ELSEVIER
Journal of Retailing xxx (xxx, 2013) xxx–xxx
Journal of Retailing

# Maximizing Profits for a Multi-Category Catalog Retailer

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## Abstract

It is a common trend in the retail industry for catalog retailers to mail multiple catalogs, each promoting different product categories. The existing catalog mailing models do not address the issue of optimizing multi-category catalog mailing. We address this research gap by introducing a model that integrates the *when* and *what* components of a customer's purchase decision into the *how much* component (number of catalogs) of a firm's cross-selling strategy. In addition to comparing the impact of category-specific versus full product catalogs in generating sales in a specific category, the study also finds relative impacts of various category-specific catalogs. We jointly estimate the probability of purchase and purchase amounts in multiple product categories by using multivariate proportional hazard model (MVPHM) and a regression based purchase amount model in a Hierarchical Bayesian framework. The model accounts for unobserved heterogeneity, and uses a control function (CF) approach to account for endogeneity in catalog mailing. The results from the Genetic Algorithm (GA) based optimization suggest that the catalog mailing policy as per the proposed model would be able to generate 38.4 percent more customer lifetime value (CLV) from a sample of 10 percent of the households as compared to the current catalog mailing policy of the retailer by reallocation of the catalogs across customers and mailing periods based on their propensity to buy.


*Keywords:* Multi-category catalog mailing; Category-specific catalog; Multivariate proportional hazard model; Control function; Genetic Algorithm based optimization

## Introduction

American catalog companies mailed 12.5 billion catalogs to US homes in 2011 according to Direct Marketing Association (DMA) data. About 90 million Americans bought an item from a catalog in 2011 (Fox 2012). Print catalogs continue to play a significant role in the retail sector and constitute an important part of a multichannel marketing mix. In a 2009 Oracle affiliate (ATG) cross-channel survey of 1,054 US consumers,[1] 79 percent of respondents said they use catalogs to browse and discover products at least four times a year, while close to half the consumers do so at least once a month. Catalogs have the lowest cost per lead/order of $47.61 as per the DMA 2010 Response Rate Trend Report; however, the average response rate for catalogs is only about 4.26 percent for existing customers according to DMA 2012 Response Rate Report (Marketingcharts.com 2012). Such low rates represent serious concerns for catalog retailers, whose printing and mailing costs average 8 percent and 9.8 percent, respectively, of the total income generated from catalog customers, thus highlighting the need for highly effective mailing strategies.

Poor response rates to catalog mailing often stem from inadequate customer selection. Furthermore, most catalog customers place an order less than 3 times annually. Because catalog orders are so irregular and infrequent, retailers cannot just identify the most responsive customers; rather, they must predict when each customer will place an order. For a single category catalog retailer, key mailing decisions include (1) how many customers should receive their catalog and (2) how often and when customers should receive catalogs. However, most catalog retailers sell products in multiple categories and customers buy from different categories in different time periods (or quarters). For instance, a customer may buy a hunting accessory during spring from the 'outdoor' category and a school bag during summer from the 'luggage' category. This pattern varies from one

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[1] Art Technology Group (ATG) White Paper (2010), "Cross-Channel Commerce: The Consumer View", [http://www.bme.eu.com/media/white%20papers/BMEU/atg-cross-channel-survey.pdf].

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http://dx.doi.org/10.1016/j.jretai.2013.05.001

customer to the other, which emphasizes the need to identify which category a customer is likely to purchase from to be able to send him the right catalogs.

In the traditional approach, retailers get around this problem by creating a catalog that has a list of products from all the categories and sending these 'full product' catalogs to all customers who are likely to purchase during a time period. An alternative approach is to develop category-specific catalogs featuring products from one category and mail those to customers who are likely to buy from that category during that time period. Recent trends suggest that many catalog retailers use the second approach following the logic that customer-specific promotions increase sales. For example, Cabela's mails separate catalogs for fishing, hunting, camping, workwear, and so forth. The traditional approach has the advantage of reducing the probability of not sending catalogs to customers who are likely to buy. However, there is likelihood that mailing full product catalogs will have a lower response rate due to information overload, and bulkier catalogs incur higher printing costs. Thus, in the traditional approach, an accurate model alone will not increase the overall response rate.

Mailing category-specific catalogs, on the contrary, is likely to have a higher response rate among customers who received catalogs related to their category of interest due to the salience and specificity of the information. Further, category-specific catalogs have the potential to enhance cross-selling. Kumar, George, and Pancras (2008) find that cross-category promotions (e.g., sending a catalog for a category from which a customer has not purchased before) have a positive impact on cross-buying, which in turn, improves the contribution margin, average revenues per year, customer lifetime value (CLV) (Venkatesan and Kumar 2004), multichannel behavior (Kumar and Venkatesan 2005), and lifetime duration (Reinartz and Kumar 2003). The risk, however, is sending wrong catalogs leading to a low response rate. Thus, the challenge here is to develop a model that can precisely identify the customers who are likely to buy from a specific category during a time period, which is addressed in this study. Despite its advantages, the use of category-specific catalogs complicates the decision to mail the catalog. To optimize multi-category catalog mailing, the retailer must identify the type of catalog to send to a customer in a specific mailing. Existing catalog mailing models do not address this, making it imperative to introduce a model that optimizes the mailing of multiple category-specific catalogs.

One of the challenges in modeling purchase timing in multiple categories is that many customers who receive catalogs might not make a purchase in the observation period, resulting in censored observations. Further, we need to link each purchase to the catalogs received prior to that purchase to understand the impact of mailing catalogs. Thus, the model should have the flexibility to account for purchases occurring on any date (rather than during a specified duration such as a week, month or a quarter) during the observation period. We also need to account for interdependence of purchases across categories. Moreover, we expect the response to direct mailing to vary across customers (Rust and Verhoef 2005; Van Diepen, Donkers, and Franses 2009a) and hence have to account for unobserved heterogeneity in the model. A multivariate proportional hazard model (MVPHM) overcomes these challenges in formulating a purchase timing model. Estimating the model using a Hierarchical Bayesian framework allows for customer-specific coefficients, thereby accounting for customer heterogeneity.

This is the first study in the discipline, to the best of our knowledge, that offers guidance to retailers on the optimal number and type of catalogs to be sent to specific customers during each mailing period in order to maximize CLV. It also compares for the first time, the impact of category-specific versus full product catalogs in generating sales in a specific category in a multi-category catalog mailing context. This is particularly important as many catalog retailers have started mailing multiple category-specific catalogs, and the findings provide valuable insights to retailers in using both types of catalogs for increasing sales. The study also finds relative impacts of various category-specific catalogs in generating sales. Moreover, we illustrate how reallocation of catalogs across customers and mailing periods based on their propensity to buy from a category improves CLV significantly.

The proposed MVPHM with both household and category-specific random effects that take into account the interdependence in purchase timing across multiple categories has not been used in the marketing literature. We believe that this model has the potential to be used in various marketing contexts like modeling category/sub-category purchases in shopping baskets, as a better alternative to commonly used purchase incidence models like multivariate probit (MVP). This is particularly true when the number of purchases for a household is very small. Since a model like MVP tracks purchase/no purchase incidences in predefined time periods, a large number of non-purchases will have to be included in the model when the frequency of purchases is small, causing bias in the parameter estimates. This study is one of the first in applying a control function (CF) approach in a multivariate hazard model to account for endogeneity in mailing decision in multiple categories. The study also applies the use of optimization (which is so far done when there is only one type of catalog) in a multi-category catalog mailing context.

## Literature review

Extant literature on optimal catalog mailing focuses on particular mailing decisions: *who* should receive a catalog, and *when* and *how many* catalogs in a time period. Studies differ according to whether they model customers' purchase probability (or timing) or dollar amount of purchase (order quantity). For example, Bult and Wansbeek (1995) estimate a binary model to identify the proportion of households that should receive mailings, and Bitran and Mondschein (1996) use enhanced RFM analysis to model catalog mailing decisions according to CLV. These models address the question of who should receive a catalog and how many, but not necessarily when, because they do not model customers' purchase probabilities explicitly.

Other studies include customers' purchase probability; Gönül and Shi (1998) propose a model that predicts whether a customer will make a purchase but not the order amount. Gönül, Kim, and Shi (2000) model purchase timing using a proportional hazard model (PHM) that incorporates unobserved heterogeneity. Simester, Sun, and Tsitsiklis (2006) use a nonparametric approach and employ dynamic optimization to develop optimal catalog mailing policy. However, neither of these models explicitly considers the purchase amount.

Gönül and Hofstede (2006) propose a Hierarchical Bayes (HB) approach to predict order incidence and order volume decisions of catalog customers, integrating the when and how much components of customers' purchase decisions, and the firm's mailing decision. However, none of these models distinguish among purchases in different categories, or predict which category a customer will purchase from in a particular purchase instance. Instead, they assume that most catalogs feature more or less the same product offerings (Gönül, Kim, and Shi 2000).

Elsner, Krafft, and Huchzermeier (2004) partially address the need for a new multi-category catalog mailing model by proposing a dynamic multidimensional marketing approach to predict optimal frequency, size, and segmentation in a multi-catalog multi-brand scenario. However, their approach segments customers according to the recency of purchase of a particular brand and uses average response rates and order sizes; it does not incorporate unobserved heterogeneity. Malthouse and Elsner (2006) use crossed-basis segmentation approach to create customized marketing contacts. Through a field study they demonstrate that this approach improves response rates and is more cost-effective compared to single sub-segmentation approaches like RFM. Even though such customized offers outperform generic offers, these approaches implicitly assume that customers within a sub-segment are homogeneous. However, customer behavior varies widely even within a particular segment, and we need to account for such unobserved heterogeneity. Moreover, catalog retailers need a customer-level optimization model for multi-category catalog mailings that helps them select the right catalog from among multiple category-specific and full product catalogs, and send them to the right customer at the right time.

As Table 1 highlights, no existing model for multi-category catalog mailing accounts for unobserved heterogeneity or endogeneity. To address this research gap, we propose an empirical model that develops an optimal mailing rule for each customer in a multi-category catalog mailing context. The proposed HB model determines *when* a customer should receive *what* type of catalog to maximize the firm's expected profits. In other words, the model integrates the *when*, *how much*, and *what* components of a customer's purchase decision into the firm's mailing decision. Since we model purchase probability for each category, unlike existing catalog mailing papers that model the probability of purchase from the firm rather than from a specific category, we are able to capture the relative impacts of category-specific catalogs and full product catalogs on purchase probability in each category. Thus, our approach directly addresses the pressing problem that catalog retailers face of having to choose from a number of catalogs and mail to the right customer in the right mailing period. We first present a framework for optimizing multi-category catalog mailing and discuss the factors influencing a household's purchase behavior, and then describe the associated study data. After explaining the joint model of purchase timing and amount, we discuss the parameter estimates from the model and the impact of the optimal catalog mailing policy. We then outline the managerial implications and academic contributions followed by future research directions.

## Multi-category catalog mailing framework

The key modeling decisions here are: (1) *when* and *what* product category a customer will buy and (2) *how much* he or she will spend on a purchase occasion. Understanding a household's probability of purchase from a category (what and when) helps retailers send the right marketing communication (i.e., catalog). Knowing the dollar amount (how much) helps to determine whether they should pursue the household and with what resources (i.e., how many catalogs).

Although our focus is to identify the impact of category-specific catalogs on purchase behavior, we also include customer-specific characteristics as covariates. The selection of covariates is based on prior studies, especially on single category catalog mailing. We also draw on theory relating to information overload, goal-oriented shopping, familiarity leading to increased trust, and category need of customers, for explaining the rationale of including each variable in the study. The retailer in this study does not change the price of same products until it sends another catalog (featuring different models of same products). Since the same products are not featured in subsequent catalogs there is no systematic way to capture the variation in price. However, we capture possible changes in prices during the holiday season by including an indicator variable. Also, we expect competition to have a very insignificant role in the purchase decision in a catalog mailing context for several reasons. Firstly, catalog shoppers are primarily driven by the convenience of shopping, and the products are not easily comparable across different catalog retailers. Secondly, catalog channel is closer to online channels than traditional channels because of similarities in terms of information provided and delivery systems (Ward 2001). The low substitutability between catalog and traditional channels suggests that catalog retailers are less likely to face direct competition from traditional retailers. In our study context, the competition from online retailers will also be less because of a relatively small percentage of sales (6 percent) online. Thirdly, the impact of competition between catalog and traditional channels will also depend on whether the products are popular products or niche products. Brynjolfsson, Hu, and Rahman (2009) find the effect of competition to be nonsignificant when a non-traditional channel sells more niche products. The retailer in our study enjoys very strong brand loyalty and most of its products can only be purchased through one of its channels, which makes the impact of competition less significant at the product level even though there is competition at the category level.

A multi-category catalog mailing framework showing the determinants of purchase probability and purchase amount and the steps involved in developing a multi-category catalog mailing policy is shown in Fig. 1.

Table 1
Comparison of present study with existing catalog mailing models.

| Study | Single category catalog mailing (*when* and *how many*) | Multi-category catalog mailing (*what*, *when*, and *how many*) | Order quantity modeled | Long-term objective for optimization | Accounts for unobserved heterogeneity | Accounts for endogeneity |
|---|---|---|---|---|---|---|
| Bult and Wansbeek (1995) | √ | | | | | |
| Bitran and Mondschein (1996) | √ | | √ | √ | | |
| Gönül and Shi (1998) | √ | | | √ | | |
| Gönül, Kim, and Shi (2000) | √ | | | √ | √ | |
| Elsner, Krafft, and Huchzermeier (2004) | | √ (multi-brand) | | √ | | |
| Gönül and Hofstede (2006) | √ | | √ | √ | √ | |
| Simester, Sun, and Tsitsiklis (2006) | √ | | | √ | | |
| Malthouse and Elsner (2006) | | √ (customized catalogs) | | | | |
| Current study | | √ | √ | √ | √ | √ |

*Determinants of the probability of purchase*

The key covariates of the probability of purchasing from a category at a given time and their expected effects are shown in Table 2. We group the determinants of the probability of purchase and purchase amount as those that are unique to the study and those based on prior studies.

While ample evidence (Gönül, Kim, and Shi 2000; Gönül and Shi 1998) supports the influence of catalog mailings on the probability of purchase across all categories, our focus is to identify the relative impacts of mailing category-specific and full product catalogs on the probability of purchase from a specific category. We also control for the effect of other category-specific catalog mailings on the probability of purchase from a category.

*Own-category catalog mailing*

The *own-category* catalog features all the main products from the focal category. When a household interested in buying from a specific category receives a catalog for the category of interest, the information has high relevance for the household, and the message relevance leads to strong positive effects on perceptions of utility (Moenaert and Souder 1996). Consumers attend to product features selectively depending on the benefits they seek (Haley 1971) and situational factors, which according to Ratneshwar et al. (1997) include benefits defined by the product usage context. Haley (1971) further suggests that consumers in the segment of interest (but not necessarily in other segments) might selectively attend to product information. Thus, a household interested in buying from the focal category is more likely to use this information, which

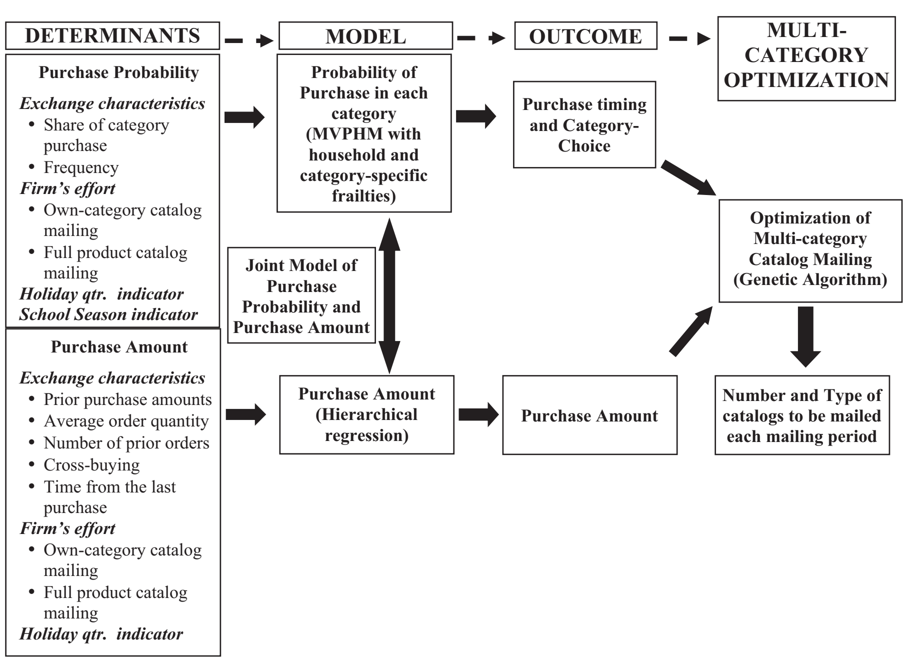


Fig. 1. Multi-category catalog mailing framework.

Please cite this article in press as: George, Morris, et al, Maximizing Profits for a Multi-Category Catalog Retailer, *Journal of Retailing* (xxx, 2013), http://dx.doi.org/10.1016/j.jretai.2013.05.001

Table 2
Determinants of the probability of purchase from a category in a given time, and purchase amount.

| Variable | Operationalization | Expected effect |
|---|---|---|
| **Probability of purchase from a category in a given time** | | |
| Catalog mailing effort | | |
| *Own-category* catalog mailing | Number of catalogs belonging to the same category mailed within 90 days prior to the purchase occasion. | + |
| *Other category* catalog mailing | Total number of all other category-specific catalogs mailed within 90 days prior to purchase. | + |
| Full product catalog mailing | Number of full product catalogs mailed within 90 days prior to the purchase. | – |
| Exchange characteristics unique to the study context | | |
| Share of category purchase | Ratio of number of orders in a given category to the total number of orders from all categories (until the previous purchase occasion). | + |
| Exchange characteristics based on the findings from prior research | | |
| Frequency of purchase | Average number of purchase occasions in a year before now. | + |
| **Purchase amount** | | |
| Exchange characteristics based on the findings from prior research | | |
| Cross-buying | Number of product categories purchased by the household before now. | + |
| Average order size | Cumulative purchase amount divided by the cumulative number of orders. | + |
| Cumulative number of orders | Total number of orders placed by the household before the last order. | + |
| Recency | Time from the last purchase occasion (log of recency[a]). | |
| Catalog mailing | Number of category-specific and full product catalogs mailed in 90 days prior to the order. | + |

[a] We use log(recency) in order to capture the non-linear relationship recency may have with the order quantity.

influences its probability of making a purchase from that category.

Moreover, the literature on goal-oriented shopping suggests that the physical properties of a retail surface will enhance consumers' reaction to the retail channel if the surface is congruent with the shopping task (Mathwick, Malhotra, and Rigdon 2002). Own-category catalogs (category-specific catalogs in general) present products within only one category in a more organized way suggesting an analytic retail surface. Goal-oriented customers (i.e., those who are interested in a specific product from the focal category) are driven by a desire to make the best purchase possible in an efficient and timely manner (e.g., Babin, Darden, and Griffin 1994). The analytic environment offered by own-category catalog is congruent with the goal-oriented (i.e., analytic) shopping task and therefore will be effective in generating sales. *Thus, we expect own-category catalog mailing to have a positive impact on the probability of purchase from the category at a given time*.

*Full product catalog mailing*

Full product catalogs, which feature all product categories, will be bulkier than category-specific catalogs and offer poorer coverage of products in a specific category. This suggests that a full product catalog presents a less analytic and more intuitive (less organized and more difficult to find a specific product due to poor coverage) shopping environment compared to an own-category catalog. Such a retail surface is less congruent with a goal oriented shopping task and is less likely to generate sales from a specific category. Therefore, the impact of a full product catalog on the probability of purchase from a specific category in a given time may be smaller than that of an own-category catalog mailing. Further, a household may find the wide range of products in the full product catalog overwhelming, resulting in cognitive burden due to information overload (Grover, Lim, and Ayyagari 2006). Prior studies suggest that satisfaction with information search declines and confusion increases when consumers are exposed to more alternatives (Malhotra 1982) and the exposure to more alternatives leads to lower decision effectiveness (Keller and Staelin 1987). Thus, information overload may create a negative impact for full product catalogs in some cases, depending on the category, household, and extent of coverage. *We expect the impact of the full product catalog on the probability of purchase to be smaller than that of an own-category catalog*.

*Share of category purchase*

Since we model the probability of purchase from a *specific category*, we use a category-specific variable, share of category purchase, as a covariate of the probability of purchase from a category. This variable is the ratio of purchase within a category to the total number of purchases across all categories and is similar to usage rate or category requirement. Prior research (Bucklin and Lattin 1991) suggests that usage rate, a measure of need, positively influences a household's decision to purchase from a category and that a higher share of category purchase indicates the household's higher need of products from the category relative to other categories. Also, share of purchase from a category indicates whether a household has purchased from a category earlier. A household that has bought from a category is more familiar with the products in that category positively influencing its probability of purchasing from the category in the current time period. Smith and Swinyard (1982) suggest that prior purchases influence repurchase intentions and current purchase behavior (Morwitz and Schmittlein 1992). Anderson, Fornell, and Lehmann (1994) argue that prior experience influences customer satisfaction, which affects repurchase intentions, and Seiders et al. (2005) find that relationship age relates positively to repurchase intentions. Further, Bridges, Briesch, and Yim (2006) find prior brand usage affects current brand usage through usage dominance (i.e., prior experience enhances likelihood of buying the same brand). Extending these findings, we expect that a household's prior category purchase positively impacts its purchase probability from that category through usage dominance. Therefore, *the higher the past share of purchases from a category, the higher would be the purchase probability from that category in a given time period*.

*Frequency of purchase*

The fact that frequency is positively linked to the probability of purchase in the future is well established (Reinartz and Kumar 2003; Simester, Sun, and Tsitsiklis 2006). However, what is new and interesting in a multi-category context is to know whether more frequent purchases (across all categories) in a given period significantly influence the probability of purchase from a specific category such as men's. Prior studies on cross-buying (Kumar, George, et al., 2008) indicate that frequency positively influences cross-buying behavior. In other words, a household that is more familiar with the firm and its products because of frequent purchases will be more inclined to purchase even from a category from which nothing had been bought earlier. Therefore, we expect that *higher the frequency of purchase, the greater will be the probability of a household purchasing from a specific category*.

*Other covariates – holiday quarter and school season indicator*

It is quite reasonable to assume that sales during the holiday quarter and school opening season are much higher when compared to other quarters. This may be the result of both price promotion and increased demand for certain categories in these quarters. We therefore include holiday quarter and school season indicators as covariates in the purchase timing equations to control for effects of price promotion and increased demand on purchase decision. We also include interactions of these indicators with full product catalogs to see whether full product catalogs have different responses during holiday or school opening season.

*Determinants of purchase amount*

To develop an optimal catalog mailing policy, we must understand the impact of mailing both category-specific and full product catalogs on purchase amounts after accounting for the impact of other covariates such as the purchase pattern of the household in the past. Prior research specifies that previous purchase amounts influence current purchase amounts and can account for model misspecifications (Niraj, Gupta, and Narasimhan 2001; Venkatesan and Kumar 2004). We therefore use 1-period and 2-period lags of the purchase amount as control variables. We also use exchange characteristics such as cross-buying, total number of prior orders, average order size, and recency as covariates. The operationalization of the key covariates is given in Table 2.

*Cross-buying*

Cross-buying indicates the breadth of relationship with a firm and reflects the household's trust in the firm. Since high cross-buy households have bought from multiple product categories the firm sells, they are more familiar with products in different categories compared to low cross-buy households. This familiarity may translate to them buying from multiple categories on each purchase occasion, and maybe, higher spend per purchase occasion. The empirical evidence also supports the notion that customers who cross-buy in general spend more and have a higher CLV (Kumar, George, et al., 2008; Venkatesan and Kumar 2004). Cross-buy also positively affects customer-based outcome variables such as profitable lifetime duration and CLV through purchase frequency and contribution margin (Reinartz and Kumar 2003; Venkatesan and Kumar 2004). Thus, we expect that a household with a higher cross-buy places a larger order (dollar amount) than one with a lower cross-buy. However, Shah et al. (2012) caution that persistency of adverse customer behavior can make certain customers who cross-buy unprofitable. Since we do not observe an unusually high percentage of merchandise return, one of the adverse behavioral traits driving an unprofitable cross-buy, in the dataset, we do not expect a very high percentage of households with an unprofitable cross-buy in our context. Thus we expect, *the higher the cross-buy, the higher would be the purchase amount in a purchase occasion*.

*Catalog mailing*

We expect *catalog mailing to positively influence the purchase amount* (Gönül and Shi 1998; Reinartz and Kumar 2000, 2003) and use the number of category-specific and full catalogs received during a 90-day period prior to a purchase occasion as covariates. Both types of catalogs enable households to become familiar with different products and special offers prompting them to purchase multiple products, resulting in a larger purchase amount in a purchase occasion. However, we also expect the impact of each type of catalog to differ.

*Other covariates*

Cumulative variables such as number of prior orders and total catalogs mailed in the past are likely to influence the familiarity with the product leading to improved trust. We capture the impact of possible changes in familiarity with the products and the trust level of the household by using the cumulative number of orders.[2] A household may also aggregate orders and place a larger order, which is captured in the variable, the average order size. A household that aggregates orders (i.e., higher average order size in the past) is likely to place a larger order in the current time period (Simester, Sun, and Tsitsiklis 2006). Also, if the time from the previous purchase is very short, the household is likely to place only a small order for items that were not available earlier. As the time elapsed increases, the household's shopping basket is likely to increase (due to aggregation) up to a threshold level. Hence, *we expect a non-linear relationship of recency with the purchase amount* (Gönül and Shi 1998).

[2] The impact of the total number of catalogs mailed was smaller compared to that of cumulative number of orders and these variables were highly correlated with each other. Hence we used only the latter in the model.

We also account for the effect of potential price promotion during holiday by including the control variable '*holiday quarter indicator*'.

## Research methodology

### *Data*

We use data from a major US catalog retailer that sells products in six major product categories: men's, women's, kids, outdoor, luggage, and home. The data is for the period January 1997–August 2004 and includes information on customer transactions, catalog mailing and customer demographics.

The transaction data from the firm capture all customer purchases in three channels – online (which only comprises 5–6 percent of the total sales), telephone, and retail stores – according to the date, category, and order amount of purchase, as well as variables such as products returned in dollars. We also have access to catalog mailing information, such as the type of catalog mailed and the approximate date customers received a catalog, which we use to match each catalog mailing to particular orders placed by customers. Specifically, we know what type of catalogs and how many catalogs customers had received before each order. The firm typically mails both full product and category-specific catalogs, such as the men's catalog. Thus, we can classify six category-specific catalogs and one full product catalog, though catalogs sent in different seasons may have different names. This categorization of the catalogs helps us identify the impact of sending a category-specific catalog compared to a full product catalog on customers' purchase behavior within each product category. The data include key demographic variables such as household income, age of the head of the household, number of people in the household, number of children in the household, home ownership, and marital status, which help explain customer heterogeneity.

The firm generally follows an RFM approach in their mailing decision with the total number of catalogs mailed being related to the number of orders and total order amount from a category to the extent that those who purchased more received more catalogs in general. However, there are lots of inefficiencies in their mailing policy for specific types of catalogs. For instance, there are many customers who received catalogs from product categories that they have not bought before. Overall, in 32 percent of the cases, a catalog is mailed to a customer who had not purchased from the category before. This proportion is as high as 69 percent for outdoor and 40 percent for kids. We also analyzed the timing of catalog mailing as percentage of customers receiving full product and category-specific catalogs in the same time period (i.e., month and quarter) and how often customers received multiple catalogs of the same type in the same time period. The firm mailed more than one category-specific catalog (i.e., men's and women's, or men's, women's and outdoor, etc.) to the same customer in the same month in 16 percent of the cases and same quarter, 32 percent of the time. Similarly, multi-product (full) catalogs and category-specific catalogs are mailed in the same month (25 percent of the time) and same quarter (47 percent of the time) to the same customer. Also, there are multiple mailings of full-product catalogs in the same quarter (52 percent of the time).

For the purpose of this study, we select a cohort of customers who made their first purchase in 1998, then consider their purchase history and catalog mailings for the period 1998–2001 to select a sample to use for building our model. We drop customers with two or fewer purchases (total number of purchases across all categories) during this period from the analysis from both practical and model building perspectives. At a practical level, customers who made two or fewer purchases in four years (i.e., interpurchase time (IPT) more than two years) in general do not show any predictable pattern of purchase. As a result, it becomes a futile exercise to develop an optimal catalog mailing policy for such customers. Instead, the retailer can follow some simple heuristics (such as sending a full product catalog every quarter) for mailing catalogs to them. From a model building perspective, the minimum number of purchases required to have one data point (i.e., one IPT) is two. Thus, customers with two or fewer purchases will have a maximum of one observed IPT and one censored observation. Inclusion of such customers may adversely affect the results especially when the estimation is done in a hierarchical framework. Also, studies involving purchase timing (e.g., Bucklin and Gupta 1992; Jain and Vilcassim 1991; Manchanda, Ansari, and Gupta 1999) often drop customers with infrequent purchases or very small purchase amounts.

Using these criteria, we identify a sample of 781 customers who collectively account for 4,547 purchase occasions. To compute IPTs in each category, we take the date of the first purchase as the starting point of our observation period for a customer and December 31, 2001 as the end of the observation period. We treat the time from the last observed purchase in a product category to the end of the observation period as a censored observation for the IPT in that particular category. The data for the period January 2002–June 2004 is used for validation of the model and for optimization.

As we show in Table 3, the average number of orders per household equals 5.8 during January 1998–December 2001, with an average order amount of $97 per purchase occasion. On average, the firm sent 17.8 catalogs to each household per year, which translates to a total of 46,162 catalogs sent during the four-year study period. The women's and men's categories have the highest number of orders, while the outdoor category has the fewest. The average IPT across all purchase occasions is 8.2 months; IPTs within different categories vary from 11.6 months for women's to 16.8 months for the home category. Own category (single category) catalogs cost 53 cents on average and the full product catalog costs $1.53, which includes both printing and mailing costs.

Table 4a shows to what extent current catalog mailing influences order generation from a category. One simple measure of the impact of catalog mailing is to calculate the number of orders generated in each category per catalog mailed. For every men's catalog mailed, 0.54 orders (i.e., 1,653 orders from 3,088 catalog mailed) are generated from the men's category. The average number of orders generated per category-specific catalog in other categories range from 0.35 for women's to 0.06 for

Table 3
Description of data used for analysis.

| Time period | January 1998–December 2001 | Total number of households | 781 |
|---|---|---|---|
| **Across all categories** | | | |
| Total number of orders or purchase occasions | 4,547 | Average order amount ($) per transaction | 97 |
| Average number of orders per household | 5.8 orders in four years | Average interpurchase time (months) | 8.2 |
| Cost of category-specific catalog | $0.53 | Cost of full product catalog | $1.53 |

| Details of purchases within categories | | | Catalog mailings | | |
|---|---|---|---|---|---|
| Category | Number of orders | Average interpurchase time (months) | Catalogs | Total number of catalogs sent January 1998–December 2001 | Avg. number of catalogs per household per year |
| Men's | 1,653 | 12.9 | Men's | 3,088 | 1.19 |
| Women's | 1,766 | 11.6 | Women's | 4,984 | 1.92 |
| Kids | 527 | 16.5 | Kids | 4,348 | 1.69 |
| Outdoor | 223 | 14.8 | Outdoor | 3,669 | 1.41 |
| Luggage | 779 | 16.4 | Luggage | 2,548 | 0.98 |
| Home | 441 | 16.8 | Home | 6,036 | 2.31 |
| | | | Full product | 21,489 | 8.28 |
| | | | All | 46,162 | 17.78 |

Table 4a
Purchase probabilities for each catalog type.

| | Men's | Women's | Kids' | Outdoor | Luggage | Home |
|---|---|---|---|---|---|---|
| **Purchase probability – number of orders/number of catalogs** | | | | | | |
| Category-specific catalogs | 0.54 | 0.35 | 0.12 | 0.06 | 0.31 | 0.06 |
| Full product catalogs | 0.08 | 0.08 | 0.03 | 0.01 | 0.04 | 0.02 |
| **Purchase probability – proportion of quarters in which a catalog generated an order from the category** | | | | | | |
| Purchase probability (category-specific catalogs) | 20.1 percent | 16.8 percent | 9.9 percent | 3.4 percent | 9.0 percent | 5.7 percent |
| Purchase probability (full product catalogs) | 8.8 percent | 8.7 percent | 4.4 percent | 1.7 percent | 4.7 percent | 2.9 percent |

outdoor and home. The number of orders per full product catalog ranges from 0.01 for outdoor to 0.08 for men's and women's categories. This measure does not take into account whether the order is placed in the same time period as the catalog mailing and from a customer receiving the catalog. So, a more meaningful way will be to see whether a catalog mailed in a specific time period (e.g., a quarter) generates an order from the respective category in the same time period. Specifically, we can calculate the purchase probability as the proportion of quarters in which a catalog is mailed from a category and a purchase is made from that category. As we can see from the table, for 20.1 percent of the mailing periods (customer-quarter combination) in which a men's catalog is mailed, an order is placed from men's category. For other category-specific catalogs, this ranges from 16.8 percent for women's to 3.4 percent for outdoor. The same for full product catalog varies from 8.8 percent for men's to 1.7 percent for outdoor.

## *Operationalization of key variables*

Catalog retailers usually change the catalog contents every quarter to feature products that are in high demand during a season. Thus, a customer typically gets a maximum of 90 days to order a product from a catalog before the prices and product offerings are changed. We therefore assume that catalogs received in a 90-day window before the purchase influence customer's purchase behavior. Thus, we operationalize 'own-category catalog mailing' as the number of catalogs from the same category (i.e., the category for which probability of purchase is modeled) mailed in the 90-day period[3] before purchase. Similarly, 'other category catalog mailing' is the total number of catalogs from any other category mailed in the 90-day period. Similar operationalization is used for the full product catalog. The operationalizations of other key variables are given in Table 2. The correlations of key variables used in the model are given in Table 4b.

The correlation table shows that the variables used in the model are not highly correlated. The highest correlation is between the number of women's catalogs and home catalogs (0.392).

## *Model selection*

Our key modeling decisions include the probability of purchase from a category and the dollar amount of purchase. Two of

[3] We however, estimated the model with catalog mailing within 60 days and 120 days prior to the purchase occasions and found that the model using catalog mailing within 90 days offers best fit (lowest DIC and lowest mean deviations of predicted interpurchase time from observed interpurchase time).

Table 4b
Correlation matrix of key variables in the proposed model.

| | Variables | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Number of men's catalog | 1 | | | | | | | | |
| 2 | Number of women's catalog | 0.233 | 1 | | | | | | | |
| 3 | Number of kids catalog | 0.022 | 0.182 | 1 | | | | | | |
| 4 | Number of outdoor catalog | 0.346 | 0.332 | 0.228 | 1 | | | | | |
| 5 | Number of luggage catalog | 0.248 | 0.320 | 0.210 | 0.270 | 1 | | | | |
| 6 | Number of home catalog | 0.239 | 0.392 | 0.244 | 0.387 | 0.366 | 1 | | | |
| 7 | Number of full product catalog | 0.224 | 0.295 | 0.258 | 0.331 | 0.208 | 0.285 | 1 | | |
| 8 | Frequency | 0.000 | −0.008 | −0.034 | 0.003 | 0.035 | 0.024 | −0.241 | 1 | |
| 9 | Holiday quarter | −0.016 | −0.062 | 0.064 | 0.061 | −0.176 | 0.005 | 0.181 | 0.067 | 1 |

the most commonly used approaches to model the probability of purchase are – survival models, which model *when* a purchase will be made and logit/probit models, which model *whether* a purchase will be made in a given time period. Both of these models can be modified to incorporate interdependencies in purchase timings across multiple categories. While multivariate survival models can capture the interdependencies using frailty terms, a correlation matrix can capture such interdependencies in a MVP model. Both approaches have their advantages and limitations. However, the fit of the model with the data is likely to depend on the variability in the data, and the number of non-purchase occasions. Our data are right-censored and represent a multi-spell, multi-category duration type, because they contain multiple purchase occasions (recurrent events) within each of the six categories. A survival model can take care of several issues related to the given data. First, the average number of purchases for a household is very small. Hence, if a model like MVP (which tracks purchase/no purchase incidences in predefined time periods) is used, we will have to include a large number of non-purchases causing a bias in the parameter estimates. Second, for studying the effects of catalog mailing, we need to track catalogs received before a purchase occasion, which means we may not be able to have prespecified time periods. Third, hazard formulation helps us to take care of the censored observations that are very common in a catalog mailing context. Therefore, we propose a customer response model consisting of (1) a multivariate survival model, which describes *purchase timing* and *category choice* and (2) a purchase amount model, which helps explain the *purchase amount* in each purchase occasion.

*Purchase timing and category choice: multivariate proportional hazard (MVPH) model*

Among the many survival models proposed to study purchase timing behavior, one of the most commonly used is the univariate PHM (for e.g., Jain and Vilcassim 1991). In PHM proposed (Cox 1972) and defended by Cox (1975), the instantaneous probability of a household making a purchase in a category, conditional on the elapsed time since the household's last purchase in the same category, is a function of a baseline hazard function and a covariate function. The baseline hazard captures the distribution of the household's IPTs after controlling for all marketing variables (Seetharaman and Chintagunta 2003), and the covariate function, which impacts multiplicatively on the individual hazard function, captures the impact of marketing variables (Seetharaman 2004).

However, univariate PHM survival models fail to account for correlations among multiple observations for each customer. With multiple categories, we need to account for correlations in a household's IPTs across multiple categories (Seetharaman et al. 2005) in addition to correlations among multiple purchase occurrences. Shared frailty models account for dependence that arises from multiple occurrences of the same event (Liu, Wolfe, and Huang 2004). The event times are conditionally independent given a random effect, called frailty (Venkatesan, Kumar, and Ravishankar 2007; Sahu et al. 1997), and ignoring these effects can result in misleading survival estimates (Klein and Moeschberger 2005). One of the most commonly used distributional specifications for the frailty term is gamma (Oakes 1982; Sahu et al. 1997).

Though the inclusion of the above-mentioned frailty term addresses dependence in survival times across multiple purchases, another level of interdependency arises in multi-category purchase context because a household's purchase from one category may be associated with its purchases from other categories. For example, a household might place orders from the men's, women's, and kids categories to give as Christmas gifts. We assume that such dependence in purchases across categories is household-specific and capture it by introducing random effects specific to the household and category. Bolstad and Manda (2001) introduce two gamma-distributed random effects specific to a community (to account for common unobserved factors in a community) and a family (to account for family related unobserved factors across multiple events in the family), which will not capture the variance–covariance of the category-frailty terms. However, a multivariate lognormal frailty approach (Ripatti and Palmgren 2000) can capture the variance–covariance across the frailty terms. We therefore include a gamma-distributed household-specific frailty term and a lognormal-distributed category-specific frailty term in the MVPHM:

$$h_{ijk}(t) = h_{0j}(t)e^{(X_{ijk}\beta_{ij}+\alpha_{ij})}w_i, \quad \text{for} \quad j = 1, \ldots, J, \tag{1}$$

where $h_{ijk}(t)$ is the household's instantaneous probability of making a purchase in product category $j$ at purchase occasion $k$, conditional on time elapsed $t$; $h_{0j}(t)$ is the baseline hazard function in category $j$ at time $t$; $X_{ijk}$ is a vector of covariates corresponding to a purchase in category $j$ at occasion $k$; $w_i$ is the household-specific frailty term – $w_i \sim$ Gamma ($\eta$,$\eta$), and $\alpha_{ij}$ is the category-specific frailty term – $\alpha_{ij} \sim$ MVN (0, $\Sigma_\alpha$). The time $t$ in the baseline hazard function is the IPT in months (calculated as time between two purchase occasions in days/30).

We thus account for two random effects, namely, $w_i$, the household-specific random effect, and $\alpha_{ij}$, the category-specific random effect.[4] The household-specific frailty term captures the unobserved factors that influence a household's purchase decision common across all categories such as the household's tendency to aggregate orders, or its pattern of placing orders during specific seasons. The category-specific random effects capture a household's behavior with regard to placing orders from different categories.[5] The mean of the gamma distribution for $w_i$ is restricted to 1 (Bolstad and Manda 2001) for identification and the variance is $1/\eta$.

Prior research suggests modeling purchase timing jointly with category choice and purchase amount to account for the interdependence of different elements of customers' purchase decision (Bucklin and Gupta 1992; Chintagunta 1993; Kumar, Venkatesan, and Reinartz 2008). We also incorporate customer heterogeneity, by allowing the coefficients to vary across customers using HB estimation. Our purchase sequence model predicts when a customer will purchase from a category (what) and how much; we then integrate this model with the firm's mailing decision to optimize the number and type of catalogs to send at different times to maximize CLV.

*Purchase amount*

The purchase amount is modeled as

$$\begin{aligned} Q_{ik} = {} & \eta_{i0} + \eta_{i1} Q_{ik-1} + \eta_{i2} Q_{ik-2} \\ & + \eta_{i3}\, No.\ \ of\ \ Orders_{ik-1} \\ & + \eta_{i4}\, Average\ \ Order\ \ Size_{ik-1} \\ & + \eta_{i5}\, Crossbuy_{ik-1} \\ & + \eta_{i6}\, Log\ \ of\ \ Recency_{ik-1} \\ & + \eta_{i7}\, No.\ \ of\ \ Men's\ \ Catalog_{ik} \\ & + \eta_{i8}\, No.\ \ of\ \ Full\ \ Product\ \ Catalog_{ik} + \varepsilon_{ik} \end{aligned} \quad (2)$$

where $Q_{ik}$ is the purchase amount at purchase occasion $k$ for customer $i$; $Q_{ik-1}$ and $Q_{ik-2}$ are purchase amounts at purchase occasions $k-1$ and $k-2$ respectively; *No. of Orders*$_{ik-1}$ is total number of orders placed by customer $i$ in the past; *Average Order Size*$_{ik-1}$ is the average amount spend per purchase in the past; and *Crossbuy*$_{ik-1}$ is the total number of product categories purchased so far by customer $i$.

The variables, *Number of Orders*, *Average Order Size* and *Crossbuy* are cumulative variables calculated using purchase history up to that time.

Building separate purchase amount models for each category may provide more insights about the contribution from each category. However, we do not have enough data points for each customer to build separate hierarchical models. We do not expect this inability to affect the optimal catalog mailing decision significantly because the contribution margins across categories do not vary considerably. The contribution margins across categories vary from 0.38 to 0.44. We calculate the weighted average of contribution margins for each purchase occasion based on the categories that a household is likely to buy from (predicted using MVPHM) and the proportion of the number of purchases from each category in the past and use it in the CLV calculation.

*Addressing endogeneity in mailing*

In catalog mailing, the decision to send a full catalog or a catalog specific to a product category may depend on many factors such as prior response rates and other RFM variables. Thus, the 'observed' catalog mailing decision may not be random. There could be some variables that impact the firm's mailing decisions as well as the household's purchase decisions that are unobserved or not available in the dataset leading to potential endogeneity. Estimating the model without accounting for endogeneity will result in biased parameter estimates.

Various solutions such as instrumental variable (IV) method (e.g., Kuksov and Villas-Boas 2008), product-market control approach (Berry, Levinsohn, and Pakes 1995 or BLP), and CF method (Blundell and Powell 2004; Petrin and Train 2010) are proposed in the literature to account for endogeneity. The CF method provides a useful alternative to BLP and IV based methods. Besides being easier to estimate, CF can also be applied in empirical settings for which other methods are not available or are difficult to implement. It can be easily applied in both linear models and a wide variety of non-linear models including mixed logit, exponential, and poisson models (Imbens and Wooldridge 2007). We use the CF approach to account for endogeneity in mailing different types of catalogs. The covariate function in MVPHM is of the following form:

$$y = \exp(x_e\beta_e + x_o\beta_o + r_1) \quad (3)$$

where $x_e$ is a set of *endogenous* variables; $x_o$ is a set of *observable exogenous*; $r_1$ is unobservable variable (*omitted variable*) that is correlated with $x_e$.

The correlation between $x_e$ and $r_1$ is the cause for endogeneity. The idea behind the CF approach is to derive a proxy variable that conditions on the part of $x_e$ that depends on $r_1$. If this can be done, the remaining variation in the endogenous variable will be independent of the error (Petrin and Train 2010). We can first express the endogenous variable, $x_e$ as a function of all exogenous variables and instruments as follows:

$$x_e = z\pi + v_2; \quad (4)$$

where $z$ includes $x_o$ and instruments.

[4] We identify the two random effects, $w_i$ and $\alpha_{ij}$, separately because the generation of $w_i$ is based on all purchases by the household $i$, whereas the random draws of $\alpha_{ij}$ are based only on the household's purchases from category $j$. Also, we were able to recover the values of $w_i$ and $\alpha_{ij}$, using simulated data.

[5] There could be within-category heterogeneity and capturing this in the model may improve the fit. However, the retailer does not have data at the sub-category level to capture within-category heterogeneity.

In this approach, even though $r_1$ and $v_2$ are not independent of each other, $(r_1, v_2)$ is independent of $z$ (i.e., exogenous variables and instruments). Then,

$$E(y|z, x_e) = E(y|z, v_2) = E[\exp(r_1|v_2)]\exp(x_e\beta_e + x_o b_o). \tag{5}$$

If $(r_1, v_2)$ are jointly normal, $E[\exp(r_1|v_2) = \exp(\rho v_2)$. Then,

$$E(y|z, x_e) = \exp(x_e\beta_e + x_o\beta_o + \rho v_2) \tag{6}$$

This suggests a two-step procedure – (i) estimate the reduced form for the endogenous variable and obtain the residual, $v_2'$ and (ii) include this residual in the covariate function (Imbens and Wooldridge 2007). Thus, we first regress the endogenous variable (i.e., the number of catalogs mailed) on observed characteristics and instruments such as prior response rates, number of orders and amount of purchase in a category in the past. In addition to these purchase related instruments, we use mailing cost as an instrument that can influence the mailing decision but not directly related to prior purchase.[6] We have included another variable that links past catalog mailing cost to past order amount in each category, operationalized as the order amount in a particular category per dollar spent on catalog mailing. Each category has two such variables – order amounts per $ of own-category (and full product) catalog mailing. These variables provide both cross-sectional and temporal variations. In the next step, the residuals of these regressions are entered as an additional variable in the respective covariate functions of the MVPHM model. The endogeneity correction using CF is applied in both probability of purchase and purchase amount models.

Prior research suggests that purchase amount may depend on the probability of purchase and accounts for such interdependence in various ways and estimate parameters of both models jointly. In one approach, both the timing and quantity models are multiplied with the probability of belonging to a latent segment (Venkatesan, Kumar and Bohling 2007). In another, Boatwright, Borle, and Kadane (2003) model purchase quantity conditional on purchase timing by using inter delivery time as a covariate in the purchase quantity model. We follow the latter approach and use estimated *time to next purchase* as a covariate in the model. Using *time to next purchase* estimated using the parameters from the MVPHM as a covariate ensures joint estimation of parameters in both models in each iteration of the Bayesian framework. Hence, we replace the $log(recency)$ in the purchase amount model with the estimated *time to next purchase* thus accounting for the interdependence of purchase timing and purchase amount.

We estimate the model in a HB framework to account for unobserved heterogeneity. The coefficients of the covariates (one set for each product category) in the MVPHM and purchase amount models are modeled as functions of a household's key demographic variables such as income, number of people, and the age of the head of the household.

[6] We thank an anonymous reviewer for this suggestion.

*Optimization*

The idea of optimally allocating marketing resources has been highlighted over several decades with early studies (Little 1970; Lodish 1971) using decision calculus and later studies employing experiments and econometric methods as well (for a comprehensive list of studies please refer Gupta and Steenburgh (2008). The studies in general suggest first estimating customer response model and then optimally allocating marketing resources to maximize an objective function. The customer response model in the current study provides the probabilities of households purchasing from a category in a given time. These future purchases are not definite but are probabilistic events, so a manager can only arrive at the expected revenue from each transaction. However, the firm incurs certain known costs, such as production and mailing costs. Thus, the challenge is to define a catalog mailing policy that maximizes the firm's objectives.

The objectives for mailing policies can be either short-term or long-term. Verhoef et al. (2010) discuss these two general approaches – the contact-strategy and myopic "scoring-model" approaches – the retailer can decide which existing customers should receive a catalog or an offer. Short-term objectives include equating marginal costs with marginal returns to obtain the optimal policy (Bult and Wansbeek 1995) and maximizing total expected profit during the planning horizon, subject to cash flow constraints (Bitran and Mondschein 1996). Gönül and Shi (1998) however take a long-term view of profit maximization and use the expected profit in the time interval $(t, \infty)$. Other long-term objectives include a discounted stream of expected future profits (Gönül and Hofstede 2006; Simester, Sun, and Tsitsiklis 2006) or a dynamic profit function that incorporates profits from multiple periods (Elsner, Krafft, and Huchzermeier 2004).

CLV is found to be a better customer selection metric than past customer value, customer lifetime duration (Venkatesan and Kumar 2004), or RFM (Reinartz and Kumar 2003). Malthouse and Derenthal (2008) suggest that approaches like RFM which rely on one previous contact (or single-proxy) performs poorly and are riskier compared to aggregated models. CLV is also linked to financial performance (Gupta and Zeithaml 2006; Kumar and Petersen 2005) and shareholder value (e.g., Berger et al. 2006; Gupta, Lehmann, and Stuart 2004). Empirical evidence suggests that using CLV as the objective function leads to optimal allocations of marketing budgets (Berger et al. 2002; Reinartz, Thomas, and Kumar 2005) and is equivalent to maximizing the long-run profitability and financial health of a company (Gupta and Zeithaml 2006). Thus, we use the CLV of all households as the objective function.

*Objective function for optimization*

We compute CLV using a formula adapted from Venkatesan and Kumar (2004). $CLV_i$ of customer, $i$ is given by:

$$CLV_i = \sum_{k=1}^{K} \frac{CM_{i,k}}{(1+r)^{k/frequency_i}} - \sum_{l=1}^{n} \frac{\sum_j c_{i,m,l} \times x_{i,m,l}}{(1+r)^l} \tag{7}$$

where $CM_{i,k}$ is the contribution margin from household $i$ from the $k$th purchase; $c_{i,m,l}$ is the cost of sending a catalog of type $m$ to household $i$ in year $l$; $x_{i,m.l}$ is the number of catalogs of type $m$ sent to household $i$ in year $l$; $m$ ranges from 1 to 7 (six category-specific and one full product catalog); $K$ is the maximum number of purchases from a category, such that $K = n \times frequency_i$; and $n$ is the number of years to forecast.

We use a finite time horizon (ten quarters) to forecast CLV, following prior research (Rust, Lemon and Zeithaml 2004; Venkatesan and Kumar 2004) and employ Genetic Algorithm (GA) to optimize the mailing decisions, subject to CLV maximization. The GA approach uses parallel evolutionary search algorithms to locate parameters that maximize the objective function (Venkatesan, Krishnan, and Kumar 2004) and has a higher probability of convergence when the number of parameters is large and the parameter space is multimodal (Del Moral and Miclo 2001).

We compare the CLV in the optimal mailing policy, $\text{CLV}_{\text{Optimum}}$ with $\text{CLV}_{\text{Existing}}$, or the CLV if the firm follows its existing mailing policy, and with $\text{CLV}_{\text{Benchmark}}$, or the CLV if the firm followed a benchmark policy and sent one full product catalog per quarter if the household had purchased from more than one category before and one category-specific catalog per quarter for every category purchased previously. To account for scenarios in which the firm suffers serious budget constraints, we also compare $\text{CLV}_{\text{Optimum}}$ with three mailing policies under budget constraints – $\text{CLV}_{\text{Budget20}}$, $\text{CLV}_{\text{Budget40}}$, and $\text{CLV}_{\text{Budget60}}$ – that set the total cost of the catalog mailing at 20 percent (severe), 40 percent (moderate), or 60 percent (small) of the costs in the existing policy.

## Results and discussion

We estimate the joint model of purchase timing (i.e., MVPHM with category-specific and household random effects[7]) and quantity (hierarchical regression) in a Bayesian framework. As explained before, we use CF approach to account for endogeneity in catalog mailing. In the MCMC estimation, we treat the first 25,000 iterations as burn-in and the remaining 5000 iterations to estimate parameters of the model. The joint model has a likelihood of −13,087 and a deviance information criterion (DIC)[8] of 37,034.

### *Parameter estimates of the determinants of the probability of purchase*

The parameter estimates from the joint model appear in Table 5a and reflect the mean values of the household-specific parameters for our sample. Thus, the signs of the parameters only indicate the sign of the mean value, not necessarily the general relationship between the covariates and dependent variables. We identify a coefficient as significant at 5 percent (or 10 percent) level based on whether the value '0' for the coefficient falls within the 95 (or 90) percentile of the coefficient distribution.

The coefficients of *share of category purchase* are 1.768 (men's), 1.958 (women's), 2.015 (kids), 0.372 (outdoor), 1.677 (luggage), and 2.193(home). These positive and significant values for all product categories suggest that a household with a higher purchase share from a category in the past has higher probability of purchase from that category. This may be because of a higher intrinsic need to purchase from that category compared to other categories or the increased familiarity with products in the category driving the future purchases from the same category.

*Frequency of purchase* has a strong positive relationship with the purchase probability in all categories, as is evident from the positive coefficients of 0.253 (men's), 0.329 (women's), 0.122 (kids), 0.046 (outdoor), 0.154 (luggage), and 0.171 (home). A household that purchases more frequently is more likely to place an order in a specific category compared to one that purchases infrequently. Thus, frequency not only affects the overall purchase probability from the retailer, as prior research shows, but also positively influences purchase probability within each category. The positive influence of frequency on cross-buying, leading to purchases from additional categories (Kumar, George, et al., 2008), may explain the positive impact of frequency on the purchase probability from a category. Greater trust in the firm due to more frequent interactions might prompt households to spend greater shares of their wallets on different categories offered.

*Own-category catalog mailing* has a strong positive impact on the probability of purchase from a category. The number of own-category catalogs that a household receives in the preceding 90 days impacts the probability of purchase from that category, as the positive sign of the coefficient for all the categories shows: men's (0.319), women's (0.468), kids (1.184), outdoor (0.034), luggage (0.151) and home (0.254). The coefficient for the *full product catalog mailing* is negative for all categories,[9] which indicates that the full product catalog is ineffective in terms of increasing the purchase probability within a category. However, the full product catalogs mailed during the holiday quarter and during school season have a positive coefficient signifying that the negative impact of full product catalogs is reduced if mailed during the holiday quarter or school season. This could be because a majority of purchases during the holiday quarter are for giving away as gifts and one may be more open to selecting a product from available options in a category rather than selecting a specific product of his or her choice when making purchases for his/her own consumption. During

[7] We compared this model with a number of competing models such as multivariate probit, univariate hazard models and multivariate hazard models with no/one random effect (as shown in the Technical appendix) and found a better fit for the proposed model.

[8] The DIC is defined as the classical estimate of fit, plus twice the effective number of parameters (representing complexity of the model). Thus, DIC can be considered as a Bayesian measure of fit (Spiegelhalter et al. 2002). We compare different models and the fit of functional forms of covariates by looking at DIC values with lower values indicating better fit.

[9] We also estimated models with quadratic term for full catalog mails and found that both the level and square terms for full catalogs are negative for all the categories.

Table 5a
Results from the joint model of purchase timing and purchase amount.

| Variables | Parameter estimates | Variables | Parameter estimates | Variables | Parameter estimates |
|---|---|---|---|---|---|
| $\gamma$[a] | 1.066 | λ (luggage) | 0.024 | Frailty (kids) | −0.016 |
| λ (men's) | 0.023 | λ (home) | 0.014 | Frailty (outdoor) | 0.016 |
| λ (women's) | 0.019 | Mean household-specific frailty | 1.002 | Frailty (luggage) | 0.013 |
| λ (kids) | 0.025 | Frailty (men's) | 0.007 | Frailty (home) | −0.009 |
| λ (outdoor) | 0.038 | Frailty (women's) | −0.008 | | |

Covariates of probability of purchase

| Covariates | Men's | Women's | Kids | Outdoor | Luggage | Home |
|---|---|---|---|---|---|---|
| Share of category purchase in the focal category | 1.768[**] | 1.958[**] | 2.015[**] | 0.372[**] | 1.677[**] | 2.193[**] |
| | (0.381)[b] | (0.248) | (0.459) | (0.321) | (0.477) | (0.765) |
| Frequency (across all categories) | 0.253[**] | 0.329[**] | 0.122[**] | 0.046[**] | 0.154[**] | 0.171[**] |
| | (0.092) | (0.078) | (0.067) | (0.056) | (0.108) | (0.190) |
| Holiday quarter indicator | 0.914[**] | 0.835[**] | 1.134[**] | 0.678[**] | 0.754[**] | 1.287[**] |
| | (0.206) | (0.186) | (0.247) | (0.324) | (0.265) | (0.454) |
| School season indicator | 0.624[*] | 0.654[**] | 1.043[**] | 0.823[**] | 1.965[**] | 1.409[**] |
| | (0.161) | (0.135) | (0.208) | (0.497) | (0.645) | (0.582) |
| Own-category catalog mails | 0.319[**] | 0.468[**] | 1.184[**] | 0.034[*] | 0.151[*] | 0.254[*] |
| | (0.128) | (0.116) | (0.142) | (0.385) | (0.104) | (0.165) |
| Other-category catalog mails | −0.096[**] | −0.064 | −0.045 | −0.227[*] | 0.102 | −0.045 |
| | (0.027) | (0.022) | (0.117) | (0.164) | (0.036) | (0.046) |
| Full catalog mails | −1.043[**] | −1.008[*] | −1.751[**] | −2.357[**] | −1.561[**] | −1.947[*] |
| | (0.149) | (0.073) | (0.324) | (0.935) | (0.356) | (0.452) |
| Holiday Qtr × full catalog mailing | 0.786[**] | 0.644[*] | 1.338[**] | 1.537[**] | 1.090[**] | 1.528[**] |
| | (0.132) | (0.064) | (0.205) | (0.609) | (0.374) | (0.624) |
| School season × full catalog mailing | 0.937[**] | 0.822[**] | 0.905[**] | 0.964[**] | 1.175[**] | 0.946[**] |
| | (0.156) | (0.093) | (0.125) | (0.347) | (0.427) | (0.278) |

| **Covariates of purchase amount** | | | | | |
|---|---|---|---|---|---|
| Intercept | 10.149[**] | Holiday quarter indicator | 6.245[**] | Number of women's catalogs | 1.462[*] |
| | (6.024) | | (7.019) | | (0.762) |
| 1-Period lag of purchase amount | −0.102 | Indicator for women's order | 18.923[**] | Number of kids catalogs | 6.806 |
| | (0.127) | | (11.026) | | (5.231) |
| 2-Period lag of purchase amount | −0.062 | Indicator for kids order | 7.046 | Number of outdoor catalogs | −2.813 |
| | (0.165) | | (7.136) | | (8.091) |
| Cumulative number of orders | 0.069[**] | Indicator for outdoor order | 13.213[*] | Number of luggage catalogs | −0.346 |
| | (0.582) | | (12.723) | | (8.051) |
| Log of estimated time to next purchase | 6.724[**] | Indicator for luggage order | 4.039[*] | Number of home catalogs | 3.095 |
| | (0.908) | | (10.126) | | (10.114) |
| Average order size | 0.278[**] | Indicator for home order | 16.838 | Number of full product catalogs | 3.051[*] |
| | (0.097) | | (16.535) | | (2.341) |
| Cross-buying | 8.015[**] | Number of men's catalogs | 1.519[*] | | |
| | (6.386) | | (1.625) | | |
| **Model performance measures** | | | | | |
| Log-likelihood | −13,087 | Deviance information criteria | 37,034 | Pseudo $r$-square | 0.708 |

[a] Even though the shape parameter is held constant across categories, it is allowed to vary freely thus taking care of variability in the data. Moreover, the results from univariate models show that the shape parameters do not vary significantly across categories (0.995–1.022).
[b] Values in parentheses are the standard deviations of parameters across households.
[*] Significant @ 10 percent.
[**] Significant @ 5 percent.

school season, customers tend to aggregate orders and full product catalog may help in the selection of products from different categories needed for the school year. The result is mixed for *other category catalog mailing*; the impact of this variable on the probability of purchase from a category is weak (significant only at 10 percent level) and negative for most of the categories, and positive for the luggage category.

The negative coefficients for *other category catalog mailing* and *full product catalog mailing* may be attributed to lost opportunity. A customer who would have purchased from a category had he or she received a catalog from the focal category, instead receives either catalogs from categories that are not in his/her consideration or a full product catalog where there is only limited coverage of the products for the category of interest. Also, the full product catalog (and catalogs from other categories) has the potential to distract/divert customers' attention to categories other than the focal category because all categories are featured in the same catalog. For instance, when a customer who was considering buying from women's category receives a full product catalog, she comes across products from other categories and might decide to make a purchase from another category, say kids, instead. Further, studies have shown that more variety or choice can be demotivating and can lead to decision avoidance. Iyengar and Lepper (2000) find that when given more choices, consumers are less likely to buy than when exposed to limited choices. In their study, 30 percent of consumers presented with 6 varieties of jam made a purchase compared to 3 percent who were exposed to 24 varieties of jam. This decision avoidance may be because of higher cognitive burden in the extensive-choice condition (Norwood 2006) or to avoid experiencing regret from making a suboptimal decision (Irons and Hepburn 2007). According to Daniel McFadden, an economist at the University of California, Berkeley, consumers find too many options troubling because of the "risk of misperception and miscalculation, of misunderstanding the available alternatives, of misreading one's own tastes, of yielding to a moment's whim and regretting it afterwards," combined with "the stress of information acquisition.[10]" Desmeules (2002) proposes that there exists a point in the amount of variety where customers experience regret caused by heightened expectations, inability to conduct all the evaluations required to make a choice, or both, resulting in a failure to choose at all. This is particularly relevant in our study context where full product catalog does not contain information on all the products in a category thus presenting incomplete information for the customer's evaluation.

In addition to the potential adverse effects of information overload and incongruent shopping environment explained, a customer's response to full product catalogs might also suffer from over-mailing. Full product catalogs are mailed in almost all time periods and sometimes multiple catalogs in the same mailing period. Essentially, a customer is receiving full catalogs in many time periods he/she has no intention of buying from a category. Over-mailing can cause irritation toward full catalog mailing as direct marketing literature suggests. The literature shows that direct mailing results in irritation (Van Diepen, Donkers, and Franses 2009b) and individuals who feel they receive too much direct mail may have lower intentions to respond to the mail they receive (Naik and Piersma 2002). Leeflang et al. (2000) also suggest that the marginal returns to excessive direct mailings might not only be decreasing, but could well become negative due to super-saturation. We also checked the correlation of purchase from a category with the full and other category catalog mailings. The correlation of category purchase incidences with full product catalog mailing is either negative or insignificant and it varies from −0.05 to 0.02. Similar negative but low correlations are also observed between category purchase incidence and other category catalog mailing. Thus, we can see that only own category catalog mailing has a positive impact on the probability of purchase from the focal category.

*Holiday quarter and school season indicators*: The coefficients for the holiday quarter are significant and positive for all categories indicating that there is a lift in the probability of purchase for all categories during the holiday quarter. Similar increases in probability of purchase are also present for School Season. This could be attributed to the price promotions that are offered during these quarters and significantly higher proportion of sales in those quarters.

The effects of the covariates on the probability of purchase vary from one household to the other and the HB estimation enables us to estimate the household specific coefficients.[11]

The correlation matrix of the category-specific random effects is given in Table 5b. The table shows that the correlations between the category-specific random effects are negligible after accounting for the covariates in the model.

### *Parameter estimates of determinants of the purchase amount*

We provide the results pertaining to the purchase amount in Table 5a. The model achieves a pseudo *r*-square of 70.8 percent, which means that the model explains considerable variation in the dollar amount of purchase. Also, the signs of parameter estimates for the key covariates are in the expected direction. The total *number of prior orders* has a positive relationship (0.069) with the purchase amount, which indicates that as the household's relationship with the firm deepens (more orders), the household becomes more likely to place larger orders. The *average order size* (0.278) also has a positive relationship with the purchase amount, as expected. However, the previous purchase amount (1-period lag) and purchase amount two periods before (2-period lag) do not have a significant relationship with the purchase amount.

*Cross-buy* has a strong positive influence (8.015) on the purchase amount, further validating its positive impact on the purchase amount per order (Kumar, George, et al., 2008), profitable lifetime duration (Reinartz and Kumar 2003), and CLV

[10] The Economist (December 16, 2010), "The Tyranny of Choice – You Choose", (accessed May 10, 2013), [http://www.economist.com/node/17723028].

[11] The distribution of household-specific coefficients can be provided upon request.

Table 5b
Correlation matrix of $\alpha_{ij}$ for the category frailty terms.

| | Men's | Women's | Kids' | Outdoor | Luggage | Home |
|---|---|---|---|---|---|---|
| Men's | 1 | 0.05 | −0.07 | 0.04 | 0.05 | −0.03 |
| Women's | 0.05 | 1 | 0.03 | 0.01 | 0.06 | 0.06 |
| Kids' | −0.07 | 0.03 | 1 | 0.01 | 0.01 | −0.01 |
| Outdoor | 0.04 | 0.01 | 0.01 | 1 | 0.07 | −0.03 |
| Luggage | 0.05 | 0.06 | 0.01 | 0.06 | 1 | −0.01 |
| Home | −0.03 | 0.06 | −0.01 | −0.03 | −0.01 | 1 |

(Venkatesan and Kumar 2004). The log of the *estimated time to next purchase* positively (6.724) impacts purchase amount, which suggests that the longer the time lapsed from the previous purchase, the higher the purchase amount up to a point beyond which we find no significant change. This may be because of aggregation of orders to reduce shipping costs or purchases coinciding with holiday seasons.

The holiday quarter indicator has a positive (6.245) influence on the purchase amount indicating the effect of price promotion on sales during this quarter. Sending men's (1.519), women's (1.462), kids (6.806), and full (3.095) catalogs have a significant positive effect on the purchase amount. However, mailing catalogs in other categories did not have any significant impact on the purchase amount.

### *Impact of optimal catalog mailing*

Since we use household-specific coefficients (rather than average values) for optimization, we predict purchase behaviors of households used in the estimation sample. We select a random sample of 78 households (i.e., 10 percent)[12] from the estimation sample, but use a different time frame (January 2002–June 2004) for optimization and calculation of CLV than the one used for model building (January 1998–December 2001). We divide the time period to 10 quarters and optimize catalog mailing for 10 quarters. Catalog mailing is developed on a quarterly basis in order to reflect the firm's practice of changing the contents of the catalogs for each quarter. This also accounts for the fact that purchases from a catalog are usually made within a 90-day period. The inputs to the optimization problem are the model parameters and data available before the validation period. The optimization problem is set up such that (i) based on the inputs, the model predicts the probability of purchase from each category and the purchase amount in Quarter 1 of the validation period, (ii) updates the values of the covariates for Quarter 2 using the predicted values for Quarter 1, and (iii) repeats the steps for subsequent quarters. The GA based optimization package[13] accomplishes these tasks simultaneously and arrives at the number of category-specific and full product catalogs to send to each household in each of the 10 quarters. To compute the CLV of each household, we use the number and amount of orders that we expect the household to place if it receives catalogs according to the optimal catalog mailing policy.

We performed model validation before developing the optimal mailing policy. We used the parameter estimates from the full model to predict purchase probability and purchase amounts in the validation period, January 2002–June 2004, and assessed to what extent the model is able to predict purchases accurately. The model is able to predict 89 percent of cases accurately. We also calculated CLV for 10 quarters (January 2002–June 2004) taking into account the actual number of catalogs mailed during this period. The predicted CLV and the number of orders are then compared with the CLV based on actual purchases during this period.

The results in Table 6a show that the model is able to predict CLV precisely, the difference from actual CLV being only 8.1 percent. Also, the difference between predicted and actual dollar amount of purchases for the selected households during the validation period is marginal (6.7 percent). Even though there is slight over prediction (11.8 percent) in the number of orders placed by households, the negligible prediction error in CLV and purchase amount gives us confidence in the CLV calculations under different scenarios that are given in Table 6b.

The outcome of the optimization in Table 6b shows that CLV[14] under the existing mailing policy for 10 percent of the households chosen is \$8,581, whereas $\text{CLV}_{\text{Benchmark}}$ is \$10,080 or an increase of 17.5 percent over $\text{CLV}_{\text{Existing}}$. The $\text{CLV}_{\text{Budget20}}$, which depicts a severe budget constraint, is \$9,986 or 16.4 percent more than $\text{CLV}_{\text{Existing}}$ and slightly less than $\text{CLV}_{\text{Benchmark}}$. The mailing policy with a 40 percent (i.e., moderate) budget constraint would generate a $\text{CLV}_{\text{Budget40}}$ of \$11,218, 30.7 percent greater than $\text{CLV}_{\text{Existing}}$, and that with a small budget constraint, or 60 percent of the actual catalog mailing cost, would generate $\text{CLV}_{\text{Budget60}}$ of \$11,875, 38.4 percent higher than $\text{CLV}_{\text{Existing}}$. Thus, as we relax the budget constraints, the CLV increases from \$9,986 to \$11,875. However, there is no improvement in CLV

[12] The decision to use only 10% of the households rather than all households is based on the computational ability of the optimization package. While optimization for all households in the validation sample is feasible, it is time consuming and puts an enormous computational burden on the optimization package without additional insights.

[13] We use Evolutionary Solver in Excel to do optimization based on GA. The various constraints we apply include – ensuring positive integer values for the number of different catalogs (total of six category-specific and full catalogs) sent in each of the 10 quarters and the budget constraint for catalog mailing cost.

[14] The CLV values reported (except the observed CLV under existing mailing policy) are the predicted values based on the parameter estimates and the optimization algorithm. The improvement in CLV is not validated in a field experiment. However, negligible prediction error in Table 6a suggests that the firm will realize CLVs similar to what are predicted if they are to follow the proposed mailing policy.

Table 6a
Model validation results.

| | Observed values | Predicted values | Percentage difference |
|---|---|---|---|
| **Predicted versus actual CLV under existing mailing policy** | | | |
| Customer lifetime value (CLV) | 8,581 | 9,291 | 8.1 |
| Number of orders | 296 | 326 | 11.8 |
| Total amount of purchase | 27,343 | 29,343 | 6.7 |

Table 6b
Comparison of different catalog mailing policies.

| Outcome of mailing policy | Firm's existing mailing policy | Benchmark mailing policy | Mailing policies under budget constraints[a] | | | Optimal mailing policy (without budget constraint)[c] |
|---|---|---|---|---|---|---|
| | | | 20 percent | 40 percent | 60 percent | |
| Customer lifetime value (CLV)[b] | $8,581 | $10,080 | $9,986 | $11,218 | $11,875 | $11,875[d] |
| Percent increase in CLV over existing mailing policy | | 17.5 percent | 16.4 percent | 30.7 percent | 38.4 percent | 38.4 percent |
| **Number of catalogs sent** | | | | | | |
| Men's | 255 | 432 | 148 | 235 | 319 | 319 |
| Women's | 344 | 419 | 153 | 242 | 335 | 335 |
| Kids | 267 | 261 | 129 | 197 | 277 | 277 |
| Outdoor | 243 | 145 | 94 | 125 | 163 | 163 |
| Luggage | 296 | 375 | 124 | 194 | 286 | 286 |
| Home | 282 | 221 | 128 | 200 | 295 | 295 |
| Category-specific catalogs | 1687 | 1853 | 776 | 1193 | 1675 | 1675 |
| Full product catalogs | 1164 | 509 | 81 | 285 | 368 | 368 |
| Total number of catalogs | 2851 | 2362 | 857 | 1478 | 2043 | 2043 |
| Total cost of catalog mailing | $2,675 | $1,761 | $535 | $1,068 | $1,451 | $1,451 |

[a] Under budget-constrained mailing policies, the total cost of the catalog mailing is set at 20 percent, 40 percent, or 60 percent of the total cost of catalog mailing under firm's existing mailing policy.
[b] The period for which we compute CLV is two and half years, and the reported CLV for each mailing policy is the sum of the CLV for 10 percent of the households.
[c] The cost of catalog mailing under the optimal catalog mailing policy without constraint ($1,451) is 54 percent of the cost of catalog mailing with the firm's existing mailing policy ($2,675).
[d] There is no improvement in CLV when we relax the budget constraint beyond 60 percent.

when we relax the budget constraint beyond 60 percent of the actual catalog mailing cost. Therefore, $CLV_{Optimum}$ is the same as $CLV_{Budget60}$, $11,875 and the cost of mailing catalogs is only 54 percent of the actual catalog mailing cost. The optimal catalog mailing policy would have generated 38.4 percent more CLV than the existing mailing policy and 17.8 percent more than the benchmark mailing policy. Part of the reason why we are seeing such a high improvement in CLV is the poor mailing practices used by the firm in the past. Thus the increase in CLV is a result of both better targeting, as evidenced by the greater total amount of purchases by households, and reduced catalog mailing costs. With its existing catalog mailing policy, the firm sent 2,851 catalogs to the 10 percent of households selected. Under the existing mailing policy, the company overspends on mailing for many customers owing mainly to poor customer selection. Along with sending more catalogs per customer, many of the customers receive catalogs that do not interest them. With more accurate prediction of who will buy from which category during a specific period, the optimal catalog mailing policy suggests that the firm needs to send only 2,043 catalogs as a result of which the total cost of mailing declines from $2,675 to $1,451.

The optimal catalog mailing policy also redistributes the type of catalogs sent to each household, one notable change being the reduction in the number of full product catalogs. With its current catalog mailing policy, the firm sends 1,687 category-specific catalogs and 1,164 full catalogs and would send 1,853 and 509 catalogs, respectively, in the benchmark policy. However, the optimal catalog mailing policy recommends sending only 1,675 category-specific and 368 full product catalogs, which is substantially fewer full product catalogs but still achieves the highest CLV. Another interesting aspect is that the number of each category-specific catalog in the optimal mailing policy is different from those under existing policy. For instance, there is considerable increase in the number of men's catalogs and reduction in the number of outdoor catalogs under the optimal policy compared to the existing mailing policy. These differences occur because of the differential impact these catalogs have on purchase probability and purchase amount. Also, the set of households that are identified to receive a particular category-specific catalog under the optimal mailing policy is not identical to those that received that type of catalog under existing policy indicating reassignment of catalogs among households.

## Managerial implications

The findings of this study have several implications for managers of catalog retailing and direct mail firms, especially those dealing with multiple, category-specific catalogs. One key benefit for retailers is the potential for greater profits from optimal catalog mailing policies, which helps to target customers with the right catalogs and thereby achieve the highest CLV in comparison to other mailing policies. The optimal mailing policy under severe budget constraint ($CLV_{Budget20}$) generates 16.4 percent more CLV than the current mailing policy and that under small budget constraint ($CLV_{Budget60}$) generates same CLV as $CLV_{Optimum}$. The optimal solution under severe budget constraint shows that predicted CLV could be increased substantially (from US$ 8,581 to 9,986) while spending only 20 percent of the current budget for mailings. This is in line with findings from a recent study (Montoya, Netzer, and Jedidi 2010) on optimal allocation of detailing and sampling efforts in pharmaceutical industry suggests that optimal allocation leads to substantial increase in profitability while reducing marketing spending by 20 percent. Managers can therefore reallocate the resources they save with budget constraints to other customers or to acquire new customers with high potential, which is especially important when firms face difficult financial situations.

The study provides valuable insights into the relative impact of mailing different catalogs on the purchase behavior of households. The purchase probabilities for all categories increase with mailing own-category catalogs, making them far more effective than full product catalogs. The lower effectiveness of the full product catalogs might be a result of consumers being less willing to leaf through bulkier catalogs to choose from a limited number of products featured in each category.

Another interesting insight pertains to relative impacts of each category-specific catalog on purchase timing and quantity decisions. The parameter estimates of own-category catalogs reveal that their impact on the probability of purchase varies, such that men's, women's, and kids catalogs sent during the 90 days prior to a purchase occasion affect the probabilities of purchase in respective categories much more than sending outdoor, luggage, and home catalogs. The relatively smaller impacts of mailing certain catalogs on the probability of purchase may be because of the poor design of the catalogs, a poor selection of featured products, or poor targeting. Identifying such differences can help firms decide which catalog has the greatest impact on generating orders and take steps when necessary to redesign certain catalogs, include the right selection of products, or both, to improve their effectiveness.

Further, the proposed model helps managers to target the right households for cross-selling different product categories. It explains purchase behavior (both probability of purchase and purchase amount) in six categories in terms of covariates, which facilitates computing the probability of each household buying from a category (including categories with no prior purchases) in a given time period. The retail manager can therefore identify the category a household is most likely to purchase in the next time period and target them with the right catalogs, which not only increases the number of orders from categories purchased before but also encourages cross-buying.

*The economic impact of redistribution of catalogs*

The economic impact of such redistribution of catalogs is further illustrated in Table 7.

The optimal mailing policy is able to generate more CLV from customers through (i) a reduction in catalog mailing cost and (ii) generation of more orders owing to reallocation of category-specific and full catalogs across customers and across mailing periods. The proposed mailing policy results in a savings of $1,224 in catalog mailing cost, which translates to $1,028 (taking into account average discount factor) gain in CLV. This is 31 percent of the total improvement in CLV over the existing mailing policy. The remaining savings come from a reallocation of catalogs among customers and across different time periods for the same customer. The positive impact of reallocation of catalogs on CLV is evident from the table. Under the current mailing policy, approximately 69 percent of the catalog mailing cost is incurred for customers who did not make any purchase (Groups I and II) in the validation period (i.e., 10 quarters). On the other hand the percentage of catalog mailing cost incurred for customers who were not predicted to purchase as per the proposed mailing policy is only 15 percent (Groups I and III). The economic impact of reallocation of catalogs is clearly evident in the case of Group II (those who did not actually purchase but are predicted to purchase in the proposed mailing policy). Even though the firm mailed 1,061 category-specific catalogs and 677 full catalogs (i.e., 60 percent of the total catalog mailing cost) in the existing mailing policy, it could not generate a single order from this group. On the contrary, the proposed mailing policy suggests sending fewer catalogs and generates a significant amount of revenue by reallocating the catalogs. A comparison of mailing in each quarter to customers in the validation sample under both existing and proposed mailing policy shows that the firm would have sent different number of category-specific catalogs 68 percent of the time and full catalogs 87 percent of the time suggesting a great deal of reallocation of catalogs. This reallocation of catalogs would have generated a CLV of $4,193 from this group, thus showing that implementation of the proposed mailing policy results in a higher CLV and thereby, better financial benefits for the retailer. This is critical for catalog retailers especially considering the fact that the ROI for catalogs is low compared to online channels such as email even though the response rate for catalogs is comparatively much higher.[15] By following optimal catalog mailing policy, retailers can reduce mailing cost while increasing revenue leading to substantial improvements in ROI.

## Academic contributions

Our study contributes to academic research in several ways. This is the first study to identify the impact of category-specific versus full product catalogs in generating sales in a specific category in a multi-category catalog mailing context. The fact that category-specific catalogs are more effective compared to full product catalogs supports the notion that when a goal – oriented

[15] DMA study (June 2012) based on a survey of 481 companies in April 2012 reveals that catalog has a response rate of 4.26% when sent to house lists while email has 0.12% response rate. Email has a ROI of 28.5 while ROI for catalog mailing is 7.0 (Marketingcharts.com 2012).

Table 7
The economic impact of redistribution of catalogs as per proposed mailing policy.

| | Group I (*No observed* purchase and *not predicted* to purchase) | Group II (*No observed* purchase, but *predicted* to purchase) | Group III (*Observed* purchase, but *not predicted* to purchase) | Group IV (*Observed* purchase, and *predicted* to purchase) |
|---|---|---|---|---|
| CLV (observed) | $−95 | $−754 | $1,187 | $8,243 |
| CLV (optimal policy) | $−130 | $4,193 | $−55 | $7,867 |
| **Catalog mailing under existing mailing policy** | | | | |
| # of category-specific catalogs | 97 | 1061 | 64 | 464 |
| # of full catalogs | 117 | 677 | 55 | 316 |
| Percent of total mailing cost | 9 percent | 60 percent | 4 percent | 27 percent |
| **Catalog mailing under optimal mailing policy** | | | | |
| # of category-specific catalogs | 128 | 861 | 76 | 610 |
| # of full catalogs | 45 | 158 | 26 | 139 |
| Percent of total mailing cost | 9 percent | 48 percent | 6 percent | 37 percent |
| **Re-distribution of catalogs across different mailing periods**[a] | | | | |
| No change in the # of category-specific catalogs | 17 percent | 32 percent | 27 percent | 42 percent |
| Increase/decrease in the # of category-specific catalogs | 83 percent | 68 percent | 73 percent | 58 percent |
| No change in the # of full product catalogs | 24 percent | 13 percent | 13 percent | 9 percent |
| Increase/decrease in the # of full product catalogs | 76 percent | 87 percent | 87 percent | 91 percent |

[a] This is calculated based on whether optimal mailing policy suggests mailing different number of catalogs to customer, $i$ during quarter, $q$.

customer (with a desire to purchase from a category) is exposed to a more analytic shopping environment such as a category-specific catalog, there is congruence which results in higher purchase probability.

The study finds differences across various category-specific catalogs in generating sales. We model the purchase probabilities in different categories, while the existing catalog mailing papers model the probability of purchase (from the firm rather than a specific category). We incorporate key exchange characteristics, such as frequency, and share of category purchase in our model, in addition to the catalog mailing effort by the firm. We also account for individual response differences by using customer characteristics.

We apply a new methodology – MVPH with category and customer-level random effects that take into account the interdependence in purchase timing across multiple categories. This can be very useful in scenarios where purchase frequency is low (such as catalog mailing) and can be used as an alternative for MVP in many shopping basket contexts. Because of the specific structures of MVPHM (joint estimation of purchase probabilities) and the Bayesian estimation (i.e., borrowing information from others), the model is able to predict who are likely to buy from which category in a given time period.

Addressing endogeneity in survival models, a commonly used approach in modeling purchase timing, has remained a challenge for researchers. To the best of our knowledge, CF approach has not been used in marketing literature to address endogeneity in survival models. We use a CF approach in a multivariate hazard model to account for endogeneity in mailing decision in multiple categories, thereby illustrating its application in purchase timing models.

The proposed model applied in a retailer to consumer (R-to-C) context as in this study can be adapted to a retailer to business (R-to-B) context. Some businesses follow the practice of sending catalogs to both consumers and businesses. For instance, retailers like Staples or Office Max face the challenge of deciding between sending a 500 or 1,000 page full product catalog or a 30–50 page catalog from a specific category such as Office Supplies or Furniture. However, one needs to keep in mind that the purchase context in R-to-B is different from R-to-C in terms of the volumes purchased, frequency of purchase, and timing of purchase, among others. As a result, the roles of full and category-specific catalogs will be different and some of the variables such as 'holiday quarter indicator' and 'school season' will have different meanings. Thus, even though the specific variables in the model may be different, a model like the one proposed will help retailers to identify the relative impacts of these catalogs and send the right catalog to businesses to maximize profits.

Another contribution of the paper is the use of optimization (which is so far done when there is only one type of catalog) in a multi-category catalog mailing context.

### *Future research directions*

In the data we used for model building, Internet transactions comprise only 5–6 percent of the total sales even though the data contain transactions from all channels – telephone, stores, and Internet. The extent of online search and use of online catalogs are limited during the period of study, which we acknowledge is a limitation of the study. The multichannel marketing context has evolved over the years with an increase in the share of purchase through online channels and more consumers using online search. Even in the changed retailing context, catalogs continue to function as an important marketing tool. Catalogs could be very effective in driving traffic to retail websites. According to 2006 DMA Response Rate Report, catalogs lead all media except telephone in traffic building with a response rate of 10.34 percent in terms of the number of prospects who visit a store, website or place of business as a result of contact. Even though the role of catalog is changing, the premise of identifying the relative impacts of full versus category-specific catalogs and optimizing catalog mailing remains more or less the same. Researchers can employ a model similar to our proposed model to link catalog mailing with online search and assess the impact of catalogs in triggering online/offline search. The new approach should essentially have an additional model that shows web traffic as a function of catalog mailing along with other covariates, and purchase timing and purchase amount models with web-traffic or online search as a covariate and jointly estimate all three models.

While we believe that category-specific catalogs are more effective compared to full product catalogs for an analytic or goal-oriented customer, it will be interesting to see whether an intuitive environment like the full catalog is more appealing to an experiential shopper who will extend the search online, which may result in a future purchase. In that sense, the findings of the study can motivate investigation of relative impacts of category versus full catalogs in both generating direct sales and traffic building, online and to the store.

We have incorporated various exchange characteristics and customer characteristics in our study. However, additional research could incorporate price promotions as covariates to identify their impact on purchase behavior. Our approach opens a way to analyze the impact of category-specific variables such as share of category purchase (addressed in this study) and other potential variables such as product mix within specific categories (in future research).

Customers who are interested in purchasing a product category, but not from the focal firm, may find a catalog from that category interesting and will have an opportunity to familiarize themselves with the products that may lead to cross-buying (i.e., buying from a category the customer has not purchased from). Thus, another interesting research that can stem from this study is to analyze the role category-specific catalogs and full product catalogs play in cross-buying.

Catalog mailing design can play a major role in purchase decisions and hence can affect the response rates and CLV. Feld et al. (2012) suggest that direct mail characteristics directly influence opening and keeping rates of mail, which influences the response rate. However, Fiore and Yu (2001) find that adding imagery to an apparel catalog did not enhance consumer's response to the product or the willingness to buy the product. More empirical evidence is required to assess the impact of other design characteristics such as the number of products displayed in each category, organization of product display on purchase behavior. While we have identified differences across various category-specific catalogs in generating sales, it will be interesting to see whether the poor performance of a catalog is a result of poor demand for that category in general or the poor design of the catalog itself. Future research can explore the effectiveness of the presentation and contents of each catalog and determine how the physical properties of a catalog influence actual purchase decision.

We use a proportional hazard specification for the purchase timing model. Another approach could be to assess the fit of a different specification such as multivariate additive risk (MVARM) or accelerated failure time (MVAFT), which future research can address. Researchers could study how the proposed MVPHM performs compared to other modeling approaches such as MVP in diverse data contexts and purchase situations.

While dynamic programming is a superior alternative to optimization based on GA, if implemented, it can become very complicated and difficult to converge given the large number of state variables and constraints in the model (e.g., we need to obtain the number of seven different types of catalogs to be mailed every quarter to each household). Our objective was to first demonstrate whether our approach has any merit. Given the interesting results from the modeling exercise, we feel that this study, which is the first one in multi-category catalog mailing, can be the foundation for future research.

In summary, the optimal catalog mailing policy enables catalog managers to determine when to send a particular catalog to a household to maximize its CLV, resulting in better targeting and more efficient and effective catalog mailing. Overall, this research represents a step in the right direction in that it demonstrates that targeted mailings in a multi-category catalog context can yield substantial gains for the retailer.

## Technical appendix.

*Comparison models.*

In addition to the proposed MVPHM with category and customer frailties, there are a number of viable alternatives to predict probability of purchase.

*MVP model.*

MVP model (Ashford and Sowden 1970) can be described as follows:

Let $Y_i$ be a vector of binary responses. Each element, $y_{it}$ in $Y_i$ is determined by a continuous latent variable,

$$Z_{it} = X_{it}\beta_t + e_{it} \quad i = 1, \ldots, N, \quad t = 1, \ldots, T \tag{A.1}$$

The relationship between $Z_{it}$ and $Y_{it}$ in the MVP model is given by

$$Y_{it} = \left\{ \begin{matrix} 1 & \text{if} \quad Z_{it} > 0; \\ 0 & \text{otherwise.} \end{matrix} \quad t = 1, \ldots, T \right\} \tag{A.2}$$

Here, $e_i$ is a $T \times 1$ vector of error normally distributed with zero mean and covariance matrix, $\Sigma$. $\beta_t$ is a vector of parameters and $X_{it}$ is a $1 \times kt$ vector of regressors.

One of the challenges in the estimation of MVP model is that the unknown parameters ($\beta$, $\Sigma$) are unidentifiable. Researchers have used various approaches to handle the identifiability issue in MVP. The approaches range from performing the analysis on the unidentified model and scaling it with the sampling variance to simulating a correlation matrix through parameter expansion and reparameterization techniques. We use a two-stage parameter expanded reparameterization and Metropolis-Hastings (PX-RPMH) algorithm developed by Liu and Daniels (2006). In Stage 1, correlation matrix, $R$ can be transformed to a less constrained covariance matrix, $\Sigma = DRD$ such that the posterior distribution of $\Sigma$ follows an inverse Wishart distribution and $D$ is the expansion parameter. In the second stage, $R$ is simulated by first drawing $\Sigma$ from inverse Wishart distribution and translating it back to $R$ through the reduction function, $R = D^{-1}\Sigma D^{-1}$ and accepting it based on a Metropolis-Hastings acceptance probability. We account for unobserved heterogeneity in a Hierarchical Bayesian framework and compare the predictive accuracy of this model to that of a multivariate survival model.

*Other proportional hazard models.*

We also benchmark our model (hereafter, the full model) against simpler models like univariate PHMs (i.e., six separate models for six categories) and MVPHM with one or no frailty terms. Since the number of data points in univariate PHM models differs from that in the *full* model, any model comparison using model fit measures such as log-likelihood or DIC may not be meaningful. Instead, we use the predictive validity of the models for comparison. Using the parameter estimates from the models and the observed covariates, we predict purchase times in each category within the model building time frame (i.e., January 1998–December 2001) and compare the mean absolute deviation in IPT in each category for the univariate and the *full* models. Validation is also done for the first quarter of the validation time period (i.e., January–March 2002). Another measure of predictive validity we use to compare the models is the hit rates in both the model building and the validation time periods. We compare the overall hit rates and the percentage of actual orders correctly predicted. We also compare the *full* model with three other multivariate models – (i) MVPHM without either household-specific or category-specific frailty terms (Model 1), (ii) MVPHM with only household-specific frailty (Model 2), and (iii) MVPHM with only category-specific random effects (Model 3). The expressions of the comparison models are:

*Univariate models (separate models for each category)*

$$h_{ijk}(t) = h_{0j}(t)e^{X_{ijk}\beta_i}w_i, \quad \text{for category, } j \tag{A.3}$$

*Multivariate models*

Model 1 (MVPHM without household-specific or category-specific random effects):

$$h_{ijk}(t) = h_{0j}(t)e^{(X_{ijk}\beta_{ij})}, \quad \text{for} \quad j = 1, \ldots, J \quad \text{and} \quad i = 1, \ldots, N \tag{A.4}$$

Model 2 (MVPHM with only household-specific random effect):

$$h_{ijk}(t) = h_{0j}(t)e^{(X_{ijk}\beta_{ij})}w_i, \quad \text{for} \quad j = 1, \ldots, J \quad \text{and} \quad i = 1, \ldots, N \tag{A.5}$$

Table A.1
Comparison of purchase timing models: hit rates.

| Model | Calibration period | | Validation period | |
|---|---|---|---|---|
| | Overall hit rate (percent) | Purchases correctly predicted (percent) | Overall hit rate (percent) | Purchases correctly predicted (percent) |
| Univariate PHM models | 78 | 51 | 75 | 38 |
| Model 1 – no frailty | 90 | 41 | 89 | 31 |
| Model 2 – only household-specific frailty | 89 | 31 | 93 | 27 |
| Model 3 – only category-specific frailty | 88 | 39 | 93 | 35 |
| MVPHM full model | 92 | 68 | 89 | 63 |
| Multivariate probit model | 78 | 35 | 75 | 30 |

Table A.2
Comparison of purchase timing models: DIC and mean absolute deviations in IPT.

| Evaluative criteria | Univariate PHM with household-specific frailty | Model 1 MVPHM with no frailty | Model 2 MVPHM with only household-specific frailty | Model 3 MVPHM with only category-specific frailty | Full model MVPHM with both household and category-specific frailties |
|---|---|---|---|---|---|
| Deviance information criteria (DIC) | NA | 34,150 | 33,876 | 33,827 | 33,357[a] |
| **Category** | **Mean absolute deviation in IPT**[b] | | | | |
| Men's | 2.85 | 3.35 | 3.33 | 3.01 | 2.68 |
| Women's | 2.66 | 2.98 | 2.90 | 2.75 | 2.28 |
| Kids | 3.31 | 3.20 | 3.19 | 3.27 | 2.69 |
| Outdoor | 3.10 | 3.32 | 3.12 | 2.87 | 2.85 |
| Luggage | 3.41 | 3.56 | 3.78 | 3.35 | 3.21 |
| Home | 3.95 | 4.07 | 3.81 | 4.02 | 3.69 |

NA = Not applicable.
[a] Full model has the lowest DIC and the best fit with the data.
[b] Absolute deviation (in months) is calculated as the absolute deviation of predicted IPT from observed IPT.

Model 3 (MVPHM with only category-specific random effects):

$$h_{ijk}(t) = h_{0j}(t)e^{(X_{ijk}\beta_{ij}+\alpha_{ij})}, \quad \text{for} \quad j = 1, \ldots, J \quad \text{and} \quad i = 1, \ldots, N \tag{A.6}$$

Because Models 2 and 3 account for at least one unobserved random effect, they are likely to have a better fit with the data than Model 1. Depending on whether household- or category-specific frailty terms capture unobserved factors better, Model 2 or 3 will have a better fit. If the random effects can be captured by just one of the two frailty terms, the full model will not improve the fit compared with Model 2 or 3, otherwise the full model will have better fit. We select the model with the best fit to use in the joint model of purchase timing and amount.

*Results – comparison of purchase timing models.*

We first compare two modeling approaches for purchase timing – MVP and MVPHM – to identify the modeling approach most suitable for the dataset. Both models used identical or comparable covariates and the estimation was done in a HB framework. The criteria used for comparison are the hit rates in both model building and validation time periods. The overall hit rate measures how well the model predicts purchases and non-purchases in a quarter. When the number of non-purchases is very high compared to purchases the model may predict the non-purchases very well while failing to predict the purchases reasonably well. We therefore calculate the percentage of purchases predicted correctly as an additional criterion for comparison. MVPHM performs much better than MVP on both these criteria as we can see from Table A.1. The overall hit rate of MVPHM is 91 percent as compared to 78 percent for MVP. Also, MVPHM is able to correctly predict higher percentage of purchases (65 percent) compared to MVP (35 percent). The superiority of the MVPHM model is more prominent in the validation time period.

We also compare the predictive accuracy of six univariate PH models, one for each category, and four MVPHMs for purchase timing – Models 1, 2, and 3 and the full model – using Markov chain Monte Carlo (MCMC) estimations. We treat the first 20,000 iterations as burn-in and use the next 5000 to estimate the model parameters and log-likelihood. We compare the performance of the full model against the respective univariate PHM in terms of the mean absolute deviation between observed and predicted IPTs in addition to the hit rates discussed above. To compare the performance of the three MVPHMs against the full model, we also use the DIC.

As shown in Table A.2, the mean absolute deviations in IPTs in all categories are smaller in the full model than those in category-specific univariate models. However univariate models perform better than Model 1 and Model 2 which do not account for interdependence in purchases across categories. Among multivariate models, Model 1 has a DIC of 34,150, Model 2 has 33,876, and Model 3 reveals a DIC of 33,827. The lower DIC for Models 2 and 3 indicate that when we allow for either category- or household-specific random effects, the fit improves. Model 3 has a better predictive performance and achieves lower mean absolute deviations in IPTs compared to Model 2, which suggests that incorporating category-specific frailty terms helps capture more random effects than do household-specific frailty terms. The full model achieves the lowest DIC of 33,357 and the best predictive accuracy with the lowest mean absolute deviations among all the models. Full model also has the best hit rates among all the models compared. Thus, accounting for both household and category-specific random effects in the model improves the fit with the data compared to models that account for only one random effect.

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