A Structural Model of Consumers' Perception of Channel Fit and Consumer Channel Choice: Evidence From a Multichannel Retailer

This study investigates how consumers learn about the perceived fit of online and in-store channels employed by a multi-channel retailer from their purchase experience. Leveraging an unique panel dataset of consumers' purchase and return of products from different categories from a multichannel department store, we build a Bayesian learning model to investigate how consumers' perception of channel fit evolve over time from their purchase experience and the effect of various types of transaction costs on consumers' channel choice. We examine the effect of various types of transaction costs (shopping cost, time cost, transportation cost, comfort cost and switching cost) on consumers' channel choice. We then cast our model in the quasi-Bayesian learning modeling framework that lets us examine how product returns can change consumers' perception of channel fit and the associated moderating factors that can amplify the effect of returns, if any. Our proposed disaggregate consumer level of channel choice accounts for the endogenous relationship between consumers' channel choice and their decision to return products, and also accounts for effects of observed and unobserved consumer heterogeneity on consumers' channel choice. We estimate our model using simulated maximum likelihood methods. The results of our study shed interesting insights on the factors that affect consumers' channel choice.
Key words: *Internet channel*; *Multichannel shopping; Bayesian learning framework; salience effects.*

1. Introduction

Consider the following scenario. Jane is a new customer of a multichannel department store retailer and is initially uncertain about the fit of the products that the retailer offers. As she buys products from different product categories of the retailer, she learns about the fit of the product categories with her taste and aesthetic appeal. Based on this learning, she forms a perception of quality or fit of the channels that the retailer employs. After a particular shopping occasion, she was unhappy with a set of products that she had bought from a particular channel, and now she decides to return them. How would the product returns affect her perception of channels, and consequently her channel choice? Will product returns help Jane learn more about the fit of the channels with her taste? Or would product returns impede her learning and lower her perception of fit of the channels? Would such behavioral consequences of product returns be more salient if she returns the entire shopping basket vis-à-vis a fraction of her shopping basket or would they vary depending on her prior expectation level? What are the factors that systematically affect her channel choice? The current study uses actual behavioral data to answer the above issues related to the behavioral consequences of product returns, and to link them to customers' shopping behavior.

More retailers are embracing the Internet channel as a part of their multichannel presence and to engage with their customers via multiple shopping touch points. As a result, consumers are increasingly using the Internet channel for their shopping needs. A recent ComScore report (*Wireless News* 2011) states that the online retail spending during one of the recent holiday season would grow by 15% to $37.6 billion. Despite these staggering numbers that indicate preference by consumers for online channel at the aggregate level, it is not yet clear at the individual-consumer level whether some consumers simply self-select into shopping via online channel as opposed to shopping from other channels employed by a retailer. Hence, it is imperative to understand the various factors that systematically affect consumers' choice of a particular channel.

As a retailer combines its clicks and bricks with the promise of bringing more foot and web traffic (*Economist* 2013), there is a gingerly issue of customer shopping behavior, and that of product returns which is a problem from both retailers and consumers point of view *(USA Today* 2011). Although extant literature in marketing has investigated the implications of product returns for retailers (e.g., Stock et al. 2006; Petersen and Kumar 2009; Shulman et al. 2011), no study thus far has explicitly studied the behavioral consequences of product returns on consumers' perceptions of fit or quality of channels and subsequently their channel choice. The objectives of this study are to empirically examine in detail the various factors that drive consumers' online versus offline channel choice with a focus of investigating the behavioral consequences of product returns on consumers' perceptions of quality of two channels.

A number of recent studies have investigated various issues related to consumers' multichannel shopping, such as customer channel migration issues (Ansari et al. 2008) and consumers' price sensitivities across various channels (Chu et al. 2008). Although these studies help shed light on consumers' multichannel shopping behavior, no study to our knowledge has examined the drivers of consumers' channel choice at the disaggregate consumer level using the *same* panel of consumers shopping via online and offline channels of a particular retailer. An important exception to this is the recent study of Chintagunta et al. (2012) that examines the role of various transaction costs in consumers' choice of an offline versus online channel. Although the study quantifies various costs (such as shopping time costs, and transportation costs) associated with consumers' channel choice, the study is based in the context of grocery shopping. Hence, their results may not be generalizable to other shopping contexts which could be perceived by consumers to be more appealing when compared to grocery shopping. The study also does not examine consumers' evolution of preferences for various channels, and more importantly, does not address the issue of consumers' product returns. Unlike in a grocery setting, products returns are particularly problematic for electronics store and departmental store retailers. From consumers' perspective, consumers' channel choice and their decision to return could be interrelated. A consumer may prefer to purchase products online *ceteris paribus*, but may prefer to visit the store if she has products to return that she bought from one of the earlier shopping trips. To that extent, it is imperative to examine the effect of various factors (or costs) on consumers channel choice in a context wherein consumers are likely to return products.

As a new customer begins to shop via online and offline (in-store) channels of a retailer, the customer may initially feel uncertain about the quality or the fit of the channels to her preference—the perceived uncertainty in channel fit stems from the inherent uncertainty associated with the products that consumers buy. As consumers buy different products from different categories, they can learn about the fit of the products and thus develop a perception of quality of channels over time. Herein, shopping into different product categories may help the customer learn more about the fit or suitability of a particular channel to her needs. For example, in the context of department store, a customer may learn more about a particular channel by buying into relatively more experiential or high involvement product categories (such as work apparel) than relatively less experiential categories (such as accessories or electronic items). However, when the customer returns a product that she bought from a particular channel, it can affect her perception of quality of the channels. Behaviorally, product returns can affect customers' perceptions of channels that they use for shopping in two different ways: (i) product return can act as a noise signal wherein it decreases consumer's confidence in her perception of channel quality, or (ii) product return can act as a signal of quality wherein customer learns about the fit of the channel that she earlier used. It is also possible that such a behavioral effect of product returns on customers' perception of quality of channels can vary across customers depending on their prior expectations, and could be more salient under different shopping conditions. No study to our knowledge has examined the behavioral consequences of product returns on customers' perception of channels employed by a retailer and none has linked these to consumers' channel choice behavior.

Against the above background, the objectives of this paper are to examine the above unaddressed research questions related to product returns and customers' multichannel choice behavior. More specifically, we examine the following: (1) the effect of various factors that affect consumers' channel choice, (2) understand how consumers learn about the quality of the channels from their product experience, and (3) investigate the behavioral consequences of product returns on consumers' perception of quality of different channels and examine the factors that moderate them. We calibrate our proposed structural model using a unique panel dataset of customers' purchase history from a department store retailer. The retailer operates via various physical stores throughout the U.S. and also has a significant online presence. The data has information on customers' choice of these two dominant channels employed by the retailer and detailed purchase history of the panel of customers. A unique feature of our data is that we have detailed information on the products that customers returned.

We look at various factors, such as transportation costs, time costs, shopping costs, convenience costs, inertia, and customers' perceived quality of channels. We examine how consumers' perceptions of quality of the two channels evolve over time as consumers gain experience by buying into different product categories. We then investigate the effects of product returns on consumers' perception of quality of the channels. We offer two alternative hypotheses with respect to the effect of product returns on consumers' perception of quality of channels. On one hand, by returning products that did not meet their expectations, consumers can further learn about the quality or fit of the channels. On the other hand, product returns could act as noises in consumers' learning of the quality of channels. In such a case, product returns can impede consumers' learning, thereby undermining the effect of prior product purchase experience. Subsequently, following the well-established notion of salience effects (Alba and Chattopadhyay 1986) and the concept of consumers' response to expectation disconfirmation (Oliver 1980), we also test for factors that can moderate the behavioral effects of product returns.

Our empirical approach is as follows. Building on the Bayesian learning framework of consumer choice under quality uncertainty (Erdem and Keane 1996; Erdem 1998), we specify a discrete individual-consumer level learning model of consumers' channel choice. Here, we allow for consumers' perception of quality (as captured by both mean and variance of quality perceptions) of offline and online channels to evolve over time as they gain actual purchase experience with the channels. We specifically focus on *new* consumers in a time period wherein the retailer opened two new physical stores. Following the recent studies that model deviations in consumer learning models (e.g., Zhao et al. 2011), we propose a quasi-Bayesian learning model that lets us examine the behavioral consequences of product returns on consumers' perceptions of channel quality and relates it to channel choice behavior. Given that consumers' channel choice and propensity to return could be inter-dependent, we propose a model of consumers' likelihood to return products, and jointly estimate our proposed models of consumers' channel choice and return behavior. We account for various costs and customer heterogeneity.

The study makes the following contributions to the literature. First, our study provides insights into factors that affect consumers' channel choice with the focus on product returns. Unlike the recent set of studies that have looked primarily into the effect of returns on issues such as firm-customer exchange process (Petersen and Kumar 2009) and how firms can manage customer returns (Shulman et al. 2011), we take a customer-centric behavioral approach towards understanding the effect of product returns on consumers' multi-channel shopping behavior. Second, from a substantive perspective, we are one of the first studies to examine the effects of various factors that affect consumer channel choice in a department store retailer setting. We do so after accounting for the correlation between consumers' product return decision and channel choice. Third, we contribute to the growing multi-channel literature by examining how consumers' learn about channel quality from their experience of purchasing into different categories and how product returns can perturb their perception of channel quality.

2. Data Description

The multichannel retailer in our study is a major department chain retailer that operates in several states in the U.S.[1] The retailer operates via two dominant channels, namely traditional physical stores and the Internet channel.[2] The retailer offers an array of product categories that include apparel and accessories for women, men and children, household electronics, and home goods. The retailer offers the same price for all the product categories in both of the channels. As a result, there is no issue of price dispersion across the channels. This feature in turn helps rule out consumers' preference for one channel over another due to better prices in one channel over another or consumers' willingness to search for better prices in a channel.

The retailer offers the same product assortment in both online and in-store channel. In other words, there is no strategic decision on the part of the retailer to offer a set of products in either of the channel. This helps rule out consumers' preference for a channel that is driven by product assortment or product exploration issues. The retailer charges a lump sum fee (during the time period studied in this paper) for delivering goods that consumers order via online. The retailer tracks the channel choice, and purchase and return behavior of customers across both channels. For the purpose of our empirical analyses, we select a random set of 876 new customers. We focus on new customers as they would be uncertain about the quality of the retailer's channels. Our estimation data set spans 24 months. Since we are interested in consumers' learning of quality of channels, we focus on consumers' purchase from two newly opened

[1] Due to confidentially agreements, we cannot disclose the retailer's identification.
[2] The retailer also operates via catalog mail orders, but the percentage of sales via this channel is negligible as compared to sales in physical stores and online channel. Therefore, we focus on consumers choosing only from these two channels.

stores (located in two different states).

For each shopping trip, we have detailed information on purchase and return information. Our empirical analysis focuses on consumers' purchases into the following five categories: women's apparel, men's apparel, women's accessories, women's shoes, and children's apparel. These five categories are the top selling categories of the retailer. Table 1 presents the descriptive statistics of consumers purchase pattern and return behavior across the five categories. In any given shopping trip, regardless of whether consumers shop via the Internet or in-store channel, consumers buy more from women's apparel as compared to the other four categories. This is valid in terms of both the number of items purchased and sales in dollar amounts. Conditional on consumers' buying into a category, the following patterns emerge: consumers buy more items from men's apparel category and spend more in men's apparel when they shop in-store; however, when they shop via online channel, while consumers spend more into women's apparel, they buy more items from children's apparel. In terms of channel choice, at the aggregate level, consumers prefer to shop via in-store channel. With respect to returns, there is considerable product returns in all of the five product categories. The rate of returns is highest in women's apparel category. Moreover, the likelihood of returns across all categories is higher when consumers shop via online channel as opposed to the in-store channel.

[Insert Table 1 about here]

We also have information on the zip codes where consumers live, which we use in two different ways. We use the information to obtain the coordinates of the consumers' residence, which we then use to compute the distances between consumers' residence and the stores in which they shopped. We also rely on the weather data that is available from National Climatic Data Center.[3] For the purpose of this study, we code weather conditions to be bad if the particular location experiences rain or snow on a particular shopping day. We use this and other information to operationalize various types of transaction costs that we describe in detail in the model section. We have consumer demographic information which we use as control variables. Table 2 presents the descriptive statistics associated with variables pertinent to shopping trips and customer demographics.

[Insert Table 2 about here]

[3] Available at http://www.ncdc.noaa.gov/land-based-station-data/find-station. Weather information for a particular zip code is based on the weather in the closest airport that is reported in the NCDC website.

In terms of channel choice, in-store trips accounts for 86.48% of channel choice in our estimation data, whereas online choice accounts for only 13.52%. Moreover, to help understand consumer's channel switching pattern in the data, we report the number and percentage of incidences when consumers switch from one channel to another or stay in the same channel. As shown in Table 3, at the aggregate level, there is significant inertia with channel choice, in particular with in-store channel choice. However, there is considerable channel switching as well, and one has to take a formal modeling approach to obtain insights into consumers' channel choice.

[Insert Table 3 about here]

3. Model Formulation And Estimation

Our goal is to model consumers' choice of the Internet versus the in-store channel with a focus on how consumers learn about the quality of the two channels of the retailer over time. To do so, we develop a structural model of consumers' evolution of perception of channel quality over time. As discussed earlier, we believe that when consumers return products, their perception of channels will be perturbed. Accordingly, we first propose a basic model of consumer learning of channel quality, which we then modify to capture the behavioral effect of returns on consumers' learning of quality of the channels. In the following sub-sections, we first present the learning model and then present our proposed modified learning model. Next, we specify the utility function for consumers' choice of channels, and then discuss the estimation procedure. We refer the readers to Erdem (1998) for a more thorough discussion on the consumer learning model under quality uncertainty, and to Zhao et al. (2011) for how a basic learning model can be modified to account for deviations in learning respectively.

3.1 Consumers' Learning of Channels' Quality

Based on the seminal study on consumer learning under quality uncertainty by Erdem (1998), we assume that consumers are uncertain about the quality of channels employed by the retailer. Consumers are also assumed to be "Bayesian updaters," and thus they update their beliefs about quality of channels based on their direct purchase experience with the different channels. Consider a consumer i ($i = 1,\ldots,I$) who needs to decide which channel to use at shopping occasion t ($t = 1,\ldots,T_i$, where T_i is the number of shopping occasions undertaken by consumer i). The customer can choose a channel j among the set J of available channels (J = {in-store, online}). Let Q_{ijt} denote the quality level of channel j as perceived by consumer i at shopping occasion t. Let $\overline{Q}_{ijt}$ denote the mean of consumer i's perception of channel j at time t, and let the variance of their perception be σ^2_{ijt}. In addition, let n_{ijkt} be the total number of products that the consumer i purchased via channel j in product category k at shopping occasion t.

In the learning process, consumers are assumed to start with an initial prior perception about the quality of the two channels under study. We assume that consumers' prior perception about the quality of the two channels (Q_{ij0}) is normally distributed in the following manner.

$$Q_{ij0} \sim N\left(\bar{Q}_{ij}(0), \sigma^2_{ij}(0)\right), \tag{1}$$

where $\bar{Q}_{ij}(0)$ is the prior mean and $\sigma^2_{ij}(0)$ is the prior variance of channel j. For the purpose of simplicity, we assume that consumers' initial perception of quality of both the channels (viz. the Internet and the in-store channels) are the same and that the prior perceptions are the same across all individuals. We believe that this assumption is not a strict one as we work with the two channels operated by the same retailer and with new customers. At each purchase occasion t, as a consumer buys products from a channel, she learns about the quality of the channel from her actual purchase experience. Because buying experience might not provide perfect signals, these signals are assumed to be normally distributed around the true mean quality of the channel, Q_j (Erdem 1998).

We would like to clarify that, consistent with past literature that has modeled consumer learning under uncertainty (e.g., Erdem and Keane 1996), we assume that the overall channel quality Q_j is a multi-dimensional unobservable experience characteristic. In our context, it stems from consumers' evaluation of products and the extent to which they are able to discern the fit of the products to their taste from the various information available via channels. To that extent, we realize that purchase experiences from different product categories can provide varying levels of accuracy of channel quality. Accordingly, we assume that purchase experience from a channel j provides signal of quality of the channel as follows:

$$E_{ijkt} = Q_j + \xi_{ijkt} \quad \text{with} \quad \xi_{ijkt} \sim N(0, \sigma^2_{jk}), \tag{2}$$

where E_{ijkt} is the signal via purchase experience that customer i receives for channel j by buying into product category k at shopping occasion t, and ξ_{ijkt} is a zero mean normal error term with constant variance (the variance is denoted σ^2_{jk}).

At the beginning of purchase occasion t, consumer i's perception about quality of a channel j, Q_{ijt}, is formed by updating the perception held at time t–1, Q_{ijt-1}, with the purchase experience signals in category

k from the last time period, E_{ijkt-1}. Let the consumer i's perception of channel j at time t (i.e., the posterior belief about channel j) be:

$$Q_{ijt} = N\left(\overline{Q}_{ijt}, \sigma^2_{ijt}\right). \tag{3}$$

Given our assumptions about the distributions of the prior quality perceptions and the purchase experience signals and the Bayesian updating rules (DeGroot 1970), we can obtain the expressions for mean and variance of the posterior belief, $\overline{Q}_{ijt}$. Due to page limitation, we do not provide these expressions. However, they are available from the authors upon request.

3.2 Learning Model that Incorporates the Effects of Product Returns

As mentioned earlier, if a consumer were to return the products that she purchased from a particular channel, her perceptions about the quality or fit of the channel could be perturbed. Returning a product or set of products bought at the previous experience can impact both the mean and the variance of the consumer's perception of quality of the channel that she used. To capture this, we modify the mean and the variance of the basic learning model. Again, the expressions are omitted for brevity.

We reckon that product returns can have two possible effects on consumers' perception of channel quality. On one hand, just like consumers can learn about the quality of a channel from their purchase experience, by retuning products (that do not meet their expectations), consumers can learn about a particular channel and its fit with their post-purchase expectations. On the other hand, product returns can act as noises, and thus can negate their prior learning. Since both such effects are possible, it is imperative to develop a flexible empirical model to assess the effect of returns on consumers' channel choice. In our model, if a customer returns a product, the variance of consumer i's perception of quality of channel j associated with product category k at time t would be higher (lower) than the variance associated with the customer's perception of channel quality at the earlier shopping occasion.

Furthermore, the effect of returns on consumers' channel choice can differ across consumers based on their prior experience and shopping occasions. Studies related to consumer psychology of expectation disconfirmation (e.g., Oliver 1980) have argued that consumer post-purchase intentions or satisfaction is a combination of extent of disconfirmation and initial expectation, as in the initial expectation plays a role in how consumers' react to the level of expectation disconfirmation. In our context, this would suggest that consumers with different levels of prior experience can have different pre-purchase expectations and thus the weights consumers place on new disconfirming information in the form of returns can vary with their overall experience. Likewise, there could be salience effects associated with product returns vis-à-vis consumers' perception of quality. Salience refers to the distinctiveness or the "*level of activation*" of an event (Alba and Chattopadhyay 1986; page 363) — in our context, if a consumer were to return a large proportion of a shopping basket, returns could have a pronounced effect on consumers' quality perception. To accommodate all these, we formulate the degree of perturbation as follows:

$$\phi_{ijkt-1} = b_0 + b_1 \times \frac{sales_{R,ijkt-1}}{sales_{ijkt-1}} + b_2 Experience_{ijkt-1}, \tag{4}$$

where $sales_{R,ijkt-1}$ denotes the value of products that were bought by consumer *i* in category *k* at shopping occasion $t-1$ and later returned. Hence, $\frac{sales_{R,ijkt-1}}{sales_{ijkt-1}}$ is the proportion of products returned by the consumer bought (via channel *j*) during last purchase. We operationalize consumer's experience by the cumulative number of products in category *k* purchased until shopping occasion $t-1$ (i.e., $\sum_{\tau=1}^{t-1} n_{ijk\tau}$). We note that the basic learning model is a special case of the modified learning model. If there are no returns, then there are no distortions to consumers' perceptions of quality of the channel.

3.3 Consumers' Utility Function

We propose that the indirect utility of consumer *i* for each channel *j* at purchase occasion t, U_{ijt}, is a function of the consumer's perception of quality of channel *j* (i.e., Q_{ijt}) and various transaction costs associated with shopping. As mentioned earlier, based on the recent study by Chintagunta et al. (2012), we consider the following costs: shopping costs, time cost, transportation cost, comfort cost, and switching cost. Shopping costs refers to the opportunity costs that consumers incur when they are engaged in shopping. This is the time that consumers could be spending on any activity other than shopping. We expect that more the number of items a customer buy in a shopping trip, higher are the shopping costs. However, in the context of department store, given that we are working with high involvement product categories, we believe that amount of dollars spent by a consumer across the different categories in a shopping trip would be more appropriate. Accordingly, we operationalize shopping costs by the sum of dollars that a consumer *i* spends in different product categories *k* (denoted by $\sum_k Sales_{ijt}^k$) at any given shopping occasion. To the extent, the opportunity costs of time are different from weekdays to weekends, we also operationalize time costs by a weekend dummy variable (denoted by *Weekend*) that is equal to 1 if a consumer undertakes a shopping occasion on a weekend (and 0 otherwise).

Customers incur transportation costs if they were to visit the physical store of a retailer, which we operationalize by the distance (in miles; denoted by *Distance*) between consumer's residence and the store that the customer visited for shopping. The equivalent of transportation costs when consumers shop via online is the cost of getting items delivered to their residence. Accordingly, we account for the delivery fees (denoted by *DeliveryFees*) that the retailer charges the consumers when they order products online. We also account for consumers' (dis)comfort costs, which they would incur if they undertake a shopping trip on bad weather days. We operationalize bad weather (denoted by *Weather*) by a dummy variable that is equal to 1 if the shopping trip is on a snowy or a rainy day. Finally, we also account for consumers' psychological or switching costs in their channel choice. We operationalize this by a dummy variable (denoted by *Inertia*) that is equal to 1 if a consumer chooses the same channel to shop at time period t as she did in the earlier shopping occasion, $t-1$.

Based on the above arguments, we specify consumers' channel choice utility function as follows:

$$\begin{aligned} U_{ijt} &= \theta_i Q_{ijt} + \rho_i \bar{\theta} Q_{ijt}^2 + \beta_{1i}^k \sum_k Sales_{ijt}^k + \beta_{2i}\text{Distance}_i \times (1 - d_{it}^{Internet}) + \beta_{3i}\text{Weather}_t \\ &+ \beta_{4i}\text{Weekend}_t + \beta_{5i} DeliveryFees \times d_{it}^{Internet} + \beta_{6i} Inertia_{ijt} + \beta_{7i}\text{Age}_i + \beta_{8i}\text{Income}_i + \varepsilon_{ijt} \end{aligned} \tag{5}$$

where θ_i is the weight that consumer i places on perceived channel quality, $\bar{\theta}$ is the mean weight of consumers' sensitivity towards channel quality, and ρ_i denotes consumer i's risk aversion towards quality uncertainty. The quadratic function of perception of quality helps capture the risk associated with the consumers' channel choice (Bell and Raiffa 1988). As per this specification, if $\bar{\theta} > 0$, consumer is risk neutral if ρ_i is zero, risk averse if ρ_i is negative, and risk seeking if ρ_i is greater than zero. The set of parameters β_{1i} to β_{8i} (denoted by β_i) capture the effect of various costs and consumer characteristics on consumers' channel choice. Next, $d_{it}^{Internet}$ is an indicator variable that is equal to 1 if the customer chooses to shop via the Internet channel at shopping occasion t (and =0 otherwise). As can be seen in Equation 5, we also account for the demographic characteristics (Age_i and $Income_i$) of the customers.

Since Q_{ijt} has a stochastic component, the utility that consumers receive (that we present in Equation 5) is not known to consumers with certainty. Hence, consumers maximize their utility based on their expectation of perceptions of quality of the two channels. The expected utility is then given by:

$$E[U_{ijt}] = \theta_i E[Q_{ijt}] + \rho_i \bar{\theta} E[Q_{ijt}^2] + \beta_{1i}^k \sum_k Sales_{ijt}^k + \beta_{2i} \text{Distance}_i \times (1 - d_{it}^{Internet}) + \beta_{3i} \text{Weather}_t$$
$$+ \beta_{4i} \text{Weekend}_t + \beta_{5i} DeliveryFees \times d_{it}^{Internet} + \beta_{6i} Inertia_{ijt} + \beta_{7i} \text{Age}_i + \beta_{8i} \text{Income}_i + \varepsilon_{ijt} \quad (6)$$

3.4 Consumers' Endogenous Decision of Product Return

In our context, one could argue that consumers' propensity to return products and channel choice decision could be interrelated. If a consumer has a set of products that she would like to return, she might prefer the in-store channel to return the products. To address this endogeneity issue, we take the approach of jointly modeling consumers' channel choice decision and their likelihood of returning products at a given shopping occasion. We propose that a focal consumer's likelihood of returning products at a given shopping occasion is determined by the following set of factors: a) the total basket size that the customer bought in the previous shopping occasion, b) whether the customer used the Internet channel for shopping in the previous shopping occasion, c) interaction between customer's channel choice and total basket size, d) whether the customer bought items from a new category (from the retailer) in the previous shopping trip, e) the customer's overall experience with the retailer and f) whether the customer returned products in the previous shopping trip. The further details of this section are omitted because of page limitation.

4. Results Of Consumer Quality Learning Model

In this section, we first discuss the comparison of our proposed model to other familiar models. Then, we present the parameter estimates of our proposed model.

4.1 Model Comparison

To benchmark the fit of our proposed model of consumers' learning of quality and the role of product returns on their perception of channel quality, we estimate a series of other more popular models in the literature. We first compare our model against a simple binary probit model (referred to as Model 1) of consumers' channel choice in which we have all the variables that enter the utility function in Equation 6 in a linear fashion. We then compare our model against a learning model that does not account for the effect of product returns (referred to as Model 2). The third model that we compare against is a learning model that accounts for the effect of product returns on consumers' perception of channel quality, but we do not jointly model consumers' channel choice and their product return decision (Model 3). Our proposed model (Model 4) accounts for the effect of product returns on consumers' perception of channel quality that accounts for the correlation between channel choice and product return decisions.

In terms of log-likelihood, Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and the hit rate[4], Model 2 fits better than Model 1. This suggests evidence of dynamic evolution of consumers' perception of channel quality. Between the two learning models, Model 3 (that accounts for the product returns on consumers' perception of channel quality) fits better than the simple learning model (i.e., Model 2) along all the four criteria, namely log-likelihood, BIC, AIC, and the hit rate. This suggests that product returns play a role in changing consumers' perception of channel quality. This is consistent with the results of the simple reduced form models that we presented earlier. Finally, in terms of comparison between Model 3 and Model 4, since the latter involves modeling of two decision variables (channel choice and decision to return product) as opposed to one decision variable (channel choice) by the former, we can use neither AIC nor BIC to compare the fit of the two. However, we can still use the hit rate to compare the fit of the two models, which suggests that our proposed joint model (i.e., Model 4) fits better than Model 3. Table 4 summarizes the model fit statistics of the four models, Model 1-Model 4.

[Insert Table 4 about here]

4.2 Parameter Estimates of the Channel Choice Component of our Proposed Model

In Table 5, we present the parameter estimates of the two learning models of channel choice, Model 2 and Model 3. In Table 6, we present the parameter estimates of our proposed model, Model 4. We note that the results of Model 2 and Model 3 and the channel choice component of Model 4 are substantively similar; however, since Model 4 has the best hit rate among the various models, we discuss the parameter estimates of the model below.

[Insert Tables 5 and 6 about here]

With respect to the learning model component of channel choice, the main parameters of interest are the category-channel specific variances. We find that the variances associated with all the five categories (women's apparel, men's apparel, women's accessories, women's shoes, and children's apparel) for both the in-store and the online channels are significant. This suggests that consumers do learn about the channel quality from their experience of purchases from the five categories. Although the absolute values of these variances have no easy interpretation (since the prior variance of channel quality is set to 1 for the purposes of identification), one could compare the ratio of these variances to assess which purchase signals serve as more accurate signals of prior quality. We find that there is considerable variance in the degree of information of these purchase experience signals, both across channels and across categories for any given

[4] See Sun et al. (2003) and Erdem et al. (2003) for details of hit rate for discrete choice models. We note that lower AIC, lower BIC, and higher hit rate indicates better model fit.

channel. For the three categories, namely women's apparel, men's apparel, and children's apparel, signals from purchases via the online channel serve as more accurate signals of channel quality as compared to purchases from the in-store channel. For the two categories of women's shoes and women's accessories, we find that purchase signals gained by purchasing via the in-store channel are more accurate than those obtained by purchasing via the online channel. Further, we find that purchase signals associated with the categories of women's accessories bought via the online channel and children's apparel bought in-store are the least informative of channel quality and that the purchase signals associated with men's apparel bought via online channel is the most informative of channel quality, as compared to all other purchase signals.

We also find that the mean quality of the in-store channel is significantly greater than that of the Internet channel (which we had set to zero for the purpose of identification). This is consistent with the finding that the share of the in-store channel of the retailer is much greater than the share of the Internet channel. The prior mean quality of the two channels (which we have set equal to each other) is significantly lower than zero. The finding that actual mean quality of the channels is greater than the prior mean qualities, along with the finding that the variances of all of the category-channel specific purchase signals are significant, suggests evidence of consumer learning of channel quality. We find that the mean of the risk coefficient is negative and significant. This result, along with the finding that consumers give positive weights to channel quality, suggests that consumers are risk-averse.

The focal parameters of our study are those that are associated with the effect of returns on consumers' perceptions. We find that all the parameters associated with the main effect of returns are significantly positive. This suggests that product returns serve as noisy signals to consumers' learning process, thus counteracting consumers' prior learning of channel fit. The positive parameter associated with the proportion of the sales being returned indicates evidence of the salience effect that we proposed — greater the proportion of items from a basket a customer returns (to the total size of the basket), greater is the effect of return on her perception of channel quality. The parameter associated with the cumulative number of product purchases is positive, which suggests that the effect of returns is greater for consumers with greater overall experience with the retailer.

With respect to the effect of various costs on consumers' channel choice, we find that the parameters associated with product sales are positive for all the five categories. This result suggests that consumers are more likely to choose the in-store channel for shopping if they were to spend more in any of the five categories. We note that we get similar results if we operationalize shopping costs by the number of items instead of prices of the items. It is worth noting that, unlike the study by Chintagunta et al. (2012) which reports that consumers choose to shop online when they buy from a large number of categories, we find that consumers prefer to shop at the store when they buy from a large number of categories. We argued in the introduction section that the study by Chintagunta et al. is based in the context of grocery, and thus their results may not be applicable to retail shopping. Along these lines, we find that, on an average, consumers prefer to shop in store when they buy more items or spend more in each shopping.

We also find significant variation in the parameters associated with shopping costs for all of the five categories. Between the five categories, we find that shopping in the women's shoes category influences consumers' channel choice the most. In other words, compared to the other four categories (women's apparel, men's apparel, children's apparel, and women's accessories), our results suggest that customers are more likely to choose the in-store channel if they were to purchase from the women's shoes category. We find that consumers exhibit significant disutility towards distance, which suggests that consumers prefer to shop online so as to minimize on transportation costs. Our results show that weather does not play a significant role on consumers' channel choice.

Further, we find that consumers prefer to shop at the physical store on weekends (as compared to weekdays). This result is also counter to the finding reported by Chintagunta et al. (2012) that suggests that consumers prefer to shop online during weekends. The above set of results delineate the difference between grocery shopping and retail shopping, and how different factors might impact differently the consumers' channel choice in these two different contexts. In our results, the coefficient of shipping fees is positive and significant, which suggests that consumers prefer to shop in-store to save on shipping fees.

4.3 Parameter Estimates of the Product Return Component of our Proposed Model

We find that customers who buy more at any given shopping occasion are more likely to return a set of items subsequently. Further, we find that consumers are more likely to return products when they use the Internet channel for shopping. We also find evidence of significant interaction between choice of Internet channel and basket size on customers' subsequent product return. More specifically, we find that those customers who buy more via the Internet channel are more likely to return products subsequently. We find that consumers who buy into product categories in which they have no prior purchase experience with the retailer (i.e., those who buy products from a category for the first time from the retailer) are more likely to return products. These results suggest for the broad role of uncertainty that consumers face in product evaluation and the role of the online channel in amplifying such uncertainty, and the ensuing consequences on product returns.

Similar to inertia in consumers' channel choice, we find evidence of persistence in consumer product return behavior. Those customers who return items from a given shopping occasion are more likely to return items that they bought in the following shopping occasion. Finally, those customers with greater overall purchase experience with the retailer are less likely to engage in product returns as compared to customers with lesser product experience. This result also highlights the role of product uncertainty that consumers face on their product return behavior. Finally, we find evidence of positive correlation between consumers' decision to shop in-store and their likelihood to return items at a prior shopping occasion.

5. Discussion And Conclusion

With most of the retailers embracing multichannel marketing strategy and offering their customers the opportunity to shop via multiple channels 24/7, studies in the area of customer multichannel shopping have highlighted the importance of understanding the drivers of customer channel choice. Recent research in marketing and several practitioner articles have cautioned the role of product returns by customers on their behavior. To the best of our knowledge, our study is the first one to link the two issues of customer multichannel shopping behavior and their product return behavior. More specifically, using a unique panel of customer multichannel shopping behavior, we investigate in detail the various factors that drive customers channel choice behavior with the focus on the behavioral consequences of product returns.

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Table 1 Descriptive Statistics: Purchase and Return

	In Store					Online				
	Number of items purchased		**Sales ($)**		**% item returned**	**Number of items purchased**		**Sales ($)**		**% item returned**
	Average shopping trip	Conditional on purchase	Average shopping trip	Conditional on purchase		Average shopping trip	Conditional on purchase	Average shopping trip	Conditional on purchase	
Women's Apparel	1.31 (2.16)	2.72 (2.42)	80.87 (169.55)	167.58 (212.23)	11.03% (0.27)	1.21 (1.66)	2.15 (1.70)	77.57 (116.56)	137.53 (125.87)	13.47% (0.31)
Men's Apparel	0.32 (1.12)	2.33 (2.07)	26.59 (109.11)	189.64 (232.45)	8.79% (0.26)	0.09 (0.50)	2.08 (1.24)	4.33 (25.77)	97.45 (76.95)	9.39% (0.27)
Children's Apparel	0.23 (1.12)	3.27 (2.77)	4.59 (22.69)	64.39 (58.13)	7.42% (0.24)	0.04 (0.39)	2.27 (1.66)	0.95 (8.35)	48.89 (35.79)	5.36% (0.21)
Shoes	0.52 (1.01)	1.66 (1.16)	38.62 (82.98)	121.40 (107.69)	11.91% (0.30)	0.54 (0.89)	1.48 (0.89)	40.20 (82.02)	110.40 (103.57)	9.88% (0.28)
Women's Accessories	0.39 (1.07)	1.91 (1.63)	23.13 (73.69)	103.77 (126.47)	7.18% (0.24)	0.29 (0.88)	1.85 (1.43)	14.16 (57.26)	91.11 (118.79)	6.45% (0.24)
Total	**2.83 (2.78)**	**N.A.**	**173.80 (218.18)**	**N.A.**	**10.26% (0.28)**	**2.18 (1.77)**	**N.A.**	**137.21 (137.23)**	**N.A.**	**17.01% (0.35)**

Note: Standard Deviation in bracket

Table 2 Descriptive Statistics: Transaction Costs and Consumer Demographic Variables

	Mean	**Standard Deviation**
Distance(miles)	44.27	66.72
Shipping Fee($)	11.61	4.22
% of Bad Weather	33.02%	
% of purchase during Weekend	30.75%	

	< 25 years	25-34 years	35-44 years	45-54 years	55-64 years	65+ years
Age	2.09%	9.39%	17.30%	41.13%	17.99%	12.11%

	< $50K	$50k-100k	$100k-150k	$150K+
Income	30.01%	39.9%	15.23%	15.72%

Table 3 Channel Switching matrix

From	To	
	Store Channel (purchase occasion *t+1*)	Online Channel (purchase occasion *t+1*)
Store Channel (purchase occasion *t*)	5558 (62.27%)	1155 (12.94%)
Online Channel (purchase occasion *t*)	1157 (12.96%)	1056 (11.83%)

Note: The numbers in the four cells indicate the number and percentage of shopping occasions (in parentheses) that correspond to the different channel switches. Total number of shopping occasions=3368

Table 4 In-sample Model Fit Comparison

Model	-LL	AIC	BIC	Hit rate Ϯ
Model 1: Probit w/o learning	-1,941.98	4,013.41	3,939.96	0.7629
Model 2: Learning model w/o product return	-1,855.57	4,136.97	3,791.14	0.7743
Model 3: Learning model with product return	-1,808.80	4,075.36	3,703.60	0.7813
Model 4: Joint model	-3,532.42	7,682.29	7,180.84	0.8362

Ϯ For the joint model, we provide the hit rate of channel choice only for easy comparison with the other models that involve only the channel choice.

Table 5 Parameter Estimates of Learning Models

	Model 2: Learning model w/o product return		**Model 3: Learning model with product return**	
Linear Parameters				
	Mean	**S.D**	**mean**	**S.D**
Sales in Women's Apparel	0.03(0.01)***	0.23(0.01)***	0.03(0.01)***	0.07(0.01)***
Sales in Men's Apparel	0.20(0.02)**	0.26(0.05)***	0.18(0.02)***	0.10(0.01)***
Sales in Children's Apparel	0.20(0.03)***	0.21(0.01)***	0.19(0.03)***	0.16(0.03)***
Sales in Shoes	0.79(0.01)	0.13(0.20)	0.33(0.16)**	0.15(0.03)***
Sales in Women's Accessories	0.09(0.01)***	0.02(0.01)**	0.09(0.01)***	0.12(0.04)***
Shipping Fee	0.06(0.00)**	0.37(0.00)***	0.25(0.42)	0.37(0.02)***
Distance	-0.22(0.03)***	0.18(0.02)***	-0.20(0.04***	0.06(0.01)***
Weather	0.02(0.02)	1.02(0.04)***	0.02(0.04)	0.77(0.03)***
Weekend	0.23(0.01)***	1.68(0.03)***	0.23(0.05)	1.33(0.04)***
Lagged choice	0.75(0.01)***	1.10(0.01)***	0.71(0.05)***	0.53(0.07)***
Income	0.04(0.01)***	0.01(0.01)	0.03(0.01)***	0.09(0.02)***
Age	-0.21(0.00)	0.26(0.00)***	0.19(0.05)***	0.28(0.01)***
Expected quality coefficient	0.41(0.01)***	1.59(0.03)***	0.13(0.02)***	0.17(0.05)***
Mean risk coefficient	-0.03(0.00)***	0.01(0.02)	-0.01(0.00)***	0.02(0.04)
Parameters of learning process				
Prior mean quality	-0.57(0.02)***		-0.39(0.06)***	
Mean quality of in-store	2.76(0.04)***		3.05(0.06)***	
Experience variability: women's apparel (in-store)	0.23(0.06)***		0.24(0.07)***	
Experience variability: men's apparel (in-store)	4.03(0.01)***		5.72(0.55)***	
Experience variability: children's apparel (in-store)	2.05(0.01)***		2.78(0.60)***	
Experience variability: shoes (in-store)	0.25(0.07)***		0.25(0.07)***	
Experience variability: women's accessories (in-store)	2.26(0.06)***		1.84(0.08)***	
Experience variability: women's apparel (online)	1.13(0.05)***		0.82(0.08)**	
Experience variability: men's apparel (online)	0.07(0.02)***		0.65(0.09)***	
Experience variability: children's apparel (online)	0.99(0.29)***		1.06(0.03)***	
Experience variability: shoes (online)	5.07(0.02)***		3.20(0.04)***	
Experience variability: women's accessories (online)	1.14(0.18)***		1.48(0.42)***	
Parameters associated with product returns				
Product returns-constant			1.21(0.01)***	
Product returns-experience			0.26(0.01)***	
Product returns-return proportion			0.52(0.00)***	
Model Fit Statistics				
Log-Likelihood	-1,855.57		-1,808.80	
AIC (BIC)	4,136.97(3,791.14)		4,075.36,(3,703.60)	
Hit rate	0.7743		0.7813	
Notes: Standard errors in brackets ****: significant at p = 0.01**: significant at p = 0.05*: significant at p = 0.01				

Table 6 Parameter Estimates of Joint Model (Model 4)

Channel Choice Component		
Linear Parameters	**Mean**	**S.D**
Sales in women's apparel	0.04(0.01)***	0.24(0.00)***
Sales in men's apparel	0.20(0.20)***	1.23(0.21)***
Sales in children's apparel	0.20(0.03)***	0.71(0.01)***
Sales in shoe	0.49(0.02)***	0.71(0.00)***
Sales in women's accessories	0.09(0.01)***	0.16(0.00)***
Shipping fee	0.45(0.04)***	1.01(0.02)***
Distance	-0.20(0.03))***	0.18(0.00)***
Weather	0.01(0.05)	1.87(0.01))***
Weekend	0.22(0.05)***	8.45(0.49)***
Lagged choice	0.85(0.05)***	7.32(0.48)***
Income	0.06(0.01)***	0.10(0.00)***
Age	-0.82(0.01)***	0.01(0.00)*
Expected quality coefficient	0.11(0.01)***	0.10(0.01)***
Mean risk coefficient	-0.06(0.02)***	0.33(0.06)***
Parameters of learning process		
Prior mean quality	-2.26(0.06)***	
Mean quality of in-store	2.96(0.32)***	
Experience variability: women's apparel(in-store)	1.78(0.15)***	
Experience variability: men's apparel(in-store)	3.09(0.01)***	
Experience variability: children's apparel(in-store)	4.85(0.93)***	
Experience variability: shoes(in-store)	1.13(0.04)***	
Experience variability: women's accessories(in-store)	1.67(0.08)***	
Experience variability: women's apparel(online)	0.91(0.12)***	
Experience variability: men's apparel(online)	0.34(0.04)***	
Experience variability: children's apparel(online)	1.11(0.06)***	
Experience variability: shoes(online)	4.83(0.02)***	
Experience variability: women's accessories(online)	2.49(0.21)***	
Parameters associated with product returns		
Product returns-constant	0.90(0.11)***	
Product returns-experience	0.04(0.00)***	
Product returns-return proportion	0.01(0.00)***	
Return Decision Component		
Constant	0.05(0.01)***	0.62(0.01)***
Number of items bought in last occasion	0.24(0.05)***	0.02(0.01)**
Lagged Returns	0.84(0.01)***	1.36(0.01)***
Online channel choice indicator	0.09(0.01)***	0.27(0.06)***
Online channel choice indicator × number of items bought in last occasion	0.22(0.00)***	0.43(0.00)***
Indicator of buying new category in last occasion	1.00(0.11)***	1.38(0.05)***
Cumulative experience	-0.56(0.04)***	3.55(0.72)***
Covariance between channel choice and return decisions	0.51(0.01)***	
Log-Likelihood	-3,532.42	
AIC (BIC)	7,180.84 (7,682.29)	
Hit rate†	0.8362	

Notes: Standard errors in brackets

† We provide the hit rate of channel choice component of our joint model for easy comparison with the other models.

****: significant at p = 0.01**: significant at p = 0.05*: significant at p = 0.01