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Ushering Buyers into Electronic Channels: An Empirical Analysis

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Despite many success stories, B2B e-commerce penetration remains low. Many firms introduce electronic channels in addition to their traditional sales channels but find that buyer usage of the *e*-channel over time does not keep up with initial expectations. Firms must understand the underlying factors that drive channel usage and how these factors change over time and across buyers. Using panel data pertaining to the purchase histories of 683 buyers over a 43-month period, we estimate a dynamic discrete choice model in a B2B setting that (i) recognizes how price, channel inertia, and inventory change over time; (ii) allows buyers to dynamically trade off these factors when making *e*-channel adoption decisions; and (iii) takes into account buyer heterogeneity. We find that channel usage is both heterogeneous and dynamic across buyers. Our findings reveal the dynamic tradeoff between channel inertia and the adverse price effect, which interact in opposing directions as the *e*-channel grows more popular over time: price increases resulting from more bids deter buyers, whereas channel inertia built from sampling experience helps retain repeat buyers for the new channel. Second, we find that the buyers' size and diversity influence purchase decisions, and the *e*-channel appears more attractive to small and/or diversified buyers. Based on our analysis, we postulate that the seller's allocation decisions of products across channels, if not aligned with buyer behavior, can alienate some buyers. Based on the parameter estimates from the buyer response model, we propose an improved channel allocation that enables firms to selectively attract more buyers to the *e*-channel and improve revenues. Channel acceptance increases as a result of smart allocation when firms understand and account for individual buyers' channel usage behavior.

Key words: electronic markets; channel choice; buyer heterogeneity

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1. Introduction

As of 2008, electronic commerce accounted for 39% of all manufacturing shipments and 20.6% of all sales from wholesalers (U.S. Census Bureau 2010). The slow acceptance of the electronic channel in business-to-business commerce has not only been well articulated in industry reports (e.g., Harmon et al. 2009) but has also been explored in theoretical work by researchers.¹ However, the challenges of obtaining detailed, micro-level data in business-to-business settings have made systematic empirical study difficult (Jap 2003, Mithas and Jones 2007).

¹This literature is far too large to survey here. See, for example, Ockenfels et al. (2006) for a discussion of the incentives to participate in online auctions and Gefen (2000) for a discussion of the implications of trust.

We study one problem commonly faced by firms that are ushering buyers into the electronic channel. Many firms engaged in business-to-business commerce operate an online auction channel while simultaneously operating another channel offline (Bucklin et al. 1997, Abele et al. 2003). A common issue for such dual channel sellers is how to encourage online auction use to increase profitability. Although a variety of papers has empirically studied the dual channel setting, examining issues such as how convenience (e.g., Forman et al. 2009), quality uncertainty (e.g., Overby and Jap 2009), and marketing efforts (e.g., Ansari et al. 2008) influence buyer choices between traditional and electronic channels, these studies for the most part have ignored buyer dynamics.

To understand how and why buyer response is essential to a firm's e-commerce strategy, we analyze

channel usage data from a third party logistics firm that traditionally used a physical channel (hereafter, *p*-channel) to dispose of its returned products. In response to heightened interest in electronic commerce and online auctions around 2000, it launched a new *e*-channel. The roll-out initially proved a huge success; buyers accepted the channel quickly. However, over a period of time, the buyers' usage of the *e*-channel did not keep up with the initial pattern, and the *e*-channel usage, although increasing over a period of time, did so at a decreasing rate.

Why did the popularity of the *e*-channel fail to live up to initial expectations? We posit that firms often do not incorporate the dynamics of buyer behavior and heterogeneity in buyer characteristics into their channel allocation decisions. Yet buyer characteristics and behavior influence the pattern of *e*-channel usage in several ways. First, buyers often face inertia when they must give up their old channel habits and proven ways to interact with the seller, which creates various levels of resistance to the new technology. Second, the auction mechanism in the online channel introduces dynamic pricing. As traffic increases on the new channel, the initial advantage of lower competitive intensity, and thus attractive prices, varies. Prices escalate in response to more traffic; therefore, some buyers deem the new channel less attractive. Third, buyers differ in their sensitivity to channel inertia and price. Their preferences for the *e*-channel, the type of products they purchase, and even their preferred order sizes differ; hence, their reactions to new technology are different.

More importantly, the factors that influence buyer usage of the *e*-channel change over time and vary across buyers, intrinsically bringing in dynamic trade-offs and conflicts that pitch buyer channel inertia against increasing competitive forces in the channel. These dynamic effects influence *e*-channel usage. Thus, the dynamics of buyer behavior and buyer heterogeneity are critical in explaining how users migrate from *p*-channel to *e*-channel. In turn, the firm faces the challenge of identifying the best strategies to employ to encourage the use of the *e*-channel when alternative channels exist. Specifically, it is important for firms to have a clear understanding of (i) what factors drive *e*-channel adoption decisions; (ii) how these factors change over time and what role the auction mechanism plays in shaping them; (iii) how the importance of these factors differs across buyers in driving their adoption decisions; (iv) whether the firm's current channel strategy (product allocation in our research context) is aligned with the buyer dynamics and heterogeneity; and (v) if not, whether there are ways to increase the popularity of *e*-channel. Prior empirical work does not focus on either the dynamics of the channel choice decision or the seller's

channel allocation strategy as we do. Answers to these questions will help managers understand the fundamental drivers determining buyer acceptance of the *e*-channel and leverage how these factors change over time and vary across buyers. It also helps management to discern why e-commerce implementations run into such response problems from potential buyers and then devise strategies to proactively manage buyer behavior by smarter allocation of products across the two channels.

Our data and setting come from the return center of a third-party logistics provider that recently introduced an *e*-channel and uses either an *e*-channel or *p*-channel to sell each bill of lading. Figure 1(a) motivates our analyses, demonstrating the slowdown in the growth of *e*-channel usage. To understand this behavior, we propose a buyer choice model in which buyers form expectations of auction prices and make channel choice decisions based on the trade-off between dynamic variables such as expected total expenditure, channel inertia, and inventory. Buyers' heterogeneous sensitivity to these variables is taken into account by allowing observed and unobserved buyer characteristics to influence buyer purchase decisions in a hierarchical Bayesian framework. By explicitly modeling how buyers form expectations and develop channel inertia, this model allows us to investigate the fundamental factors that drive buyers' dynamic adoption decision process and how the dynamic decision rule differs across buyers.

We estimate the model parameters using field data and identify factors that influence buyers' usage of the *e*-channel. We find that buyers demonstrate channel inertia; i.e., past use of a channel increases the likelihood of present use. We also demonstrate an adverse dynamic price effect: more usage of the new channel and consequently more intensified competition raises prices expected to be paid on the *e*-channel. This discourages further buyer participation, which in turn decreases usage of the *e*-channel. Buyer sensitivity to each of these effects in our model depends on buyer characteristics. Smaller buyers and those that purchase a more diversified set of products tend to overcome channel inertia more quickly and adopt the new channel; they are also less sensitive to higher prices resulting from the increasing popularity of the *e*-channel. By identifying these dynamic competing forces, we point out that by ignoring buyer behavior and heterogeneity, the firm's current allocation strategy enlists the wrong types of buyers and excludes other buyers as the *e*-channel grows more popular. This helps explain the slowdown that we observe in Figure 1(a).

Using these parameter estimates, we simulate a different channel allocation strategy in which the firm considers both buyer dynamics and heterogeneity.

By listing specific products suitable for the *e*-channel, the new strategy invites buyers of the right type: those who are smaller and more diversified. Being less price sensitive, these buyers are less likely to be discouraged by the increasing prices from mounting competition in the *e*-channel. We show that by doing so, firms can anticipate the dynamics of pricing changes, identify selective strategies to allocate preferred product offerings online, and overcome buyer resistance. Not only are more buyers ushered to the *e*-channel, but total revenues also increase.

From a managerial standpoint, we show that the mere adoption of technology will not lead to firm benefits; instead, companies must anticipate buyer behavior to harness the new technology, assess its impact on buyers, and provide the best value to both the existing and the targeted buyer base. Thus, firms should shape their micro-marketing strategy for the *e*-channel and leverage their understanding of dynamic adoption behavior and buyer heterogeneity.

Although recent research has begun to examine strategies that firms can use to encourage buyer use of the *e*-channel (e.g., Knox 2006, Ansari et al. 2008), the issues of buyer dynamics that we study have not been addressed in detail, mainly because of a paucity of micro-level data. We demonstrate that properly accounting for buyer dynamics and individual-level heterogeneity brings several new insights. In particular, we demonstrate that buyer purchase decisions depend largely on the effects of price and channel inertia, which drive purchase behavior in differing ways as *e*-channel use grows over time. Further, buyer demographic variables also allow us to identify the profiles of buyers who have heterogeneous sensitivities to the main factors affecting their adoption decisions. This is in contrast to the previous literature in information systems, which usually classifies buyers based on their observed characteristics. Third, we provide specific insights for seller channel allocation strategies: by better regulating the product type and size allocated to each channel, the seller can target smaller and more diverse buyers. We show that usage of such strategies can rejuvenate adoption that has stalled, increasing both *e*-channel usage and net revenue. In summary, we contribute to the literature by estimating a dynamic discrete choice model in a B2B setting that (i) recognizes how price, channel inertia, and inventory change over time; (ii) allows buyers to dynamically trade off these factors when making *e*-channel adoption decisions; and (iii) takes into account buyer heterogeneity.

In §2 we discuss related research and our contributions to the literature. Next, we describe the research context and data in §3. We then develop the buyer response model in a Bayesian specification and discuss the empirical results in §§4 and 5. In §6 we

present the seller's objective function and the simulation results. We conclude with some managerial implications and limitations in §7.

2. Related Research

Our research contributes to emerging work on the interaction between online and offline markets by combining marketing concepts with those from information systems research. We contribute to three fields of study. First, we contribute to recent research examining consumer substitution between online and offline channels. Second, we add to literature that examines how changes to design parameters can influence participation in and outcomes of online auctions. Last, we add to theoretical and empirical work that has documented buyer inertia (or state dependence) online and has investigated ways that sellers can contribute to and leverage buyer inertia.

2.1. Electronic and Physical Channel Substitution and Management

An emerging stream of research in information systems and other fields has investigated buyers' use of electronic and physical channels and substitution between them. Although prior research has examined parts of the phenomenon we study, to our knowledge no prior work has studied all of these elements together.

One strand of research has examined the factors influencing buyers' channel choice such as channel attributes like price (e.g., Brynjolfsson and Smith 2000, Goolsbee 2001), convenience (Forman et al. 2009), lower presentation and transaction costs (Kambil and van Heck 1998), product selection (Brynjolfsson et al. 2003, 2009), and product and market state information (Kuruzovich et al. 2008, Koppius and van Heck 2002, Koppius et al. 2004, Overby and Jap 2009). Further, buyer characteristics such as age, income, education, and skill can influence channel choice (e.g., Ansari et al. 2008, Hitt and Frei 2002, Xue et al. 2007).

At the same time, extant literature has investigated ways in which sellers can encourage *e*-channel use, for example, by improving some of the channel attributes described above (e.g., Verhoef et al. 2007) or through explicit marketing efforts (e.g., Ansari et al. 2008).

Although these research lines have made important contributions, they focus on B2C rather than B2B markets. Further, they do not investigate how retailers should allocate products across dual channels, nor do they examine how sellers can incorporate the dynamics of buyer behavior as we do. In particular, at present there seems to be a limited understanding of how changes in channel loyalty and price over time influence buyer behavior.

2.2. Business-to-Business Online Auctions

By lowering the transaction costs of auction participation, the IT artifact has spurred the growth of online auctions. Information systems researchers have actively been seeking to understand how to encourage participation in online auctions (e.g., Choudhury et al. 1998, Mithas et al. 2008). Further, by studying how sellers can selectively allocate products to the *e*-channel, our research contributes to work that seeks to understand how changes to auction design influence seller and buyer surplus (e.g., Jap 2003, 2007). Much prior research focuses on auction design parameters, addressing issues such as auction length (e.g., Mithas and Jones 2007), bid increment (e.g., Bapna et al. 2001, Mithas and Jones 2007), strategies for allocating multiple units (e.g., Bapna et al. 2007), and different auction mechanisms (e.g., Lucking-Reiley 1999). However, the dynamics of buyer response have largely been unexplored.

Our paper is also related to recent theoretical research that evaluates the optimal sales mechanism for a set of goods: in other words, when a seller should use fixed prices, dynamic posted prices, or an online auction (e.g., Gallien 2006, Etzion et al. 2006).

Overall, our paper addresses a problem faced by many sellers that is receiving increasing attention in the literature: buyer and seller behavior in the context of an online auction and some alternative (often physical) channel. Note, however, that we differ from papers in the auction literature in that we do not seek to explicitly model buyers' bidding behavior. Rather, we model auction prices as a function of the number of bids and allow both to influence buyer decisions to purchase from the *e*-channel. This modeling choice allows us to capture buyers' key tradeoff that alters incentives to purchase from the *e*-channel over time: increasing prices caused by a larger number of bids versus increasing *e*-channel channel loyalty.

2.3. Channel Loyalty and State Dependence

Researchers in information systems and other fields have examined the factors influencing buyers' loyalty to websites and, more broadly, to *e*-channels (Chen and Hitt 2006). Online switching costs have been found to be significant (Smith and Brynjolfsson 2001, Moe and Fader 2004), and firms have invested considerable sums in increasing website loyalty by increasing website quality and personalization (Chen and Hitt 2002, Chellappa and Sin 2005). Researchers have also examined how increasing trust in sellers and websites facilitates loyalty. For example, sellers who provide positive service quality experiences in the same or other channels may have greater channel loyalty (Gefen 2002, Chen and Hitt 2002, Kim et al. 2008).

A variety of theoretical work has explored how changes in switching costs—either exogenous or endogenous—can lead to changes in firm conduct and market structure (e.g., Chen and Hitt 2006, Xue et al. 2006, Viswanathan 2005). However, this work has primarily been theoretical rather than empirical and has not investigated how sellers should incorporate customer loyalty into their strategies for ushering buyers into the electronic channel.

3. Background of Field Study and Data Description

3.1. TPL: Our Field Study Company

We examine buyer usage of an *e*-channel offered by a third-party reverse logistics provider located in the United States. For reasons of confidentiality, the name of this provider must remain anonymous, and for the purposes of this paper we label it as TPL. The returns include merchandise returned to the store, damaged merchandise, and unsold seasonal toys and electronics from major retailers. The retailer salvages a variety of items using TPL and combines returns in a particular product category into a single salvage order, referred to as a bill of lading (BoL). The number of units, or quantity, in a particular order is predetermined and fixed, and the units are packed into larger units, called pallets, for ease of handling and transportation. TPL buys returned products (mostly toys and electronic gadgets) at a deep discount from selected large U.S. retailers, processes the returns, and resells the products to other buyers, with revenues defined by the price paid.

Prior to June 2002, TPL sold all its products through an offline (physical) channel by informing a list of registered bidders about the details of the returns available for purchase. Interested buyers then placed bids on the available merchandise in the BoL. In June 2002, TPL also opened a business-to-business (B2B) online marketplace in which all buyers could purchase the salvage items. This *e*-channel uses a first price ascending auction mechanism; the rules of the auction are similar to those of online auctions examined in other settings (e.g., Ockenfels et al. 2006). Bidders may observe the numbers of bids and distinct bidders for a particular auction, but not the identities of those other bidders. Those who participate in the *p*- and *e*-channels come from the same list of registered buyers.

For either channel, the information available to the buyers is similar: the product category, the number of pallets, and the number of units offered in the BoL as well as the suggested retail price, which indicates how much the buyer might regain from purchasing this BoL. Most buyers are aware of the retail price of such goods and can gauge how much they should

bid. In either channel, the winning bidder pays for the transaction with an electronic funds transfer, and TPL ships the BoL to the buyer. Furthermore, TPL bears the operational costs of processing, shipping, and handling, which increase with the number of pallets.

Upon receiving a BoL of returned goods from retailers, TPL chooses a channel for product disposal. According to TPL's management, after some initial experimentation, it allocated products on the basis of a simple and ad hoc algorithm developed by a revenue management firm to be described later. That is, TPL makes channel decisions independent of buyer responses.

3.2. Data

We collected data from TPL, which include the sales histories of all bills of lading of toys and electronics sold through both *p*- and *e*-channels from June 2002 (when the *e*-channel was adopted) to December 2005. Our data are unique in that we observe individual buyers' purchase histories over time, which enables us to examine their intertemporal channel usage patterns. Buyer demographic variables also allow us to identify the profiles of buyers who are more likely to adopt the *e*-channel. Furthermore, in contrast with most prior dual-channel research, for which service and quality attributes may differ across channels and potentially confound estimates, no quality differences exist among the products offered in the two channels.

The panel data include product category, order size, number of pallets, number of units in the BoL, its retail price (i.e., the dollar amount the products would fetch at retail), the sales channel deployed, actual purchase price in the auction, buyer identification, and the number of bids and bidders. We also obtained data on buyer characteristics, namely, size (*SIZE*) and diversity (*DIVERSITY*). TPL categorizes buyers into small (coded as *SIZE* = 0), and large (*SIZE* = 1), based on the average number of units they purchase. Large buyers are assigned to senior auction managers.

Similarly, we find that some buyers consistently purchase from only one category. TPL categorizes buyers as more or less diverse based on their purchase pattern across different product categories. Thus, buyers are categorized as less diverse or specialist retailers (*DIVERSITY* = 0) if they purchase from a single category more than 90% of the time and more diverse or generalist retailers (*DIVERSITY* = 1) otherwise.

In Table 1, we provide the sample statistics for all variables in our analysis. For example, 46.7% of the bills of lading consist of electronics; the rest are toys. The average numbers of units (items) in a BoL for toys and electronics are, respectively, 1,214 and 450. *RPRICE* indicates the potential salvage value for the buyer. Because the bills of lading vary in the number of units and pallets, we use a normalized price, thus *RPRICE* is the per unit retail price (*PRICE*) in the BoL. For toys, the average is \$19.86; for electronics, it is \$81.19. The average number of bids (*NBIDS*)

Table 1 Sample Statistics

Variables	Explanation Category	Mean or frequency (SD)	
		Toys	Electronics
Buyer			
Units (<i>Q</i>)	Number of units in a bill of lading (BoL).	1,214.136 (2,079.859)	449.616 (362.741)
Unit retail price (<i>RPRICE</i>)	Average unit retail price.	19.856 (18.591)	81.185 (44.455)
Bids (<i>NBIDS</i>)	Number of distinct bids.	3.084 (5.039)	7.737 (13.346)
Unit sales price (<i>PRICE</i>)	Unit sales price.	2.730 (2.871)	15.704 (15.903)
Size (<i>SIZE</i>)	Size of buyers: = 0 for small buyers; = 1 for large buyers.	22.89%	
Diversity (<i>DIVERSITY</i>)	Diversity of product types carried by buyer: = 0 for less diverse buyers; = 1 for more diverse buyers.	42.04%	
Firm			
Channel (<i>E-CHANNEL</i>)	Equal to 1 when the firm uses the electronic sales channel.	0.249 (0.432)	
Electronics (<i>ELECTRONICS</i>)	Equal to 1 when the product category is electronics; 0 otherwise.	0.467 (0.499)	
Log of pallets ($\ln(PALLET)$)	Log of the number of pallets in the BoL.	1.927 (1.002)	
Unit sales price for the <i>e</i> -channel (<i>PRICE</i>)	Unit sales price for the electronic channel.	9.254 (19.893)	
Unit sales price for the <i>p</i> -channel (<i>PRICE</i>)	Unit sales price for the physical channel.	8.632 (9.369)	

Note. The number of buyers is 683, and the number of observations (purchase occasions) is 9,879.

for a BoL equals 3.08 for toys and 7.74 for electronics. *PRICE*, or the marginal sales price paid by the buyer averages at \$2.73 for toys and \$15.70 for electronics. Since its adoption, the *e*-channel is used in 24.9% of the BoL sales. The average prices per unit recovered in the *e*- and *p*-channels are \$9.25 and \$8.63, respectively. Approximately 23% of the buyers are the large buyers, and 42% are diverse.

4. Buyer Response Model

Suppose that the firm sells $j \in \{0, 1\}$ types of products, such that $j = 0$ denotes toys and $j = 1$ denotes electronics, through $k \in \{0, 1\}$ channels, with $k = 0$ representing the *p*-channel and $k = 1$ representing the *e*-channel. We use $t = 1, \dots, T$ to represent time stamps that indicate when the firm decides to sell a product of category j and (predetermined) size Q_{jt} through either channel.

We assume there are $i = 1, \dots, I$ buyers in the market who are informed of product availability on channel k for each sales occasion $t = 1, \dots, T$. Thus, each product sales event initiated by TPL counts as one purchase occasion for all potential buyers. The buyers decide whether to purchase or adopt a particular channel.² We use a dummy variable $D_{ikt}(j, Q_{jt})$ to denote the buyer purchase decision, given by

$$D_{ikt}(j, Q_{jt}) = \begin{cases} 1, & \text{if customer } i \text{ purchases the product} \\ & \text{of type } j \text{ and quantity } Q_{jt} \text{ from} \\ & \text{channel } k \text{ at time } t, \\ 0, & \text{otherwise.} \end{cases} \quad (1)$$

The buyer purchase decisions are product type and quantity specific; this takes into account the effects of any product and quantity differences on buyer purchase decisions. Note that on any purchase occasion, the product type and quantity are predetermined for both buyers and the firm, so neither the buyer nor the firm changes the product type or size during each sales occasion. For simplicity, we denote them D_{ikt} in the subsequent discussion.

4.1. Buyer Purchase Decision

Intuitively, buyers tend to make purchase decisions on the basis of their consideration of economic factors, such as price and inventory cost, and psychological factors, such as familiarity with a channel. Let U_{ijkt} be the latent utility that determines buyers' purchase

decisions, as given by the following equation:

$$U_{ijkt} = \beta_{0i} + \beta_{0ij} + \beta_{0ik} + \beta_{0ijk} + \beta_{1i} \cdot PRICE_{jkt} \\ + \beta_{2i} \cdot \ln[PRICE_{jkt} \cdot Q_{jt}] + \beta_{3i} \cdot FAMILIARITY_{ikt} \\ + \beta_{4i} \cdot \ln[INV_{ijt}] + \zeta_{ijkt}, \quad (2)$$

where coefficient β_{0ij} represents buyer i 's intrinsic preference for purchasing product type j , which takes into account buyer specialization in toys or electronics products. The parameter β_{0ik} captures the intrinsic preference for purchasing through channel k , such that if β_{0ik} is positive for the *e*-channel, everything else being equal, the buyer is more likely to purchase from the *e*-channel. The parameter β_{0ijk} measures the interaction between electronics and *e*-channel; thus if β_{0ijk} is positive, the buyer is more likely to buy electronics products from the *e*-channel. $PRICE_{jkt}$ is the expected marginal price paid by the buyer for product category j offered on channel k at sales occasion t , or the expected marginal winning price of that auction. Then $PRICE_{jkt} \cdot Q_{jt}$ represents the total expenditure incurred by the winning buyer for the BoL that consists of Q_{jt} units. We use a log transformation of the total expenditure to correct for its skewness (Greene 2002). Coefficient β_{1i} measures the buyer's sensitivity to price, and coefficient β_{2i} measures the buyer's sensitivity to total expected expenditure, similar to price sensitivity. The higher expected price and hence total expected expenditure lowers a buyer's probability of purchasing this product from that particular channel.

$FAMILIARITY_{ikt}$ is the channel familiarity index for channel k developed by buyer i prior to time t , measured as an exponentially smoothed weighted average of past experiences with a particular channel; we elaborate on this subsequently. Coefficient β_{3i} measures how prior use or familiarity with a particular channel changes the propensity to use the same channel again. If β_{3i} is significantly positive, buyers develop inertia toward the same channel with which they are familiar; in contrast, if it is insignificant, prior use of a channel does not matter for channel inertia. Finally, INV_{ijt} represents the inventory of product j at buyer i a time t ; we again use a log transformation of the inventory to correct for its skewness (Greene 2002). Coefficient β_{4i} measures the impact of inventory levels on the purchase decision, such that a buyer with enough inventory to sell may be less willing to purchase a BoL, despite any appeal of price or other factors.

Normative and empirical information systems studies show that buyers who have access to a familiar alternative will be reluctant to switch to new channels (e.g., Gefen 2002, Hitt et al. 2007, Kim et al. 2008). As a governance mechanism in exchange relationships characterized by uncertainty, vulnerability, or dependence (Bradach and Eccles 1989), trust develops through increased familiarity with a

² All the users in the firm's registered database in the two channels have the same information on the availability of auctions. There may be occasions when a user is not engaged for reasons other than the fundamental economic drivers we listed in the utility function. We model these in the unobserved random error in the utility function. Without observing what causes them to be disengaged, we are uncomfortable to make assumptions about who and why some of the 683 buyers are not active.

channel over time and more transactions.³ Repeat visits enhance buyers' perception of the sellers' reputation. (Jarvenpaa et al. 2000); positive service quality experiences (Parasuraman et al. 1985) in online stores also may improve channel loyalty (Gefen 2002, Chen and Hitt 2002), improving trust and purchase rates. In turn, trust increases channel familiarity and inertia, such that buyers develop resistance to searches for other channels, all else being equal (Gefen 2000). We expect that trust and familiarity with a channel build over time. However, introducing the *e*-channel without taking into account buyers' sensitivity to channel familiarity may prove detrimental for TPL.

To capture all these aspects, we define *FAMILIARITY*_{ikt} as the channel familiarity index for channel *k* developed by buyer *i* prior to time *t*, measured as an exponentially smoothed weighted average of past experiences with a particular channel. Specifically,

$$FAMILIARITY_{ikt} = \phi_i FAMILIARITY_{ik(t-1)} + (1 - \phi_i) D_{ikt-1}, \quad (3)$$

where $0 < \phi_i < 1$ is a parameter denoting that as time passes, the importance of past experiences or comfort with a particular channel may decay. In addition, $(1 - \phi_i)$ measures the weight that buyer *i* places on the most recent experience with this channel. This measure is similar to the brand familiarity variable first introduced by Guadagni and Little (1983) to capture consumer brand loyalty.⁴ This measure is also similar to state dependence (Seetharaman 2004); it captures the positive gains that buyers expect from reinforced behavior (Baker 2001). Before the firm introduced the *e*-channel, only the *p*-channel was available; therefore, the buyers were familiar with only the *p*-channel. Thus, at the beginning of our observation period, familiarity with *e*-channel is 0 and for the *p*-channel is 1 (*FAMILIARITY*_{i10} = 0 and *FAMILIARITY*_{i00} = 1).

FAMILIARITY is a weighted average of past accumulative experience and new usage, with ϕ representing the importance of past accumulative experience in determining channel familiarity. In other words, it measures state dependence, that is, how past usage

affects current channel choice. State dependence can be positive or negative at the same time: past usage can increase current choice of channel because of learning and reduction of uncertainty as well as switching costs. Past usage can decrease current choice of channel because the user finds a mismatch between her taste and the channel offering and may have loss of memory within the organization. Note that *FAMILIARITY* is a dynamic variable that applies to both the *e*- and the *p*-channel and changes with purchase history.

This is a general formulation that nests the special case when $\phi = 0$ and new usages just add up to the past experience. By allowing channel experience to be a summary statistic of all past channel usages, an organization can keep a memory of all past experiences (with weight ϕ) while updating that memory with the new experience (with weight $(1 - \phi)$). Our modeling approach is thus flexible enough to nest the case when all the past usages build up without any decaying effect. The coefficient of state dependence is only a statistical coefficient that represents the net magnitude of both effects. We rely on the data to tell us how important past accumulative experiences and the very last choice updates are.

Another important factor that affects the buyer's purchase decision is inventory. To be operationally efficient, buyers reduce their holding costs by avoiding excess inventory. We let *INV*_{ijt} denote the inventory level of product *j* that buyer *i* has in stock at occasion *t*. We follow the marketing and operations management literature (e.g., Ailawadi and Neslin 1998, Gupta 1988, Neslin et al. 1985, Sun 2005) to derive the evolution of per period inventory:

$$INV_{ijt} = INV_{ij(t-1)} + Q_{j(t-1)} - S_{ij(t-1)}, \quad (4)$$

where *INV*_{ij(t-1)} is the inventory that buyer *i* has of product type *j* and *Q*_{j(t-1)} is the quantity purchased of product *j* during the last purchase occasion (*t* - 1). Note that *S*_{ij(t-1)} is the average volume of product *j* that buyer *i* sells since the last purchase occasion.⁵ We assume that at *t* = 0, the starting inventory of the product is zero, and after, *t* = 1, inventory gets updated according to purchase quantity and sales reflected in Equation (4). The change in inventory levels drives buyer purchase decisions. For example, when the purchase online is of a large order, the user

³ Although the literature on B2B *e*-channels focuses on bilateral electronic integration between the firms, where firms need to make relationship-specific investments (see, for example, Clemons et al. 1993), which raises the issue of trust (Jap 2003, 2007; Hart and Saunders 1997), we note that TPL has a transactional relationship with its buyers where the products being sold in both the *p*- and the *e*-channel are commodities (return goods). Thus concerns about opportunism and dependence are not warranted in our setting. At the same time, the issues of trust and familiarity are important in the context of channel selection by buyers, and therefore pertinent for our research.

⁴ Kopalle et al. (2009) compute a buyer loyalty program participation measure using a concept similar to Guadagni and Little's brand loyalty measure. We model the outside option in a similar manner.

⁵ Because of TPL's reluctance to share information, our data do not contain information about buyers' sales volume. To approximate the sales volume, we assume that the average sales rate stays constant over time and calculate the sales rate using the aggregate purchase volume observed in our sample, divided by the number of observation periods. This approximation follows existing marketing literature (Ailawadi and Neslin 1998, Gupta 1988, Sun 2005). We also ran the model without using inventory and found that our results are robust. Additional research might measure inventory more accurately using observed sales data.

is less likely to make another purchase at subsequent sales occasion because she still has ample inventory in stock.

To simplify the notation, we use the vector $\beta'_i = [\beta_{0i} \beta_{0ij} \beta_{0ik} \beta_{0ijk} \beta_{1i} \beta_{2i} \beta_{3i} \beta_{4i}]$ to represent all the coefficients representing preferences for the product channel. We allow all the coefficients to be buyer specific to take into account heterogeneous buyer price and total expenditure sensitivity, channel inertia, and inventory effect, as we explain in §4.3.

Also in Equation (2), ζ_{ijkt} represents the unobservable factors that influence buyer purchase decisions. We assume that the error term $\zeta_{ijkt} \sim N(0, \sigma_\zeta^2)$, and for identification we assume $\sigma_\zeta^2 = 1$. Let W_{ijkt} represent all explanatory variables in Equation (2), which we cast as a binary probit model for buyer purchase decisions:

$$\text{Prob}(D_{ikt} = 1) = [1 - \Phi(\beta'_i W_{ijkt})]^{D_{ikt}} \cdot [\Phi(\beta'_i W_{ijkt})]^{(1-D_{ikt})}. \quad (5)$$

The buyer purchase model represented by Equation (5) describes the relationship between an observed purchase decision at a sales event in a channel and its key economic and psychological determinants. From Equation (2), we also note the likelihood of buying a product from the e -channel depends on the tradeoff among the relative strength of the price effect (price and total expenditure), channel inertia (channel familiarity), and inventory costs (current inventory stock). All the three factors change over time, and their evolving relative strengths shape buyers' patterns of channel migration for that particular product.

4.2. Purchase Price

The auction mechanism introduces dynamic pricing, such that prices change according to the popularity of a particular channel. We treat the buyer purchase price in Equation (6) as a changing variable that depends on the product's resale value, number of bids, and past prices paid for a similar product sold through the same channel. Thus,

$$\begin{aligned} \ln[PRICE_{jkt}] &= \alpha_{0jk} + \alpha_1 \cdot \ln[RPRICE_{jkt}] + \alpha_2 \cdot NBIDS_{jkt} \\ &\quad + \alpha_3 \cdot \ln[PRICE_{jk(t-1)}] \\ &\quad + \alpha_4 \cdot \ln[PRICE_{jk(t-2)}] + \varepsilon_{jkt}, \end{aligned} \quad (6)$$

where $RPRICE_{jkt}$ equals the unit retail price of product type j at time t . It provides a proxy for buyers' resale revenue generated and should affect buyers' willingness to pay and the observed purchase price. In addition, $NBIDS_{jkt}$ is the number of bids entered in the online auction for the same product j in the same channel k during sales occasion t . Auction theory finds that in the case of first price auctions, the number of bids proxies for competition and hence impacts the winning price (for example, see

Porter 1995, Hendricks et al. 2003).⁶ For example, Engelbrecht-Wiggans (1987) suggests that in expectation the number of bids is associated with a higher winning price. When the buyer observes a large number of bids, she interprets it as an intense competition and hence higher prices (if she wins and then pays). Extant literature confirms that increases in the number of bids in first price auctions signal the common value of the auctioned item and thus increase winning price (Krishna 2002).⁷ We include $PRICE_{jk(t-1)}$ and $PRICE_{jk(t-2)}$, the previous prices paid by the winning buyer for product type j disposed of through channel k at times $(t-1)$ and $(t-2)$, respectively, to control for possible persistence in prices over time.

In Equation (6), coefficient α_1 captures how the observed winning price relates to the product's resale value, or the buyer's revenue, and we expect it to be positive. The sign of coefficient α_2 indicates whether more bidders increase the winning price, as predicted by auction theory. Coefficients α_3 and α_4 measure the persistence of prices over time for a particular product type sold through the same channel. For notational convenience, we use the vector $\alpha' = [\alpha_{0jk} \alpha_1 \alpha_2 \alpha_3 \alpha_4]$ for all j and k to represent all the coefficients in the price equation. Furthermore, ε_{jkt} represents all unobserved factors that affect the observed winning price, such that $\varepsilon_{jkt} \sim N(0, \sigma_\varepsilon^2)$. Thus, Equation (6) can be estimated using a log-linear regression model.⁸

Equation (6) is estimated for each product category and each channel. This allows us to take into account the price differences across product categories as well as across the two channels. This price equation defines the price included in the buyer purchase equation (Equation (2)), and the dynamic pricing model introduces dynamics into the buyer's purchase decision. For example, the increasing popularity of a particular channel may increase purchase prices, which may discourage the appeal of purchasing through that particular channel.

4.3. Heterogeneity

Existing IS literature has explored how observed buyer characteristics influence buyer channel choice

⁶ It is not our interest to model the bidding process. We present the statistician's point of view and focus instead on the observed bidding outcome to identify factors that might predict the final purchase price paid by the (winning) buyers. Because our research purpose is to demonstrate a sequence of better allocations, Equation (6) serves as a predictive model that allows both the buyers and the firm to gauge the expected price.

⁷ However, if bidder entry decisions are endogenous, more expected bidders should reduce the expected price by deterring auction entry (Harstad 1990) or by underbidding. We evaluate such strategic buyer behavior while discussing the results.

⁸ As a robustness check, to account for potential correlation in the error terms in Equations (2) and (6), we estimated a Seemingly Unrelated Regression (SUR) model. These results are similar to our results in Tables 3(a)–3(c).

(e.g., Brynjolfsson et al. 2009). Although we can classify buyers based on their observable characteristics, we do not know a priori how these characteristics would affect the buyer dynamics. Methodologically, prior literature in economics and marketing has noted that the extent to which price, past channel experience, and inventory affect buyer purchase propensity varies across buyers. If buyer heterogeneity is ignored, the parameter estimates in Equation (2) will likely be biased (Gonul and Srinivasan 1993, 1996; Heckman 1981; Jain et al. 1994). It is important to take into account both observed and unobserved buyer heterogeneity in order to obtain more accurate estimates.

There are two common ways to represent buyer heterogeneity in choice models: continuous and discrete heterogeneity.⁹ We estimate a continuous heterogeneity model in which the mixing distribution is continuous (e.g., normal) and individual-specific parameters are drawn from this distribution.¹⁰ This approach offers computational ease, but in addition, we have only sparse observations for some buyers, and classical inference methods, which rely on the asymptotic properties of large samples, may not provide meaningful estimates at the individual parameter level. The continuous method instead allows for partial pooling of the data and offers more information that can help estimate the individual-specific parameters.

As we discussed previously, our discussion with TPL and a preliminary analysis of the data reveal that buyers differ in terms of the order size (*SIZE*) and diversity of the product types (*DIVERSITY*) they buy. For example, small buyers tend to be specialty resellers that cater to niche markets and thus have different perceptions of expenditure, inertia, and inventory than do large buyers. We allow two observable characteristics, *SIZE* and *DIVERSITY*, to affect the magnitude of price, channel familiarity, and inventory effects on a buyer's purchase decision and specify the following multivariate regression:

$$\beta_i = \delta_0 + \delta_1 \text{SIZE}_i + \delta_2 \text{DIVERSITY}_i + v_i, \\ v_i \sim \text{iid } N(0, V_\beta). \quad (7)$$

⁹In the case of discrete heterogeneity, the mixing distribution is discrete with mass points, which correspond to buyer segments or latent classes (e.g., Kamakura and Russell 1989). In this case, a finite mixture model can estimate segment-specific parameters, and the number of segments depends on parameters such as the AIC or BIC. As a robustness check, we estimate the latent class model using the Latent Gold package and find that the results are similar to what we find for the model with continuous heterogeneity. These results are available from the authors upon request.

¹⁰We need not consider buyer heterogeneity for the purchase price Equation (6) because the expected price (and expenditure) comes from a common information pool. As a robustness check, we allow for but do not find any significant heterogeneity; the estimates are similar to those we report in Table 3.

The individual-specific parameters $\beta'_i = [\beta_{0i} \ \beta_{0ij} \ \beta_{0ik} \ \beta_{0ijk} \ \beta_{1i} \ \beta_{2i} \ \beta_{3i} \ \beta_{4i}]$ from Equation (2) all then become a function of two observable buyer characteristics: size, and diversity. Recall that β_i captures the effect of the product category, channel, interaction between product and channel, price, total expenditure, channel familiarity, and inventory on the buyer's purchase decision. In this specification, the coefficients δ_1 and δ_2 indicate how a buyer's size and diversity might modify the coefficients of the covariates in Equation (2). For example, the effect of size on β_{2i} indicates the varying effect of total expenditure on purchase between larger and smaller buyers. If $\beta_{2i} < 0$ and $\delta_1 < 0$, higher expenditure tends to make buyers less likely to buy, and the reduction in purchase likelihood is more for larger buyers. In other words, larger buyers are shown to be more price sensitive compared to smaller buyers.

The random variable v_i is an unobservable component of buyer heterogeneity, assumed to be distributed normally with mean 0 and variance covariance matrix V_β . Then V_β determines the spread of the unobserved component. Using Equation (7), we allow buyer characteristics, both observable and unobservable, to affect our model parameters. Our intent is to demonstrate that accounting for buyer heterogeneity can help the firm to profile buyers and identify characteristics correlated with *e*-channel usage. Using this information, firms can design more customized product allocation strategies that entice buyers to adopt the *e*-channel.

4.4. Estimation

The buyer response model specified by Equations (5)–(7) in a hierarchical Bayesian framework takes buyer dynamics and heterogeneity into account, which we estimate jointly. More specifically, we use the hierarchical Bayesian model for inference, which involves computing the exact information about the posterior distribution of the model parameters (see Rossi et al. 1996, 2005).

As in standard Bayesian models, we set diffuse priors for the model parameters, then apply Markov Chain Monte Carlo (MCMC) methods (Gibbs sampler) and data augmentation coded in *R* for our estimation. This approach is especially well suited for the hierarchical structure of the inference model, for which we build a Markov chain that has a stationary distribution as the posterior. The approximations involve a series of draws, following guidelines related to the convergence of this posterior distribution. We run the MCMC simulation for 50,000 draws and discard the first 20,000 as burn in. We also use a thinning parameter of 20, such that we retain every 20th of the remaining draws for the posterior distribution. This technique helps reduce the storage space and mitigates the computational burden of analyzing stored draws.

As discussed earlier, in our model setup buyers' purchase decisions depend on tradeoffs among price, channel familiarity, and inventory effects. Price in turn is affected by the popularity of the *e*-channel. For each buyer, the tradeoff among these three dynamic effects (price, channel familiarity, and inventory) shapes the pattern of buyer channel usage over time. For example, after its initial introduction, most buyers likely are not to be familiar with the *e*-channel and therefore display a lower purchase probability (*channel inertia*). Because fewer buyers participate in the auction, the winning price should be lower, which in turn encourages (price sensitive) buyers to purchase from the *e*-channel (*price effect*). As more buyers accumulate experience and familiarity with the *e*-channel, prices tend to escalate over time.¹¹ Thus, buyer decisions about whether to purchase from the *e*-channel depend on the dynamic tradeoff between the price and familiarity effects. Sellers can take actions to influence these tradeoffs by, for example, changing the products offered in the *e*-channel. These relationships become even more complicated by the addition of buyer heterogeneity. The prevailing price, total expenditure, channel familiarity, and inventory effect dynamically affect buyer propensity of purchasing from the *e*-channel, and this differs across buyers with different profiles.¹²

5. Empirical Results

In this section, we discuss the model fitting statistics and parameter estimates, with an emphasis on the results related to dynamics and buyer heterogeneity. We then highlight how the focal firm's current ad hoc channel introduction ignores these aspects and alienates potential buyers.

5.1. Model Comparison

To demonstrate the importance of taking into account buyer dynamics and heterogeneity in modeling buyer purchase decisions, we estimate two benchmark models for comparison with our proposed model. The first benchmark is our proposed Model (1) without channel familiarity, dynamic price, or buyer heterogeneity; it assumes that the purchase decision relies solely on past price and inventory and that the buyer pool is homogeneous. The second benchmark, Model (2), assumes that the buyers develop channel familiarity but are homogeneous. Dynamic pricing is also not taken into account. Finally, the proposed

¹¹ Extant literature discusses the winner's curse, that is, the auction winner in a common value auction may overpay for the auction item (Krishna 2002, Bajari and Hortaçsu 2003). We discuss this in detail in the results section.

¹² Increases in number of bidders may also influence the attractiveness of the *e*-channel by changing the bidder to auction ratio and thereby influencing market efficiency. See Kauffman et al. (2009) for further details.

Table 2 Model Comparison

Model selection criteria	Model 1	Model 2	Model 3
	Without dynamics and heterogeneity	Without heterogeneity	Proposed model
Log-likelihood	-23,009.186	-22,948.947	-16,211.996
AIC	46,032.37	45,913.89	29,550.814
BIC	46,115.74	46,009.17	30,331.965

Model (3) assumes all three effects: channel familiarity, dynamic pricing, and buyer heterogeneity.

We conduct two diagnostic tests to check for convergence, namely, the Geweke convergence test (Geweke 1992) and Heidelberger and Welch's (1983) stationary test, both of which indicate adequate convergence until the estimation is stable and convergent. For our proposed model, the mean rejection rate for the Metropolis-Hasting (MH) algorithm is 0.84 (desired rejection rate is 0.6–0.9). In Table 2, we report the model fitting statistics for the three competing models; our proposed model outperforms the two benchmark models. That is, allowing for buyer dynamics and buyer heterogeneity is critical to capture variation in buyer purchase decisions over time. Furthermore, the improvement is greater from Model 2 to Model 3, which indicates that heterogeneity significantly improves the data fit. Our proposed Model 3 is clearly the best fitting model. Our subsequent discussion focuses on Model 3.

5.2. Estimation Results

In Table 3(a), we report the parameter estimates from the price equation (Equation (6)) for each channel and product category. The coefficient of unit retail cost is significant and positive; that is, a higher resale price relates to a higher observed winning price. The coefficients suggest that for both product categories, unit retail price impacts the price paid by the buyer. The coefficient estimates also suggest that the marginal effect of unit retail price is greater on electronics than on toys, ($0.370 - 0.234 = 0.135$, $p < 0.001$ versus $0.164 - 0.136 = 0.028$, $p < 0.001$) and conveys information on the intrinsic value of the BoL.¹³ As expected, more bids lead to a higher winning price in the current period; specifically, one additional bid increases the unit price bid of the buyer by \$0.13 for toys and \$2.78 for electronics—this translates into a 4.7% increase in the unit price of toys and a 17.7% increase in the unit price of electronics. Clearly, a larger number of bids in the electronics category drives up the winning prices far more than it does in the toy category ($\chi^2(1) = 20.154$, $p < 0.001$). These results are all significant at the 1% level.

¹³ For this, we compare the standardized coefficients across the two categories using a standard χ^2 test.

Table 3(a) Estimation of Purchase Price Equation

	Unit purchase price			
	Toys		Electronics	
	<i>e</i> -Channel	<i>p</i> -channel	<i>e</i> -Channel	<i>p</i> -channel
Intercept	−0.412 (0.003)**	−0.0267 (0.002)**	−15.434 (0.060)**	−5.568 (0.021)**
Unit retail cost	0.164 (0.000)**	0.136 (0.000)**	0.370 (0.000)**	0.234 (0.000)**
Number of bids	0.129 (0.000)**		2.783 (0.003)**	
Purchase price at (<i>t</i> − 1)	0.010 (0.000)**	0.052 (0.000)**	0.006 (0.001)**	0.046 (0.001)**
Purchase price at (<i>t</i> − 2)	0.008 (0.000)**	0.000 (0.000)	0.045 (0.001)**	0.040 (0.001)**

Notes. Standard errors are in parentheses.

+Significant at 10%; *significant at 5%; **significant at 1%.

Table 3(b) Estimation of Purchase Equation

	Proposed model
Intercept	−5.793 (0.045)**
Intercept-electronics	1.086 (0.011)**
Intercept- <i>e</i> -channel	0.901 (0.015)**
Intercept-electronics * <i>e</i> -channel	0.632 (0.071)**
Unit price	−0.093 (0.003)**
Log(expenditure)	−0.049 (0.002)**
Channel familiarity	2.252 (0.341)**
Log(net inventory)	−0.055 (0.004)**
Smoothing parameter	0.747 (0.023)**

Notes. Standard errors are in parentheses.

+Significant at 10%; *significant at 5%; **significant at 1%.

First price auctions encourage bidders not to bid their willingness to pay at the beginning and instead to bid incrementally (Porter 1995, Hendricks et al. 2003). Furthermore, because expected price (Equation (2)) may form a common information pool, this lends common value properties to the *e*-channel auction. Thus, an alternative explanation for Figure 1(a) could be that smarter buyers may want to avoid winner's curse (e.g., Milgrom and Weber 1982, Thaler 1988). Our model takes this into account by allowing buyers to form expected price based on the total number of bids. When the *e*-channel is too crowded, buyers expect higher bidding prices. The fear of the

winner's curse prevents them from purchasing from the *e*-channel. They could thus behave strategically by either not participating in the auction or by bidding less aggressively.

Past purchase prices for the same product category and channel remain persistent over time (significant at the 1% level for all channels and product categories, except for toys in the *p*-channel in period (*t* − 2)).

In Table 3(b), we report the estimation results from the purchase equation, including the posterior distributions of individual-specific means (β_i s), which we collect by averaging the mean value of the parameter estimates for each buyer. The positive constant term for electronics (1.086) indicates that buyers intrinsically are more likely to buy electronics in the *e*-channel. Similarly, all else being equal, buyers prefer the *e*-channel (0.901), in support of our conjecture that the *e*-channel is more flexible and convenient and hence attractive to the buyers. We further find that buyers are also more likely to buy electronics from the *e*-channel, as indicated by the positive interaction coefficient (0.632). Because electronics can often be described by a vector of characteristics that describe performance, this result is consistent with prior work that suggests that search goods are more likely to be purchased electronically whereas experience goods are more likely to be purchased through physical channels (e.g., Gupta et al. 2004). However, both the price (−0.093) and the total expenditure

Table 3(c) Estimation of the Heterogeneity Equation

Covariates	INTERCEPT	SIZE	DIVERSITY
Intercept	−5.788 (0.028)**	2.008 (0.057)**	0.635 (0.064)**
Intercept-electronics	1.087 (0.015)**	−0.646 (0.015)**	−0.037 (0.004)**
Intercept- <i>e</i> -channel	0.889 (0.020)**	−1.576 (0.039)**	0.694 (0.051)**
Intercept-electronics * <i>e</i> -channel	0.631 (0.015)**	−0.283 (0.029)**	0.332 (0.038)**
Unit price	−0.064 (0.001)**	−0.121 (0.003)**	0.004 (0.002)*
Log(expenditure)	−0.060 (0.002)**	−0.150 (0.005)**	0.105 (0.006)**
Channel familiarity	2.246 (0.028)**	1.329 (0.053)**	−0.528 (0.66)**
Log(net inventory)	−0.055 (0.003)**	0.029 (0.006)*	−0.011 (0.008)**

Notes. Standard errors are in parentheses.

+Significant at 10%; *significant at 5%; **significant at 1%.

Figure 1(a) Buyers' Usage of *e*-Channel over Time

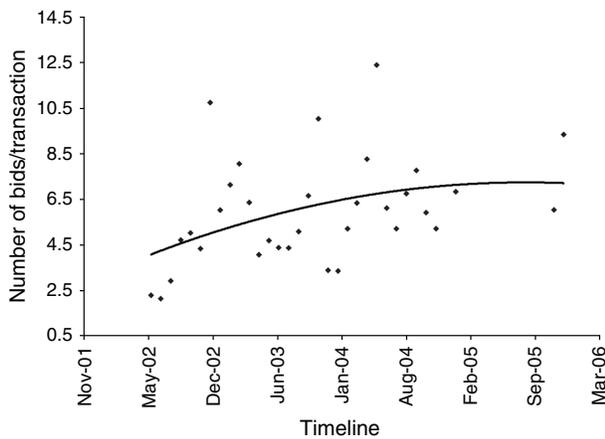


Figure 1(c) Average Order Size Allocated to *e*-Channel

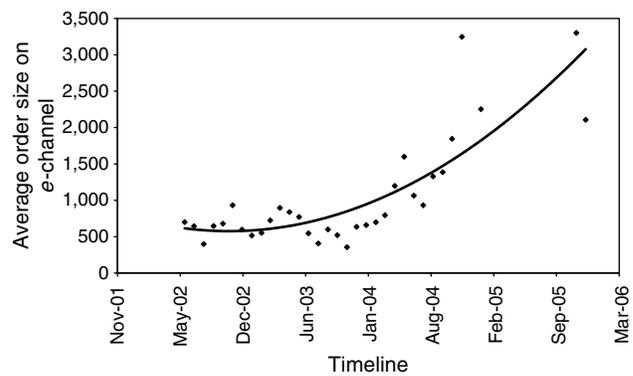


Figure 1(b) Number of Products Allocated to *e*-Channel

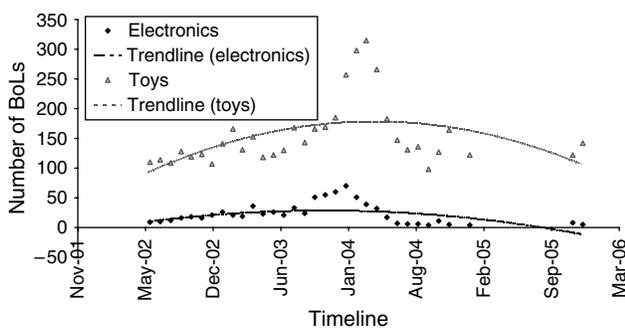
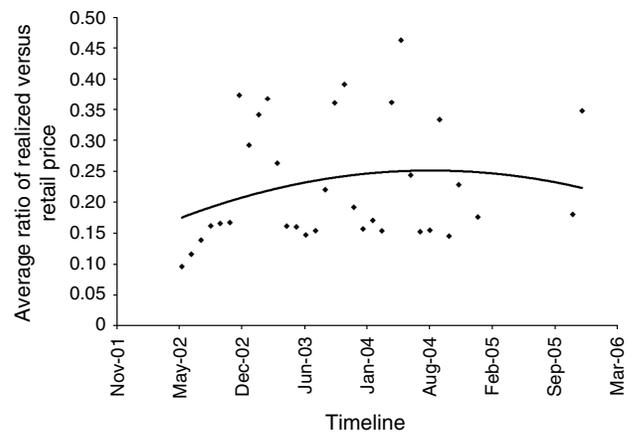


Figure 1(d) Average Unit Sale Prices in the *e*-Channel



(−0.049) effects are negative, such that higher prices and total expenditure decrease the likelihood that a buyer will purchase at all, from either channel.

The effect of channel familiarity is positive and significant (2.252, $p < 0.001$), suggesting that buyers display channel inertia because of channel familiarity and hence prefer to buy from a familiar channel rather than from new channels. Recent research similarly demonstrates the important role of past experience on channel migration (Ansari et al. 2008). Finally, as expected, the effect of net inventory is negative (−0.055); when inventory levels are high, buyers are less likely to purchase in either channel.

Finally, we report the estimation results of the posterior distribution of the hierarchical regression coefficients in the heterogeneous Equation (7) in Table 3(c). Buyers are clearly heterogeneous. The effects of price, total expenditure, channel familiarity, and inventory on their purchase propensity vary significantly across buyers. The coefficients of size and diversity for the constant term (−0.646 and −0.037) for electronics in Equation (2) reveal that on average buyers tend to purchase electronics (1.086 in Table 3(b)), and smaller buyers and less diversified buyers are even more likely to do so. The negative coefficient of size in the *e*-channel (−1.576) indicates that compared with

larger buyers, smaller buyers are more likely to purchase from the *e*-channel. This may be because their size attracts them to the convenience, flexibility, and lower transaction costs offered in the *e*-channel. The positive coefficient of diversity (0.694) further shows that diversified buyers prefer the *e*-channel more than less diversified ones do. The coefficient for the interaction term between the dummies for electronics and *e*-channel is negative for size (−0.283), suggesting that larger buyers are less likely to purchase electronics from the *e*-channel. Similarly, this interaction coefficient is positive for diversity (0.332); thus, more diverse buyers are more likely to buy electronics from the *e*-channel.

Buyers' price sensitivity also varies with size and diversity, such that smaller and more diversified buyers are less price sensitive; this effect is seen for both unit price and total expenditure (−0.121 and 0.004 for price; −0.150 and 0.105 for expenditure). Smaller and more diversified buyers may be specialty retailers, who often cater to broad demand and offer better services, enabling them to extract higher retail prices. Similarly, diverse buyers may be confident about their ability to sell the salvage items because they likely target a variety of products to select buyers and hence

extract a better price, so they are less sensitive to the price. The magnitude of channel familiarity also changes with size and diversity. The positive coefficient for *SIZE* on channel familiarity (1.329) indicates that though all buyers are reluctant to adopt a new channel, the attachment is stronger for larger buyers. In other words, larger buyers shy away from unfamiliar channels, making them less likely to buy products offered through the *e*-channel and consequently limiting their *e*-channel familiarity.¹⁴ The opposite is true for smaller buyers, who are more likely to overcome inertia and thus are willing to adopt the *e*-channel. Similarly, we find that less diverse buyers (−0.528) are more likely to try the new *e*-channel.

Buyers also demonstrate differential sensitivities to inventory, such that the larger buyers care less about inventory levels (0.029). This may be in part because large buyers often have outside relationships with other salvage dealers, which makes them less sensitive to observed inventory at TPL. This positive coefficient for large buyers may also be indicative of the scaling effect; that is, given their larger size and likely higher sale volumes, they are likely to sell any given level of inventory more quickly and so are less sensitive to any given inventory level, other things equal. More diversified buyers also are more sensitive to inventory (−0.011). This negative coefficient is indicative of the greater complexity that diverse buyers have to manage.

To summarize, our estimation results reveal that buyers are heterogeneous in their sensitivity to price, channel inertia, and inventory cost. In general, smaller buyers tend to exhibit a greater intrinsic preference for *e*-channels; are more likely to purchase electronic products and more likely to purchase these products through the *e*-channel; and are less dependent on channel familiarity, less price sensitive, and more sensitive to inventory stockpiles. Diversified buyers prefer the *e*-channel but are also less likely to purchase electronic products and are less price sensitive, less sensitive to channel familiarity, and more sensitive to inventory cost. Taken together, the heterogeneity results suggest that smaller and diversified buyers are the ideal candidates for the *e*-channel because they not only overcome their channel inertia to try the new channel but also will be less sensitive to higher prices caused by the increasing popularity of the *e*-channel.

¹⁴ Although familiarity has a stronger influence on large buyers, a pertinent question to ask is what attracts these large buyers to the *e*-channel to begin with. Our discussion with some of these large buyers revealed that these buyers were initially attracted to the *e*-channel because of the lower acquisition costs, that is, lower transaction costs as well as lower prices. This is also borne by our results; the probability of purchase from *e*-channel for large buyers, although low, is never zero. However, over time, as the size of the orders as well as the unit prices increased on the *e*-channel, it became less attractive (but never unattractive) to the large buyers.

5.3. Buyer Dynamics

Our results also demonstrate the dynamic nature of buyer channel usage: a buyer's past experience with a channel increases the chance that it uses the same channel in the future. Greater use of the *e*-channel builds the *e*-channel familiarity and decreases the *p*-channel inertia, which increases the probability of using the *e*-channel (even if the price is slightly higher). Another source of buyer dynamics involves the auction mechanism, such that the more popular the *e*-channel, the higher the purchase price, which should have an adverse appeal. These dynamic effects differ between large and small buyers and more and less diversified buyers. Based on our understanding of buyer dynamics and heterogeneity, we now explain the rising and then declining pattern of *e*-channel usage in Figure 1(a).

To investigate the source of this pattern, we report the percentage of product types and average order sizes allocated to the *e*-channel in Figures 1(b) and 1(c) to characterize the allocation rule currently adopted by the firm. Most products allocated to the *e*-channel are toys (see Table 1), and most importantly, the average order size increases over time. Recall that smaller and more diversified buyers are more likely to purchase online and prefer electronics. When a large quantity of toys appears online, many smaller buyers are automatically prohibited from adopting the *e*-channel, and only larger buyers are attracted, which represents a mismatch with the buyer preferences as revealed by our findings.

The current allocation rules also ignore buyer dynamics. During the early stage of *e*-channel introduction, larger buyers find good bargains online because of the minimal competition between bidders (Harstad 1990). Because they are more price sensitive, more large buyers are attracted to the *e*-channel, in line with the initially increasing usage. In other words, the initial increase in usage is mainly caused by larger buyers who are attracted by the good bargains usually found in an online market in its infant stages. Observing that its initial policy of allocating large orders and toys to the *e*-channel worked well, TPL kept increasing order size and decreasing product diversity (Figure 1(c)). However, as more large buyers flocked to the *e*-channel, the greater was the competition, which in turn increased the winning price and decreased *e*-channel attractiveness among price-sensitive buyers.¹⁵ This has a detrimental effect: The increasing order size not only deters smaller and

¹⁵ As we discuss previously, the fear of the winner's curse in this auction setting may prevent buyers from participating in the *e*-channel. The detrimental effect of higher price and total expenditure is also felt more by the larger buyers, thus diminishing the appeal of the *e*-channel. Our discussion with the large buyers revealed that enhanced competition and the prohibitive lot

less diversified buyers but also discourages existing buyers because the increasing prices and larger quantities demanded higher total expenditure. As a result, despite their familiarity with *e*-channel, buyers are turned away from the *e*-channel and usage grew at a slower rate, as observed in Figure 1(a). The smaller buyers, who are less price sensitive, at this late stage of our observation period, are deterred by the large order sizes and consequently larger inventory constraints. For the larger buyers, who continue to purchase from the *p*-channel, channel familiarity and thus inertia for the *p*-channel increase, whereas familiarity for the *e*-channel decreases; as borne out in our results, larger buyers exhibit greater channel familiarity. Thus, when the order size considerably increased, the negative effect of channel inertia and net expenditure on buyer utility dominates the price effect, resulting in the pattern we observe.

In short, by ignoring buyer dynamics, the firm did not realize the same factor that helped the initial build-up in online traffic became detrimental to the adoption of *e*-channel as time progressed. Furthermore, by ignoring heterogeneity, the firm's current allocation enlisted the wrong type of buyers right from the start. The initially increasing popularity of the *e*-channel resulted from users attracted by the bargain price instead of an inherent preference for the *e*-channel. Smaller and more diverse buyers, who are inherently interested in the *e*-channel, are excluded. Furthermore, TPL ignored the effect of popularity on prices and the resulting alienation of price-sensitive buyers. Instead of lowering the order size to mitigate the price effect and inventory constraints, the firm kept increasing the order size and eventually drove away even more buyers. As Figure 1(d) shows, the declining popularity adversely affected the realized sales prices (as a ratio of the retail prices).

TPL's allocation scheme seems to contribute to the declining popularity of the *e*-channel over time and lost revenue opportunities because it fails to align with dynamic and buyer heterogeneity. As discussed before, the observed allocations are *ad hoc* and follow past policies. TPL first allocates large bills of lading and toys to the *e*-channel and later seems to adopt an "if it ain't broke, don't fix it" attitude. The large bills of lading and toys work well during the initial stages, with the firm allocating greater amounts of toys to the *e*-channel. This policy, which at first seems logical, soon fails to recognize the potential negative impact of escalating prices and excludes buyers who are initially excluded and subsequently alienated. The firm's

prices were their primary reasons for dropping out of the *e*-channel, whereas they continued to use the *p*-channel. Smaller buyers felt that the prohibitively large order sizes that were available on the *e*-channel imposed higher inventory costs and thus were not suitable.

allocations, if changed, could influence buyers' channel usage positively, if the allocations took advantage of buyer dynamics and heterogeneity. By strategically selecting the product type and size according to buyer preferences, the firm has an opportunity to entice buyers to overcome their channel inertia. Such an alternative allocation strategy is discussed in the next section.

6. Ushering Channel Allocation

In this section, based on parameter estimates, we simulate an alternative allocation scheme that assumes buyer response parameters stay the same as determined in the previous section. We use a dummy variable $A_t(j, Q_{jt})$ to denote the seller's decision at time t about whether to allocate product j of quantity Q_{jt} to either the *e*-channel or the *p*-channel:

$$A_t(j, Q_{jt}) = \begin{cases} 1, & \text{if product of type } j \text{ and quantity } \\ & Q_{jt} \text{ is allocated to } e\text{-channel,} \\ 0, & \text{if product of type } j \text{ and quantity } \\ & Q_{jt} \text{ is allocated to } p\text{-channel.} \end{cases} \quad (8)$$

Because the order size Q_{jt} in this setting is predetermined, the firm only decides which channel to use for an order of this size and type.

6.1. Firm's Objective Function

To make channel allocation decisions, firms usually consider the revenue expected from the designated channel as well as handling costs. As demonstrated by prior literature, self-service channels may save significant operating and processing cost (e.g., Apte and Vepsalainen 1993, Bitner et al. 1997, Chase 1981). Because costs increase with the number of pallets, we use the number of pallets as a proxy for the costs associated with processing a BoL. That is, the number of pallets affects TPL's decision to use a particular channel (Tirole 1988). Let $\ln[E[\Pi]_{kt}]$ denote the expected revenue of a BoL available at time t and allocated to channel k . Let $PALLET_{jt}$ represent the number of pallets in this order. The firm's channel allocation decision becomes an optimization problem,

$$\begin{aligned} \text{MAX}_{A_t} V_{kt} &= \gamma_{0jk} + \gamma_1 \cdot \ln[E[\Pi]_{kt}] \\ &+ \gamma_2 \cdot \ln[PALLET_{jt}] + e_{kt}, \end{aligned} \quad (9)$$

for product type j of size Q_{jt} sold on channel k during occasion t . When the firm makes its allocation decision, it has information about the number of pallets in the BoL, but not about the expected revenue. If the firm takes into account buyer behavior, the expected revenue can be written as

$$E[\Pi_{kt}] = E[PRICE_{jkt}] * Q_{jt}, \quad (10)$$

where $E[PRICE_{jkt}]$ is the expected purchase price predicted by Equation (6). With this term, the firm can consider ex ante the dynamic pricing created by the auction mechanism. Because the firm does not know the number of bids that will be placed for the online auction, we first compute the $\text{Prob}(D_{ikt} = 1)$ for each buyer, then use a cutoff ($\text{Prob}(D_{ikt} = 1) \geq 0.5$) to evaluate who is likely to participate in the auction. We then sum the average number of bids for these particular buyers to approximate the number of bids, where $\text{Prob}(D_{ikt} = 1)$ describes the buyer response to the firm's allocation, as in Equation (2). It contains information on both buyer heterogeneity and dynamics. By including $\text{Prob}(D_{ikt} = 1)$, the firm can thus anticipate behavioral reactions into its allocation process. The parameter γ_{0jk} then captures the firm's intrinsic preference to allocate product of type j to channel k , and γ_1 measures the importance of revenue and cost on the firm's allocation decision. Note that Equation (9) describes a more general and realistic situation that nests the special case in which γ_{0jk} and γ_2 are close to zero, and the firm's allocation is driven solely by expected revenue.

We assume that e_{kt} is an error term that summarizes all unobservable factors affecting the firm's channel choice, with a standard Type-I extreme value distribution. Therefore, the binary logit model for the firm's channel choice is¹⁶

$$\text{Prob}(A_t = 1) = \frac{e^{V_{kt}^*}}{1 + e^{V_{kt}^*}}. \quad (11)$$

The estimation results for the firm's model appear in Table 4. Our estimates for the firm's channel choice indicate that TPL is intrinsically less likely to sell electronics through the e -channel. Both expected total revenue and transactional cost, as proxied by the number of pallets, play significant roles. Using the estimates of α' , β'_i , λ' , and γ' , we can run a simulation with Equation (10) to assess whether TPL can improve roll-out for the new channel by forward looking allocation rules.

¹⁶ To obtain the values of $\gamma' = [\gamma_{0jk}, \gamma_1, \gamma_2]$, we estimate the objective function describing the current decision rule using the observed firm's allocation decisions. According to the current allocation rule, the expected revenue equals the last-period price obtained from the same channel. The expected revenue according to the current allocation is $E[\Pi]_{kt} = E[PRICE_{jkt-1}] * Q_{jt}$. Clearly, the firm's current allocation decision is independent of buyer response in general and ignores buyer dynamics and heterogeneity in particular. We apply the firm's channel choice (Equation (9)) with expected profit being replaced by the above equation) to the observed data to obtain the estimates of $\gamma' = [\gamma_{0jk}, \gamma_1, \gamma_2]$ using a standard binary logit model with the lagged price as the expected purchase price. In the simulation, we treat these parameters as known.

Table 4 Estimation for Firm's Channel Decision

Variables	Estimates
Intercept	-2.370 (0.182)**
Intercept-electronics	-0.797 (0.097)**
Log of expected revenue	0.310 (0.028)**
Log of number of pallets	-0.280 (0.048)**

Notes. Standard errors are in parentheses.

*Significant at 10%; **significant at 5%; ***significant at 1%.

6.2. Simulation Results

For the simulation, we use data from another regional TPL center to measure the profitability improvements achieved by incorporating buyer heterogeneity into the channel choice decision. Using coefficients α' , β'_i , λ' , and γ' , we let the firm predict its expected purchase price according to Equation (6) for each order. Assuming each order is offered on both channels, we calculate the probability of purchase using Equation (5) for each buyer, then compute the total expected profit with Equation (10) for each channel. The allocation decision depends on Equation (11). After this decision, we update buyer channel familiarity and inventory and repeat the process for each buyer and each sales event. Thus, we obtain an alternative channel allocation decision for each BoL with revised prices and buyer channel usage.

Figures 2(a)–2(d) serve as contrasts to Figures 1(a)–1(b). In particular, Figure 2(a) confirms that by recognizing buyer heterogeneity and dynamics, the proposed channel allocation significantly increases the popularity of the e -channel over time. More buyers are attracted to the new channel, and the trend keeps increasing during the observation period. As Figures 2(b) (number of bills of lading of each product type allocated to the e -channel) and 2(c) (average order size allocated to the e -channel) show, the proposed allocation differs from that observed in the data in several ways. First, it changes the composition of offered product types to include more electronics on the e -channel. This increases the diversity of the product offering. Second, the average size of orders placed on the e -channel is significantly smaller than those observed in the original data, with only a slight increase in size over time. As channel familiarity for the e -channel builds, buyers tend to overcome their inertia for the e -channel adoption, and the firm can slowly then increase the size without worsening the adverse price effect. That is, through careful modulation of orders, the e -channel can attract small and diversified buyers. This translates to engaging in micro-marketing strategies to reach out to niche buyers who value diversity and small purchase quantities.

The new allocation decisions also are better aligned with buyer heterogeneity and tailored to the interests

Figure 2(a) Buyers' Usage of *e*-channel over Time (Simulated Allocation)

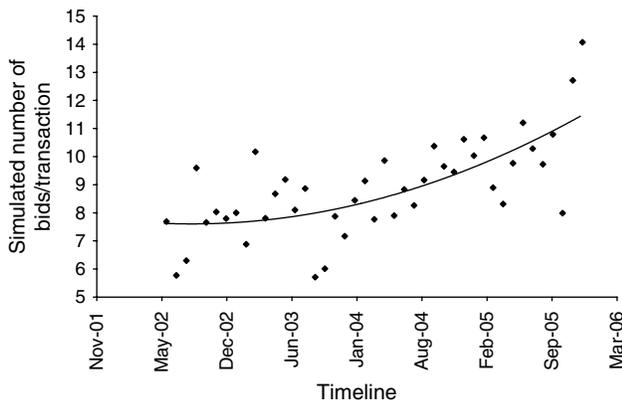


Figure 2(c) Average Order Size Allocated to *e*-Channel (Simulated Allocation)

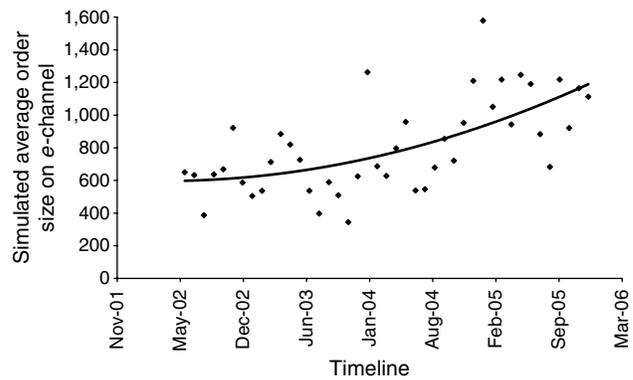


Figure 2(b) Number of Products Allocated to *e*-Channel (Simulated Allocation)

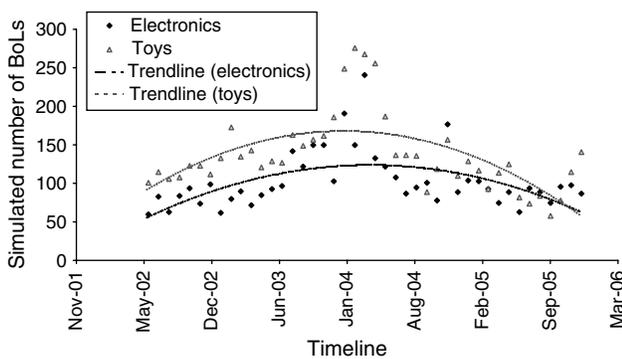
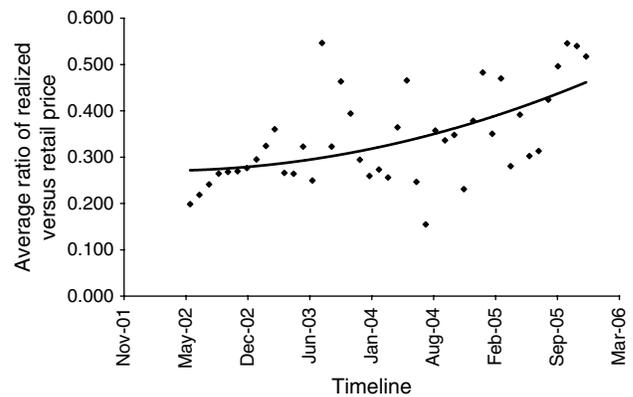


Figure 2(d) Average Unit Sale Prices in the *e*-Channel (Simulated Allocation)



of smaller and more diversified buyers: lower order sizes, greater diversification, and preferred product types. With this approach, when the *e*-channel gets crowded, smaller and more diversified buyers are less likely to be alienated by rising prices. The significantly lower order sizes also reduce total expenditure, which helps mitigate the adverse price effect and thus the channel continues to remain attractive to these buyers. Furthermore, as buyers accumulate experience with the *e*-channel, increased familiarity with this channel makes them more tolerant of higher prices, further offsetting the adverse impact of price escalation because of competition. The ratio of average winning price over the retail price increases over time, as confirmed by Figure 2(d). Thus, the firm can earn greater revenues over time. The average price on the *e*-channel in our proposed allocation is seen to be higher than that observed in the data.

By taking into account dynamic and heterogeneous buyer response, the firm can improve the popularity of the *e*-channel. By recognizing preferred product types, size, and diversity, the firm attracts more buyers to the *e*-channel, which underscores the initial rationale for adopting it. That is, it can reach buyers that have been previously unwilling to purchase from

the *p*-channel because of large order sizes or minimal product diversification. With the right buyers purchasing from the *e*-channel, the firm can initiate price increases, though it must regulate the order size to be attractive to small buyers and those seeking diversity. The lesson to be learned from this is to place the interests of buyers first. Only after attracting appropriate buyers should the firm seek to reap the benefits of greater revenue from the increased competitive intensity of buyers in the auctions. And only then can firms usher buyers successfully into *e*-channels.

Although we focus mainly on how the proposed allocation improves *e*-channel revenue, we also examine whether the *e*-channel revenue comes at the expense of the *p*-channel through channel cannibalization. The results are encouraging. We compared aggregate revenues and channel revenues from the observed allocation scheme with the same measurements with our proposed allocation scheme. In general, the average revenue per unit is higher in the *e*-channel than in the *p*-channel. Furthermore, the firm's revenue from the *e*-channel increases as it becomes more popular in our proposed allocation. Although the *p*-channel revenues decrease, aggregate

revenues, considering both channels, accumulate as more revenue comes from the *e*-channel. Thus, the net impact is positive, and by carefully designing an allocation decision, the firm can benefit from channel migration that recognizes heterogeneity and dynamics. Graphs of these results are included in the online appendix.¹⁷

7. Conclusion

Electronic sales channels offer sellers a great opportunity to increase their buyer base and reduce costs. Although B2C online auctions are usually the focus of attention, similar *e*-channels are increasingly being adopted by companies in a B2B setting. Such auctions enable firms, such as those in the reverse logistics sector, to clear out excess and discontinued inventory for a better price, to gain market share, and to increase profitability in the long run (AllBusiness.com 2008). A common mistake has been to ignore heterogeneity among buyers and the dynamics of buyer purchase behavior, which causes sellers to ignore the opportunity to offer higher value and gain buyers that seek diversity and smaller sizes. Adopting a buyer mindset and leveraging buyer heterogeneity and dynamics have a profound impact on channel profitability. Given that e-commerce sales are in the region of \$7 trillion, such decisions can have considerable impact on firm profitability. Industry practice and most existing literature ignore the dynamics of technology use. We attempt to address this void by investigating the dynamic and heterogeneous behavior of buyers in a new channel and thereby provide guidance regarding how firms may establish proactive strategies.

In this paper, we examine buyers' dynamic and heterogeneous responses to the introduction of an *e*-channel. Using micro-level data gathered from a third party logistics provider that operates both physical and electronic sales channels, we propose a buyer response model in which buyers make channel choice decisions based on expected prices, channel inertia, and inventory, and their heterogeneity is addressed by a hierarchical Bayesian framework. Several key insights emerge from our model estimation. First, buyers' purchase decisions depend largely on the price effect and channel inertia, which interact in opposing directions as the *e*-channel grows more popular over time. Price increases resulting from more bids deter buyers, whereas channel inertia built from sampling experience helps retain repeat buyers for the new channel. Second, buyers' size and diversity influence purchase decisions, and the *e*-channel appears more attractive to small and/or diversified

buyers. These buyers are both more likely to overcome channel inertia and less sensitive to the rising prices caused by *e*-channel popularity.

Although the *e*-channel we study attracted many buyers initially, over time the rate of increase in buyer usage of the *e*-channel slowed. To demonstrate how important it is for the firm to take into account the behavioral aspects of the technology introduction, we simulate an alternative channel allocation strategy. This strategy establishes that by better regulating the product type and size listed on its *e*-channel, taking into account buyer dynamics and leveraging heterogeneity, the firm can target smaller and more diverse buyers. With the right mix of buyers in the *e*-channel, the firm also can cope with the adverse dynamic price effect because the targeted buyers who get attracted to the *e*-channel are less price sensitive. We show that a simple revision of current policy such as selling smaller orders online is more aligned with the buyer dynamics and can rejuvenate the *e*-channel. Over time, the proposed allocation increases both *e*-channel usage and net revenues, despite some channel cannibalization. We thus demonstrate that the mere adoption of *e*-channel may not be enough to sustain long-term profitability; rather, sellers must strategically and tactically manage channel choice and product offerings in respective channels so as to entice the right buyers and build *e*-channel familiarity.

Our results further provide managerial implications that can help firms develop smart, buyer-centric allocation strategies. First, firms should be aware of the key factors determining buyer channel adoption and how these factors vary across time. The same factors that facilitate the adoption of modern technology can also slow down the adoption for the same reason. In particular, larger buyers get attracted to the *e*-channel initially because of its lucrative prices, but later on, as the competition increases on the *e*-channel, they shy away because of the adverse price effect. Second, sellers must recognize the effect of order size and product diversity on different buyers because all buyers are not the same. By offering more diverse products through the *e*-channel, the firm makes the channel attractive to more buyers, especially the small and diverse ones. Third, firms should allocate smaller quantities per order, which runs contrary to conventional wisdom. In the *e*-channel, smaller works better because it lowers buyers' total expenditure and thus mitigates the effect of increased marginal prices in the *e*-channel. These efforts make the *e*-channel more inviting, especially to smaller, less price-sensitive buyers, and enable the firm to improve its *e*-channel profits.

With detailed sales data for both *p*- and *e*-channels operated by the same seller, we are able to examine how buyers shift between channels and thereby

¹⁷ An electronic companion to this paper is available as part of the online version at <http://dx.doi.org/10.1287/isre.1110.0410>.

suggest important consequences for sellers who add an electronic sales channel to their traditional physical channels. The mere adoption of technology may not lead to benefits for the seller; rather, the firm must undertake a tactical approach to harness the technology, assess its impact on buyer reactions, and provide the best value to both existing and potential buyers. Although the data we examine pertain to a specialized setting in the B2B market, our model has wider implications. Any electronic market design should take into account individual buyers' dynamic response, often ignored in practice. Sellers also must consider how to allocate products between channels and adopt a more dynamic, responsive channel introduction strategy. If firms recognize buyer response and heterogeneity and then fine-tune their allocation mechanism, they increase their profitability, and smaller and diversified buyers can also find deals. Our research sheds light on those settings where factors such as price effects, trust, and inventory affect buyer-seller dynamics.

More generally, our research diagnoses a problem with modern technologies that relate to the way firms use them (Jap and Mohr 2002). As illustrated for our research site, companies must understand, deploy, and manage buyer behavior and dynamic aspects proactively to influence target buyers. Our study thus highlights the need for strategic fit between technology and marketing strategy.

Although our results provide valuable insights, they also must be interpreted within the limitations of our study. First, our analysis demonstrates the importance of adapting channel allocation strategies to buyer dynamics but also suggests the need for research into other types of settings. Second, we focus on an existing buyer base, without examining the acquisition of new buyers. Third, as is typical in exploratory studies, we assume buyers are reactive and measure their channel inertia statistically. Further research should treat buyers as active learners who strategically sample to gain information and reduce uncertainty about a newly introduced channel. It may also be interesting to model the dynamic game between the buyers, such that the buyers' bidding decisions are not independent of each other. Fourth, we obtain our data from a single firm. This research design facilitates the collection and examination of the micro-data that are necessary for the research question at hand. However, as with all such studies, it means our results could reflect in part the idiosyncrasies of this particular firm. We expect that our research will be informative in settings in which sellers face similar problems such as tradeoffs between channel inertia and price and significant buyer heterogeneity. Although our results appear intuitive and are based on theoretical concepts and rigorous analytical

decision making, they should be interpreted with caution. Further research might investigate the sales strategies of multiple firms in diverse industries that relate to more product categories. In that sense, we hope this study triggers research exploring ways that companies can leverage technologies to the benefit of both buyers and sellers.

Electronic Companion

An electronic companion to this paper is available as part of the online version at <http://dx.doi.org/10.1287/isre.1110.0410>.

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