MANAGING MARKETING MIX AND COMMUNICATIONS IN A DIGITAL ERA: THE ROLE OF TRADITIONAL AND NEW MEDIA IN A MULTICHANNEL ENVIRONMENT

by

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To my family, friends and faculty

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ABSTRACT

Fueled by technological advancement firms' marketing mix strategies with respect to price, promotion, product, and place (4Ps) have been redefined and restructured several times. For example, firms' existing communication methods such as newspaper, radio, catalog, and television are now being supplemented with emerging and technology driven media such as email, mobile communication, e-catalogs, and social media. Furthermore, such advances not only enable firms to expand their modes of distribution beyond their traditional outlets to include multiple channels (e.g. brick and mortars stores, online stores, catalogs) but also to sell multiple product categories across these different channels. In such a multi-communication, multichannel environment consumers could well exhibit differential responses to various marketing and communication elements because of their intrinsic preferences, behavioral, and consumption pattern across multiple categories. This dissertation consists of three essays that investigate firms' marketing mix strategies with respect to price, promotion, product, and place. In this technology driven marketing environment characterized by adoption of multiple communication and multiple channels, we offer a technique that allows firms to better allocate their marketing resources.

The first essay seeks to study the interplay and effectiveness of different communication media adopted by the firms, including traditional as well as emerging media in a multichannel multi-category environment that affect consumers' purchase incidence and quantity decisions. Here, we investigate the dynamic effects of traditional and emerging communication media and the interplay among them. This study helps understand how emerging media (such as email, educational programs, e-catalogs) augment traditional media (such as television, newspaper, radio) and marketing mix variables (e.g., price and promotion).

In the second essay we study three critical consumer decisions in a multichannel environment: namely channel choice, inter-purchase time, and quantity decision. We account for the effects of multiple communication media, marketing mix elements, and consumer intrinsic variables that could affect these decisions. The combination of scanner panel data with consumers' multiple media usage and their intrinsic behaviors collected through surveys lend greater insight into these decisions - critical in better managing customer relationship and developing strategies for effective allocation of promotional dollars.

The third essay seeks to understand the role of digital and online communications in influencing consumer perceptions, attitudes and shopping behavior in a multichannel environment. Specifically, we consider issues pertaining to email marketing and analyze their effectiveness using an integrated framework that encompasses other traditional marketing and communication variables.

1. INTRODUCTION

In recent years technological advancements have facilitated firms to reach their consumers using multiple channels and multiple communication media. The traditional channel of brick and mortar store has been supplemented with online channels. The traditional communication media such as newspaper, television, and radio have been extended to encompass emerging media such as emails, e-catalogs, educational programs, and social media to constantly engage with consumers at mass as well as at individual levels. Furthermore, firms are offering multiple categories across these multiple channels. On one hand expansion of firms' marketing strategies in terms of price, promotion, place and products (4Ps) has facilitated them to engage and interact with consumers in this highly integrated environment, and on the other hand it has posed several challenges regarding proper execution of these strategies.

In this dynamic marketing environment several issues emerge. First, how effective are the various communication media in this multichannel environment? What role does the interplay of these communication media play among themselves i.e. where do emerging media fit in the realm of traditional media? Second, how are different consumer decision makings such as channel choice, category incidence, and quantity decisions affected by firms' marketing mix and communications in this highly integrated environment and how do their differential responses to these vary across categories? Third, how these decisions are also affected by consumer characteristics or consumer intrinsic variables in this technology driven marketing environment? Finally, what is the role of digital and online communications in influencing consumer perceptions, attitudes, and shopping behavior in multichannel environment? Specifically, what are the factors that determine the success of firms' digital marketing campaigns? This dissertation consists of three essays that systematically address the issues posed above in this multichannel multi-communication environment.

The first essay addresses the issue of effectiveness of multiple communication and marketing mix elements in a multichannel environment across multiple categories. In this essay we propose a disaggregate, joint channel choice, category incidence, and purchase quantity/order-size model of consumer shopping behavior in the presence of multiple elements of communication media and marketing mix. The communication media include blend of both traditional (e.g., television, radio, newspaper) and emerging (e.g., email, educational programs, e-catalogs) media. The proposed model not only captures the dynamic effects of communication media but also the interplay among them across categories.

The second essay seeks to understand the shopping experience of consumers in this multichannel environment in the presence of multiple communication media. Understanding of factors influencing consumer shopping behavior across multiple channels is important to provide seamless shopping experience across channels. Multichannel shopping experience is conceptualized by modeling three critical consumer decisions namely, channel choice, inter-purchase timing, and quantity decision. We combine scanner panel data of consumer purchase histories with their communication media usage sent by the firm along with consumer intrinsic variables collected through surveys to model consumer channel choice behavior.

In the third essay we seek to understand the antecedents and consequences of firms' digital and online communications. Specifically we propose an integrated framework with respect to firms' email marketing to measure its effectiveness in the presence of traditional marketing and communication variables. We use an extensive email database of a firm's digital marketing campaign to find out the factors that influence the success of an email campaign.

Then, based on this information we conduct natural/randomized field trials to study the effectiveness of emails in influencing consumer purchase behavior. Furthermore, the proposed lab experiments and artefactual field experiments will unravel the different attributes/features of an email that make it either a successful or a failed campaign.

We perform all our empirical analysis on scanner panel data from a large regional retailer selling specialty beverages. The retailer engages with its consumers using multiple communication media that include traditional media such as newspaper, television, and radio as well as emerging media such as emails, catalogs, social media (Facebook and Twitter), specialized in-store activities (e.g., information shelf talker), web ads, and educational programs. The retailer maintains individual databases for all these different communication media that contain detailed information pertaining to each communication media. The interesting aspect of the dataset is that we are able to survey the same set of consumers from the scanner panel data. We expect our study will help firms allocate their marketing resources effectively in this multichannel multi-communication environment.

2. INVESTIGATING THE IMPACT OF MULTIPLE COMMUNICATION AND MARKETING MIX ELEMENTS IN A MULTICHANNEL ENVIRONMENT

2.1 INTRODUCTION

Technological advancements have recently enabled firms to reach consumers more efficiently resulting in a new dynamic marketing landscape. This environment is characterized by retailers trying to reach consumers with the help of multiple channels such as offline, online, catalog, personal selling etc. In fact, 75% of retailers today either have a multichannel retailing strategy or are planning one that includes physical stores, kiosks, wireless channels, catalogs and the internet (Direct Marketing News, 2002). Furthermore, across these multiple channels retailers are also adopting new media to communicate with consumers. Thus in addition to traditional media such as television and radio, firms also have access to newer means such as email, educational programs, web ads etc. Online channels are indeed used by consumers to learn about the product and compare prices, sometimes before coming to the store for actual purchasing (The Economist 2009). Clearly, retailers are adopting a blend of traditional (such as price and promotions) as well as new communication methods (such as social media and online advertising) to reach their consumers (eMarketing 2010b, eMarketing 2010c).

This practice, adoption of multiple marketing communications and multiple channels, has required re-evaluation of effectiveness of marketing communications and marketing mix in influencing consumer shopping behavior. Given such a highly interactive environment where not only can consumers use multiple channels to access the product, there are also several means of communication that can be used to gather product and retailer related information, several issues emerge.

First, consumer purchase decisions have become complex as understanding of purchase incidence alone is not sufficient to unravel the effectiveness of firms' marketing efforts but one has to understand consumers' other decisions too such as channel choice and quantity decision. Given retailers offer multiple categories across different channels; understanding multichannel consumer shopping behavior in multi category offerings becomes even more critical. Moreover, firms' adoption of multiple touch-points to engage with consumers entails understanding their roles in influencing consumer purchase decisions which are important in order to allocate resources efficiently across multiple communication media as well as across multiple channels.

Second, in this highly interactive environment different factors possibly interact among themselves. For example, multiple categories could be viewed as complements or substitutes across different channels; different communications could have either synergistic or anti-synergistic effects on consumer decisions. Therefore, capturing possible interactions that influence consumer purchase decisions is critical in this environment.

Third, in order to capture consumers purchase decisions in such a highly interactive environment and predict their behavior is challenging from data collection perspective. The traditional scanner panel data only provides consumer purchase history but lacks their complete communication media usage. Therefore, the scanner panel data that constitute consumers' purchase history have to be supplemented with other individual databases that contain the consumers' media usage behavior. Furthermore, modeling consumer purchase behavior in such an interactive environment at individual household level, accounting for their category/purchase incidence, quantity decision and channel choice is formidable given one has to account for effects of these multiple communication media usage and possibly all relevant interactions.

This study addresses these challenges posed by new emerging marketing landscape shaped by technological advancement where consumers use a firm's multiple channels to purchase multiple categories and firm employs both traditional and new media to reach their consumers. The digital world not only allows consumers to embrace new channels in much more active ways facilitated by various communication media but also is transforming how consumers shop, live, develop and interact. Therefore, it is very important for retailers to understand not only the shopping behavior across multiple channels in multiple categories but also the effectiveness of various communication media across categories. This research combines the unique scanner panel data set with the databases of consumers' communication media usages to model jointly consumers' channel choice, category/purchase incidence and quantity/order-size decisions accounting for the dynamic effects of marketing as well as communication mix. Understanding such behavior across multiple channels influenced by multiple touch-points or multiple communication media adopted by firms will facilitate better allocation of resources to attract multichannel consumers.

2.2 Conceptual Development

In developing a conceptual framework as a precursor to model development, we draw from prior literature. We first discuss prior studies in this area followed by the conceptual framework.

2.2.1 Related Literature

The two dominant characteristics of the new marketing landscape that is the focus of our research are, first, the use of traditional as well as new media to communicate with consumers, and second, the use of alternative distribution channels (such as online websites) in addition to the primary brick and mortar store to offer products. Academia is giving due importance to this emerging landscape with literature that focuses on one or more of these characteristics. Thus, in concentrating on the channels available to the firm, many researchers have studied the impact of traditional methods of communication on multichannel behavior and consumer equity (Verhoef and Donkers 2005; Thomas and Sullivan 2005; Villanueva, Yoo, and Hanssens 2008, etc.). Much work also exists in specific online versus offline comparisons, be it in terms of variation in price dispersion across the channels (Tang and Xing 2001; Pan, Ratchford, and Shankar 2004), channel/consumer characteristics (Balasubramanian, Raghunathan, and Mahajan 2005; Burke 2002; Gensler, Dekimpe, and Skiera 2004; Kumar and Venkatesan 2005) or category characteristics (Chintagunta, Chu, and Cebollada 2010). Furthermore, researchers have also studied various drivers of channel adoption behavior (Inman, Shankar, and Ferraro 2004; Venkatesan, Kumar, and Ravishanker 2007; Verhoef, Neslin, and Vroomen 2007). While limited in quantity, some work also (Kushwaha and Shankar 2008) studies the firm's optimal resource allocation for emerging marketing activities over multiple channels, thus combining both elements of focus. Nevertheless, the adoption of the internet as a channel is not in itself a successful strategy. Websites without a catalog, TV, radio or print promotion to drive people to visit them do not usually fare well (Blattberg, Kim, and Neslin 2008).

Our work differs significantly from existing literature in several ways. Firstly, the scope of our research extends to include all the elements of firms' marketing efforts (marketing and communication mix) across different categories contributing to a richer set of results and implications. Secondly, we develop a disaggregate multivariate, joint category incidence, purchase quantity and channel choice model necessary to address all the interrelated components of our scenario in the presence of multiple channels and multiple communication media. Our research is thus driven by this need for a robust measurement tool which will allow for a comprehensive study of an integrated communication strategy in a multichannel shopping environment.

2.2.2 Conceptual Framework

We use the findings from prior literature as well as industry evidence to identify the various components required to build a comprehensive model. We thus present our conceptual framework with a description of these components and their potential role in shaping consumer shopping behavior.

Multiple channels: Firms utilize multiple channels to offer their products. Since consumers will ultimately purchase from just one channel, they will essentially be competing in each purchase occasion. The two dominant channels that have become integral to any multichannel strategy are offline and online channels. Since a physical trip to the store is an option, environmental and situational factors such as weather and distance to the physical store might well influence a consumers' decision in channel selection. Clearly, if weather conditions are poor and the store is situated a significant distance away, the online channel becomes a more attractive option for purchasing.

Multiple communication media: The blend of traditional and new communication media provide multiple means of interacting with consumers while posing new challenges for researchers. Media integration, planning and measurement, take on far more complex roles, having to integrate elements that now have new relevance. These elements include the dynamic effects of these media such as their decay effects, their possible interactions with other new media, and ultimately the influence on actual consumer purchase behavior.

Category experience: Experience – whether referring to product categories or on line channels will have a significant effect on shopping behavior and consumer choices. We thus propose that consumer choice behavior, as exhibited through response to marking mix, will evolve as a function of category experience.

Promotional activities: Much of the promotional activity implemented by firms tends to be channel specific – thus, display and features (as currently understood in the literature) is only relevant for physical stores while web-based ads or promotions are often specific to online channel. These channel specific promotional activities play a significant role in shaping multichannel consumer shopping behavior must be appropriately accounted for.

Formalizing Choice Behavior: In this multichannel multi-communication environment consumers are making various decisions. A formal study of any such consumer choice behavior must capture the different elements impacting these decisions. To this end, we offer a comprehensive model in this environment that models choice, incidence and quantity decisions in a single framework.

2.3 Model Development

We model consumers' channel choice, purchase incidence, and order-size decisions. The channel choice decision is modeled using probit framework, and decisions related to purchase incidence and order-size are modeled using Type II Tobit specification. We follow the standard random utility framework for joint modeling of all three consumer decisions. Let z_{ct}^{h} be the indicator variable that records consumers' channel choice c for a given purchase occasion t, this is 1 for offline channel choice 0 otherwise (online channel), and let Z_{ct}^{h} be a latent variable representing the difference between consumers' latent utilities of selecting offline and online channel. Let y_{kct}^{h} be the observed binary choice of consumer h purchasing in category k through channel c at purchase occasion t, this is 1 when category incidence occurs 0 otherwise, and let U_{kct}^{h} be the latent variable related to the decision regarding whether to buy in the category.

Finally let q_{kc}^{h} be the observed order-size (in *ml*) of consumer h ordering in category k through channel c at purchase occasion t, this is positive number when incidence occurs 0 otherwise, and Q_{kct}^{h} be the partial latent variable that is related to the observed order-size. The specifications of latent and partial latent variables are as follow:

$$Z_{ct}^{h} = \rho_{c}^{h} + \kappa_{c}^{h} DIST_{ct}^{h} + \pi_{c}^{h} TMP_{ct}^{h} + \varphi_{c}^{h} PRCP_{ct}^{h} + \tau_{c}^{h} FAMIL_{ct}^{h} + \eta_{ct}^{h} \tag{1}$$

$$\boldsymbol{U_{kct}^{h} = \alpha_{k}^{h} + \beta_{k}^{h}(t) MKT_{kct}^{h} + \sum_{I \in COM} \delta_{kI}^{h} f_{2}(I_{kct}^{h}) + \sum_{I,I' \in COM,COM'} \delta_{kII'}^{h} g_{2}(I_{kct}^{h} I_{kct}^{'h}) + \varsigma_{kt}^{h} HOL_{kct}^{h} + \varepsilon_{kct}^{h}} \tag{2}$$

$$Q_{kct}^{h} = \boldsymbol{\phi_{k}^{h} + \theta_{k}^{h}(t) MKT_{kct}^{h} + \sum_{I \in COM} \mu_{kI}^{h} f_{3}(I_{kct}^{h}) + \sum_{I,I' \in COM,COM'} \mu_{kII'}^{h} g_{3}(I_{kct}^{h} I_{kct}^{'h}) + \phi_{kt}^{h} HOL_{kct}^{h} + \xi_{kct}^{h}} \tag{3}$$

Channel choice is a function of consumers' distance to the store, environmental conditions during the purchase occasion such as temperature and precipitation, and consumers' familiarity with the channel. Since consumers' channel choice decision cannot be influenced by limited categories (Chu, Chintagunta, and Cebollada 2008) under investigation, we do not include any category specific characteristics in Equation 1. The latent utilities of purchase incidence and partial latent variables of order-size across categories are function of firms' marketing, MKT, and communication mix, COM, variables, and holidays, HOL. Marketing mix variables constitute prices and promotion i.e., $MKT = \{Price, Promotion\}$, and communication mix variables constitute blend of both traditional and new media e.g., *COM={Email, Catalog, Educational program, Newspaper, Television, Radio, IST, Web ads}*. The details of these variables are discussed in the data section.

We assume consumer responses to marketing mix variables evolve as purchase experience is gained, therefore the corresponding parameters of marketing mix are made function of category purchase experience. Communication mix variables act as stock and their effects decay over time, therefore communication mix variables are also dynamic in nature. We also capture the possible interactions among these communications. The dynamic specifications of marketing and communication mix variables are explained in following sub sections.

The unobserved factors that affect channel choice, purchase incidence, and order-size are represented by error terms $\eta_{ct}^{h}, \boldsymbol{\epsilon}_{\mathbf{kct}}^{\mathbf{h}}, \boldsymbol{\xi}_{\mathbf{kct}}^{\mathbf{h}}$ respectively. The error terms are assumed to be distributed multivariate normal, $\mathrm{N}(0, \boldsymbol{\Sigma})$. For identification, we estimate the correlation matrix. Furthermore, for incidence and order-size we use the same set of covariates, therefore for identification purpose we restrict the covariance between $\boldsymbol{\epsilon}_{\mathbf{kct}}^{\mathbf{h}}, \boldsymbol{\xi}_{\mathbf{kct}}^{\mathbf{h}}$ to be zero. Finally the relationship between latent/partial-latent variables and observed variables are as follow:

$$z_{ct}^{h} = \begin{cases} 1 & if \quad Z_{ct}^{h} > 0 \\ 0 & otherwise \end{cases} \tag{4}$$

$$y_{kct}^{h} = \begin{cases} 1 & if \quad U_{kct}^{h} > 0 \\ 0 & otherwise \end{cases} \tag{5}$$

$$q_{kct}^{h} = \begin{cases} \exp(Q_{kct}^{h}) & if \quad U_{kct}^{h} > 0 \\ 0 & otherwise \end{cases} \tag{6}$$

The exponentiation of Q_{kct}^{h} ensures the predicted order-size is positive. Equation 4 is binary probit specification for channel choice and Equations 5 and 6 are Type II Tobit specification for purchase incidence and order-size decisions.

2.3.1 Dynamics of Marketing Mix

Consumer response to marketing mix may evolve over time as a result of exposure to firms' communication media and purchase itself that result in the formation of category experience. To account for the evolution of consumer response to marketing mix we allow corresponding parameters to vary systematically with category purchase experience (Heilman, Bowman, and Wright 2000; Papatla and Krishnamurthi 1996). We assume a nonlinear, monotone functional form for the evolution of marketing mix response parameters as follow:

$$\boldsymbol{\beta}_k^h(t) = \boldsymbol{\beta}_{0k}^h + \boldsymbol{\beta}_{1k}^h \ln(CatExp_{kt}^h) \quad (7)$$

$$\boldsymbol{\theta}_k^h(t) = \boldsymbol{\theta}_{0k}^h + \boldsymbol{\theta}_{1k}^h \ln(CatExp_{kt}^h) \quad (8)$$

The operationalization of category experience, $CatExp$, is explained in the data section.

2.3.2 Dynamics of Communication Mix

Communication mix variables act as information source to consumers sent by the firms at different points of time to engage and interact with them continuously. The repetition of communication serves two purposes, first during the course of time consumers tend to forget the reciprocated information therefore repetition reinforces their recall, and second subsequent communication acts as stock that helps building better customer relationship. To account for effect of forgetting or decay effect of communication media and their stock building nature we adopt finite duration adjustment of the geometric lag with unequally spaced observations, similar to Ansari, Mela, and Neslin’s (2008) approach.

Communication i is defined as particular communication received at some particular time t by consumer h. Since there are number of same communications received by the consumer at different time, for the sake of parsimony we divide communication i into groups of communication I(e.g., multiple emails received by consumers at different times are classified as email communication i.e. we assume communication of same kind have same effect). Next, we also account for the time since communication was received in order to model communication decay over time. Furthermore, we model direct effect of communication as well as its interactions with other communications. Accounting for all these, considering purchase incidence, Equation 1, the total direct effect of communication I (without interaction e.g. *I={Email, Catalog, Newspaper}*) for consumer h at time t for category k is specified by defining function f_1 as follow:

$$f_1(I_{kct}^h) = \sum_{i \in I} \lambda_{Ik}^{r_{hit}} d_{hit} \qquad (9)$$

where the variable d_{hit} indicates whether customer h received communication i at on or before time t. It is zero before consumer receives the communication i and remains one thereafter. The variable r_{hit} is the number of periods elapsed since consumer received communication i. Thus the more is the elapsed time since consumers received the communication, the lesser is its impact on their subsequent purchase decisions. The parameter λ_{Ik} incorporates the dynamics capturing the 'decay' effect of communication. The expected value of this decay parameter is between 0 and 1 to ensure that the effect of communication is diminishing over the time. The larger value of decay parameter implies its persistent impact into the future. To achieve this, we specify the logistic transformation of the decay parameter λ_{Ik} as follows:

$$\lambda_{Ik} = \frac{\exp(\omega_{Ik})}{1+\exp(\omega_{Ik})} \qquad (10)$$

As firms use multiple communication media to engage with the consumers, there are possible interactions among these communications. To capture interaction effects of communications, considering purchase incidence, Equation 1, the interaction effect of communication $I$and I' (e.g. *I-I' ={Email-Email, Email-Catalog}*) for consumer h at time t for category k is specified by defining function g_1 as follow:

$$g_1(I_{kct}^{h} I_{kct}^{'h}) = \sum_{i,i' \in I,I'} \lambda_{Ik}^{r_{hit}} \lambda_{I'k}^{r_{hi't}} d_{hit} d_{hi't} \qquad (11)$$

Similar specification of f_2 and g_2 for order-size decision, in Equation 2, is followed.

We have six communication groups with dynamic effects, therefore accounting for possible interactions among communication groups we end up with all together 19 interaction parameters. This creates too many parameters to estimate; therefore we use managerial judgment to select possible interactions which is mentioned in the data sections. Capturing total direct as well as interaction effects of various communication media and their dynamics poses computational burden which is solved using recursive scheme outlined in Appendix A. Dynamic specification of different communication variables for purchase incidence and order-size are given in Table 1.

Table 1: Communication Variables in Purchase-Incidence/Order-Size Equations

Variable	Purchase-Incidence Equation	Order-Size Equation
Email	$\sum_{i \in Email} \delta_{hk1}\lambda_{email}^{r_{hit}} d_{hit}$	$\sum_{i \in Email} \mu_{hk1}\Delta_{email}^{r_{hit}} d_{hit}$
Catalog	$\sum_{i \in Cat} \delta_{hk2}\lambda_{cat}^{r_{hit}} d_{hit}$	$\sum_{i \in Cat} \mu_{hk2}\Delta_{cat}^{r_{hit}} d_{hit}$
Education Program	$\sum_{i \in Edu} \delta_{hk3}\lambda_{edu}^{r_{hit}} d_{hit}$	$\sum_{i \in Edu} \mu_{hk3}\Delta_{edu}^{r_{hit}} d_{hit}$
Newspaper	$\sum_{i \in News} \delta_{hk4}\lambda_{news}^{r_{hit}} d_{hit}$	$\sum_{i \in News} \mu_{hk4}\Delta_{news}^{r_{hit}} d_{hit}$
Television	$\sum_{i \in Tel} \delta_{hk5}\lambda_{tel}^{r_{hit}} d_{hit}$	$\sum_{i \in Tel} \mu_{hk5}\Delta_{tel}^{r_{hit}} d_{hit}$
Radio	$\sum_{i \in Radio} \delta_{kh6}\lambda_{rad}^{r_{hit}} d_{hit}$	$\sum_{i \in Radio} \mu_{kh6}\Delta_{rad}^{r_{hit}} d_{hit}$
Interactions	$\sum_{i,i' \in I,I'} \delta_{kh7}\lambda_{Ik}^{r_{hit}} \lambda_{I'k}^{r_{hi't}} d_{hit}\, d_{hi't}$	$\sum_{i,i' \in I,I'} \mu_{kh7}\Delta_{Ik}^{r_{hit}} \Delta_{I'k}^{r_{hi't}} d_{hit}\, d_{hi't}$
IST	$\delta_{kh8} IST_{kct}^{h}$	$\mu_{kh8} IST_{kct}^{h}$
Web Ad	$\delta_{kh9} WebAd_{kct}^{h}$	$\mu_{kh9} WebAd_{kct}^{h}$

Note: Decay parameters δs, Δs are estimated alongside other parameters

2.3.3 Unobserved Heterogeneity and Estimation

Given multivariate specification of the model that incorporates both marketing mix and communication mix, we have at least 32 parameters to estimate not accounting for interactions of communication mix across category. Therefore, we specify customer-specific random effects for model intercepts correlated within and across equations. We use Bayesian estimation methods in which multivariate normal distribution is used to model unobserved heterogeneity. Markov chain Monte Carlo (MCMC) techniques are used to estimate the parameters of the model. We make use of data augmentation for the latent variables of the model. We specify uninformative priors for the model parameters. When a full conditional posterior distribution is of unknown form, we use Metropolis-Hastings (MH) algorithm. Further description of the priors and full conditional distributions for the unknown parameters and sampling details are given in the Appendix B.

2.4 Data

Our dataset comes from a leading regional retailer of liquor products in the state of New York. The retailer is one of the largest in the region and has also received recognition nationally (e.g., *Wine Spectator* Retailer of the year). The retailer sells its products through three distinct physical stores located in the region and a centrally managed website that contains three distinct links directing to three stores. Consumers could purchase from any of the offline physical stores or online websites. Online orders are processed by the corresponding individual offline stores. Consumers have the option of their online orders either to be shipped to their addresses or they can come to the store for pick-up. An important feature of the online orders is that the retailer could not ship the order outside the state.

The dataset contains rich information on various aspects of marketing and communication mix. The data span over two and half year period, a total of 135 weeks, from

January 2008 to July 2010. The prices and promotions are usually same across the channels. However, some promotions such as web advertisements and in-store display could vary across the channels. The retailer's store week is same as the calendar week. Different kinds of promotions as well as advertisements are run on a weekly basis. Therefore, weekday prices are same as weekend prices. Furthermore, different variables pertaining to marketing and communication mix are operationalized on weekly basis. Scanner panel data of household purchase history were combined with various other databases such as email, catalog, newspaper, television, radio, and educational program databases to get the individual level communication media usage sent by the retailer over the data period.

Two main liquor product categories were used for this research- wine and spirit. These categories were selected because most of the communications sent by the retailer to engage with the consumers are pertaining to these categories. Therefore we expect various communication media to affect consumer purchase behavior across these categories. The wine category constitutes over 30000 SKUs which covers 80% of the retailer's sales from wine. Similarly, the spirit category constitutes over 5000 SKUs which covers 80% of the retailer's sales from spirit.

Households having minimum of three purchases across these two categories during 135 week period were selected. This resulted in a sample of 4000 households out of which 124 were shopping across online and offline channels, 232 were shopping exclusively across online channel and the rest 3644 were exclusively shopping at offline channel. From this sample we randomly select 500 households, where 400 households shop exclusively at the retailer's offline stores, 50 households shop exclusively at the retailer's online outlet, and 50 households use both the channels. The data descriptive of household purchase behavior is given in Tables 2-5.

Table 2: Pairwise Category Purchase Incidence in Estimation Sample

Category	Wine	Spirit
Wine	5830	…
Spirit	3771	2804

Table 3: Purchase Quantity Details in Estimation Sample

Category	**Mean (in ml)**
Wine	3273.00
Spirit	1170.79

Table 4: Channel Usage Details in Estimation Sample

Channel	**Usage (%)**
Offline	97.80
Online	2.20

Table 5: Household Distribution across Channels in Estimation Sample

Household Distribution	**Percentage (%)**
Pure Offline	80.00
Pure Online	10.00
Multichannel (Offline + Online)	10.00

2.4.1 Variable Definition

In the model consumers' purchases incidence and quantity decision are affected by marketing mix variables that constitute price and promotion. The marketing mix variables evolve as a function of category experience. These variables were constructed as follow:

Price: We use 'category-price' variable ($/ml) for each household on each shopping trip. The category price is operationalized as weighted average price of brands where the weights are given by the share of each brand bought by each consumer.

Promotion: A brand was considered to be on promotion if it was on discount. The ‘category promotion’ variable was constructed in similar manner to that of category price. This resulted in category promotion variable that took value between 0 and 1. The descriptive statistics of marketing mix variables across two categories are given in Table 6.

Table 6: Summary Statistics for Marketing Mix

Marketing Mix	Category	Mean	SD
Price ($/ml)	Wine	0.0136	0.0087
	Spirit	0.0217	0.0104
Promotion Depth (%)	Wine	97.82%	0.1448
	Spirit	37.04%	0.3607

Category Experience: Category experience variable is operationalized as the number of cumulative purchases in the category made by a consumer at a given purchase occasion.

The communication mix variables with dynamic effect constitute blend of new/emerging media such as email, catalog, and educational program, as well as traditional media such as newspaper, radio, and television. The dynamic communication mix variables were constructed as follow.

Email: The retailer sends 5-7 emails every month to consumers. These emails communicate information related to products, promotions, events and firms. We have detailed database of retailer’s email marketing activities from which we can track down how many emails were sent, how many emails were opened and how many times, how many emails were undelivered due to hard or soft bounce and how many consumers unsubscribed from email list. We operationalize email using indicator variable which takes value 1 if a particular email sent during a week was opened by the consumer, 0 otherwise.

Catalog: Catalogs are booklets sent by retailers to consumers on an average 3 to 4 times a year. These catalogs contain detailed information on products, prices, and calendar of in-store activities such as tasting and sampling programs. Sometimes catalogs contain recommendations and ratings given by experts as well as store staffs. We operationalize catalog using indicator variable which takes value 1 if a particular catalog sent during a week was received by the consumer, 0 otherwise. Since, the retailer uses catalogs as a means to communicate with consumers about product related information rather than a channel or outlet to sell products; catalog is treated as new/emerging media.

Educational Program: The educational programs are in-store promotional/informational activities whereby the retailer organizes various events to which consumers can register and come to the store to get detailed information on liquor products such as country of origin, varietals, grape type etc. Furthermore, sometimes they can also sample the selected wine during the event. We have detailed records on these education programs organized by the retailer which include registered households as well as households who actually attended the event. On an average the retailer organize 2-3 events per month. We operationalize educational program using indicator variable which takes value 1 if a particular event organized during a week was attended by the consumer, 0 otherwise.

Newspaper: The newspaper ads are posted on weekly basis and they contain various promotions such as discounts, rebates, buy one get one free, coupons etc. We assume all selected consumers in the sample receive these newspaper ads, therefore the indicator variable for newspaper is 1 every week if the retailer’s ads were featured in the newspaper. However, newspaper ads are operationalized as interaction of the indicator with sum total of number of SKUs advertised across all ads per week.

Television: Television ads are about the retailer and sometimes about sales promotion events. We have information on GRP ratings of the television programs in which the retailer's ads were featured. We assume all households in our database view these television ads, therefore the indicator variable for television is 1 every week if any of the television programs broadcast the retailer's ads. However, television variable is operationalized as interaction of the indicator with sum total of GRPs of all the television programs broadcast during a week where the retailer's ads were featured weighted by the length of the program (for television the unit program length is 30 seconds).

Radio: Radio ads are mostly about the retailers. These ads are featured during talk shows, bulletins, game show, infomercial, and infotainment. We have information on GRP ratings of the radio programs in which the retailer's ads were featured. We assume all households in our database listen to these radio ads, therefore the indicator variable for radio is 1 every week if any of the radio programs featured the retailer's ads. However, radio variable is operationalized as interaction of the indicator with sum total of GRPs of all the radio programs broadcast during a week where the retailer's ads were featured weighted by the length of the program (for radio the unit program length is 60 seconds).

Information received through these media by households will have contemporaneous as well as future effects. Furthermore, during the course of time they will build stock of these information variables which might influence their future purchases. Therefore, we incorporate these communication variables in the model with household level dynamics with unequally spaced purchase cycles.

Apart from the above mentioned communication media the retailer adopts channel specific campaigns which are modeled as having contemporaneous effects only. These communication media are web ads over online channel and information shelf-talkers (IST) in the store. These non-dynamic communication variables are operationalized as follow.

Web Ads: The retailer campaigns for *Wine of the Week*, *Spirit of the Week*, for selected products which are recommended either by the expert or by the staff personnel on its website. We merge all these online campaigns under web ads. The web ads variable is operationalized as dummy variable which takes value 1 if any product item for either of the categories purchased by the household contains web featured product.

Information Shelf Talker (IST): The retailer has special in-store campaigns where they promote certain products. One of the in-store campaigns is providing expert ratings and product details for the products on the shelf using small placards. We call these campaigns as *Information Shelf Talker (IST)*. We operationalize IST as proportion of product items from their purchased basket which contained ISTs. The data descriptive for these communication mix variables is given in the Table 7.

Table 7: Summary Statistics for Communication Mix

Variables	Mean	SD	Max	Min
Emails (per month)	6.17	1.74	9	3
Catalogs (per year)	3.33	0.57	4	3
Catalog share (of items)	37.03%	0.44	100%	0%
Education Program (per month)	7.72	4.66	12	2
Newspaper Ad (per week)	2.02	1.06	4	1
Newspaper Ad share (of items)	88.05%	0.27	100%	3%
Television Ad (weekly GRP)	71.39	68.77	300.00	0.00
Radio Ad (weekly GRP)	26.26	10.29	37.70	10.36
IST (share of items)	14.48%	0.27	100%	0%

We include situational variables for the consumers' channel choice decision. These variables are operationalized as follows.

Distance: The household location data constitute their latitude and longitude information. We use this information with stores' location data to calculate household distance to the store.

Temperature: Temperature is collected from weather data. It is operationalized as absolute value of temperature in degree Fahrenheit. We expect high temperature will drive consumers' offline channel choice.

Precipitation: Precipitation is collected from weather data. It is operationalized as dummy variable which takes value 1 when precipitation is higher than 0 (i.e. there was snow fall in that week) otherwise 0. We expect high precipitation i.e. snowy condition will drive consumers' online channel choice.

Channel Familiarity: Channel familiarity is operationalized as $\log(\frac{1+offline\ channel\ use\ to\ date}{1+online\ channel\ use\ to\ date})$.

The data descriptive of these variables are given in Table 8.

Table 8: Summary Statistics for Covariates in Channel Choice

Variable	Mean	SD
Store Distance (miles)	16.72	73.40
Temperature ($^{\circ}$F)	48.54	18.58
Precipitation (inch)	0.13	0.27

2.5 Results

We use Markov chain Monte Carlo techniques to obtain parameter draws from their posterior distributions. The significant parameters are at 90% levels i.e. 90% confidence intervals of significant parameters excludes zero. We present the results of our estimated model in Tables 9-12. We discuss our results separately for channel choice, incidence, order-size, and correlation in decisions.

2.5.1 Channel Choice

The parameter estimates of channel choice decision are given in Table 9. The channel choice is modeled as binomial probit, with online channel as the base. Environmental conditions of a given purchase occasion such as temperature and precipitation and familiarity with channel influence consumers' channel choice decisions (Park, Iyer, and Smith 1989). Specifically, in high temperature and low precipitation (high precipitation in the area indicates high snow fall) conditions consumers prefer visiting the retailer's physical store. Similarly, high familiarity with channel facilitates consumers' choice for the offline channel. Therefore, it is important for retailers to maintain high store traffic in order to drive consumers to the stores. Consistent with the law of retail gravity (Ghosh and Craig 1983) we find store distance is still a critical factor that influence consumers' store choice decision. Therefore, in this changing environment retailers adopting multichannel strategy with physical stores as one of their channels should decide on location very carefully.

Table 9: Parameter Estimates: Channel Choice

Parameter	M	SD
Intercept	**-0.6887**	0.3063
Store Distance	**-0.1742**	0.0545
Temperature	**0.2617**	0.1131
Precipitation	**-0.3062**	0.1193
Channel Familiarity	**0.1037**	0.0466

Notes: Bold indicates that the 90% posterior interval excludes zero.

2.5.2 Purchase Incidence

The parameter estimates of purchase/category incidence are given in Table 10. Notably, we find most of the parameters including marketing mix are significant and we also find some significant interactions among communication parameters. Furthermore, we find differential impacts of communication mix across the categories.

Table 10: Parameter Estimates: Purchase Incidence

Parameter	Wine		Spirit	
	M	SD	M	SD
Intercept	**3.4775**	1.8361	**2.8193**	0.7036
Price	**-5.2006**	1.2753	**-5.5786**	1.2748
Promotion	**3.2226**	1.8125	**0.4942**	0.1114
Email	0.6771	5.1736	0.8006	5.0952
Catalog	**0.4227**	0.1292	**0.3849**	0.1127
Educational Program	**0.1810**	0.0583	-0.1498	5.3049
Newspaper	**1.1809**	0.3298	**1.1058**	0.2889
Television	**1.0087**	0.2656	**4.7711**	1.1668
Radio	**1.5441**	0.8497	**1.8562**	0.9137
Email_Email	**0.6056**	0.3072	**0.6043**	0.3031
Catalog_Catalog	0.9857	4.8655	0.2365	0.5392
EduProg_EduProg	0.1337	0.5526	-1.1417	5.4306
Television_Television	**2.9727**	0.7739	**3.1331**	0.7588
Email_Catalog	1.7399	1.2199	-1.6128	1.2046
Catalog_Newspaper	**0.2064**	0.1215	-0.1746	0.1156
Television_Email	**0.8798**	0.3145	**0.8738**	0.3101
Television_Catalog	**4.9611**	1.4626	**4.8081**	1.3445
Television_Newspaper	**0.4810**	0.1322	**0.4758**	0.1219
IST	**0.6088**	0.0906	**0.5850**	0.1223
Web-Ads	**4.5210**	1.8770	**0.5526**	0.1220
Holiday	**0.2805**	0.0960	**0.1842**	0.0440
Price*ln(CatExp)	**0.2779**	0.0663	**0.1935**	0.0391
Δ_{Email}	**0.1897**	0.0004	**0.1154**	0.0035
$\Delta_{Catalog}$	**0.3454**	0.0016	**0.4280**	0.0002
$\Delta_{EduProg}$	**0.8412**	0.0011	**0.1120**	0.0663
$\Delta_{Newspaper}$	**0.6645**	0.0033	**0.6623**	0.0115
$\Delta_{Television}$	**0.2450**	0.0021	**0.2245**	0.0018
Δ_{Radio}	**0.2135**	0.0132	**0.2016**	0.0031

	M	SD
Preference correlation	-0.5825	0.2001

Notes: Bold indicates that the 90% posterior interval excludes zero.

Both, traditional media and emerging media have significant impact on purchase incidence. However, effects of traditional media are higher than new media on purchase incidence. Specifically we find television media tends to have highest impact consistent with prior literature (Pedrick and Zufryden 1991). There are significant interaction effects among communication media. Notably we find within communication interaction is more effective than across communication interactions. The interaction between catalog-catalog and television-television tend to have significant impact on incidence. These two communication media (especially television) expose consumers to the product and retailer related information allowing them to overcome uncertainties by imparting greater learning (Rethans, Swasy, and Marks 1986), therefore repetition reinforces consumers' purchase incidence. Also we find traditional media, television, have significant interaction with email and newspaper. These results contrast sharply with earlier findings reported in Ansari, Mela, and Neslin (2008) where interactions had negative impact on category incidence. Most of the decay parameters (e.g., email, television, and radio) are smaller in magnitude implying they do not change consumer attitude over time. However very personalized communication such as educational programs where consumers put conscious effort to attend and learn about product has long term impact. Newspaper also tends to have longer effect attributed to coupons and sales promotion that they contain and are valid over a week in those newspaper ads.

Web ads and Information Shelf Talker (IST) significantly influence the purchase incidence across the categories. Web-ads in the form of *Wine of the Week* and *Spirit of the Week* are ads that suggest specific products either by the experts or by the staff based on ratings and other product information on the retailers' websites. Similarly, Information Shelf Talkers (ISTs) are product ratings and reviews from experts and staffs that are attached to specific products on the shelf. Therefore, in-store and web based promotional activities are still relevant in today's dynamic retailing environment.

Marketing mix, price and promotion, have expected signs. Price sensitivity tends to be higher for spirit category. The sensitivity to price decreases over the time. Consumers are promotion sensitive across both the categories. Also we find for purchase incidence, more price sensitivity in a category leads to higher consumer sensitivity towards retailers' communication mix for that category. Therefore, retailers need to coordinate their marketing and communication mix decisions to maximize benefits (Kaul and Wittink 1995). Furthermore, inherent preference for the wine category is higher than the spirit category. Preferences across these two categories are negatively correlated implying that consumers tend to regulate their alcoholic product consumption. Special occasion such as holidays tend to positively influence consumers' category purchase incidence.

2.5.3 Order-Size

The parameter estimates of order-size are given in Table 11. Consumer sensitivities to the retailers' marketing efforts have differential impact across categories in their quantity decisions. More importantly, we find the impacts of different communication media have contrasting results to that of purchase incidence.

Table 11: Parameter Estimates: Order-Size

Parameter	Wine		Spirit	
	M	SD	M	SD
Intercept	**4.8878**	0.0482	**1.8196**	0.0336
Price	**-3.1753**	0.1743	**-3.8308**	0.1116
Promotion	**2.0076**	0.0426	**0.4681**	0.0249
Email	1.0109	1.8352	0.6933	1.3802
Catalog	**2.6051**	0.6722	**2.2831**	0.5004
Educational Program	**2.2653**	1.2598	-1.6690	1.0006
Newspaper	**0.2698**	0.0229	**0.2306**	0.0169
Television	**0.9440**	0.0571	**0.7544**	0.0430
Radio	**0.3730**	0.1140	**0.1750**	0.0684
Email_Email	**2.1901**	0.8500	**1.6320**	0.6374
Catalog_Catalog	1.3699	2.2971	0.2666	1.1489
EduProg_EduProg	0.8508	1.8669	0.6479	1.4115
Television_Television	**3.6033**	0.2478	**2.6256**	0.1802
Email_Catalog	0.0735	0.2691	0.1075	0.1936
Catalog_Newspaper	**0.0449**	0.0252	**0.0467**	0.0200
Television_Email	**0.4228**	0.1789	**0.3238**	0.1297
Television_Catalog	**1.2099**	0.2850	**0.9488**	0.2026
Television_Newspaper	**0.1178**	0.0094	**0.0932**	0.0066
IST	**0.6488**	0.0352	**0.5731**	0.0340
Web-Ads	**0.9046**	0.0204	**0.5024**	0.0210
Holiday	**0.1438**	0.0216	**0.0979**	0.0213
Price*ln(CatExp)	**0.1326**	0.0666	**0.1521**	0.0445
Δ_{Email}	**0.4929**	0.0015	**0.4957**	0.0011
$\Delta_{Catalog}$	**0.3978**	0.0003	**0.4889**	0.0015
$\Delta_{EduProg}$	**0.4963**	0.0018	**0.4446**	0.0028
$\Delta_{Newspaper}$	**0.4314**	0.0003	**0.5230**	0.0019
$\Delta_{Television}$	**0.5047**	0.0002	**0.5320**	0.0022
Δ_{Radio}	**0.4502**	0.0143	**0.5625**	0.0097
	M		SD	
Preference correlation	-0.5293		0.0469	

Notes: Bold indicates that the 90% posterior interval excludes zero.

In quantity decisions we find new/emerging media have more influence than traditional media. However, traditional media are still significant though their magnitudes are smaller which is consistent with prior literature that purchased quantities are adjusted on the basis of brand choice (Tellis 1988). Specifically, we find among new media, catalog and educational program have significant positive impact on quantity decision. These communication media are very much personalized in nature suggesting consumers about their consumption which tends to increase purchase quantities (Wansink, Kent, and Hoch 1998). There are significant interactions among communication media. Interaction between email-email tends to have negative impact on wine quantity decision. This could be due to the frequency with which emails are sent that tend to decrease the marginal return of email (Ansari, Mela, and Neslin 2008). Among various own-communication interactions educational programs have highest positive impact on quantity decision. Traditional media such as television have significant positive interaction with catalog and newspaper with respect to consumers' quantity decision. Most of the decay parameters are higher in magnitude when compared with purchase incidence decision. This implies that consumers tend to remember about these communications longer when it comes to quantity decision.

In-store activities such as ISTs and web-based activities such as web-ads also positively affect consumers' quantity decisions; however their magnitudes are smaller than purchase incidence. Therefore, variations due to in-store and web activities are explained more by consumers' purchase incidence decisions across categories. However, these store and web activities are important factors that influence consumers' purchase as well as quantity decisions across various categories.

Marketing mix, price and promotion, have expected signs. The sensitivity to price decreases over the time. Preferences across these two categories are negatively correlated implying that consumers tend to regulate their alcoholic product consumption in their quantity decision too. This is consistent with the results we find for consumers' purchase incidence decision. Special occasions such as holidays tend to increase consumers' quantity purchase.

2.5.4 Correlation of Decisions

We present the correlation results across decisions in Table 12. We find that for incidence and order-size cross category correlations are negative (it is significant for order-size but insignificant for purchase incidence). This again implies that impact of unobserved factors on alcoholic product consumption is regulatory in nature. The channel choice is negatively associated with spirit category in both incidence and order-size. However, channel choice is positively associated with the wine category in both incidence and order-size. Since the store has larger assortment of wine products, it is understandable that consumers tend to visit store to purchase their wine products. Furthermore, given sensory nature of wine category consumers prefer buying these products from offline channel or the retailer's physical stores (Chu, Chintagunta, and Cebollada 2008).

Table 12: Decision Correlations

		Incidence		**Order-Size**		**Channel**
		Wine	Spirit	Wine	Spirit	**Choice**
Incidence	Wine	1.0000	…	…	…	…
	Spirit	-0.3155	1.0000	…	…	…
Order-Size	Wine	0.0000	0.0000	1.0000	…	…
	Spirit	0.0000	0.0000	**-0.3580**	1.0000	…
Channel Choice		0.0207	**-0.0278**	**0.0426**	-0.0263	1.0000

Notes: Bold indicates that the 90% posterior interval excludes zero.

2.6 Media Planning Simulations

The basic purposes of marketing communications are message creation and message dissemination. The various tasks associated with media planning involve setting media objective, developing media strategy and evaluating their effectiveness. In this regard we look into some media planning simulations that would provide managers some guidelines for media planning. These simulations are with respect to media scheduling, media targeting, media selection, and communication and marketing mix interactions.

2.6.1 Media Schedule Decision

One of the important decision retailers have to take is ‘when’ to communicate with their consumers. Given limited media budget, they have to consider whether to spread the budget equally across periods (continuous scheduling), or to alternate advertising in certain period and no advertising in at all in some periods (flight scheduling), or combining first two strategies with heavy media spending in certain periods and moderate media spending in other periods (pulse scheduling).

With respect to these three kinds of media scheduling mechanisms we carry out policy simulations to see the change in quantity bought when different scheduling schemes are used. Wherever possible we either reallocate the existing resources or simulate them with appropriate scheduling scheme. The result of this simulation is given in Table 13.

Table 13: Impact of Media Scheduling Decision

	Percentage Change in Quantity					
	Continuous Campaign		**Burst Campaign**		**Pulsing Campaign**	
	Wine	*Spirit*	*Wine*	*Spirit*	*Wine*	*Spirit*
Email*	0.5305	0.4727	0.0077	0.0239	1.0425	0.4907
Catalog†	0.0258	0.0086	1.6615	0.4348	1.6747	0.0930
Edu. Prog. †	1.6362	-0.0386	0.0675	-0.0338	1.6725	-0.0062
Newspaper*	0.9079	0.4816	0.0053	0.0003	0.9140	0.4842
Television*	0.4352	0.4470	0.0060	0.0003	0.4515	0.4488
Radio*	0.4276	0.0523	0.0006	0.0047	0.4289	0.0484

* Reallocation of the existing amount

† Reallocation with simulating the amount

We find that pulsing campaign mechanism is the best scheduling scheme. It has best result not only for traditional media but also for emerging media. Therefore, in the multichannel environment retailers should not only continuously engage and interact with consumers but they have to vary the intensity of the interaction depending on the occasion.

2.6.2 Targeting the Consumer Segment

Given plethora of communication mix that retailers use nowadays, it is very important that right segment of consumers are targeted with right communication mix. In this regard we carry out simulation analysis to see the most profitable consumer segments (in terms of volume bought) in a multichannel environment. We divide consumers into three segments, pure offline consumers, pure online consumer, and multichannel consumers. Then we target these consumers with personalized media (email, catalog and educational program) following pulsing media scheduling scheme. We report the percentage change in quantity bought for these three segments in Table 14.

Table 14: Targeting Consumers with Personalized Media

	Percentage Change in Quantity					
	Pure Online Consumers		**Pure Offline Consumers**		**Multichannel Consumers**	
Media	*Wine*	*Spirit*	*Wine*	*Spirit*	*Wine*	*Spirit*
Email	0.0109	0.0045	0.6986	0.1302	1.4138	0.3934
Catalog	0.0188	0.0545	0.8040	0.5983	2.0688	0.7509
Edu. Prog.	*NA*	*NA*	0.9414	-0.0291	0.9345	0.0004

NA – Not Applicable

Consistent with prior literature we find that multichannel consumers are most profitable segment. Furthermore, we find that catalog tend to have highest compared with emails and educational programs.

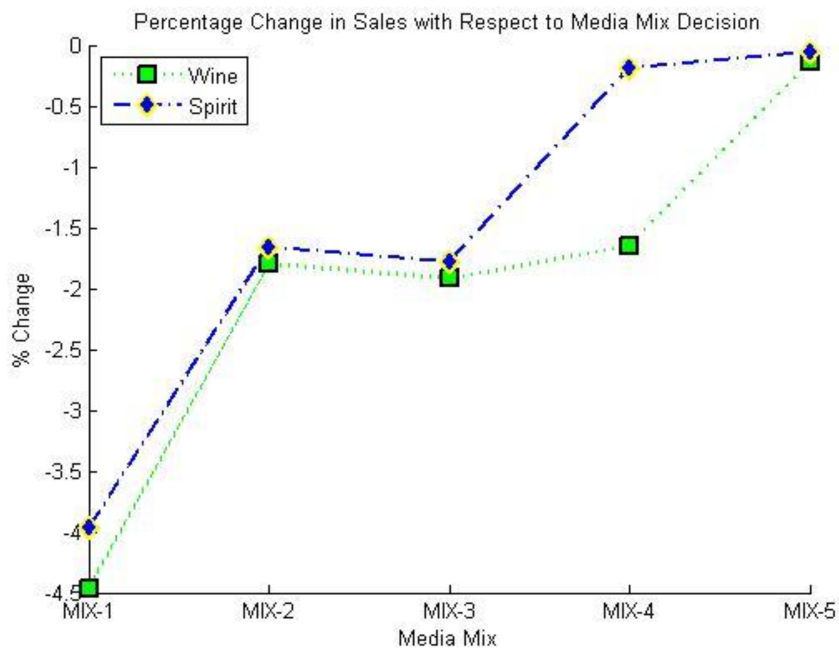
2.6.3 Media Mix Strategy: Concentration vs. Dispersion

With respect to communication media mix strategy retailers can either go for media concentration strategy where they use fewer and same type of media or they can adopt media dispersion strategy where they can adopt multiple media categories. We look at both types of strategy where we simulate for change in quantity for five different kinds of media mix strategies, first and second mix strategies consisting of traditional media only and new media only respectively, third and fourth mix strategies use selected combination of traditional and new media whereas fifth media strategy uses comprehensive combination of traditional and new media based on parameter estimates. The percentage change in quantity resulting from these different media mix strategies is given in Table 15. Figure 1 depicts the percentage dip in quantity bought when different media mix strategies are used.

Table 15: Selecting Mix of Communication Media

Percentage Change in Quantity	
Wine	**Spirit**
Mix 1: Use of only Traditional Communication Media (Television, Newspaper, and Radio)	
-4.4631	-3.9730
Mix 2: Use of only New Communication Media (Email, Catalog, and Educational Program)	
-1.8025	-1.6598
Mix 3: Use of Mixed Media (Newspaper, Email, Catalog)	
-1.9166	-1.7822
Mix 4: Use of Mixed Media (Television, Email, Catalog)	
-1.6467	-0.1872
Mix 5: Use of Mixed Media (Television, Newspaper, Email, Catalog)	
-0.1436	-0.0561

Figure 1: Media Mix Strategy



We find that in a multichannel environment it is beneficial for retailers to go for media dispersion strategy where they should use combination of both traditional and new media.

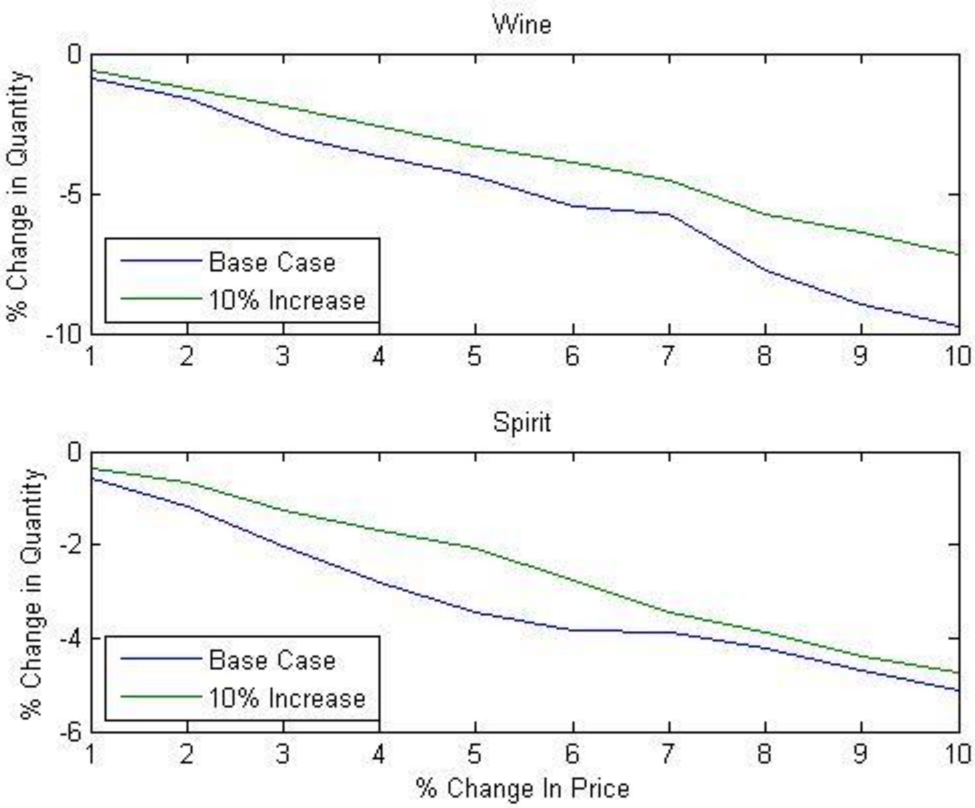
2.6.4 Marketing and Communication Mix

Finally, we look into the effect of marketing mix and communication mix together. We estimate the change in quantity bought price increases from 1% to 10% for base case, and then we increase all communication mix by 10% and re-estimate the change in quantity bought as price increases from 1% to 10%. The results and the corresponding graphs are shown in Table 16 and Figure 2 respectively.

Table 16: Effect of Marketing Mix on Communication Mix Strategy

	% Change in Quantity			
% Increase in Price	Base Case		10% Increase in Communication Mix	
	Wine	*Spirit*	*Wine*	*Spirit*
1	-0.9027	-0.5539	-0.6267	-0.3776
2	-1.6010	-1.1834	-1.2164	-0.6855
3	-2.8834	-2.0196	-1.8814	-1.2558
4	-3.6486	-2.7875	-2.6284	-1.6890
5	-4.4139	-3.4314	-3.3008	-2.0835
6	-5.4804	-3.8318	-3.9066	-2.7782
7	-5.7708	-3.8803	-4.5064	-3.4559
8	-7.7549	-4.2344	-5.7167	-3.8608
9	-8.9301	-4.6758	-6.3939	-4.3789
10	-9.7452	-5.1304	-7.1994	-4.7329

Figure 2: Marketing and Communication Mix Strategies



We find that effect of price change is similar in both the cases i.e. they follow the similar pattern. Therefore, we conclude that without proper marketing mix strategies the communication mix strategies are ineffective.

2.7 Implications, Limitations, Future Research and Conclusion

2.7.1 Managerial Implications

The proposed model and the estimated empirical analysis have some important managerial implications. The model facilitates the estimation of integrated retailing environment at individual level accounting for both marketing and communication mix in multichannel environment. The model accounts for dynamic effects of both marketing and communication mix. We allow marketing mix to evolve over time as a function of consumers' category experience. Dynamics in communication mix are accounted by explicitly modeling decay and stock nature of these variables. Furthermore, the modeling framework allows cross-category analysis accounting for three critical consumer decisions, purchase incidence, order-size, and channel choice, at disaggregate level.

The estimated empirical analysis sheds following important managerial insights. Communication mix, consisting of blend of both traditional and new media, has differential impact not only across categories but also across different consumer decisions namely incidence and quantity decision. We find traditional media have greater effect in influencing consumers' purchase incidence decisions whereas new media play greater role in influencing their quantity decisions. We find some interaction effects among communications to be significant and positive implying marginal return of repetitions as well as adoption of multiple communication media benefit the retailer.

One of the important questions that managers are interested in is where these new/emerging communication media fit in the traditional communication media used by the firms. Given our parameter estimates, we can say that new/emerging media and traditional communication media act synergistically in influencing consumer purchase behavior across multiple channels. However, their impact across categories may vary. Other forms of promotional activities such as in-store activities in the form of information shelf talker (IST) and web-activities in the form of web ads are also important for firms to influence consumer shopping behavior.

Email tends to decay faster than other forms of communication media. Personalized form of communication where consumers put extra effort and time to participate and engage such as educational program tends to have longer effect.

Some of the communication mix in our analysis acts as promotional support (e.g., email, television, radio, educational program, and IST) whereas others act as promotional volumes (e.g., newspaper), some act as both (e.g., catalog, web-ads). Notably, consumers are not always interested in promotional volumes (i.e. price cuts or sales promotion) but promotional support (giving product related information) also plays critical role in influencing consumer shopping behavior across multiple channels.

2.7.2 Limitations and Future Research

The research has some limitations that could be addressed by the future research. First, we assume that traditional communication mix is received by all the consumers in equal amount for a given period of time. However, this scenario could not be completely valid. Therefore, future research could model individual consumer’s usage of traditional communication mix probabilistically. Second, we do not account for the content of the communication media. For example all emails are treated equally. However, depending on message content some emails could be more important than others. Therefore, future research could look into the details of communication content itself that could possibly influence consumer shopping behavior in multichannel environment. Third, we do not model the differential impact of communication mix across the channel. Future research can address this problem by looking at differential impact of marketing as well as communication mix not only across categories but also across the channels.

2.7.3 Conclusion

In conclusion, we addressed the impact of multiple communication and marketing mix elements in multichannel environment across categories. We developed and estimated a disaggregate level model of consumer shopping behavior in multichannel environment in the presence of multiple communication (that comprised of blend of both traditional and emerging media) and marketing mix elements across categories by explicitly accounting for three critical consumer decisions, purchase incidence, order-size, and channel choice. We also incorporate dynamic effect of communication mix elements. The results from the empirical estimates of our model show that communication mix elements have differential impact across categories. Furthermore, emerging and traditional communication media tend to act synergistically in this integrated environment.

3. THE ROLE OF COMMUNICATION MEDIA, MARKETING MIX AND CONSUMER INTRINSIC VARIABLES ON CHANNEL CHOICE

3.1 Introduction

Consumers today face an entirely different market place as compared to even a decade ago. For example, consumers can make purchases across many outlets or channels such as ‘brick and mortar’ stores (offline channel/physical store) and online channels (retailer websites). Furthermore, retailers are adopting a blend of traditional media (e.g., television, radio, in-store displays and catalogs), emerging media (e.g., emails, e-catalogs, web ads) and social media (e.g., Twitter, Facebook, blogs) to engage and interact with consumers in this multichannel environment in order to build better consumer relationships. Given the interplay of these multiple communication media across multiple channels, retailers face increasingly complex issues. Understanding consumers’ channel choice behavior along multiple dimensions of their purchase behavior (such as channel choice - where to buy, inter-purchase timing – when to buy, and expenditure across these multiple channels – how much to buy) and the various correlates that affect these behaviors is critical for retailers to estimate efficient responses and effectively allocate resources. Such an understanding will help target specific consumers with the appropriate marketing tools (marketing and/or communication mix) via the appropriate channels.

The importance of a multichannel strategy has been recognized by both the industry (e.g., McKinsey Marketing Solutions 2000; Wall Street Journal 2010) as well academics (e.g., Venkatesan, Kumar, and Ravishanker 2007). In 2010, 69% of the retailers were using multiple channels and service initiatives for at least a year, of which the leading were online (84%); and brick and mortar channels (73%) (Aberdeen Research 2010). Sophisticated online consumers, many of whom are heavy spenders, expect their retailers to provide a seamless multichannel shopping experience that includes browsing print catalogs, buying from e-catalogs, researching and ordering goods online and offering in-store pickup (eMarketer 2006). Furthermore, same consumers nowadays are increasingly using these different channels for their purchases. Thus multichannel strategy has not only become a means to tap into larger consumer base but also to provide seamless shopping experience to existing consumers across different channels.

Nevertheless, adoption of multichannel strategy with the use of multiple communication media to engage and interact with the existing and potential consumers presents some unique challenges. First, in a multichannel environment, a retailer's blend of communication mix (such as traditional, emerging, and social) is clearly not exclusive to a specific channel. In fact these communication media may play a synergistic role across the retailer's multiple channels. Second, consumers adopting an online channel might show a differential response to the various variables as a function of their intrinsic preferences. Third, the above issues need to be studied in conjunction with behavioral/consumption variables (e.g., quantity choice). Moreover, this process may also be complicated because multiple data sources need to be integrated. For instance, to comprehensively describe shopping behavior in a multi-channel context, wherein consumers' are subjected to multiple marketing/communication variables, data from disparate sources needs to be merged and analyzed. However, these distinct data sources have different decision periods. For instance, in store promotions are set weekly while emails may be occasion specific and television advertising which is planned in advanced may have different units.

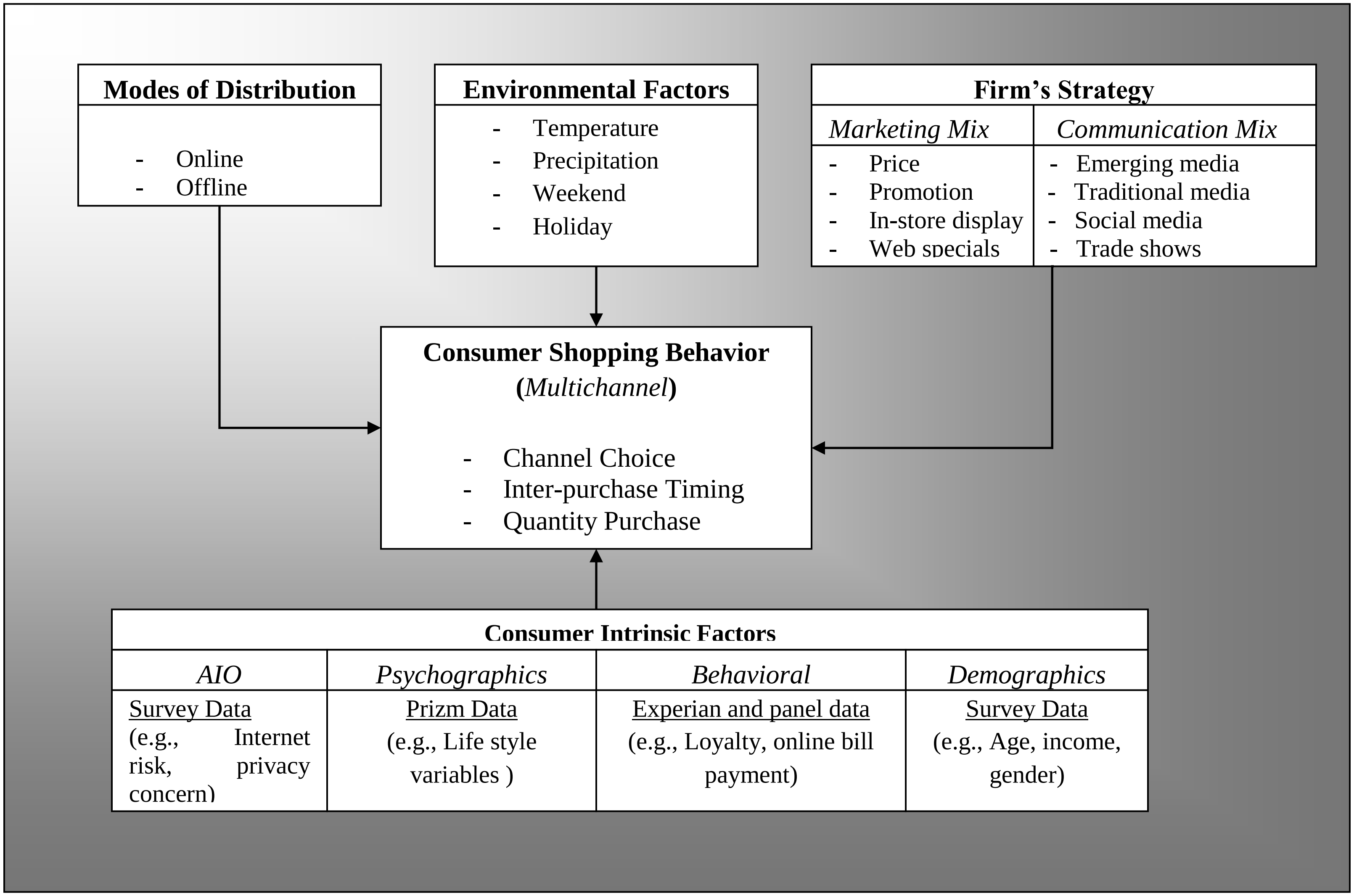
Given this complex environment, we seek to examine the role of traditional and new media (along with other communication and marketing mix variables) in influencing consumer information seeking and purchase behavior in a multi-channel context. An understanding of the above issues will prove useful for firms in better managing their customer relationships while enabling them to compare the effectiveness of diverse communication/marketing strategies for effective allocation of promotion dollars.

3.2 Background

The literature on multichannel marketing is fairly recent and deals with a multitude of problems concerning multichannel customer management (Balasubramanian, Raghunathan, and Mahajan 2005; Neslin and Shankar 2009). Specifically, researchers have analyzed channel choice (Kumar and Venkatesan 2005), channel migration (Ansari, Mela, and Neslin 2007; Venkatesan, Kumar, and Ravishankar 2007), response to marketing mix (Chu, Chintagunta, and Cebollada 2007; Zhang and Krishnamurthi 2004), relative benefits of shopping online vs. offline (Forman, Ghose, and Goldfarb 2008) and impact of online transaction cost on order incidence and size (Lewis, Singh, and Fay 2006). However, multichannel customer management still poses several research questions open to academicians and practitioners (Rangaswamy and van Bruggen 2005).

The first problem is with respect to formulation of the multichannel decision process itself and the various covariates affecting it. Multichannel decision process can involve decisions relating to channel preference, channel inertia (Valentini, Neslin, and Montaguti 2009), and order-size (Lewis, Singh, and Fay 2006; Ansari, Mela, and Neslin 2007). The various covariates that affect this decision processes could be marketing mix variables (Valentini, Neslin, and Montaguti 2009), communication media (Thomas and Sullivan 2005), situational factors, and utilitarian values related to information seeking, price comparison, possession and assortment (Noble, Griffith, and Weinberger 2005). Moreover, consumer attitudinal, lifestyle and behavioral variables may affect this process (Kwon and Jain 2009). We present our conceptual framework of this integrated decision model as well as correlates affecting it in Figure 1. The framework includes comprehensive marketing and communication efforts adopted in multichannel environment and captures extensive consumer characteristics to explain this process.

Figure 3: Conceptual Framework



In this research, we develop a framework for analyzing consumers' multichannel shopping behavior. In order to accomplish this holistically, we use varied marketing and communication activities spanning multiple data sources. Moreover, we also attempt to combine consumer purchase data (obtained through retail stores) with attitudinal data (from surveys). We, thus seek to enrich our understanding of the above issues by utilizing not only the actual purchase behavior but also the attitudinal behavioral aspects of consumers. Specifically we seek plan to address following issues pertaining to consumer channel choice behavior.

First, how consumers' channel choice across multiple outlets is influenced by blend of traditional and emerging communication media. Specifically we plan to measure differential impact of communication media across different channels. We control for the effects of other relevant factors that significantly influence consumer channel choice such as consumer attitudes, situational factors and consumer perception and preference. Second, we formalize the multiple dimensions multichannel shopping behavior. Specifically we model channel choice, inter-purchase timing, and quantity decision. These decisions will provide more insights into the effectiveness of various cofactors in influencing different aspect of multichannel shopping behavior. Third, we account for the effect of consumer intrinsic behaviors or consumer characteristics (e.g., internet risk, technology comfort, motivation, privacy concern etc.) on their multichannel shopping behavior. Finally, we address the issue of how can firms' better assess the effectiveness of multiple marketing and communication activities for optimal ROI for their multichannel strategy.

We develop an individual level model of consumers' multichannel shopping behavior (online/offline) and utilize multiple data sources to estimate it. Our approach differs significantly from that typically used by researchers. First, we model multiple dimensions of consumer shopping decisions: channel choice, inter-purchase timing, and quantity choice. Second, we capture the effect of various communication media (traditional, emerging, and social) on consumer shopping decision. Finally, we use multiple methodologies (e.g., scanner panel data combined with the survey data) to capture the effect of consumer intrinsic factors on their shopping decisions. Given diverse nature of multiple channels (e.g., offline vs. online) and different degree of sophistication required to shop across these channels we expect the consumer intrinsic factors to be salient in this regard.

3.3 Model

We model three consumer decision processes to capture multichannel shopping behavior, namely, channel choice, inter-purchase timing, and quantity decision. We assume each time period t $(t = 1, 2, ..., T)$ household h $(h = 1, 2, ..., H)$ decides which one of the channel j $(j = \begin{cases} 1 & Online \\ 2 & Offline \end{cases})$ to visit (for a given multichannel retailer), when to visit, and how much quantity Q to buy. Furthermore, these three decision processes (channel-choice, inter-purchase timing, and quantity) are affected by retailer' marketing strategy X that includes marketing and communication mix variables, consumer intrinsic factors Z that includes AIO, behavioral, psychological and demographic variables and finally by situational/environmental factors W for a given purchase occasion t. Next we describe the modeling approach for each of these decision processes.

3.3.1 Channel Choice

Using standard random utility framework we assume the indirect utility household h derives from visiting channel j on shopping trip t:

$$U_{hjt} = \alpha_{hj} + \beta_{hj} X^{C}_{hjt} + \delta_{hj} W^{C}_{hjt} + \omega_{hj} Z^{C}_{hjt} + \varepsilon_{hjt} \tag{12}$$

The superscript C stands for covariates in channel choice. Since there are only two channels, online and offline, and consumers visit only one for a given purchase occasion, the above formulation leads to binary probit model (Rossi, Allenby, and McCullouch 2005).

3.3.2 Inter-purchase Timing

We use competing risk proportional hazard model (PHM) to operationalize consumers' inter-purchase timing. Note that in a multichannel environment consumers can shop across any of the multiple channels (e.g., online and offline) provided by the firms, therefore competing risk model for purchase timing is appropriate which captures the differential impact of various factors on different channel patronizing behavior.

The proportional hazard function for household h selecting channel j with respect to covariates in our study is specified as follows:

$$\lambda_{hj}(t) = \lambda_{0j}(t;\theta_{oj})\exp(\varphi_{hj} + \eta_{hj}X^{I}_{hjt} + \mu_{hj}W^{I}_{hjt} + \varpi_{hj}Z^{I}_{hjt} + \nu_{hjt}) \tag{13}$$

The superscript I stands for inter-purchase timing. The dependence between selecting offline or online channel is specified by assuming $\boldsymbol{\nu}_{hjt} \sim MVN\ (0,\Omega)$. For identification purpose we estimate the correlation matrix of Ω and use exclusion restriction criterion (i.e. include at least one exogenous regressor that differs across offline and online hazard equations) (Gordon 2002). We use the exponential distribution for the baseline hazard function (Gupta 1991; Seetharaman and Chintagunta 2003). The detail of the likelihood function is provided in the Appendix C.

3.3.3 Quantity Decision

Consumer h conditional on making a shopping trip at time t decides how much quantity Q to buy. The quantity decision model is specified as follow:

$$\ln(Q_{hjt}) = \gamma_{hj} + \kappa_{hj} X_{hjt}^{Q} + \pi_{hj} W_{hjt}^{Q} + \phi_{hj} Z_{hjt}^{Q} + \xi_{hjt} \tag{14}$$

The superscript Q stands for quantity decision. The error term $\xi_{hjt} \sim iid\ N(0, \sigma^2 I)$.

3.3.4 Other Model Details

We model three decisions independently i.e. covariance between error terms of equations (12), (13), and (14) is zero. The heterogeneity is specified is parsimonious way using random effect where we assume intercept terms of each equation to follow normal distribution. The dependence between online and offline channels' inter-purchase timing is captured using frailty specification. The specification for the variables in X, W, Z across the equations varies and details are provided in Table 17.

Table 17: Covariates in the Model

Channel Choice (Equation 1)		
$\boldsymbol{X^C}$	$\boldsymbol{W^C}$	$\boldsymbol{Z^C}$
- Promotion - Communication Mix ○ Email ○ Catalog ○ Newspaper	- Temperature - Precipitation - Day of the week - Distance	- Shopping convenience - Shopping enjoyment - Privacy concern - Web site navigation - Internet risk - Sales consciousness - Deal proneness
Inter-purchase Timing (Equation 2)		
$\boldsymbol{X^I}$	$\boldsymbol{W^I}$	$\boldsymbol{Z^I}$
- Inventory - Communication Mix ○ Email ○ Catalog ○ Newspaper ○ Web-Ad	- Holiday dummies - Social Media	- Financial security concern[*] - Technology comfortness[*] - Possession - In-store display usage - Time pressure - Impulsive buying - Sales consciousness - Feature usage[‡] - Infotainment
Quantity Decision (Equation 3)		
$\boldsymbol{X^Q}$	$\boldsymbol{W^Q}$	$\boldsymbol{Z^Q}$
- Price - Promotion - Communication Mix ○ Email ○ Catalog ○ Educational Program ○ Newspaper ○ TV ○ Radio ○ Web Ad ○ IST	- Special occasion	- Variety seeking - Innovativeness

[*]Offline Channel only
[‡] Online Channel only

We estimate our model using Markov Chain Monte Carlo (MCMC) techniques since our approach to inference is Bayesian. We specify the prior distributions for the parameters of the model by using diffuse priors and conjugate distributions whenever possible. In the absence of conjugate priors we use Metropolis-Hastings (MH) algorithm to draw the parameters from the posteriors.

3.4 Data

We construct the data set for this study using multiple sources. The transaction/purchase data comes from a leading retailer in the state of New York for wine and spirit products (over 100,000 SKUs of wine alone) spanning more than seven years (2004-current). Thus, we have purchase histories for large number of households. For these *same* households we obtain data pertaining to psychographics and behavioral measures by conducting a survey. Moreover, we also have rich/detailed information about the firm's communications targeted to these consumers. Summary statistics of the dataset is given in Table 18 and 19.

Table 18: Data Description of Households

Description	Value (in %)
Offline consumers	80.00
Online consumers	20.00
Consumers receiving emails	49.55
Consumers receiving catalogs	83.22
Consumers receiving educational programs	1.66

Table 19: Data Description of Dependent Variable

Description	Value
Offline channel choice (%)	85.00
Online channel choice (%)	15.00
Average offline interpurchase time (weeks)	1.29
Average online interpurchase time (weeks)	31.03
Average quantity bought offline (in ml)	7415.24
Average quantity bought online (in ml)	9321.58

3.4.1 Offline/In Store Marketing

Consumer transaction data. This data obtained through loyalty cards for all the products sold in the store contains information pertaining to regular prices, all types of promotions, discounts etc. at the individual SKU level. Additionally, it also contains very accurate/ "true" wholesale price (or retail cost) of the SKU.

In store promotion activities. The dataset captures all in store promotions. These include aspects regarding displays, store layout, in store media, product ratings, in store tastings/sampling and educational programs and charity based promotions.

3.4.2 Online/ Web Marketing

Consumer online purchase data. Information relating to consumers' online purchases is also available and can be linked to their offline purchases. Moreover, for the individual SKUs the relevant price/cost information is also available.

Web based marketing activities. These include e-catalogs and other consumer driven internet promotions conducted through the firm's web site; and the data set capture this information.

3.4.3 Multiple Communication Media

Traditional Media. The dataset contains detailed information on traditional advertising media such as television ads, radio ads, and newspaper ads. These include when and where the advertising was done including the media ratings (e.g., the specific network/cable channels, the specific programs, duration of the commercial).

Emerging Media. The dataset contains detailed information on emerging media such as email, catalog/e-catalog (here catalogs serves more as source of information than buying outlet), Information-Shelf Talker (IST – these are in-store product reviews and rating information), educational programs (the store conducts wine tasting and wine education class). All these dataset contains rich information such as products being advertised, record of households who received and assessed these media etc.

Social Media. The retailer has its presence on social networking websites such as Facebook and Twitter where it advertises various events such as sales/promotion, educational class event, ratings and reviews of products. Also, the retailer maintains a blog on its website where they post various topics on wine/spirit related information.

3.4.4 Consumer Characteristics/Consumer Intrinsic Factors

We conduct a survey for the same set of consumers form the scanner panel data. The survey was sent to them in early 2010. This survey that was sent to 5000 customers featured a questionnaires intended to capture following aspect of consumers' psychographic and behavioral characteristics.

Attitude, Interests and Opinion (AIO). The intended survey tries to capture consumers' attitude, interest, and opinion on factors such as their internet risk, privacy concern, social and mass media usage, and others which influence their multichannel shopping behavior.

Demographic variables. In the survey we also added a section intended to captures consumers' demographic characteristics such as their age, gender, income, education etc.

Location Data. We also have access to the consumer location data facilitating us to measure their distance from the physical store, critical factor in their channel choice decision of offline vs. online channel.

The designed survey to capture such consumer intrinsic factor is provided in the Appendix D. The survey had 1249 valid questionnaires returned representing a response rate of 24.98%. After coding the data we retain 785 consumers for our analysis who filled the survey completely. In our sample we have 20% (157) online consumers and rest 80% (628) are offline consumers.

3.5 Results

We present the results of our model in Tables 20-22. The channel choice decision is modeled using binary probit where online choice is normalized as base i.e. difference of offline and online latent utilities is observed as choice outcome. For inter-purchase timing we use competing risk proportional hazard model where the effects of covariates are assumed to be different across the online and offline channel purchase timings. Finally, the quantity choice model is estimated using the generalized least square method. All three decisions are estimated independently.

3.5.1 Channel Choice

The parameter estimates for the channel choice decision are given in Table 20. We see that communication media have differential impact on consumers' channel choice. Specifically, catalog helps in consumers' offline channel choice, whereas newspaper has negative impact on consumers' offline channel choice. We do not find significant impact of emails on consumers' channel choice. The retailer sends catalogs as a means of communication informing consumers about the products and the some promotion related information such as *'double up for a buck*'.

Emails are frequent communication media that contains fewer products, promotions, and events related information, and these are context dependent such as holidays, weekend sales etc. Note that emails and catalogs serve mainly as promotional support. Contrary to this, newspaper ads are weekly circulars advertising mainly about sales promotions. Therefore, from the parameter estimates we can conclude that mass communication such as newspaper drives consumers away from offline channel whereas personalized communication such as catalogs and emails drives them to offline channel.

Table 20: Parameter Estimates for Channel Choice

Parameter	Mean	SD
Intercept	**1.1035**	0.4003
Email	0.0045	0.0483
Catalog	**0.8136**	0.0891
Newspaper	**-0.0134**	0.0064
Temperature	**0.0145**	0.0022
Precipitation	**-1.1288**	0.2176
Weekend	**-0.3732**	0.0758
Distance	**0.0102**	0.0020
Distance^2	-0.0010	0.0001
Shopping Convenience	**0.1287**	0.0581
Shopping Enjoyment	**-0.1123**	0.0423
Privacy Concern	**0.1290**	0.0108
Web Site Navigation Comfort	**-0.1719**	0.0494
Internet Risk	**0.2308**	0.0815
Sales Consciousness	**-0.2897**	0.0566
Deal Proneness (Coupon)	**0.1430**	0.0415

Note: Parameters in bold indicate they are significant at 95% level i.e. their confidence intervals at 95% level do not contain 0.

The situational variables have expected signs. We find that high temperature drives consumers to offline channel whereas snowy condition drives them away from offline channel. Distance is still an important factor on consumers' offline channel choice. It has non-linear concave effect implying consumers like to travel to a certain distance but beyond a point it becomes an added cost to visit the store. Therefore, the retail mantra of yester years where there was no presence of online channel, '*location, location and location*' is still relevant for today's multichannel retailers. Interestingly weekend has negative sign. This is because the state law requires liquor stores to close early on during weekends.

We find consumer intrinsic factors play greater role in influencing consumers' channel choice. Specifically we find significant impact of shopping convenience, shopping enjoyment, privacy concern, web-site navigation comfort, internet risk, sales consciousness, and deal proneness. Offline channel choice is preferred by consumers who like convenience and are deal prone. Consumers who perceive internet poses greater risk and concerned for their privacy also prefer shopping from offline channel. Consumers comfortable with web-site navigation prefer online channel. Also, sales conscious consumers tend to prefer online channel which could be due to better deals available online and low search cost associated with finding them. Interestingly, we find consumers find more shopping enjoyment in online channel than in offline channel. This could be due to the fact that consumers can do online shopping at any time convenient to them which gives them maximum shopping satisfaction.

3.5.2 Inter-purchase Time

The parameter estimates for inter-purchase timing is given in Table 21. We find that inventory lowers the hazard thereby increasing the inter-purchase timing for both online and offline channels. Higher inventory will lead to longer time of consumption thereby increasing the inter-purchase time. However, its effect is more in offline channel. This could be attributed to convenience of shopping in offline channel. Furthermore, impulse buying behavior is more pronounced in online channel than offline thereby reducing the inter-purchase timing of online channel choice (Parboteeah, Valacich, and Wells 2009).

There are different impacts of communication media on consumers' inter-purchase timings across online and offline channel. In general we find mass media such as newspaper reduces the inter-purchase time of offline channel whereas new media such as email increases the inter-purchase time of online channel. Personalized communications such as catalog which are sent not as frequent as email tend to reduce inter-purchase times of both offline and online channel.

Table 21: Parameter Estimates for Inter-purchase Timing

	Offline Channel		Online Channel	
Parameter	**Mean**	**SD**	**Mean**	**SD**
Inventory	**-0.2931**	0.0246	**-0.0430**	0.0146
Email	0.0473	0.0216	**0.8380**	0.1161
Catalog	**2.9343**	0.1775	**2.1352**	0.1344
Newspaper	**0.2089**	0.0261	0.3025	0.3475
Web Ads	-0.1422	0.2205	**0.4888**	0.0588
Holidays	**0.0560**	0.0091	**-0.0695**	0.0228
Social Media Participation	0.0351	0.9132	**0.1236**	0.0485
Possession	**5.3857**	2.6970	**-4.9484**	1.5866
Time Pressure	**2.4931**	0.4417	**4.4150**	0.3125
Impulsive Buying	**3.8115**	0.2949	**7.8330**	0.2863
Sales Consciousness	**-5.3302**	0.3744	**-5.1030**	0.1132
Infotainment	0.0354	0.1775	**0.4403**	0.0789
Financial Security Concern			**-0.0534**	0.0140
Technology Comfortness			**0.0293**	0.0135
Display Usage	**-8.2347**	2.1736		
Feature Usage	**2.2602**	1.1851		
Shape Parameter	**0.8216**	0.1212	**0.2567**	0.1104
	Mean		SD	
Frailty Correlation	0.6523		0.2145	

Note: Parameters in bold indicate they are significant at 95% level i.e. their confidence intervals at 95% level do not contain 0.

Consumer attitudes also play a significant role in inter-purchase times of online and offline channels. We find 'possession' and 'time pressure' increase the hazard or decrease the inter-purchase time of offline channel. However, 'possession' decreases the hazard or increase the inter-purchase time of online channel attributed to delivery time associated with online order.

The effect of 'time pressure' is more pronounced in inter-purchase time of online channel. This could be attributed to time saved in making a trip to store's online chanel. Furthermore, sales consciousness of consumer makes them wait for the deals thereby increasing the inter-purchase times of both online and offline channel. In online environment if consumers are more concern for their financial security and less comfort with technology usage then their inter-purchase time decreases. Similarly in offline environment display and feature usage influence consumers' inter-purchase time. If consumers participate in online social media it tends to decrease their online inter-purchase time. Holidays motivates consumers' offline channel visit rather than online.

Finally, the shape parameter of offline channel is greater than online implying consumers still prefer visiting the retailers' offline channel. Also, we find that frailty correlation between online and offline inter-purchase timing is positive and significant. This implies that online and offline channel play synergistic role in retailers multichannel strategy. Furthermore, these outlets, online and offline, tend to supplement the consumers' channel choice. Thus, adoption of multichannel strategy facilitates consumers varied shopping needs which are not only influenced by the retailers' marketing strategies but also the consumer attitudes towards technology driven channel such as online.

3.5.3 Quantity/Order-Size

The parameter estimates for the quantity/order-size is given in Table 22. We find that price and promotion are still important determinant of consumers' quantity decision. However, traditional media such as newspaper, television, and radio positively affects consumers' quantity purchase decision. With respect of new media we find that effect of email is insignificant however catalog positively influence consumers' quantity decision. Consumers' personalized effort to participate in firms' marketing campaign such as attending educational program have positive and significant impact on their quantity decision. Similarly in-store activity such as information shelf-talker (IST) positively affects consumers' quantity decision. Consumer intrinsic variables have lesser role to play in their quantity decision. However, we find that consumer innovativeness i.e. their propensity to try out new products positively affects their quantity decision. The results show that price and promotion are still significant influencers of consumer quantity decision, however promotional support programs through traditional as well as new media could influence their order-size decision marginally.

Table 22: Parameter Estimates for Quantity Choice

Parameter	Mean	SD
Intercept	**2.2421**	0.0480
Price	**-0.2532**	0.0264
Promotion	**0.4777**	0.0118
Email	0.0247	0.0432
Catalog	**0.0128**	0.0028
Educational Program	**0.5514**	0.2955
Newspaper	**0.0034**	0.0011
Television	**0.0021**	0.0006
Radio	**0.0112**	0.0039
Web Ads	**-0.1601**	0.0113
IST	**1.1679**	0.4152
Holiday	0.0062	0.0174
Variety Seeking	-0.0045	0.0077
Innovativeness	**0.0035**	0.0014

Note: Parameters in bold indicate they are significant at 95% level i.e. their confidence intervals at 95% level do not contain 0.

3.6 Managerial Implications and Conclusion

In this research we find that communication media (blend of both traditional and emerging media) along with firm's marketing mix strategy and consumer intrinsic variables are important determinants of consumer channel choice. We find that consumer channel choice for online and offline channel is significantly influenced by consumer intrinsic variables.

Furthermore, situational factors such as temperature, precipitation, and weekend are also important determinant of consumers' channel choice. Catalog, as a means of communication media, tend to drive consumers to offline channel. Consumers' inter-purchase timing for these channels is greatly influenced by communication media. Specifically, email, catalog, and newspaper shorten consumers' inter-purchase timing. Therefore, firms should be in constant touch with consumers using multitude of touch points to engage them and to increase their visit to the firms' channel. Some of the consumer intrinsic factors such as possession, time pressure, and feature usage also decrease consumers' inter-purchase timing. Consumers' quantity decision is still greatly influenced by the firms' marketing mix strategy namely price and promotion. Therefore, without proper marketing mix strategy firms can not engage consumers to their channels merely using the multitude of touch points. Proper marketing mix strategy along with other touch points used to communicate with consumers tends to influence their channel activity positively. Thus, a profitable channel strategy for firms is to provide multiple channels or outlets to consumers to have satisfactory shopping experience and to engage with consumer using multiple communication media or touch points that tend to increase consumers' channel activity favorably.

In conclusion, we model consumer channel choice behavior for multichannel firm accounting for three distinct channel activities of the consumers namely channel choice, inter-purchase timing, and quantity decision in the presence of firm's communication and marketing mix. Furthermore, we account for consumer intrinsic variables that are important determinant of consumer channel activity specifically channel choice. Our research gives important insight on important role played by firm's communication and marketing mix. We find that without proper blend of marketing mix, firm's adoption of multiple communication mix is not very effective.

Firms' adoption of blend of traditional as well as emerging communication media along with proper marketing mix helps engaging consumers over multiple channels favorably.

4. WHAT MAKES EMAILS CLICK: THE IMPACT OF DIGITAL ADVERTISING ON SALES

4.1 Introduction

Digital advertising which is broadly defined as the dissemination of marketing messages using the internet is becoming increasingly important for firms (Berkman 2008). These promotional tools are different from traditional advertising tools such as television and newspaper ads because firms can communicate with their consumers interactively, thereby engaging them mutually and creating a superior shopping experience for them. Moreover, they provide several other benefits over the traditional advertising tools. Firstly, understanding how consumers respond to such digital advertising helps firms to formulate better behavioral targeting strategies- defined as the practice of reaching out to consumers based on where they are located and what their interests are (*Forrester Research* 2007). Secondly, firms can benefit through other advantages such as low-cost, speed (instantaneous communication), geographic barrier reduction and efficiency (e.g., forwarding emails by consumers can lead to viral marketing and online word of mouth effects).

The different digital communication media, which seem distinct depending on the mechanisms through which messages are delivered to consumers, are actually quite related. Thus, firms need to be cognizant of the above when designing their digital marketing strategies. For instance, the factors that make emails more effective are likely to be the same as those that make social media campaigns succeed. Moreover, the efficacy of communications may depend on situational or contextual factors. For example, accessing email through smart phone is the top choice for mobile users. According to a study by *Nielsen* (2010) mobile users spent more time on emails than social networks/blogs. Additionally, consumers may prefer to receive promotional material through a certain digital medium. A recent study by *eConsultancy* (2010) notes that more consumers prefer to receive marketing promotional messages via email (42%) than social networking sites (3%). Given the above, email marketing is itself becoming more social with companies investing in relevant technologies. Examples include *Constant Contact* and *MailChimp* which are managing their social networking through emails and integrating Facebook "like" buttons to campaigns respectively (*Advertising Age* 2010). Thus, firms are integrating social media with emails, such as tweeting email newsletters and broadcasting blog entries to email lists, to create better marketing campaigns (Consumer Behavior 2011). Therefore, managers need to understand the effectiveness of digital media especially emails to efficiently leverage their communications, not only for cultivating a deeper bond with consumers and influencers but also to maximize their return on investment (ROI).

However, to investigate the success of digital advertising campaigns, several challenges need to be overcome. Firstly, access to an extensive database of a firm's e-communications needs to be obtained. Secondly, detailed behavioral information about consumers' who receive these messages should be procured. Thirdly, since companies also engage in other forms of promotions (e.g., traditional media such as TV advertising) as a part of their integrated marketing communication (IMC) strategy, they need to be accounted for. Finally, the above should also be linked to actual purchase data through multiple outlets (e.g., online and offline).

In this research, we seek to investigate the effectiveness of digital advertising in an integrated framework that includes traditional media. Specifically we focus on email marketing. We use extensive email database of a firm that contains detail information about email campaign including the features of the email. We use seemingly unrelated regression model (SUR) to explain the factors that make an email campaign click/unclick, i.e. factors that triggers the open and unsubscribe rate of an email campaign and its impact on sales. The spillover effect of indirect sales is also accounted for in the model.

4.2 Background

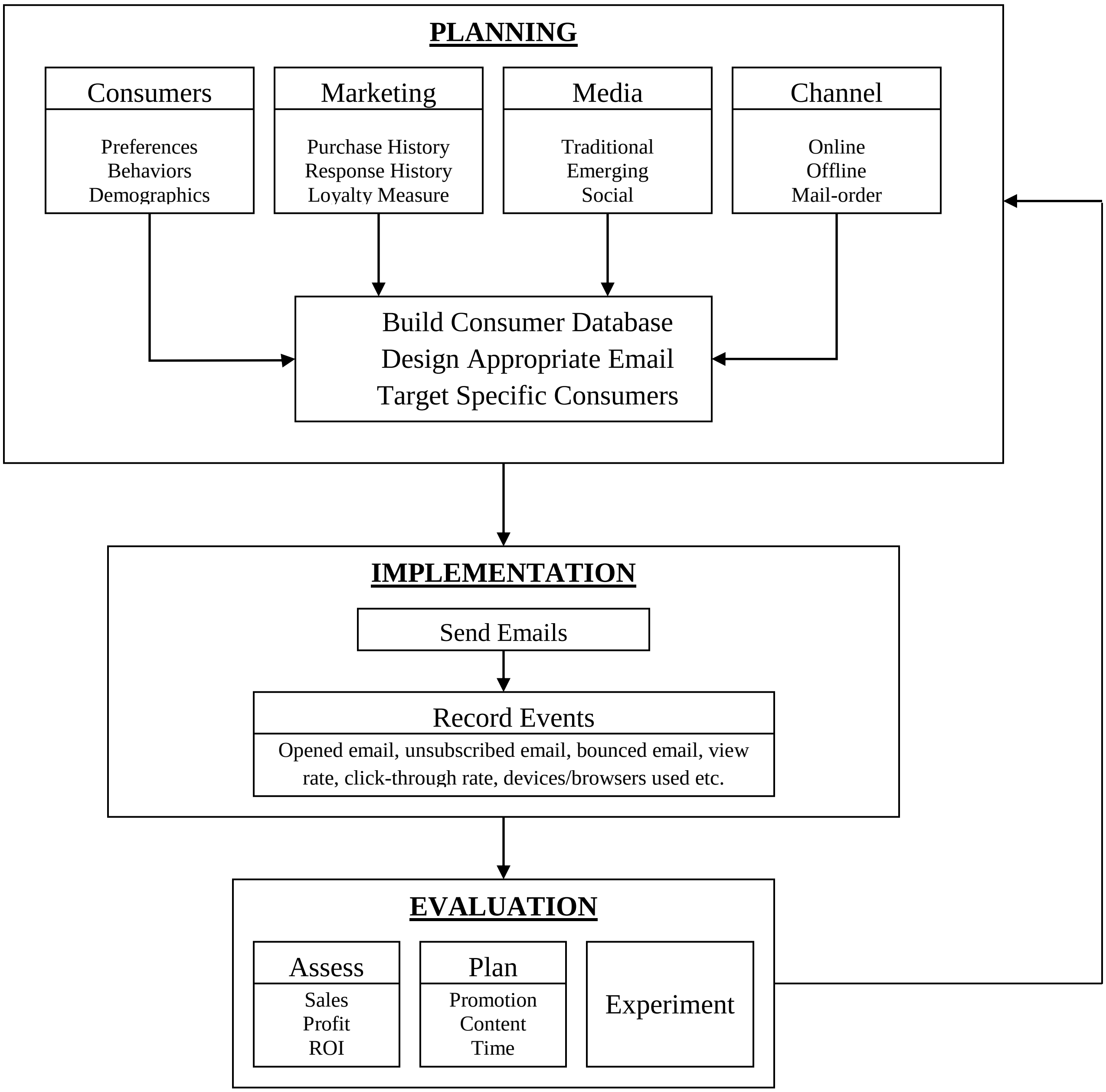
In 2010 projected electronic marketing spending was $3.89 billion with an estimated growth rate of 6% (*Forrester Research 2007*). Furthermore, the recent survey by *StrongMail* (2012) suggests that email marketing is one of the top areas of investment with 60% firms planning to increase email marketing budget. Moreover, maintaining high email deliverability is recognized as one of the top challenges for businesses (*Strong Mail* 2010) which is reflected in the following statement from *eMarketer* (2009), “If retailers want to avoid being ignored- or blacklisted - they must improve the relevancy of their email programs.” However, certain challenges remain which primarily include trust of email messages (*eMarketer* 2011a), effectiveness of digital ads across different devices (*eMarketer* 2011b) and decline in email open/response rates (*M+R Strategic Services* 2007).

The industry realizes following challenges with respect to email marketing (*enter:marketing* 2011), targeting with highly relevant content, quantifying return on investment (ROI) of email marketing, improving email deliverability, getting people to opt-in to email list, email being viewed as spam, and lack of an effective email marketing strategy. Academic research concerning electronic marketing has addressed some of these issues. For example researchers have investigated effect of email on consumers’ channel choice decision(Martin et al. 2003), electronic media as in integral part of integrated marketing communication strategy (Peltier, Schibrowsky, and Schultz 2003), use of email to manage customer lifetime value (Kumar et al. 2008) and impact of color on email response rate (Zviran, Te’eni, and Gross 2006).

Academic literatures have also looked into real-time evaluation of e-mail campaigns (Bonfrer and Dreze 2009) customer relationship management through emails (Lewis, Whitler, and Hoegg 2009) and customization of email messages (Ansari and Mela 2003). Furthermore, Pavlov, Oleg, and Plice (2008) investigate the impact of spam on email marketing. The unsubscribe rate of email campaign could be influenced by consumer concern for privacy, trust and attitude towards company's web-site (Cases et al. 2010). The design of an email campaign, the content and the layout, could substantially influence the click rate (Marketing Management 2007).

Our study differs significantly from the existing literature both in terms of research objective and application. We present our conceptual framework in Figure 4. This is an integrated framework that includes planning, implementation, and evaluation of email marketing strategies and the various factors that need to be taken into consideration for the success of an email campaign.

Figure 4: Conceptual Diagram of Email Marketing Strategy



In this study we focus on the following aspects of email marketing. First, with respect to implementation of email marketing strategy we account for the factors that influence open and unsubscribe rate of an email campaign. These factors will provide greater insights into the design of an email campaign both in terms of its content and layout. Second, with respect to evaluation of email marketing we quantify the lead generation of email campaign. Email lead generation is accounted by the sales impact of the campaign. We also account for the possible spillover effect of email campaign over the sales of other categories not advertised in the email campaign. The factors that we include in our model contain information on various aspects of email campaign attributes. Furthermore, we simultaneously model these three impacts namely open rate, unsubscribe rate and lead generation. The simultaneous modeling helps us capturing the correlation in these three events shedding some light on impact of unobservable. In the next section we describe the dataset used in our study followed by the model formulation and estimation method used.

4.3 Data

The dataset for this study comes from a large retailer in the Northeast United States. The retailer specializes in selling wine products. It has multiple stores in the region as well it maintains web-outlets. Thus, consumers can buy from the retailer using both offline (brick and mortar) and online channels. The retailer is one of the largest in the state and has received national recognition (e.g., Wine Spectator Retailer of the year). The retailer records the transaction data of consumers both online and offline through loyalty card relational marketing program. This scanner panel data that spans several years contain information pertaining to regular prices, all types of promotions, discounts etc. at the individual SKU level. The panel data also captures the store promotions.

Furthermore, as a part of integrated marketing communication strategy the retailers adopts blend of both traditional and new communication tools. It sends printed catalogs to consumers five to six times a year. It also organizes wine educational programs in the store where registered consumers can come to the store and get involved in wine tasting and sampling apart from getting information pertaining to wine ratings, varietals etc. It also advertises through local television and radio programs. The dataset pertaining to television and radio ads include information such as when and where the advertising was done and the media ratings (e.g., the specific network/cable channels, the specific programs, duration of the commercial).

Early 2008 the retailers started email marketing program. This program is managed by professional and fully functional email marketing application called Sage E-Marketing. Almost every week the retailer sends emails of various kinds (e.g., sales related, event related such as holiday specials or weekly specials, product related, reminder related such as catalog reminder, weekly specials reminder) to the consumers in its email recipient list. We discuss below the main features of the email database. We use two years of data from 2009-2010 that resulted in total of 820 email campaigns.

4.3.1 Email Marketing Database

The retailer’s email recipient list consists of consumers from the panel data. Therefore, there is always possibility of tying back email marketing activities to the actual purchases through panel data. The database consists of detailed information on following aspects of email activities.

Email Sent. The total number of individual consumers to whom an email campaign was sent to. This also include time and date. The database contains the consumers’ loyalty card number.

Email Opened. This is the total number of individual consumers who opened an email campaign. This also has information on how many times and when consumers opened them. The database contains the consumers' loyalty card number.

Email Unsubscribe. This is the total number of individual consumers who after opening the email campaign decided to unsubscribe from the email list. The database contains the consumers' loyalty card number.

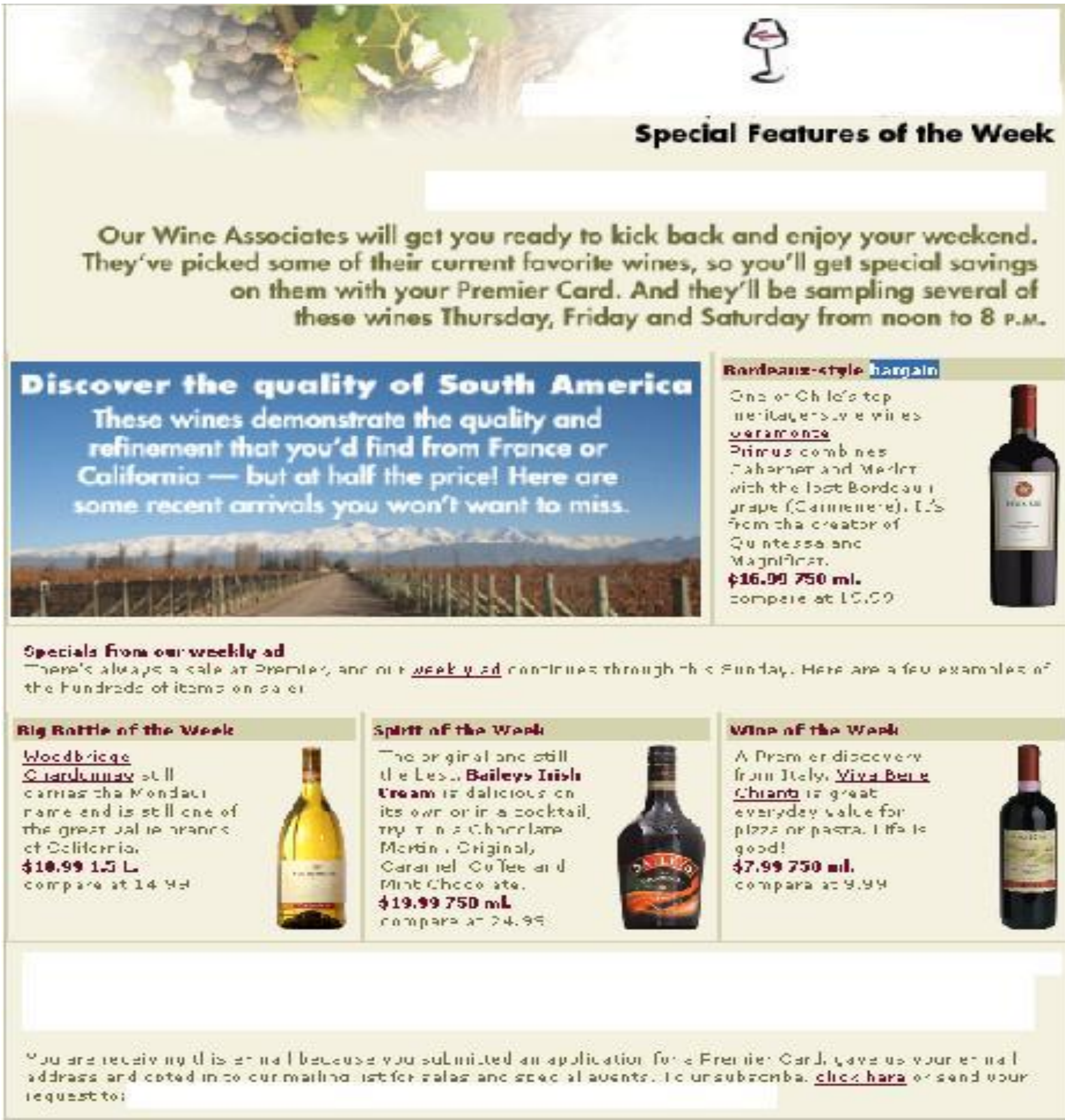
Browser and Device Breakdown. The database contains detailed information on the browsers (e.g., IE8, Firefox, Safari) as well as devices used for opening email campaigns (e.g., Blackberry, iPhone, iPad, PCs etc.). We find consumers use both, personal computers and hand-help devices to access these email campaigns.

Email Recipient. One of the interesting features of the email database is that most of the email recipients can be tied back to the scanner panel data so that one can actually look at the impact of email campaign on consumer purchase behavior. Thus, all email database has field corresponding to consumers' loyalty card number. Thus, consumers' email activities can be tied back to the retailer's other marketing campaigns such as catalog, television or radio ads.

Emails. The database contains the actual email (with all images, content, products advertised, events discussed, and layout preserved as it was sent to the users). This helps in measuring the attractiveness of emails using their attributes. Furthermore, it enables us to see the direct impact of specific advertised product by interfacing scanner panel data. A picture of typical email campaign is given in the Figure 5.

Figure 5: Illustration of a typical Email Campaign

(Note: Image is smudged for Privacy Concern**)**



The various attributes of these actual email campaigns were coded. Next we present these various coded attributes of the email campaigns.

4.3.2 Email Campaign Attributes

The email database contains the actual emails that were sent to the consumers. We downloaded these emails and printed it out. Then, either using the soft or hard copy of the email, wherever appropriate, we coded following attributes of each email campaign.

Weekend. Each email campaign has date when it was sent. This variable which takes value of 1 if the campaign was sent during weekend, otherwise it is 0.

Holiday. We use Memorial Day, Independence Day, Labor Day, Halloween, Thanksgiving, Christmas, New Year, Valentine's Day, Easter, and Yom Kippur as holidays or special occasion. This variable takes value 1 if an email campaign was sent on those special occasions otherwise it is 0.

Launch Time. The database contains the exact time when the email campaign was launched. This variable takes value 1 if an email campaign was launched before noon otherwise it is 0.

Size. This variable is the size of HTML format of an email campaign in kilo bytes. This includes all text, banner, and images.

Images. This variable is operationalized as total number of images in an email campaign.

Printed Page Size. Each email campaign was printed on page. If the email took 3/4th of the page printed page size was operationalized as 0, if it took 1 page this value is 1, if it took 1 and a quarter of the page this value is 1.25, if it took 1 and half of the page the value is 1.5, if it took 1 and three quarter of the page the value is 1.75, if it took two pages the value is 2, and if it took 3 pages the value is 3. The maximum of all printed pages was 3.

Number of Words in the Subject Line. This is the total number of words in the subject line of each email campaign.

Number of Words in the Email. This is the total number of word texts in the body of an email campaign.

Number of Purchase Links. This is the total number of links (hyperlinks) that directs consumers to the retailer's web-page where they can order recommended products in an email online.

Number of Non Purchase Links. This is the total number of links (hyperlinks) contained in an email campaign other than purchase links. This allows user to click their way from email to other web-pages.

Facebook Link. This is a dummy variable that takes value 1 if there is link for retailer's Facebook page otherwise it is 0.

Twitter Link. This is a dummy variable that takes value 1 if there is link for retailer's Twitter account otherwise it is 0.

Email Theme. This is a dummy variable that takes value 1 if an email campaign's core message concentrate on one idea (e.g., promotion or sampling or reminder) otherwise it is 0 i.e. the campaign sends multiple messages (e.g., promotional events with educational programs).

Banner. This is a dummy variable that takes value 1 if an email campaign contains banner otherwise it is 0.

Web Ad. The retailer advertises on its online web-site about *wine of the week* recommending consumer to buy that wine for the week. This dummy variable takes value 1 if the retailer's web ad is mentioned in the email otherwise it is 0.

Catalog. This is a dummy variable that takes value 1 if the catalog sent by the retailer in mentioned in the email otherwise it is 0.

Weekly Specials. The retailer has weekly specials on certain products items. This dummy variable take value 1 if weekly specials in mentioned in the email otherwise it is 0.

Educational Class. The retailer organizes wine educational classes that include sampling and tasting. This dummy variable takes value 1 if educational class related event is mentioned in the email otherwise it is 0.

Email Ranking. We used subjects to rank these emails based on their attractiveness on a scale of 1 to 7 where 1 is not attractive at all and 7 is highly attractive.

Computer used to open email. This is the proportion of consumers who opened the email on their personal computers.

Handheld Device used to open email. This is the proportion of consumers who opened the email on their hand held devices such as smart phones or tablets.

Time Gap. This variable is operationalized as time in days between two consecutive email campaigns.

4.3.3 Operationalizing Impact of Email Campaign on Sales

As with any marketing mix, communication strategy must take into account the profitability of the firm first. However, sometimes measuring the immediate effectiveness of marketing communication is not easy. The effectiveness of marketing communication tools is often measured using lead generation. The most commonly used metric for lead generation is sales. The current email marketing dataset allows us to measure the effect of email campaign on purchases or sales. Furthermore, note that most of the advertising communication tools not only will have the direct impact on sales of the products advertised but also it could have spillover effect on the products that are not advertised. Keeping the spillover effect of marketing communication tools in mind we operationalize following two variables to measure the impact of email campaign on sales (or lead generation).

Direct Lead Generation. The email database contains the loyalty card number of the consumers to who opened the email campaigns. Therefore, using panel data we can track the purchase history of those consumers. Furthermore, the actual email contains the details of the products that were advertised. Thus, direct lead generation for an email campaign is operationalized as the sum total of the sales generated for the advertised products in the campaign by the consumers who opened the email campaign. We use one week period from the date email campaign was sent to calculate this sum total.

Indirect Lead Generation. The sales generated from the non-advertised products items is termed as indirect lead generation of the campaign. The indirect lead generation for an email campaign is operationalized as the sum total of the sales generated by the consumers who opened the emails from the purchase of non-advertised product items. We use one week period from the date email campaign was sent to calculate this sum total.

Retailers also use traditional communication media, television and newspaper, to communicate with its consumers. We operationalize these variables as dummy if during a particular email campaign the retailer advertised using either of these traditional medium. The data descriptive of the variables are given in Table 23.

Table 23: Data Summary

Variable	Mean	SD
Emails Sent (Customers/Campaign)	25945.35	2355.28
Emails Opened (Customers/Campaign)	6568.55	400.23
Direct Lead Generation (in $)	16.45	44.09
Indirect Lead Generation (in $)	2779.20	2942.15
Size of Email (in Kilobytes)	51.06	11.13
No. of Images per Campaign	9.08	3.66
Printed Page Size	1.30	0.42
No. of Words in Subject Line	7.88	2.28
No. of Purchase Links	3.96	2.68
No. of Non Purchase Links	5.68	1.79
Email Ranking	5.59	0.77
Emails opened on Computers	170.76	347.32
Emails opened on Handheld devices	43.37	90.45
Time Gap between Emails	3.36	2.22
Emails having Facebook Link (%)	68.05	
Emails having Twitter Link (%)	49.75	
Emails Sent on Weekends (%)	2.19	
Emails Sent on Holidays (%)	3.54	
Emails Launched before Noon (%)	76.22	
Emails containing Web Ads (%)	23.41	
Emails containing Catalog reminder (%)	85.36	
Emails containing Weekly specials (%)	21.83	
Emails containing Educational Class Information (%)	68.78	

4.4 Model

Our modeling framework accounts for two aspects of email marketing, first we explain the email marketing strategy about a successful email campaign, and second we explain the impact of email marketing on lead generation. The success of an email campaign is decided by its open rate and unsubscribe rate. Therefore, it is important to understand the effect of various factors that influence these two rates. Furthermore, as with any marketing program it is important to understand its influence on lead generation mostly through sales. Therefore, we model the impact of email campaign on direct lead generation or direct sales. Note that consumer purchases for the product items not advertised through a marketing campaign could also influence the purchase of product items advertised through a campaign. This trigger effect of non-advertised product items on advertised product items is termed as spillover effect that is accounted for in the model.

For each email campaign e carried out at time t we model following:

$$
\begin{aligned}
\ln(EmailOpen_{et}) = {} & \beta_e^0 + \beta_e^1 Weekend_{et} + \beta_e^2 Holiday_{et} + \beta_e^3 LaunchTime_{et} + \\
& \beta_e^4 Size_{et} + \beta_e^5 Images_{et} + \alpha_e^6 PrintedPageSize_{et} + \beta_e^7 WordsInSubLine_{et} + \\
& \beta_e^8 NoOfPurLinks_{et} + \beta_e^9 NoOfNonPurLinks_{et} + \beta_e^{10} FacebookLink_{et} + \\
& \beta_e^{11} TwitterLink_{et} + \beta_e^{12} EmailTheme_{et} + \beta_e^{13} Banner_{et} + \beta_e^{14} WebAd_{et} + \\
& \beta_e^{15} Catalog_{et} + \beta_e^{16} WeeklySpecials_{et} + \beta_e^{17} EduClass_{et} + \beta_e^{18} EmailRank_{et} + \\
& \beta_e^{19} Computer_{et} + \beta_e^{20} HandHeldDevice_{et} + \beta_e^{21} TimeGap_{et} + \beta_e^{22} TimeGap_{et}^2 + \zeta_{et}
\end{aligned} \tag{15}
$$

$$
\begin{aligned}
\ln(EmailUnsubscribe_{et}) = {} & \alpha_e^0 + \alpha_e^1 Weekend_{et} + \alpha_e^2 Holiday_{et} + \alpha_e^3 LaunchTime_{et} + \\
& \alpha_e^4 Size_{et} + \alpha_e^5 Images_{et} + \alpha_e^6 PrintedPageSize_{et} + \alpha_e^7 WordsInSubLine_{et} + \\
& \alpha_e^8 NoOfPurLinks_{et} + \alpha_e^9 NoOfNonPurLinks_{et} + \alpha_e^{10} FacebookLink_{et} + \\
& \alpha_e^{11} TwitterLink_{et} + \alpha_e^{12} EmailTheme_{et} + \alpha_e^{13} Banner_{et} + \alpha_e^{14} WebAd_{et} + \\
& \alpha_e^{15} Catalog_{et} + \alpha_e^{16} WeeklySpecials_{et} + \alpha_e^{17} EduClass_{et} + \alpha_e^{18} EmailRank_{et} + \\
& \alpha_e^{19} Computer_{et} + \alpha_e^{20} HandHeldDevice_{et} + \alpha_e^{21} TimeGap_{et} + \alpha_e^{22} TimeGap_{et}^2 + \xi_{et}
\end{aligned} \tag{16}
$$

$$
\begin{aligned}
\ln(DirectLeadGeneration_{et}) = {} & \theta_e^0 + \theta_e^1 \ln(IndirectLeadGeneration) + \theta_e^2 \ln(EmailOpen_{et}) + \\
& \theta_e^3 \ln(EmailUnsubscribe_{et}) + \theta_e^4 WebAd_{et} + \theta_e^5 Catalog_{et} + \\
& \theta_e^6 WeeklySpecials_{et} + \theta_e^7 TimeGap_{et} + \theta_e^8 TimeGap_{et}^2 + \\
& \theta_e^9 NoOfPurLinks_{et} + \theta_e^{10} EmailTheme_{et} + \psi_{et}
\end{aligned} \tag{17}
$$

The error term $\varepsilon = [\zeta_{et}, \xi_{et}, \psi_{et}]'$ is distributed independent normal i.e. $\varepsilon \sim MVN(0, \sigma^2 I)$. We model the heterogeneity in a parsimonious way using random effects for the intercept terms of each equation. We assume $\Phi_e = [\beta_e^0, \alpha_e^0, \theta_e^0]'$ is distributed normal with $\Phi_e \sim MVN(\Phi, \Lambda)$, covariance restricted to zero. Note that same set of covariates appear in equation (1) and (2), therefore simultaneously modeling them is equivalent to running independent ordinary least square regression (OLS). Furthermore, dependent measure of equation (1) and (2) appear as covariates in equation (3). Therefore, we estimate these three equations independently.

4.4.1 Estimation

We estimate our model using hierarchical Bayesian approach. The model is the specification of seemingly unrelated regression (SUR) with continuous dependent measure. Therefore, the full conditional of the posterior density of unknowns have closed form solution (Rossi, Allenby and McCulloch 2005). Repeated draws were made for the parameters using MCMC sampling from their posteriors. The Gibbs sampler was run for a total of 50,000 iterations for the proposed model. The convergence of the parameters was ensured by plotting the time-series of the draws. The initial 40,000 iterations were used as “burn-in” period. The last 10,000 iterations were retained to calculate the posterior means and the standard deviations of the model parameters. However, the sequential draws could be highly correlated. Therefore, we resort to “thinning the chain” whereby every fourth draw from the retained chain was used. Thus we use 2500 draws from the retained chain to calculate the means and the standard deviations of the parameters.

4.5 Results

We present the results of our model in Table 24 and Table 25. In Table 24 we present the parameter estimates of email open rate (equation 15) and email unsubscribe rate (equation 16). In Table 25 we present the parameter estimates of direct lead generation (equation 17). Note that parameters in bold are significant at 95% level i.e. their confidence interval does not contains zero.

Table 24: Parameter Estimates of Email Open and Unsubscribe Rate

	Open Rate		Unsubscribe Rate	
Parameter	**Mean**	**SD**	**Mean**	**SD**
Intercept	**8.8077**	0.6618	**3.3609**	0.5839
Weekend	**-0.6906**	0.2528	**-0.6366**	0.2559
Holiday	0.4060	0.3222	0.0403	0.3190
Launch Time	**-0.5151**	0.0921	**-0.2379**	0.0918
Email Size	0.0104	0.0062	**0.0112**	0.0061
No. of Images	-0.0421	0.0254	-0.0292	0.0254
Printed Page Size	-0.0917	0.1049	0.0117	0.1054
Words In Subject Line	**-0.0870**	0.0170	**-0.0398**	0.0172
No. of Purchase Links	**-0.1103**	0.0274	**-0.0749**	0.0278
No. of Non-Purchase Links	**0.0778**	0.0247	0.0175	0.0249
Facebook Link	**0.9489**	0.1413	**0.4721**	0.1437
Twitter Link	-0.0786	0.1013	0.0568	0.1022
Email Theme	**-1.2122**	0.1112	**-0.5921**	0.1110
Banner	-0.7349	0.6229	-0.0112	0.5782
Web Ad	**-0.7673**	0.1146	**-0.2766**	0.1147
Catalog	**-0.3190**	0.1755	**-0.4647**	0.1770
Weekly Specials	**0.3729**	0.0545	**-0.5095**	0.1104
Educational Class	**0.4978**	0.1089	**-0.3934**	0.1087
Email Rank	**0.1285**	0.0552	0.0165	0.0549
Computer	**0.0022**	0.0005	**0.0015**	0.0005
Handheld Device	**-0.0043**	0.0017	**-0.0045**	0.0017
Time Gap	**0.3402**	0.0467	**0.1996**	0.0471
Time Gap^2	**-0.0232**	0.0060	**-0.0126**	0.0061

Note: Parameters in bold indicates significance at 95% level i.e. their 95% confidence intervals do not contain 0.

Table 25: Parameter Estimates of Direct Lead Generation

Parameter	Mean	SD
Intercept	**-7.1522**	1.1258
Indirect Lead Generation	**0.0829**	0.0332
Email Open Rate	**0.0269**	0.0095
Email Unsubscribe Rate	**-0.4469**	0.0637
Web Ad	-0.1452	0.0855
Catalog	**8.3514**	1.1310
Weekly Specials	**0.2476**	0.0543
Time Gap	**-0.1018**	0.0460
Time Gap^2	**0.0107**	0.0059
No of Purchase Links	**0.0502**	0.0179
Email Theme	**-0.7606**	0.0691

Note: Parameters in bold indicates significance at 95% level i.e. their 95% confidence intervals do not contain 0.

4.5.1 Email Open Rate

The average open rate of email, ceteris paribus, is 6685 ($\exp(\beta^0) = \exp(8.8077) = 6685$). We find the open rate per email campaign to be 25.71%, given the average number of users these campaigns are sent to be around 26000. Email open rate is positively influenced by number of non-purchase links ($\beta^9 = 0.0778$) especially having Facebook page link ($\beta^{10} = 0.9489$) triggers the open rate. Furthermore, advertising weekly specials ($\beta^{16} = 0.3729$), informing consumers about the wine educational classes ($\beta^{17} = 0.4978$) positively influence the open rate. Consumers prefers opening these emails on computers ($\beta^{19} = 0.0022$) rather than on handheld devices ($\beta^{20} = -0.0043$). Repetition or reminder about catalog ($\beta^{15} = -0.3190$) or web ads ($\beta^{14} = -0.7673$) tends to decrease the open rate of an email campaign. This could be due to other sources from which consumers might be getting promotional information. Email campaign conveying just one core message also tend to decrease the open rate ($\beta^{13} = -1.2122$). Therefore, it is better for an email campaign to have multiple messages. Purchase links also tend to decrease the open rate of the campaign ($\beta^8 = -0.1103$). This could be due to some restrictions involved (such as age limit and no shipping out of state) in selling wine products in the state. Longer subject line of an email campaign also tends to decrease the open rate ($\beta^7 = -0.0870$). Email campaigns launched before noon tend to decrease the open rate ($\beta^3 = -0.5151$). Interestingly we find email campaigns sent during weekend tend to decrease the open rate ($\beta^9 = -0.6906$). This could be due to the fact that during weekend state law requires liquor stores to close early. Size of the email, number of images, twitter link and banner do not have significant effect on email open rate. The time gap between two subsequent email campaigns has inverted-U shaped relationship ($\beta^{21} = 0.3402$, $\beta^{22} = -0.0232$) making timing decision between campaigns a critical decision. Open rate of an email campaign increases with time gap but at decreasing rate. Therefore, it is important to constantly engage consumers using email campaign that is neither too intrusive nor too disengaged. We also find that if the ranking of an email campaign is high ($\beta^{18} = 0.1285$) it increases its open rate.

4.5.2 Email Unsubscribe Rate

The average unsubscribe rate of an email campaign, ceteris paribus, is 29 ($\exp(\alpha^0) = \exp(3.3609) = 28.81$). Thus, considering 6685 to be average open rate we find 0.43% to be the unsubscribe rate per email campaign. Size of the email ($\alpha^4 = 0.0112$) and presence of Facebook link ($\alpha^{10} = 0.4721$) tend to increase the unsubscribe rate of an email campaign. On the other hand presence of web ad ($\alpha^{14} = -0.2766$), catalog ad ($\alpha^{15} = -0.4647$), weekly specials ($\alpha^{16} = -0.5095$), educational class ($\alpha^{17} = -0.3934$) tend to decrease the email unsubscribe rate. Consumers tend to unsubscribe over computers ($\alpha^{19} = 0.0015$) rather than on handheld devices ($\alpha^{20} = -0.0045$). Consumers tend not to unsubscribe if an email campaign have only one core message ($\alpha^{12} = -0.5921$) as against having multiple themes or information which consumers may find harder to concentrate. Long subject line ($\alpha^{7} = -0.0398$) in email campaign tends to decrease the unsubscribe rate. This could possibly due to the fact that consumers are not even opening the email campaign with long subject line (note that in order to unsubscribe one had to open the email). Campaigns having purchase links tend to lower the unsubscribe rate ($\alpha^{8} = -0.0749$).We find during campaigns sent during weekend ($\alpha^{1} = -0.6366$) and before noon ($\alpha^{3} = -0.2379$) tend to decrease the unsubscribe rate. However, this could possibly due to the fact that during those occasion consumers are not even opening the email campaign and unsubscribing from the email requires opening it. The time gap between two successive email campaigns tends to increase the unsubscribe rate ($\alpha^{21} = 0.1996$) however it happens at decreasing rate ($\alpha^{22} = -0.0126$). Therefore, consumers might not care for the email campaign if it arrives after certain period. The decreasing unsubscribe rate could be due to the fact that consumers are not even opening the email if time gap between two campaigns are high.

4.5.3 Direct Lead Generation

Direct lead generation which is dollar sales generated for the advertised products in an email campaign by the consumers who actually opened it is positively affected by email open rate ($\theta^{2} = 0.0269$) and negatively affected by email unsubscribe rate ($\theta^{3} = -0.4469$). It is evident that unsubscribe rate hurts more than the gain of open rate on direct lead generation. Furthermore, the indirect lead generation has positive effect on direct lead generation ($\theta^{1} = 0.0829$). In fact this effect is larger than the email open rate. Therefore, it seems that consumers' regular purchases for unadvertised products tend to have positive spillover effect over the sales of advertised products by a marketing email campaign. Moreover, catalog ($\theta^{5} = 8.3514$), weekly specials ($\theta^{6} = 0.2476$), and purchase links in the email ($\theta^{9} = 0.0502$) tend to influence direct lead generation positively. Campaigns having single theme tend to influence direct lead generation negatively ($\theta^{10} = -0.7606$). We find U-shaped relationship between direct lead generation and time gap between successive email campaigns. Therefore, sending frequent emails is not helpful in picking up the advertised items' sales. However, this effect tends to decrease as time gap widens. This indicates that long term impact of an email campaign on the sales of advertised product items is not a cause of concern if marketing managers increase the frequency of emails.

4.6 Managerial Implications

The attractiveness of email-marketing due to its cost-effectiveness, personalization, interactive and convenience makes it an important proposition for marketing communication as an integral part of integrated marketing communication strategy. Since emails are used for business as well as well personal communication they provide an incredible reach which happens to be very personal and interactive. However, for successful email marketing strategy it is very important to measure its effectiveness. Our study addresses towards this need in following ways.

First, we measure the success of an email campaign by modeling open and unsubscribe rate that are critical for email response. Furthermore, we also account for the effect an email campaign on direct lead generation in terms of sales. These three factors together, open rate, unsubscribe rate, and direct lead generation, helps quantify the effectiveness of an email campaign. Second, we account for the various email campaign characteristics that possibly influence these three factors. We expect the parameter estimates from these email campaign characteristics will help better design and execution of the campaign. Third, the sales from non-advertised product items could also drive the sales of advertised products through email campaign. We call this spillover effect of non-advertised products. Since, only few products sold by a firm are advertised in general we expect regular purchase of consumers mostly will constitute products that are not advertised. Therefore, accounting for the effect of this spillover is critical in order to measure the effectiveness of the campaign. Our study accounts for this spillover.

4.6.1 Design and Execution of an Email Campaign

Parameter estimates from the model of several of email campaign characteristics provide the general guidelines about the design and execution of an email campaign. The design of an email campaign constitutes the contents in the email that increases the response rate either by increasing the open rate (or direct lead generation) or by decreasing the unsubscribe rate. The execution constitutes timing of the campaign that increases its response rate.

The content of an email campaign should cautiously remind consumers about the firms' other promotional offerings. For example, reminding consumers about their weekly specials or sampling programs increases the open rate and decreases the unsubscribe rate. However, reminding about other promotional offering such as web ads and catalog have mixed effect, they adversely affect the open rate whereas favorably affects the unsubscribe rate. One possible reason could be the consumer response towards these advertising programs. We expect if consumers are more responsive towards a firm's promotional offerings then having them in an email campaign as reminder increase the campaign's response rate. However, for other kinds of promotional activities where consumer response is low, firms should include them in an email campaign cautiously. Links in an email campaign also have mixed response rate. Purchase links do not favor open rate whereas they decrease the unsubscribe rate. However, open rate tend to decrease faster than the unsubscribe rate. Therefore, the possible suggestion is instead of directing to purchase link direct consumers to product description link where they option of buying the product. Having Facebook link (of the firm's Facebook page) in an email is good as it outweighs the benefits of open rate to that of increase in unsubscribe rate. It is better to have an email campaign shorter subject line to increase its response rate. We find handheld devices such as smartphone or tablets tend to diminish the response rate of the campaign. Consumers do not prefer opening ad related email on their handheld devices possibly due to high cost of data rate on these devices. Interestingly size of an email does not have influence on open rate but it increases unsubscribe rate. Therefore, it is better to have email campaigns that are not very large. Interestingly we find no significant effect of images in an email campaign. Since email ranking have significant impact on email response rate it would be good idea to pilot test the attractiveness of an email campaign before sending them out. It is better to have one core message in an email to increase its open rate and decreases the unsubscribe rate. However, having multiple themes in an email is better than one theme as far as direct sale is concerned. Therefore, if an email campaign is concentrating on sales promotion, it is advisable to design email with multiple themes or messages.

The timing of an email campaign is very important factor for its success. It is better to launch emails campaigns in the afternoon than before noon as people are too busy with their important works before noon to open a promotional email campaign from a firm. The time gap between two successive email campaigns is very important. The results suggest these email campaigns should neither be too intrusive (should not be sent too frequently because even though open rate increases the direct sales goes down) not be too reclusive (should not be sent too far apart as its effect on response rate fades away). Interestingly we find the relationship of time gap with open rate (as well as between unsubscribe rate) is concave whereas this is convex with direct sales. Therefore, time gap could have a significant influence on managing customer relationship through an email campaign but as far as direct lead generation in terms of sales is concerned this might be not so critical factor. Thus, depending on objective of an email campaign the time gap between two successive email campaigns could have a significant influence.

4.6.2 Direct Lead Generation: Does it Matter?

The effectiveness of marketing campaign is measured in terms of lead generation. Most often than not, in order to measure the return on investment this is measured in terms of sales. However, there are two aspect of lead generation. First, the direct lead generation which is the sales generated by the products advertised through a campaign. Second, the indirect lead generation which is the sales generated by the non-advertised products. Note that most of the products sold by a firm are not advertised through marketing campaigns. It is always a very small subset of products that are advertised. Therefore, the regular purchases of most of the consumers might constitute a large proportion of products that are not advertised. However, due to marketing campaign during these regular purchases consumer might be involved in the purchase of advertised products. We term this as spillover effect of indirect lead generation on direct sales of advertised products. We find the evidence of this spillover effect. Furthermore, spillover effect tends to be larger than the email open rate on direct lead generation. However, the unsubscribe rate of email tend to decrease the direct sales of advertised products. Therefore, we suspect marketing promotional campaigns such as emails are more helpful in customer relationship management than generating the leads.

In order to test this out we carry out other test. First, we estimate equation (3) without indirect lead generation and find most of the parameters become insignificant including email open rate. Second, we remove indirect lead generation from equation (3) and make it a function of other variables that appear in that equation and estimate all four equations. Interestingly we find the effect of email open rate on both direct and indirect lead generation to be insignificant. Thus, we conclude that marketing campaigns such as email which is personalized in nature tend to help maintain the customer relationship more than helping directly in lead generation.

4.7 Conclusion

In this research we focus on success of digital marketing specially looking at emails. We provide a modeling framework that measures the effectiveness of an email campaign. The effectiveness of an email campaign is captured using two aspects. First, the response rates which is captured using email open and unsubscribe rate and, second direct lead generation operationalized in terms of sales generated from the advertised product items. Furthermore, we also account for the effect of indirect lead generation i.e. sales generated from non-advertised product items on direct lead generation. We find several email characteristics such as links, reminder ads, and theme tend to have significant effect on response rate of an email campaign. The timing between two consecutive emails also has significant effect on response as well as lead generation. The results indicate this time gap should neither be too intrusive (i.e. sending too frequent) nor too reclusive (i.e. sending with long time gaps) to the consumers. Interestingly our results suggest that email campaign is more important towards customer relationship management than in direct lead generation. Marketing campaigns like email influence direct lead generation indirectly through consumers' regular purchases for non-advertised products.

There are some limitations of this study which future research can address. First, we model the three equations independently. However, there could be some correlations between these three metrics sign of which could be interesting to look at. Second, though our study highlights the importance email marketing on customer relationship management, it would be interesting to look at the impact of email marketing on customer life time value.

5. CONCLUSIONS

Marketing communications is the science and art of communicating relevant marketing information that firms want to convey either publicly or personally. Fueled by technological advancement firms are not only adopting blend of traditional (e.g., newspaper, radio) and new/emerging (e.g., email, educational programs) marketing communications but also offering their products using multiple channels (e.g., online channel, brick and mortar store). This practice, adoption of multiple marketing communications and multiple channels, has required re-evaluation of effectiveness of marketing communications and marketing mix in influencing consumer shopping behavior. In the first essay, we propose a disaggregate, joint channel choice, purchase/category incidence and quantity/order-size model of consumer shopping behavior in the presence of multiple elements of the marketing communications and marketing mix in a multichannel environment. Our results suggest new/emerging marketing communications significantly influence consumers' order-size decision, however, the significance of traditional marketing communications cannot be neglected as they have greater influence on consumers' purchase incidence decision. Therefore, traditional marketing communications are still relevant in this multichannel multi-communication environment. Furthermore, marketing communications cannot exert desired level of output without appropriate marketing mix. Thus, in this technology driven marketing environment firms should have right blend of both traditional and new/emerging marketing communications with right marketing mix.

Multichannel strategy has become an integral part of current marketing environment whereby firms offer their products or services using multiple channels. This not only gives an opportunity to firms to tap into their larger consumer base but also enhances the shopping convenience of today’s consumers who happen to use multiple channels for their purchases. However, reaching and understanding the needs of such a larger consumer base poses daunting task to firms. Therefore, firms are using multiple communication methods such as new/emerging communication options (e.g., social media) apart from traditional marketing methods (e.g., television advertising) to reach and interact with their existing and potential consumer base across their multiple channels. Thus, managing this complex communications process across multiple channels is important for firms to provide seamless shopping experience for consumers. However, measuring the effectiveness of multichannel retailing in the presence of multiple communication mix becomes challenging since consumers could well exhibit differential response to the various marketing/communication elements because of their intrinsic preferences, behavioral and consumption patterns. In the second essay we address the above issues by modeling three critical consumer decisions- channel choice, inter-purchase time, and quantity decision across multiple channels (offline and online channels). For this purpose, we utilize multiple methodologies, that is, we combine consumers’ store level purchase data with their attitudinal data obtained through surveys. We adopt a competing risk modeling framework augmented with multinomial probit for our purpose. We believe an understanding of the above issues will prove useful for firms in better managing their customer relationships and developing strategies for effective allocation of promotion dollars.

The penetration of the internet in day to day life has given marketing managers a new tool of promotion, digital-advertising or web-advertising or online advertising. Initially web-advertising started as a mass communication tool taking forms such as banner ads, sidebar ads (also known as skyscraper ads), pop-up ads, floating ads to name a few. With the advent of content communities (e.g., YouTube), social-networking sites (e.g., Facebook) the digital advertising has taken a whole new dimension. However, these forms of digital advertising could not target the consumers at individual level on one to one basis. The reinvention of email beyond just as a personal or business communication tool by marketing managers gave rise to email marketing whereby they can target individual consumers by sending promotional emails. Given the widespread use of email marketing by small and large firms it has generated a new gamut of web-advertising such as viral marketing, online word of mouth. The factors driving the growth of email marketing are low cost, ability to target individually or selectively, and high response rate. However, research in this area lacks in explaining factors that makes an email campaign a successful marketing campaign and the impact of email marketing on sales. In the third essay using a novel email marketing database we explain the factors that make an email campaign click/unclick, i.e. factors that triggers the open and unsubscribe rate of an email campaign and its impact on sales. We find that among others links, reminder ads, and theme of the email tend to influence the campaign response rates. We find the evidence of spillover effect on direct sales attributed to an email campaign. Importantly, we find email marketing cater more towards customer relationship management than generating the leads in terms of direct sales.

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APPENDIX A

Firms tend to interact with consumers using multiple communication media. This poses computation burden to measure their direct as well as interactions effects. Furthermore, information communicated through various media acts as stock to the consumer i.e. their effects do not fade away immediately. In order to simplify the computational complexities and to operationalize stock variable we make following two assumptions. First, communication of a given type has same effect (e.g. all individual emails affect consumer shopping behavior similarly), thereby allowing different communications to be grouped together. Second, all communications are exchangeable i.e. their impact on subsequent observations are same.

Considering, purchase incidence equation, the direct effect of grouped communication I (e.g. email) for consumer h at time t is given by:

$$f_1(I_{kct}^{h}) = COM_{Ikht} = \sum_{i \in I} \delta_{hkI} \lambda_{Ik}^{r_{hit}} d_{hit}$$

Note that the effect of all communications in a group has same effect (δ_{hkI}) therefore, the above equation can be written as:

$$COM_{Ikht} = \delta_{hkI} \sum_{i \in I} \lambda_{Ik}^{r_{hit}} d_{hit}$$

Now the recursive definition can be applied to the terms in summation. Let's define

$$RCOM_{Ikht} = \sum_{i \in I} \lambda_{Ik}^{r_{hit}} d_{hit}$$

The assumption of exchangeability allows all information received in a given week to have the same r_{hit}. Therefore, in week 1 we have:

$$RCOM_{Ihk1} = \sum_{i \in I} d_{hi1} = N_{Ih1}$$

because $r_{hi1} = 0$ for all I received in week 1 by customer h. This is basically the number of communication information I received in week 1 which is given by N_{Ih1}.

In week 2 the direct effect of communication group I is given by:

$$RCOM_{Ihk2} = N_{Ih2} + \lambda_{Ik} RCOM_{Ihk1}$$

The first term is the number of communication information I received in week 2 and second term is discounted effect of communication received in week 1. Thus, the recursive definition allows us to write the raw effect of communication I for given period t as follow:

$$RCOM_{Ihkt} = N_{It} + \lambda_{Ik} RCOM_{Ihkt-1}$$

The total effect is calculated multiplying $RCOM_{Ihkt}$ with coefficient δ_{hkI}.

The interactions effect constitutes within and across communication group interactions. When I and I' are same communication group, we call it within communication group interaction represented by COM_COM_{Iht} . Thus we have:

$$g_1\left(I_{kct}^{h} I_{kct}^{h}\right) = COM\_COM_{Ihkt} = \sum_{i,i' \in I,I'} \delta_{hkII} \lambda_{Ik}^{r_{hit}} \lambda_{Ik}^{r_{hi't}} d_{hit} d_{hi't}$$

Since all interactions have same effect δ_{hkII}, we can write it as,

$$COM\_COM_{Ihkt} = \delta_{hkII} \sum_{i,i' \in I} \lambda_{Ik}^{r_{hit}} \lambda_{Ik}^{r_{hi't}} d_{hit} d_{hi't}$$

Let's define the term is summation as $RCOM\_COM_{Ihkt}$. Thus:

$$RCOM\_COM_{Ihkt} = \sum_{i,i' \in I} \lambda_{Ik}^{r_{hit}} \lambda_{Ik}^{r_{hi't}} d_{hit} d_{hi't}$$

For week 1, when r_{hit} and $r_{hi't}$ are 0, given the exchangeability assumption we have,

$$RCOM\_COM_{Ihk1} = \sum_{i,i' \in I} d_{hit} d_{hi't} = \binom{N_{Ih1}}{2} = \frac{N_{Ih1}(N_{Ih1} - 1)}{2}$$

Similarly, for week 2 we have:

$$RCOM\_COM_{Ihk2} = \frac{N_{Ih2}(N_{Ih2} - 1)}{2} + N_{Ih2}\lambda_{Ik}N_{Ih1} + \lambda_{Ik}^2 \frac{N_{Ih1}(N_{Ih1} - 1)}{2}$$

which can also be written as,

$$RCOM\_COM_{Ihk2} = \frac{N_{Ih2}(N_{Ih2} - 1)}{2} + N_{Ih2}\lambda_I RCOM_{Ih1} + \lambda_I^2 RCOM\_COM_{Ihk1}$$

The first term represents interactions of all the communication I received in current week, the second term is the interaction between current week communication I and communication I received in past week, the third term is discounted impact of interactions of communication I received in the last week. Thus we have the recursive definition of the within communication group interactions:

$$RCOM\_COM_{Ihkt} = \frac{N_{Iht}(N_{Iht} - 1)}{2} + N_{Iht}\lambda_I kRCOM_{Ihkt-1} + \lambda_{Ik}^2 RCOM\_COM_{Ihkt-1}$$

The cross communication group interaction is given by:

$$RCOM_{Iht}\_COM_{I'ht} = RCOM_{Iht} \times RCOM_{I'ht}$$

Thus, all the interactions effects involve calculation of direct effects first.

APPENDIX B

In our dataset we have 500 consumers, 2 marketing mix variables (price and promotion), 6 dynamic communication mix variables and their interactions and 2 non-dynamic communication mix variables apart from seasonal variables. For channel selection we have 4 explanatory variables. There are two categories in our model. Since for the sake of parsimony we capture unobserved portion of heterogeneity using customer-specific random effect for model intercepts only, the three equations can be written as follow (holiday parameters are suppressed for the sake of exposition):

$$Z_{ct}^{h} = \rho_c^h + \kappa_c DIST_{ct}^h + \pi_c TEMP_{ct}^h + \varphi_c PRECIP_{ct}^h + \tau_c FAMILIAR_{ct}^h + \eta_{ct}^h$$

$$\boldsymbol{U_{kct}^h = \alpha_k^h + \beta_k(t) MKT_{kct}^h + \delta_k COM\left(\lambda_k^{DCOM}\right)_{kct}^h + \epsilon_{kct}^h}$$

$$\boldsymbol{Q_{kct}^h} = \boldsymbol{\phi_k^h + \theta_k(t)MKT_{kct}^h + \mu_k COM\left(\Delta_k^{DCOM}\right)_{kct}^h + \xi_{kct}^h}$$

Note that out of eight communication mix variables, dynamics is incorporated for only 6 variables, therefore they are conditioned on $\boldsymbol{\lambda}, \boldsymbol{\Delta}$ signifying they are composed of decay parameters. Marketing mix and dynamic communication mix is represented by the variables $\boldsymbol{MKT}$ and $\boldsymbol{COM}$ respectively. We use different decay parameters for same communications across different equations. We place diffuse but proper priors on parameters.

The error terms $\boldsymbol{\epsilon_{kct}^h}, \boldsymbol{\xi_{kct}^h}, \eta_{ct}^h$ is distributed multivariate normal with $N(\boldsymbol{0}, \boldsymbol{\Sigma})$. For identification we estimate correlation matrix and following structure is imposed on $\boldsymbol{\Sigma}$.

$$\Sigma = \begin{pmatrix} 1 & \sigma_{11} & 0 & 0 & \sigma_{31} \\ \sigma_{11} & 1 & 0 & 0 & \sigma_{32} \\ 0 & 0 & 1 & \sigma_{22} & \sigma_{33} \\ 0 & 0 & \sigma_{22} & 1 & \sigma_{34} \\ \sigma_{31} & \sigma_{32} & \sigma_{33} & \sigma_{34} & 1 \end{pmatrix}$$

We assume Wishart distribution for prior of $\boldsymbol{\Sigma}$ and put a very diffuse value.

The heterogeneous terms $\mathbf{A} = \{\boldsymbol{\alpha}_k^h, \boldsymbol{\phi}_\mathbf{k}^\mathbf{h}, \omega_c^h\}$ is assumed to be distributed multivariate normal with $\mathbf{A} \sim MVN(\bar{\mathbf{A}}, \Sigma_\mathbf{A})$. We again assume diffuse but proper priors for $\bar{\mathbf{A}}$ and $\Sigma_\mathbf{A}$. Since the decay parameters $\boldsymbol{\lambda}, \boldsymbol{\Delta}$ lie in the interval 0 and 1 we apply logit transformation to these vectors. Specifically:

$$\boldsymbol{\lambda} = \frac{\boldsymbol{exp}(\boldsymbol{\omega})}{\mathbf{1} + \boldsymbol{exp}(\boldsymbol{\omega})}$$

$$\boldsymbol{\Delta} = \frac{\boldsymbol{exp}(\boldsymbol{\Omega})}{\mathbf{1} + \boldsymbol{exp}(\boldsymbol{\Omega})}$$

We assume independent univariate normal prior over each elements of $\boldsymbol{\omega}$ and $\boldsymbol{\Omega}$.

Latent variables of the model are drawn using data augmentation. The full conditional distributions for model parameters (other than decay parameters) are multivariate normal given the conjugacy of their priors. These parameters are simulated from their posterior distributions using MCMC techniques. The full conditional distribution for $\boldsymbol{\omega}$ is proportional to the likelihood times the prior. The likelihood of $\boldsymbol{\omega}$ is given by,

$$L(\boldsymbol{\omega}) \propto \prod_{h,t} \exp\{-\frac{1}{2}\left[\boldsymbol{\alpha}_k^h + \boldsymbol{\beta}_k(\boldsymbol{t})\boldsymbol{MKT}_{kct}^h \quad + \boldsymbol{\delta}_k\boldsymbol{COM}_{kct}^h(\boldsymbol{\omega})\right]' \Sigma^{-1}[\boldsymbol{\alpha}_k^h + \boldsymbol{\beta}_k(\boldsymbol{t})\boldsymbol{MKT}_{kct}^h$$

$$+ \boldsymbol{\delta}_k\boldsymbol{COM}_{kct}^h(\boldsymbol{\omega})]\}$$

Given our assumption of normal prior $p(\boldsymbol{\omega})$ for $\boldsymbol{\omega}$, the posterior is proportional to $L(\boldsymbol{\omega})p(\boldsymbol{\omega})$. We draw elements of $\boldsymbol{\omega}$ using random-walk Metropolis-Hastings (MH) algorithms since prior is not conjugate to the likelihood. The candidate draws are generated normal proposal distribution centered on the previous draw with a variance of 0.02 (Ansari, Mela, and Neslin 2007). Similar approach is adopted for $\boldsymbol{\Omega}$ also.

The correlation matrix Σ is bounded and constrained, therefore to ensure it is positive definite we use guided walk Metropolis algorithm to generate each correlation separately.

APPENDIX C

Duration models are used in marketing to model inter-purchase timing. In such model the observation which is a time-gap between shopping trips (either online or offline) is modeled as a random process. Specifically the time to shop either online or offline channel, t, follows an underlying probability density function given by:

$$f(t) = \Pr(t \le T \le t + \mathrm{d}t)$$

The corresponding cumulative density function is given by:

$$F(t) = \Pr(T \le t) = \int_0^t f(s)\mathrm{d}s$$

In line with typical survival analysis we are interested in two other quantities which are survival function and hazard rate. The survival function, $S(t)$, is complement of the *cdf* which represents the probability that an observation has survived until time t (i.e. consumer has not visited either online or offline channel till time t). The hazard function, $\lambda(t)$, is the instantaneous probability of failure (i.e. visiting either online or offline channel) in tiny interval $\mathrm{d}t$ following t, given survival up to that point. These functions are defined as follow:

$$S(t) = 1 - F(t)$$
$$\lambda(t) = \Pr(t \le T < t + \mathrm{d}t) = \frac{f(t)}{S(t)}$$

The effect of covariates on hazard rate is often modeled as proportional hazard function where individual hazard rate is a product of baseline hazard and an exponential function of independent variables given by:

$$\lambda(t) = \lambda_{0t} \exp(X\beta)$$

Note that in our model consumer can visit the shop either using the firm's offline channel (brick and mortar store) or online channel. Therefore we use competing risk model to captures the differential impact of various factors on different channel patronizing behavior (online vs. offline channels). Let $\boldsymbol{T}$ be the time to visit and $J \in (1,2)$ be the set of channels (offline and online respectively) that a consumer visits. To model inter-purchase time using we consider the shopping behavior across each channel as being distinct, and consider the rate at which this channel visit occurs (the hazard rate). For this purpose, we use the competing risk model specification using latent visiting times. If $T_{Offline}$ and T_{Online} are time (or event time) to visit the offline and online channels (these are the events), then in competing risk situation only one event is observed, therefore event time, T , is the earliest of these hypothetical unobserved times i.e. $T = \min(T_{Offline,}\ T_{Online})$. Thus, the joint probability that the consumer selects one of the channels (e.g., offline) in the tiny interval $(t + \mathrm{d}t)$ and not the other (online) is given as:

$$f_1(t) = \Pr_1\{T_1 \in (t + \mathrm{d}t),\ T_2 \geq t + \mathrm{d}t \mid \beta\} = \left. \frac{-\partial S(t_1, t_2; \beta)}{\partial t_1} \right|_{t_1 = t_2 = t}$$

Here, $S_1\left(t_1, t_2; \theta_1\right) = \Pr(T_1 > t_1, T_2 > t_2 \mid \theta)$ is the latent bivariate survivor function for offline inter-purchase timing. Note that subscript 1 and 2 refer to offline and online channels respectively. Because the purchase timing is latent, we assume that $t_1 = t_2 = t$.

We model the competing risks associated with the inter-purchase times of the respective channels as being independent (however, note that we induce dependence through a "frailty" specification). Therefore the overall likelihood for household h for inter-purchase time T^* and channel choice J^* given parameters β is given by:

$$\ell(T^*, J^*; \beta) = \prod_{i \in 1} f_1(T_i^*; \beta_1) S_2(T_i^*; \beta_2) \times \prod_{i \in 2} f_2(T_i^*; \beta_2) S_1(T_i^*; \beta_1)$$

Note that there are no censored observations in the likelihood function. Since, whenever a consumer takes a shopping trip, either he visits offline channel or online channel.

The proportional hazard function is specified in equation (5). For baseline hazard function we use exponential independent distribution function. For independent exponential baseline hazard the various functional specifications are as follows:

$$
\begin{gathered}
f(t) = \alpha e^{-\alpha t} \\
F(t) = 1 - \alpha e^{-\alpha t} \\
S(t) = e^{-\alpha t} \\
\lambda(t) = \alpha
\end{gathered}
$$

Where α is the rate parameter. Thus following independent exponential hazards the likelihood function for the competing risk inter-purchase time for online and offline channel is as follow:

$$\ell(T^*, J^*; \beta) = \prod_{i \in 1} \alpha_1 e^{-(\alpha_1 t_i + \alpha_2 t_i)} \times \prod_{i \in 2} \alpha_2 e^{-(\alpha_2 t_i + \alpha_1 t_i)}$$

The dependence between inter-purchase timings of online and offline channels is specified using “frailty” specification as follows:

$$
\begin{aligned}
\lambda_{Offline}(t) &= \lambda^{0t}_{Offline} \exp(X_{Offline} \beta_{Offline} + \nu_{Offline}) \\
\lambda_{Online}(t) &= \lambda^{0t}_{Online} \exp(X_{Onine} \beta_{Online} + \nu_{Online})
\end{aligned}
$$

Where we assume vector of frailties $\nu_{Offline}$ and ν_{Online} is distributed multivariate normal with mean vector zero mean and covariance matrix Ω. For identification the shared frailty, $[\nu_{Offline}, \nu_{Online}]$, should be distributed either with zero mean or explanatory covariates, $[X_{Offline}, X_{Onfline}]$, should omit the intercept (Sahu et al. 1997).

APPENDIX D

Survey

This survey is intended for the principal adult shopper in your household.

PART A- OPINIONS

In this section I have listed a number of statements about everyday activities, interests, and opinions. I would like to know whether you agree or disagree with each of the statement. After each statement, there are five numbers ranging from 1 to 5. The **higher** the number, the more you tend to **agree** with the statement. The **lower** the number, the more you tend to **disagree** with the statement. The numbers from 1 to 5 may be described as follows:

Strongly Disagree	Somewhat Disagree	Neutral	Somewhat Agree	**Strongly Agree**
1	2	3	4	**5**

For each statement, ***please circle the one number*** that best describes your feelings about the statement. You may think many statements are similar. Actually, no two items are exactly alike, so ***be sure to circle one number for each statement***.

	Strongly Disagree				**Strongly Agree**
I use the Internet because it makes acquiring information inexpensive.	1	2	3	4	5
I use the Internet with my friends.	1	2	3	4	5
I have plenty of free time.	1	2	3	4	5
I use the Internet so that I can learn about things happening in the world.	1	2	3	4	5
I can quickly gain an overview about products through print catalogs that I receive at home.	1	2	3	4	5
It is convenient to shop from home.	1	2	3	4	5
I shop because buying things makes me happy.	1	2	3	4	5
People will admire me for using the Internet for shopping.	1	2	3	4	5
I set aside time each day for myself.	1	2	3	4	5
When I shop in a store, I often gather information from in-store flyers/displays, etc.	1	2	3	4	5
I am not willing to go to extra effort to find lower prices.	1	2	3	4	5
If I have little experience with a product, I gather information from newspapers, magazines and other consumer reports.	1	2	3	4	5
Often, I talk to my friends about websites on the Internet.	1	2	3	4	5
When I shop in a store, to make sure I buy the right product, I often look at in-store flyers/displays etc.	1	2	3	4	5

	Strongly Disagree				Strongly Agree
I feel out of touch when I do not log onto a social networking website.	1	2	3	4	5
I like a great deal of variety.	1	2	3	4	5
The time it takes to find low prices is usually not worth the effort.	1	2	3	4	5
When I send a message over the Internet, I feel concerned that it may be read by some other person or company without my knowledge.	1	2	3	4	5
I hate to spend time gathering information on products.	1	2	3	4	5
I often make unplanned purchases.	1	2	3	4	5
Information available through technology assisted shopping on the Internet (e.g., shop bots) is a good substitute for that available through an “up-close' personal examination.	1	2	3	4	5
When I visit my friends we often use the Internet.	1	2	3	4	5
If I decided to use Internet to buy and something went wrong with my transaction others would think less of me.	1	2	3	4	5
I get a real "high" from shopping.	1	2	3	4	5
I enjoy using coupons regardless of the amount I save by doing so.	1	2	3	4	5
I use the Internet because it gives me the control over what and when I want to use it.	1	2	3	4	5
I enjoy telling people about the websites I like.	1	2	3	4	5
Chances are high that I will not receive the product that I order on the Internet.	1	2	3	4	5
When I order a product I do not want to wait for it to arrive.	1	2	3	4	5
I’m concerned about not being able to get the assistance of a store employee when buying through the Internet.	1	2	3	4	5
I often tweet.	1	2	3	4	5
The money saved by finding lower prices is usually not worth the time and effort.	1	2	3	4	5
I think twice before committing to myself.	1	2	3	4	5
I do not mind ordering product through the Internet or catalog and waiting for the product to arrive.	1	2	3	4	5
I am more likely to buy brands that are on sale.	1	2	3	4	5
I detest the fact that the Internet is becoming a haven for electronic junk mail.	1	2	3	4	5
I like to purchase things on a whim.	1	2	3	4	5

	Strongly Disagree				Strongly Agree
I would be sorry if my social network website shuts down.	1	2	3	4	5
I use the Internet because it gives quick and easy access to large volumes of information.	1	2	3	4	5
I have favorite brands, but most of the time I buy the brand that's on sale.	1	2	3	4	5
I do things every day that are for "me".	1	2	3	4	5
I like new and different styles.	1	2	3	4	5
When I buy a brand that's on sale, I feel that I m getting a good deal.	1	2	3	4	5
I do not fear viruses when I open email attachments.	1	2	3	4	5
Redeeming coupons make me feel good.	1	2	3	4	5
Use of technology assisted shopping on the Internet (e.g., shop bots) offers product knowledge that is similar to that of 'up-close' personal examination.	1	2	3	4	5
I would rather buy a product at a store than order it in-home and wait for it to arrive.	1	2	3	4	5
Beyond the money I save, redeeming coupons gives me a sense of joy.	1	2	3	4	5
I will grocery shop at more than one store to take advantage of low prices.	1	2	3	4	5
I like to experiment with new ways of doing things.	1	2	3	4	5
I follow commercial companies and their brands using social networking websites or online blogs.	1	2	3	4	5
I enjoy clipping coupons out of the newspaper.	1	2	3	4	5
Overall, I learn a lot from using the web.	1	2	3	4	5
Social networking websites such as Facebook are a part of my everyday activity.	1	2	3	4	5
I am concerned that my personal financial information may be shared with online businesses without my consent.	1	2	3	4	5
Shopping is fun.	1	2	3	4	5
Overall, information obtained from the Internet is useful.	1	2	3	4	5
I use the Internet because it is part of my usual routine.	1	2	3	4	5
It is easy to deal with print catalogs which contain product information that I receive at home.	1	2	3	4	5
I never seem to have enough time to do the things I want to.	1	2	3	4	5
I fear that my order for product bought on the Internet will not be processed.	1	2	3	4	5

	Strongly Disagree				Strongly Agree
I take time off for leisure activities every day.	1	2	3	4	5
To make sure I buy the right product, I often look at newspapers, magazines and other consumer reports.	1	2	3	4	5
I am an avid online blogger.	1	2	3	4	5
I am uncomfortable giving my credit card number on the Internet.	1	2	3	4	5
If a product is on sale, that can be a reason for me to buy it.	1	2	3	4	5
I am uncomfortable conducting personal banking transactions via the Internet.	1	2	3	4	5
I like to try different things.	1	2	3	4	5
I do not like complicated things.	1	2	3	4	5
There is risk of fraud when using the Internet to buy.	1	2	3	4	5
I wish I had more control over unwanted messages sent by businesses over the Internet.	1	2	3	4	5
If I use the Internet to buy others may think that I am just being showy.	1	2	3	4	5
I always stick to my shopping list.	1	2	3	4	5
When I shop in a store, and I have little experience with a product, I often gather information from in-store flyers/displays, etc.	1	2	3	4	5
I use the Internet because I like scrolling through websites.	1	2	3	4	5
I always seem to be in a hurry.	1	2	3	4	5
When I shop, product information gathered from newspapers, magazines and other consumer reports helps me choose the best alternative.	1	2	3	4	5
I would never shop at more than one store to find low prices.	1	2	3	4	5
I am concerned about using the Internet to buy because other people may be able to access my private information.	1	2	3	4	5
When I shop in a store; in-store flyers/displays, etc., help me choose the best alternative.	1	2	3	4	5
I use the Internet because I find it exciting.	1	2	3	4	5
I like to take chances.	1	2	3	4	5
Use of technology assisted shopping on the Internet allows me to judge a product's quality as accurately as that of an “up-close' personal examination.	1	2	3	4	5
I use the Internet because it is interactive.	1	2	3	4	5
I use the Internet because I enjoy it.	1	2	3	4	5

	Strongly Disagree				Strongly Agree
It is easy to locate the information I want on the Internet.	1	2	3	4	5
When I purchase a product I want to use it immediately.	1	2	3	4	5
I use the Internet because it is thrilling.	1	2	3	4	5
Use of technology assisted shopping on the Internet (e.g., shop bots) will allow me to form an impression about a product that is similar to that of an "up-close" personal examination.	1	2	3	4	5
Most days, I have no time to relax.	1	2	3	4	5
I follow user comments on social networking websites and online blogs.	1	2	3	4	5
I prefer to read information on the Internet rather than in a brochure.	1	2	3	4	5
I am interested in new technologies.	1	2	3	4	5
Print catalogs which contain product information, that I receive at home, encourage me to explore them further.	1	2	3	4	5
Print catalogs which contain product information, that I receive at home, offer useful advice on their use.	1	2	3	4	5
Products bought through the Internet are unlikely to be of good quality.	1	2	3	4	5
To me, the use of the Internet will be more appealing if proper safeguards were in place.	1	2	3	4	5
New products are usually gimmicks.	1	2	3	4	5
Compared to most people, I am more likely to buy brands that are on special.	1	2	3	4	5
I dislike the fact that marketers are able to find out personal information of on-line shoppers.	1	2	3	4	5
I am proud to tell people that I am on a social networking website.	1	2	3	4	5
When I use coupons, I feel that I am getting a good deal.	1	2	3	4	5
I often gather product information from newspapers, magazines and other consumer reports before shopping.	1	2	3	4	5
It is easier to send email than to send a postal letter.	1	2	3	4	5
I am concerned over the security of personal information on the Internet.	1	2	3	4	5
I am worried about the security of financial transactions on the Internet.	1	2	3	4	5
I often post comments on blogs and social networking websites.	1	2	3	4	5
Print catalogs which contain product information, that I receive at home, makes searching for products easier.	1	2	3	4	5

PART C – CHANNEL AND COMMUNICATION MEDIA USAGE

In this section we are going to ask you questions regarding your involvement with different shopping channels such as store, catalog, and the internet. Please ***fill in the blanks*** with appropriate response or ***choose from the options given***.

1. How many times during the last **six months** have you searched for information about a product or service through the following methods? (Please specify the *number*)

Retail Store ___________ Catalog ___________ Internet ___________

2. How many times during the last ***six months*** have you purchased any type of products or services through the following methods? (Please specify the *number*)

Retail Store ___________ Catalog ___________ Internet ___________

3. How many ***hours per day*** do you access the Internet using following devices?

Personal Computers (e.g. Desktop or Laptop)		Mobile Phone (e.g. iPhone or Blackberry)	
☐ Don't use	☐ Less than 1 hour	☐ Don't use	☐ Less than 1 hour
☐ About 1 to 2 hours	☐ About 2 to 3 hours	☐ About 1 to 2 hours	☐ About 2 to 3 hours
☐ About 3 to 4 hours	☐ More than 4 hours	☐ About 3 to 4 hours	☐ More than 4 hours

4. How many emails do you receive ***per day***?

☐None ☐1 – 10 ☐11 – 20 ☐21 – 30 ☐31 – 40 ☐41 –50 ☐More than 50

5. How many emails do you open and read ***per day***?

☐None ☐1 – 10 ☐11 – 20 ☐21 – 30 ☐31 – 40 ☐41 –50 ☐More than 50

6. Do you read commercial emails sent to you?

☐ Never ☐ Rarely ☐ Sometimes ☐ Often ☐Very Often

7. Do you click on banners while surfing online?

☐ Never ☐ Rarely ☐ Sometimes ☐ Often ☐Very Often

8. How many ***minutes per day*** do you listen to following Radio Stations?

Radio Station 1	Radio Station 2	Others (Please specify)
☐ Don't listen	☐ Don't listen	**Radio Station … Time**
☐ Less than 15 mins.	☐ Less than 15 mins.	___________ … _____
☐ About 15 to 30 mins.	☐ About 15 to 30 mins.	___________ … _____
☐ About 30 to 45 mins.	☐ About 30 to 45 mins.	___________ … _____
☐ About 45 to 60 mins.	☐ About 45 to 60 mins.	___________ … _____
☐ More than 1 hour.	☐ More than 1 hour.	___________ … _____

9. How many ***hours per week*** do you watch following TV Channels?

Channel 1	Channel 2	Channel 3	Channel 4	Others (Please specify)
☐ Don't watch	☐ Don't watch	☐ Don't watch	☐ Don't watch	**TV Channel … Hrs.**
☐ 1 to 3 hrs.	☐ 1 to 3 hrs.	☐ 1 to 3 hrs.	☐ 1 to 3 hrs.	_______ … ______
☐ 3 to 6 hrs.	☐ 3 to 6 hrs.	☐ 3 to 6 hrs.	☐ 3 to 6 hrs.	_______ … ______
☐ 6 to 9 hrs.	☐ 6 to 9 hrs.	☐ 6 to 9 hrs.	☐ 6 to 9 hrs.	_______ … ______
☐ More than 9 hrs.	☐ More than 9 hrs.	☐ More than 9 hrs.	☐ More than 9 hrs.	_______ … ______

10. How often do you **research** products **online** before you buy them?

☐ Never ☐ Rarely ☐ Sometimes ☐ Often ☐Very Often

11. Which **categories** do you **research online** before you buy them? (Please check all that apply)

☐ Books/Music ☐ Apparel/Jewelry ☐ Furniture/Home Appliances ☐ Electronics ☐ Food ☐ Wine

12. What kind of product **information** do you seek online**?** (Please check all that apply)

☐ Price ☐ Deals ☐ Product Description ☐ Product Reviews ☐ Others:(Please Specify) ____________

PART D – PERSONAL INFORMATION

Finally, we would like to get some background information for **CLASSIFICATION PURPOSES ONLY**. Remember, all responses will remain **STRICTLY CONFIDENTIAL**. Please answer each question by marking an **"X"** or circling as appropriate.

1. Your sex ☐Male ☐Female

2. Your age category

☐Under 21 ☐21-25 ☐26-30 ☐31-35 ☐36-40 ☐41-45
☐46-50 ☐51-55 ☐56-60 ☐60-65 ☐Over 65

3. Number of years of formal education completed by you (Please **circle** one):

less than 9	9 10 11 12	13 14 15 16	17 18 19 20+
	high school	college	beyond college

4. How many people, including yourself, are presently living in your household?

☐1 ☐2 ☐3 ☐4 ☐5 ☐6 ☐More than 6

5. Are you responsible or share responsibility for financial decision making in this household? ☐Yes ☐No

Note: The survey contained more questions. This is an excerpt from the full survey.