later listing. Not surprisingly, only 0.08% of cars first listed in the physical channel eventually sell in the Internet channel. Thus, we can say that virtually no migration occurs from the physical to the Internet channel and it is not necessary to talk of more than two Internet listings. Note, however, that some sellers listed on the Internet many times, but this did not translate to a substantial probability of eventual sale. Collectively, these findings are consistent with the notion that sellers might view the physical channel as a more robust channel for quick sale.

Migration from the Internet to physical channel is far more common. Of 11,845 cars that were first listed online, the majority of them (M = 8,029) do not sell on their first listing. 49.7% eventually sold in the Internet channel. However, the second Internet listing fared much worse. Only 17% of those second-time-Internet-listed cars were sold in that listing. Only 5.5% of these cars sold on the Internet in some subsequent listing. Thus, the overwhelming majority of cars listed the second time and failing to sell ultimately never sell in the Internet channel.

Of the nearly 12,000 cars first listed only, 44.4% eventually sold in the physical channel, and the remaining 5.9% went unsold. Moreover, sellers appear to quickly lose patience with the Internet channel. Cars listed once online and failing to sell at that listing will very often (M = 69% of these cars) be offered in the physical channel, where it will then be sold. Thus, a failure to sell on the Internet in the first listing is more likely to lead to a channel migration than to a relisting on the Internet. This is consistent with the insight generated by the theoretical model as to which channel should initially carry the product as well as how and when sellers should switch the sale of their products across channels, taking into account their differential probability of sale.

Is there evidence of channel overlap? Out of all observations in which a physical auction follows an Internet listing, 92% of these begin one or more days after the Internet auction ended, 6% begin on the day that the Internet auction ended (presumably no overlap occurs), and only 2% begin before the Internet auction ended (overlap occurs). We have no instances of an Internet auction ending a week or more after the physical auction that succeeded it. So we attribute the 2% overlap to error.

Generalizability

Up to now, our analysis is aggregated across all makes and models and quality levels (e.g., vehicle condition within model, but also differences across models). However, it would also be informative to consider models that are more like a commodity, such as Toyota Corollas which are also a very popular model.. Again, we observe substantial evidence for the model.

Do the channel and premium differences persist? We first examined how price premiums and probabilities might vary across the channel and car condition for Corollas. When we do this, we observe that the foregoing differences in the probability of sale across channel type persist, despite variation in car condition, with the sales probability gap between the two channels decreasing the better the car condition (i.e., 4 and 5, versus 0 and 1). These differences are displayed in Figure 3A and 3B. The decrease in the gap at the extreme ends of the scale attests to the information quality – i.e., extreme ratings are clearer signals of high or low quality than intermediate ratings (Fleder and Hosanagar 2007; Shardanand and Maes 1995). In fact, the market maker‘s criteria for a good versus low condition car rating is clear and subject to little interpretation.

Channel differences conditioned on car condition are also informative. See figure 2A and 2B. For Toyota Corollas, we observe that cars in condition 1 and 2 have a significantly lower probability of sale on the Internet channel (M = 0.18 in Internet; M = 0.71 in physical, $p<0.0001$), but a higher expected premium on the Internet channel (lower expected discount): M = -$398 in internet vs. M = -$1079 in physical ($p<.0001$). For cars in condition 3 and 4, the difference in sales probabilities and expected premium shrink but are still significant. Cars have a significantly lower probability of sale on the Internet channel (M = 0.48 in Internet; M = 0.77 in physical, $p<0.0001$), but not significantly different expected premium across channels: M = $78 in internet vs. M = $87 in physical ($p=0.61$). Thus, for Toyota Corolla, cars in conditions 3 and 4 are better off in the physical channel.

Is it the case that sellers choose the car condition that is best suited for the Internet channel versus the physical channel? For example, could sellers be –dumping” certain types of cars into the channels differentially? Figure 4 suggests that this is not the case. Both channels have similar distributions of cars ranging from condition 0 to 5. However, as noted in Figure 4, the car condition is systematically related to its sale probability; i.e., lower condition cars in the internet channel are less likely to sell, as there may be more uncertainty about the level and variance of quality heterogeneity in these vehicles.

Hence, we observe evidence that our general model might also generalize to commodity-like products. Together with the foregoing aggregated results, these differences illustrate the nature of the tradeoffs that sellers face across their channel choice. Collectively, the path-to-sale sequence that we observe in the data is consistent with our conceptualization of profit maximization by a rational forward-looking seller. The considerable heterogeneity among sellers, also suggests these performance differences are likely to be a function of strategic choice. Our hope is that these findings and more would stimulate further inquiry in this important aspect of channel management.

Discussion

Our goal in this research has been to inform the seller's go to market strategy in multigenerational, heterogeneous product markets. To this end, we make a number of advancements.

We develop a selling strategy based on channel selling costs

In Figure 1, we showed the optimal seller strategy depends on the Internet channel cost and the physical channel cost. We were able to derive, using our theoretical framework, regions corresponding to the optimal forward-looking strategies, taking the price distributions as given. We showed that sellers with high costs in both channels are better off immediately selling the car in the physical channel. Thus, we can say that sellers with high costs in both channels never list online and just dump the car into physical. For these high-cost sellers, failure to sell right away (which would result with the highest likelihood in the physical channel) is too costly, to the point that it exceeds any potential gain in premium that the Internet channel might offers. Sellers with moderate channel costs can afford few Internet attempts, and then they sell the car in the physical channel if unsold on the first attempt. Finally, our analysis suggests that low-cost sellers find it optimal to list on the Internet multiple times before switching to the physical channel.

We develop implications for market and channel design

From a design point of view, the market maker would be most interested in targeting channel specific costs that would affect the channel choices of the market participants. We grouped these costs into physical channel costs and Internet channel costs. Physical channel costs may include the cost of holding the car at the physical market location, the associated labor and overhead costs, and the lane fee. Internet costs involve the Internet listing fee, the cost of monitoring the auction over its duration, and the affiliated labor and overhead. An important point is that we can predict the effect of changing channel-specific listing fees. Specifically, in the second period, the optimal Internet posted price is decreasing in the physical cost because this cost needs to be incurred in the third period if the second-period Internet listing does not sell. This means that shifting the business to the Internet channel can be achieved with an increase in the physical channel listing fee ("lane fee"), but not with a change in the Internet listing fee. Another important point here is that different combinations of channel cost magnitudes can recreate the different selling strategies we see in the data, including the fact that the Internet posted prices are generally high, implying patience and generally low physical channel costs.

We are able to prescribe and identify key “switching points” in a Seller’s go-to-market strategy

In short, our prescriptive model allows us to identify the seller‘s ―switching points” where it migrates from one channel form to the other and show that this switching point depends on the relative cost listing in each channel. Identification of these switching points is a non-trivial task involving a dynamic programming model conditional on the car‘s past history. However, these insights can prove useful in both the channel design and in characterizing seller heterogeneity. Assuming each seller faces a different combination of channel costs, the mapping we discussed assisted us in "inverting" the observed listing behavior into a range of costs the seller must be facing.

We connect channel costs to a key performance outcome, the dynamic selling price across channels

We can also map the relationship between channel costs and pricing in the Internet channel. We find that price in the Internet channel appears to be affected by the physical channel cost, but not by the Internet channel cost. The first period Internet price does not depend on the Internet channel cost because Internet demand is fairly inelastic in the first period. The second period Internet price does not depend on the Internet cost because the Internet cost is already fully sunk by the time the buyers consider the second-period Internet price, whereas the physical cost is still looming as a potential future cost if the car fails to sell.

We consider the external validity of our theoretical model

We go beyond the development of a theoretical model to assess the external validity of our proposed model in a real multichannel market context. While we are not able to fully vary and assess the channel cost structures as prescribed by the model, we do observe that our theoretical model is capable of resonating with the real institutional context and find some empirical support for various assumptions that our model makes.

Future research

Our research has focused on the sale of individual products, versus assortments of products or products for which there might be interdependencies with substitutes (e.g., Mahajan and van Ryzin 2001a, 2001b). However, an important direction for future work would be efforts that expand the unit of analysis to account for the entire assortment and considers bottom line implications; i.e., maximization of basket profit as opposed to individual product profit or basket size .

Future work might also consider the management of more channel choices; e.g., Venkatesan, Kumar, and Ravishanker (2007) examine three channel options or account for competitive intermediaries with similar channel structures (cf., Ofek, Katona and Sarvary 2011) and even consider alternative channel structures and market environments (e.g., Yoo and Lee 2011).

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Figure 1

Cost Regions For A Specific Case

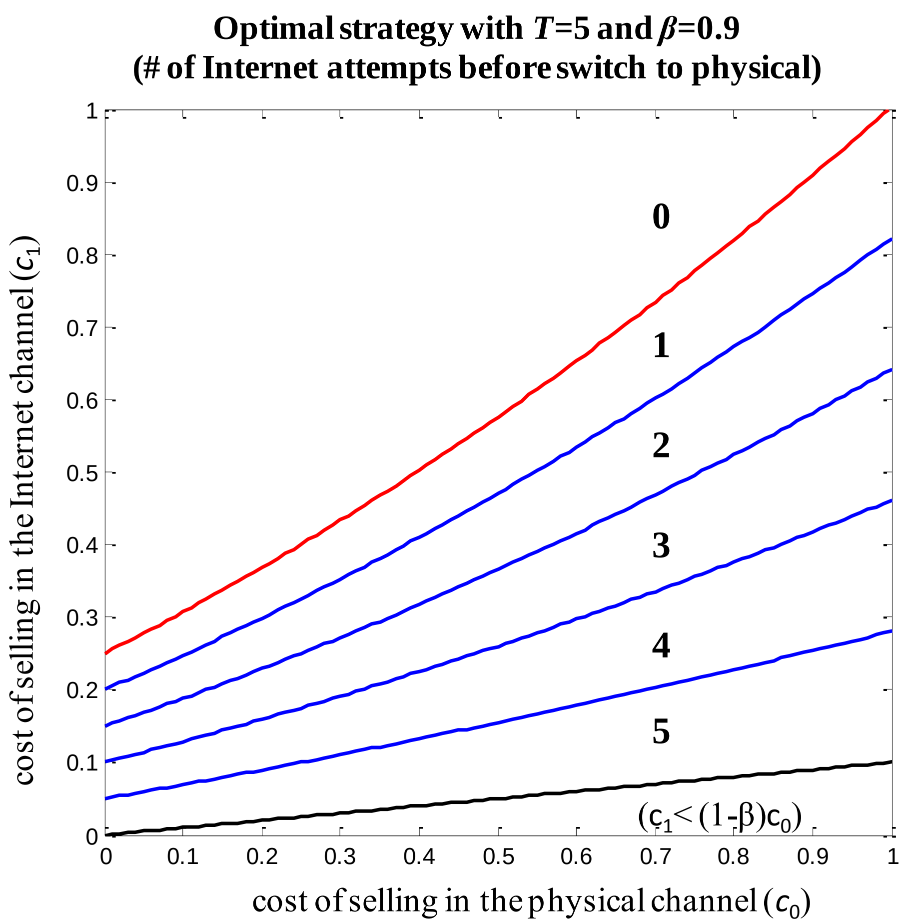
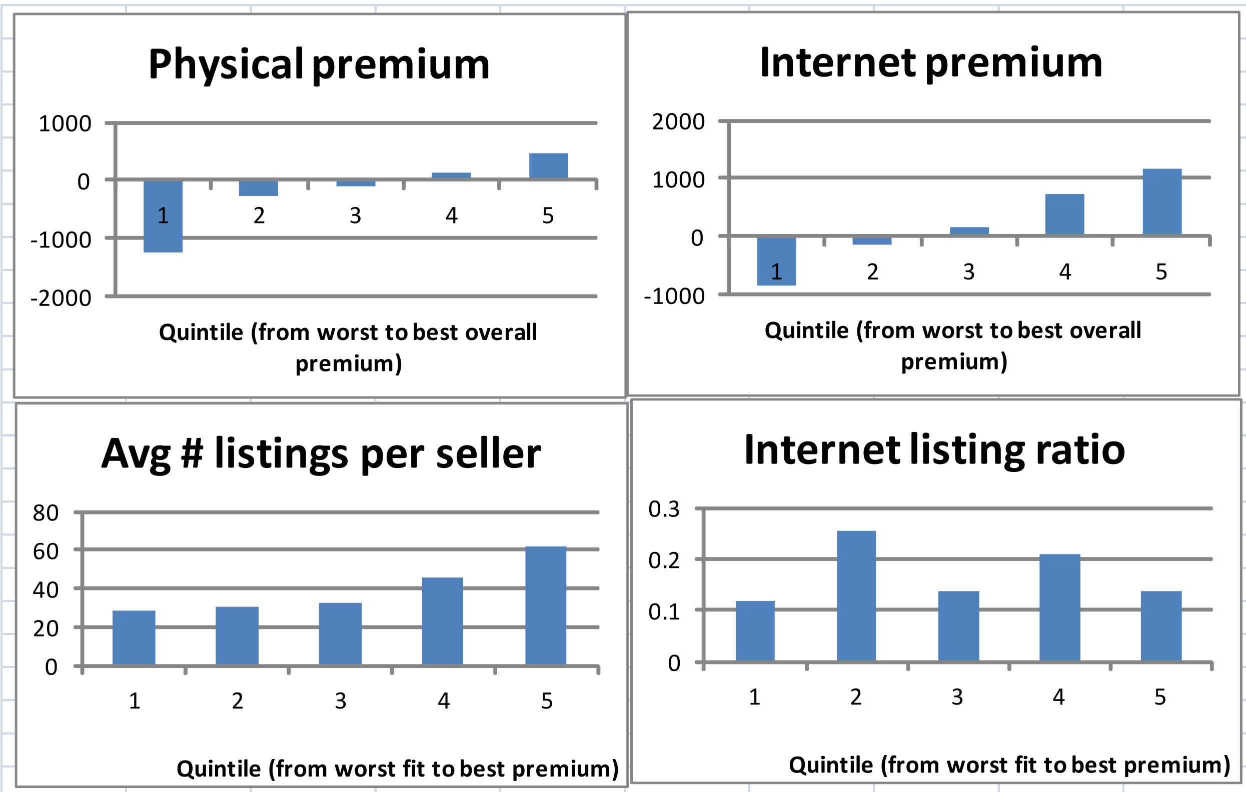


Figure 2

Earned Channel Premiums Among Sellers

Sellers are split into quintiles based on their earned overall premiums above the market maker's price expectation across the channels

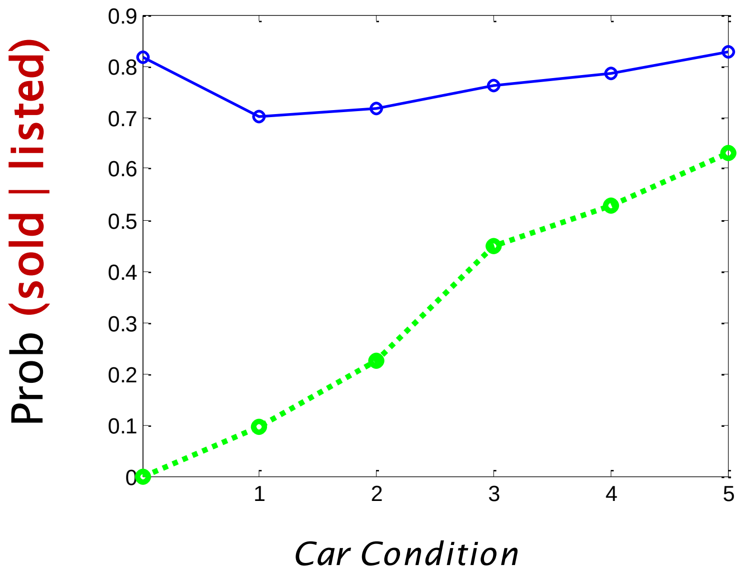


The premium represents the difference between the sold price and the market maker's price expectation.

Figure 3

Toyota Corolla Sales Probabilities Across Channels And Car Condition

3A.



The green, dotted line represents the Internet channel, while the blue solid line represents the physical channel.

3B.

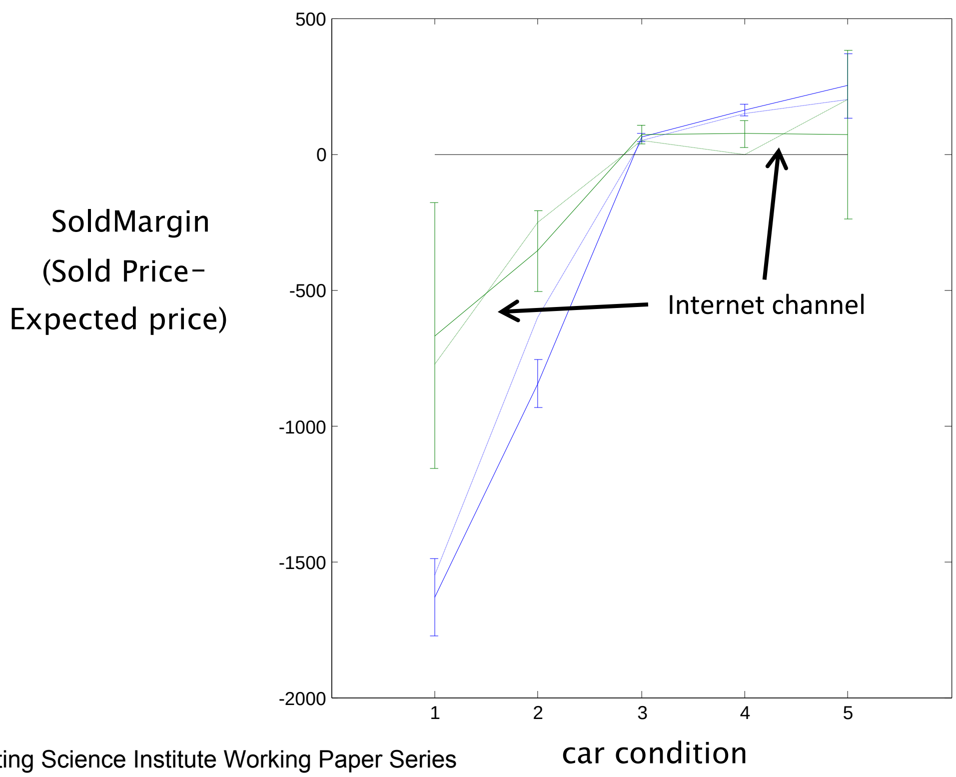
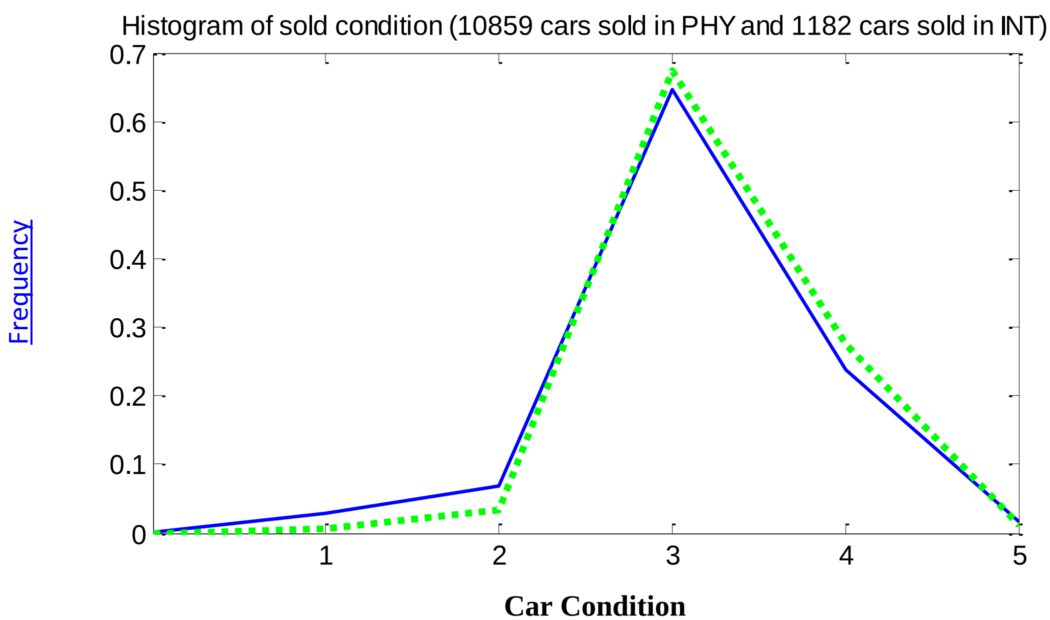


Figure 4

Toyota Corolla Condition Distribution Across The Channels

The vertical axis represents the frequency each condition was sold. Specifically, over 60% of all Toyota corollas sold were of condition 3. Over 20% were of condition 4 and the rest were conditions 1, 2, and 5.



The green, dotted line represents the Internet channel, while the blue solid line represents the physical channel.