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Multichannel Shopping: Causes and Consequences

The authors explore the drivers of multichannel shopping and the impact of multichannel shopping on customer profitability. Through a longitudinal analysis, the authors provide evidence that multichannel shopping is associated with higher customer profitability. Using the social exchange theory, they develop hypotheses regarding the impact of several customer–firm interaction characteristics on customer channel adoption duration. They propose a shared-frailty hazard model for testing the proposed hypotheses. They use the customer database of an apparel manufacturer that sells through three distinct channels for the empirical analysis and find that frequency-related interaction characteristics have the greatest influence on second-channel adoption duration. In contrast, proportion of returns, a purchase-related interaction characteristic, has the greatest influence on third-channel adoption duration. Variation across customers in purchase-related attributes has a greater impact on the duration to adopt the second channel than the duration to adopt the third channel. In contrast, variation across customers in the channel-related attributes has a greater impact on the third-channel adoption duration than on the second-channel adoption duration. The customer–firm interaction characteristics identified in this study and the proposed model framework allow for forward-looking allocation of multichannel marketing resources.

Maintaining multiple channels of transaction with a customer is considered essential for sustained growth in the current competitive environment (Wind and Mahajan 2002). Our study investigates three critical aspects of the customer–firm relationship in a multichannel environment. First, many retailers employ various strategies that are designed to encourage customers to shop in multiple channels. For example, PetSmart prints $10 coupons on store receipts that are valid only for online purchases (Sandsmark 2001). To a large extent, the retailer's attempts to encourage customers to shop in multiple channels are based on the belief that multichannel customers have a higher annual purchase volume than single-channel customers (e.g., DoubleClick 2004; Jupiter Research 2005). Thus far, and on the basis of a cross-sectional analysis of the total profits provided by multichannel versus single-channel customers, academic research has found that multichannel shoppers are significantly more profitable than single-channel shoppers (Kumar and Venkatesan 2005; Thomas and Sullivan 2005). However, a cross-sectional analysis precludes researchers from understanding whether profitable customers tend to shop in multiple channels and whether shopping in multiple channels leads to higher customer profits. Extending previous findings, we use longitudinal information on customer transactions with a firm that is typically available in customer relationship management (CRM) databases to explore whether shopping in multiple channels increases customer profits.

Second, predicting the time a customer takes to adopt an additional channel (i.e., channel adoption duration) would help multichannel retailers in various resource allocation decisions. The focus on marketing accountability has spurred the allocation of marketing resources at each business cycle (e.g., quarters) to individual customers, products, and channels to maximize return on marketing investments (Rust, Lemon, and Zeithaml 2004). If multichannel shopping leads to higher profits and given that marketing communications have a positive influence on customer channel choice (Kumar and Venkatesan 2005; Thomas and Sullivan 2005), predicting customer channel adoption duration would help managers further refine their resource allocation decisions at each quarter by prioritizing channel adoption campaigns among the profitable customers to those who are likely to adopt a new channel in that quarter. For example, PetSmart can expect better returns by providing coupons to customers who are likely to start shopping online. Even if a firm decides not to encourage multichannel shopping proactively, predicting channel adoption duration would enable a firm to obtain a better understanding of the level of resources required in each channel. For example, predicting when offline-only customers would adopt an online channel would help a "bricks-and-click" retailer better forecast the progress in the level of online orders and correspondingly plan the level of resources (e.g., inventory) that would be required to fulfill the online orders satisfactorily.

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Third, we attempt to develop a theoretical basis for the identification of the customer–firm interaction factors so that the proposed framework is sufficiently generalizable across various contexts. Therefore, we propose a conceptual framework that explores the impact of customer–firm interaction characteristics on channel adoption duration.

To summarize, the objectives of our study are as follows:

- To explore the influence of multichannel shopping on customer profitability,
- To provide a conceptual framework for evaluating the influence of customer–firm interactions on customer channel adoption duration, and
- To develop a model formulation for empirically testing the proposed conceptual framework and predicting customer channel adoption duration.

We use the customer database of a large apparel manufacturer that provides three channels for transactions: full-price bricks-and-mortar stores, discount bricks-and-mortar stores, and a Web site. In the next section, we perform an exploratory data analysis to investigate whether multichannel shopping leads to increased customer profitability.

Exploring the Impact of Multichannel Shopping on Customer Profits

In this section, we use a cohort of customers who made their first purchase from the apparel retailer during April 2000, and we observe their transactions until October 2003. All three channels were available to the customers during the observation window.

Longitudinal Analysis[1]

Our intuition for understanding the impact of multichannel shopping on customer profits is to track customer profits each year and to explore whether profits are higher in years when customers engage in multichannel shopping, after we account for (1) any general time trends, (2) purchase activity, and (3) customer-specific variation in profits due to omitted variables.[2] In each year (t), we calculate the total profits from customer i ($Profit_{it}$) and create a binary (1/0) indicator of multichannel shopping ($Multi\_Ind_{it}$). The $Multi\_Ind_{it}$ measure can be confounded by transaction activity when customers make only a single transaction in a year. Because we observed that some customers made only one transaction in a year, we conducted our analyses only on customers who had at least two transactions in each year. This represents a conservative setting for observing the influence of multichannel shopping on profits because each customer included in the analysis has an opportunity to shop in multiple channels.

Partial regression plots and extra sum-of-squares F-tests are useful in multiple linear regression analysis to quantify whether a variable had additional significance in explaining the predictor variable in a model with a basket of possibly correlated predictors (Ravishanker and Dey 2001). In our context, this structure is useful for understanding whether a single predictor variable (in our case, $Multi\_Ind_{it}$) is a useful addition to a model for explaining customer profits when $Multi\_Ind_{it}$ is probably correlated with preexisting covariates in the model, such as purchase activity.[3] In other words, the partial regression plots would enable us to disentangle the effects of multichannel shopping and purchase activity on customer profits. We randomly sampled 8882 customers from the cohort for our analysis.

Step 1

We model profits as a linear function of (1) t, or time index in years (i.e., t = 1 for the first year, and so forth); (2) $Tran_{it}$, or the number of transactions that customer i makes in time t (i.e., purchase activity), (3) lagged profits ($Profit_{it-1}$), and (4) lagged multichannel shopping ($Multi\_Ind_{it-1}$):

$$(1)\quad Profit_{it} = \gamma_{1,0} + \gamma_{1,1} \times t + \gamma_{1,2} \times Tran_{it} + \gamma_{1,3} \times Profit_{it-1} + \gamma_{1,4} \times Multi\_Ind_{it-1} + \varepsilon 1_{it}.$$

We allow for potential correlation in profits from the same customer over years through the error term, $\varepsilon 1_{it}$. Let the vector $\varepsilon 1_i = (\varepsilon 1_{i1}, \ldots, \varepsilon 1_{i4})'$ represent the error terms that correspond to customer i over the four years in our analysis. We assume that $\varepsilon 1_i$ follows a multivariate normal distribution with zero mean and variance–covariance matrix $V1_i$. The off-diagonal elements of $V1_i$, $\alpha 1_{jk}$ ($j \neq k$), capture the correlation in profits across years for a single customer. We use a generalized linear model (GLIM) formulation to estimate the parameters in Equation 1 (i.e., we use Proc Genmod in SAS with normal distribution, an identity link function, and the repeated option) and obtain the Pearson residuals ($\hat{\varepsilon} 1_{it}$). The results from estimating Equation 1 appear in Table 1, Panel A.

As we expected, the estimates in Table 1, Panel A, indicate that time index (coefficient of t = 50.6), purchase activity (coefficient of $Tran_{it}$ = 12.5), lagged profits (coefficient of $Profit_{it-1}$ = .03), and lagged indicator of multichannel shopping (coefficient of $Multi\_Ind_{it-1}$ = 15.8) have a positive, significant influence on profits.

Step 2

For each customer i, we assume that the various binary indicators of multichannel shopping ($Multi\_Ind_{it}$) are correlated Bernoulli random variables with parameter p_{it}. We model the logit transformation of p_{it} as a linear function of the same independent variables in Equation 2 (i.e., t, $Tran_{it}$, $Profit_{it-1}$, and $Multi\_Ind_{it-1}$:

$$(2)\quad logit(p_{it}) = \gamma_{2,0} + \gamma_{2,1} \times t + \gamma_{2,2} \times Tran_{it} + \gamma_{2,3} \times Profit_{it-1} + \gamma_{2,4} \times Multi\_Ind_{it-1}.$$

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[1]We replicated the cross-sectional analysis in Kumar and Venkatesan (2005) and Thomas and Sullivan (2005) and obtained similar results.

[2]We also replicated the analysis with quarterly and semiannual data, and the substantive conclusions do not change with the level of data aggregation. For interested readers, the results are available on request.

[3]The partial regression analysis satisfies the condition that Cox (1992, p. 293) proposes for statistical causality—namely "a variable x_c is a cause of y_E if it occurs in all regression equations for y_E irrespective of the other variables x_b that are included."

TABLE 1
Longitudinal Analysis of Consequences of Multichannel Shopping

A: Longitudinal Customer Profitability Model	
Dependent Variable = $Profit_{it}$*	
Independent Variables	**Coefficient**
Intercept	3.9
Time (t)	67.9
$Tran_{it}$	7.6
$Profit_{it-1}$	.03
$Multi\_Ind_{it-1}$	15.8

B: Longitudinal Multichannel Shopping Model	
Dependent Variable = $Multi\_Ind_{it}$*	
Independent Variables	**Coefficient**
Intercept	–1.4
Time (t)	.1
$Tran_{it}$	.02
$Profit_{it-1}$	.01
$Multi\_Ind_{it-1}$	1.2

C: Impact of Multichannel Shopping on Customer Profitability	
Dependent Variable = $\hat{\varepsilon}1_{it}$	
Independent Variables	**Coefficient**
Intercept	.01
$\hat{\varepsilon}2_{it}$	33.1*

*Significant at $\alpha < .01$.

We model the correlation in p_{it} over years for customer i similar to $V1_i$ in Equation 1. We use a GLIM formulation to estimate the parameters in Equation 2 (i.e., using Proc Genmod in SAS with Bernoulli distribution, a logit link function, and the repeated option) and obtain the Pearson residuals ($\hat{\varepsilon}2_{it}$). The results from estimating Equation 2 appear in Table 1, Panel B.

The GLIM formulation for Equations 1 and 2 is equivalent to a linear regression and a logistic regression, respectively. However, the GLIM formulation enables us to estimate the residuals ($\varepsilon 2_{it}$) in Equation 2 (which is essential for Step 3), something that is not possible in a logistic regression formulation. The significant influence of time index (coefficient of t = .4), purchase activity (coefficient of $Tran_{it}$ = .10), lagged profits (coefficient of $Profit_{it-1}$ = .01), and lagged indicator of multichannel shopping (coefficient of $Multi\_Ind_{it-1}$ = 1.2) provides justification for using a partial regression plot.

Step 3

Finally, we run a regression of $\hat{\varepsilon}1_{it}$ (residuals from a regression of profits on the predictors, including purchase activity) on $\hat{\varepsilon}2_{it}$ (residuals from a regression of multichannel shopping on the predictors, including purchase activity):

$$\hat{\varepsilon}1_{it} = \gamma_{3,0} + \gamma_{3,1} \times \hat{\varepsilon}2_{it} + \varepsilon 3_{it}. \quad (3)$$

We use the GLIM formulation similar to Equation 1 to estimate Equation 3. The results appear in Table 1, Panel C.

From Table 1, Panel C, we observe that $\hat{\varepsilon}2_{it}$ has a positive, significant influence on $\hat{\varepsilon}1_{it}$ (.10), and the intercept is not significant. In other words, a plot of $\hat{\varepsilon}1_{it}$ versus $\hat{\varepsilon}2_{it}$ has a positive slope and crosses the origin. This indicates that multichannel shopping has a positive effect on customer profits, even after we remove the effect of other potential confounding variables, such as purchase activity, on both the profits and multichannel shopping. Similar to previous research, the results from estimating Equation 2 show that customers who are more profitable are also more likely to shop in multiple channels (Neslin et al. 2006).[4] In addition, the estimates of Equation 3 indicate that there is a positive reinforcement effect of multichannel shopping on customer profits beyond that of other factors, such as purchase activity. We also estimated Equation 1 with $Multi\_Ind_{it}$ as an additional independent variable. A likelihood-ratio test indicated strong support ($\lambda = .0032$, $\alpha < .01$) for a profit model that includes $Multi\_Ind_{it}$ as an independent variable relative to Equation 1, which does not include $Multi\_Ind_{it}$ as an independent variable.

Conceptual Framework

Fournier (1998) proposes that the everyday marketing-mix decisions constitute a set of behaviors enacted on behalf of the brand and form the cornerstone for considering the relationships between customers and brands (or firms), similar to interpersonal relationships between two human beings. Under this assumption, the social exchange theory of interpersonal relationships is applicable for studying channel adoption duration. According to social exchange theory, the interactions between people form the basis for the development of their relationship. People form and maintain a relationship as long as they believe and subsequently find it in their mutual interest to do so (Burgess and Huston 1979). The relationships are assumed to grow, develop, deteriorate, and dissolve as a consequence of the social exchange process (i.e., the interactions). Interacting in a widening array of settings (i.e., transacting across multiple channels) is considered one of the several behavioral consequences of relationship development (Berscheid, Snyder, and Omoto 1989; Burgess and Huston 1979).

Although several behavioral and psychological (or perceptual/subjective) aspects can determine the rate of relationship development (Hinde 1995) and channel adoption duration, we are interested in exploring only the impact of behavioral factors that are easily evident from CRM databases. We view the various purchase occasions and the communications from the firm to the customer as the inter-

[4]Note that a pure causal effect of multichannel shopping on customer profitability can be assessed only through a field experiment.

actions between partners in a relationship. The differences in interaction characteristics across customers affect the rate of relationship development and therefore explain the variation in the channel adoption duration. In addition to the interaction characteristics, individual differences, or observed customer heterogeneity, are expected to affect the rate of relationship development (Hays 1985) and, therefore, channel adoption duration. Figure 1 summarizes the proposed interaction characteristics and their expected effects on customer channel adoption duration. We classify interaction characteristics into purchase-related attributes, channel-related attributes, and frequency-related attributes.

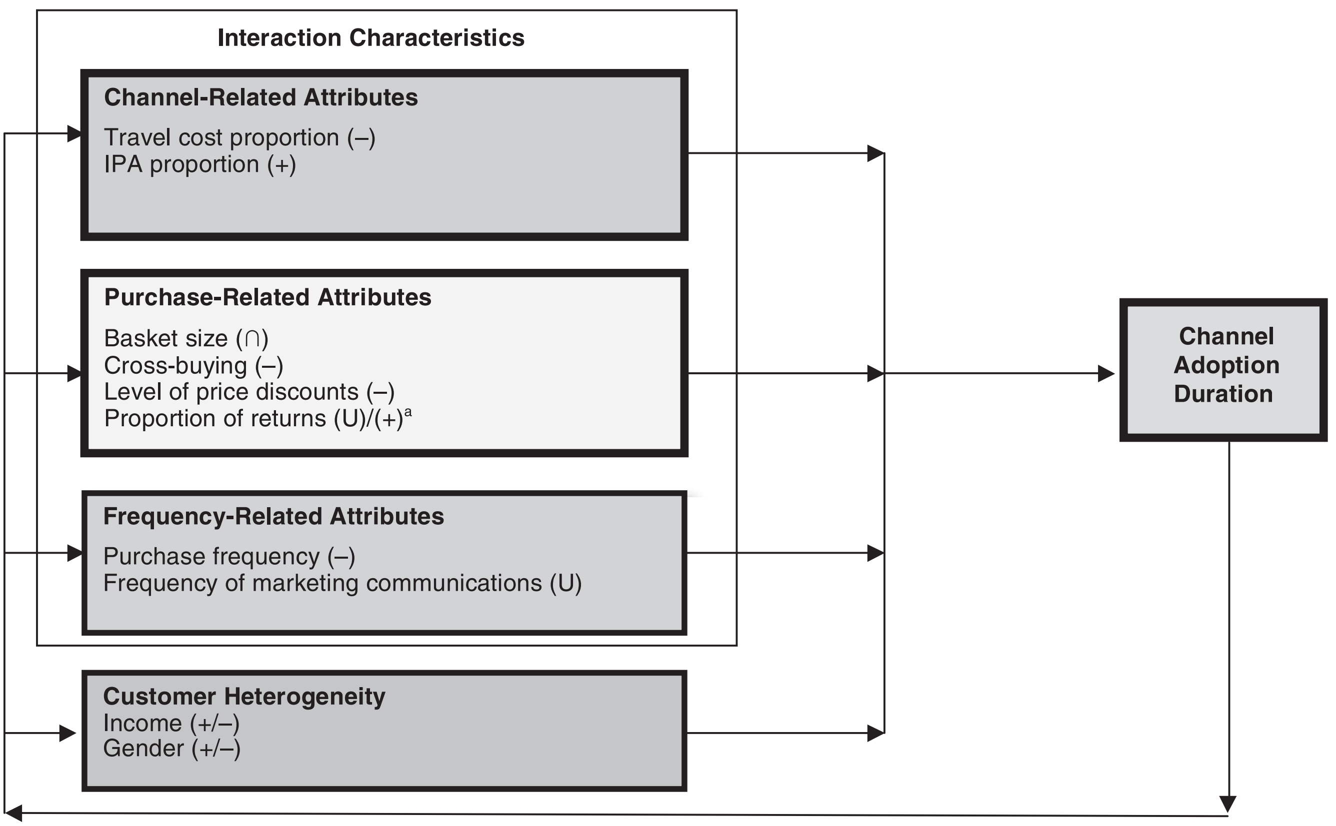
Interaction Characteristics: Purchase-Related Attributes

Basket size. Basket size is defined as the total quantity of items a customer purchases in a single shopping trip (Bell, Ho, and Tang 1998). It could be inferred that the larger the basket size (i.e., more products purchased in a transaction), the higher the utility provided by each interaction. In general, customers with smaller basket sizes (fill-in trips) are expected to pay higher prices because they have an immediate, unplanned consumption need that must be fulfilled. To the extent that the firm's products satisfy customers' immediate needs, customers who have smaller basket sizes are expected to derive higher utility from each interaction. It can be expected that customers who have very large basket sizes (planned trips) with a particular firm are satisfied with the firm's offerings because they are making consistent, planned visits and are purchasing large quantities.

Previous research has found that customers with intermediate basket sizes pay the lowest prices and purchase more items that are on feature and display (Mazumdar and Papatla 1995), implying that these customers are more focused on lower prices than on developing a relationship with the firm. Therefore, we propose that each interaction contributes more to relationship development for customers who have very small and very large baskets than for customers who have intermediate basket sizes. Given an equal number of interactions, relationship development is faster (and therefore channel adoption duration is shorter) for customers with either very small or very large basket sizes than for customers with intermediate basket sizes. Thus:

H_1: There is an inverted U-shaped relationship between an increase in basket size and channel adoption duration.

FIGURE 1
Conceptual Model of Drivers of Channel Adoption Duration



[a]The positive sign is for the third-channel adoption.
Notes: IPA = immediate product availability.

Cross-buying. We define cross-buying as the number of different product categories a customer purchases from in a single shopping trip. Although the degree of cross-buying is associated with variation in customer demographics (Kamakura, Ramaswami, and Srivastava 1991), cross-buying is also found to be associated with customer satisfaction, after variation in customer demographics are controlled for. Specifically, for longer duration customers, a higher level of satisfaction with a firm's products leads to an increase in cross-buying, and regardless of relationship duration, lower satisfaction leads to a decrease in cross-buying (Verhoef, Frances, and Hoekstra 2001). In turn, customer satisfaction has been found to be positively associated with relationship duration and relationship development (Bolton 1998). Given an equal number of interactions, customers who have a higher degree of cross-buying are expected to develop greater familiarity (Kumar and Venkatesan 2005) and maintain their levels of satisfaction with a firm's products at each interaction. Thus:

> H_2: The higher the level of cross-buying, the shorter is the channel adoption duration.

Level of price discounts. Customers perceive a price discount on a product as a gain because the price they pay for the discounted product is less than their reference price for the product (Kalyanaram and Winer 1995). The availability of a discount can lead to relationship development because of the potential for savings the discount provides to the customer. This implies that relationship development is faster for customers who take advantage of the discounts presented to them. However, some customers may obtain a higher level of price discounts than others because they actively seek lower prices. These customers would be motivated to scan channels to obtain lower prices and thus would be associated with shorter channel adoption duration. Thus:

> H_3: The higher the level of price discounts a customer obtains, the shorter is the channel adoption duration.

Proportion of returns. We define proportion of returns as the ratio of the number of returns to the number of products a customer purchases. Product returns represent an instance in which customers explicitly express their dissatisfaction with the firm and can be perceived as bargaining efforts on the part of customers for better coordination of their interactions (Dwyer, Schurr, and Oh 1987). Studies that explore product returns from the customers' perspectives (rather than from the firm's perspective) find that when customers attribute the blame for product returns to themselves rather than to the firm, a product return can lead to higher repeat purchase and relationship development (Bower and Maxham 2006).

If firms treat customers who return products satisfactorily and make every effort to solve their problems, these customers can become loyal and exhibit positive word-of-mouth behavior (Reicheld 1998). Therefore, a customer's initial product returns are critical because they have the potential to strengthen the customer–firm relationship. However, a firm's failure to solve the customer's problem results in a persistence of return behavior, leading to the dissolution of the relationship or slowing the rate of relationship development (or longer channel adoption duration). Previous research has found that the influence of returns on customer purchase behavior is nonlinear (Venkatesan and Kumar 2004). Specifically, if the increase in returns exceeds a certain threshold, a customer may be more inclined to dissolve his or her relationship with a firm. Therefore, among single-channel shoppers, customers who have either a low or a high proportion of returns have a longer duration to adopt a second channel than customers who return products at moderate levels.

A customer is expected to exhibit a higher proportion of returns even when shopping in two channels if the firm had not satisfactorily managed his or her previous (probably when shopping in a single channel) product return occasions. Thus:

> H_{4a}: There is a U-shaped relationship between the proportion of returns when a customer shops in a single channel and the duration for the customer to adopt a second channel.
>
> H_{4b}: The higher the proportion of returns when a customer shops in two channels, the longer is the duration for the customer to adopt a third channel.

Interaction Characteristics: Frequency-Related Attributes

Purchase frequency. Customers who have a higher frequency of purchases are expected to develop familiarity with the products and transaction channels the firm provides at a faster rate than those who seldom purchase. Morgan and Hunt (1994) argue that to the extent that the interactions are satisfactory, frequent interactions might increase trust (in other words, reduce perceived risk) at a faster rate. Although quality of interaction is more important than frequency in determining the development of a relationship, an increase in the frequency of interactions also allows customers to increase the rate at which they form impressions of the firm's products and the benefits of interacting with the firm (Hinde 1979). Thus:

> H_5: The higher the purchase frequency, the shorter is the channel adoption duration.

Frequency of marketing communications. Marketing communications are critical in influencing customers' channel choices (Ansari, Mela, and Neslin 2005; Thomas and Sullivan 2005). Suppliers can use their contact strategy in one channel to motivate customers to migrate to other channels. However, the influence of marketing communications on customer behavior is nonlinear in nature (Fournier, Dobscha, and Mick 1997; Reinartz, Thomas, and Kumar 2005; Venkatesan and Kumar 2004). Up to a certain threshold, customers perceive higher levels of marketing communications as reciprocal communications from the firm with the intention of developing a mutually beneficial relationship. However, an increase in the level of marketing communications beyond this threshold can have dysfunctional consequences (Fournier, Dobscha, and Mick 1997) because customers begin to perceive the firm as not understanding their needs and simply pushing its products. This implies that relationship development is slower for customers who receive either very low levels or very high levels of marketing communications than for customers who receive an intermediate (or optimal) level of marketing communications. Thus:

> H_6: There is a U-shaped relationship between frequency of marketing communications and the channel adoption duration.

Interaction Characteristics: Channel-Related Attributes

The various channels differ on several factors, including time between ordering and receiving a product, richness of information presented, and accessibility/convenience (Ward 2001). Remote channels, such as Web sites and mail-order catalogs, are characterized by no traveling cost, and they can be used to order products at any time of the day, leading to greater accessibility/convenience. However, in these channels, there is a larger time difference between ordering and receiving a product, and the products cannot be physically examined, which leads to less product information than is the case for bricks-and-mortar stores. Conversely, the offline channels are characterized by no time difference between ordering and receiving the product as well as richer information about the product. However, these channels also have a nonzero traveling cost and are accessible only during the day. Therefore, we measure channel-related interaction attributes through (1) travel cost proportion and (2) immediate product availability (IPA) proportion.

Travel cost proportion. A customer's travel cost for a channel is defined as the distance between the customer's residence and the closest store in that channel. The travel cost proportion for a customer is measured as the ratio of the sum of the travel costs for all the channels the customer currently adopts to the sum of the travel costs of all the channels the firm provides. Typically, it is assumed that the travel cost for the online channel and the mail-order channel is zero.

In the context of packaged goods, studies have found that customers choose to shop in stores that are associated with lower travel cost (Bell, Ho, and Tang 1998). Given equal levels of relationship development, customers who are currently shopping in a channel that has a larger travel cost than other channels offered by a firm have a greater scope for reducing their travel cost by shopping in the firm's other channels. The incentive for customers to reduce their travel cost proportion and the greater scope for such reduction for customers who currently have a higher travel cost proportion are reflected in them having a shorter channel adoption duration. Thus:

> H_7: The higher the travel cost proportion in the current channels, the shorter is the channel adoption duration.

IPA proportion. A channel provides IPA if a customer is able to consume the product immediately after purchase. Channels that do not have IPA cannot provide customers with a rich interaction/experience with the product. For example, both the online channel and the mail-order catalogs do not have IPA and cannot provide a rich interaction experience with the product. Bricks-and-mortar stores provide customers with a rich interaction with the product, and the customers can also consume the product immediately in these channels, so a bricks-and-mortar store would have IPA.

Immediate product availability measures the costs related to both the time lag between product purchase and consumption and the nonavailability of the hedonic pleasure of the shopping process itself. The existence of IPA in a particular channel decreases the cost of transacting in that channel. We measure IPA proportion as the ratio of the number of channels that have IPA among a customer's current transaction channels to the number of channels that have IPA among all the channels the firm offers. Given that customers prefer to maximize the total utility of their shopping experience (Bell, Ho, and Tang 1998), we expect that customers who have a lower IPA proportion will be associated with shorter channel adoption duration. Thus:

> H_8: The higher the IPA proportion in the customer's current channels, the longer is the channel adoption duration.

Observed Customer Heterogeneity

Given previous findings of significant heterogeneity in channel migration behavior (Thomas and Sullivan 2005), it is important to include elements of observed customer heterogeneity in our framework. Sociodemographic variables, such as income and gender, have been found to affect customer store choice (Popkowski-Leszcyc and Timmermans 1997), channel choice (Inman, Shankar, and Ferraro 2004), and profitable lifetime duration (Reinartz and Kumar 2003).[5] Because of the lack of a convincing theory about gender and income effects on store and channel choice, we do not formulate a formal hypothesis, but we include gender in our model as a control variable.

Model

In our data, we observe the date and channel for each customer transaction. By definition, the time when a customer makes his or her first purchase in a second channel (T_2) is later than the time when a customer first transacts with the firm in any channel (T_1), and the time a customer makes his or her first purchase in a third channel (T_3) is later than T_2 (i.e., $T_3 > T_2 > T_1$). We study the impact of interaction factors on the duration it takes for a customer to adopt a second channel ($t_2 = T_2 - T_1$) and the duration it takes for a customer to adopt a third channel ($t_3 = T_3 - T_2$). When operationalized as such, the durations for adoption of the second and third channel (t_2 and t_3) are not ordered in time (i.e., t_3 can be greater or less than t_2) and are similar to interpurchase times, which are used widely in the literature (Jain and Vilcassim 1991). However, we also expect that the duration to adopt the third channel (t_3) is dependent on the duration to adopt the second channel (t_2). Given this expectation of dependence, multispell hazard models used to model customer interpurchase times are inappropriate

[5]Although several other demographic factors could affect channel adoption duration, we use gender and income because only these demographic factors have reliable information (i.e., no missing values) in the customer database used in this study.

because they assume that multiple events (i.e., the durations to adopt the second and third channels) are independent.

We model the duration to adopt a channel using a shared-frailty model framework (Hougaard 2000), which assumes that the second-channel adoption duration (t_2) and the third-channel adoption duration (t_3) are independent, given a common unobserved risk factor (w_i) that is specific to each individual i. Under this framework, the instantaneous probability (also called the customer's "hazard function") that customer i will adopt the jth channel (i.e., the second or third channel) follows the modified proportional hazards form:

$$(4)\quad h(t_{ij}, X^*_{ij}) = \frac{\left[F(t_{ij}) - F(t_{ij} - \Delta)\right]}{1 - F(t_{ij})} = h_0(t_{ij}) \times \psi(X^*_{ij}, \beta) \times w_i,$$

where Δ is the level of aggregation used in the analysis. For example, in our analysis, we measure t_{ij} in number of days, so Δ represents a day. For customer i, t_{ij} denotes the observed value of the random time to adopt the jth channel, $h(t_{ij}, X^*_{ij})$ represents the corresponding hazard function (i.e., the instantaneous probability of adopting the jth channel at time t_{ij} given no adoption until time t_{ij}), $h_0(t_{ij})$ represents the baseline hazard, X^*_{ij} denotes the antecedents of channel adoption duration, $\psi(X^*_{ij}, \beta)$ represents the influence of the antecedents on the hazard of channel adoption, and w_i is the customer-specific frailty or the common risk factor. The observed durations t_2 and t_3 are independently conditional on w_i. In this model, the baseline hazard represents the probability distribution that characterizes a customer's channel adoption durations, and $\psi(X^*_{ij}, \beta)$ shifts the hazard up or down. We assume a Weibull baseline hazard for the time until the jth channel adoption:

$$(5)\quad h_0(t_{ij}) = \lambda_j \gamma t_{ij}^{\gamma - 1},$$

where γ (>0) is the shape parameter common to both second- and third-channel adoption duration[6] and λ_j (>0) is the adoption-specific scale parameter that allows the baseline hazard to vary between the second- and the third-channel adoption durations. We vary only the scale parameter to ensure identification of model parameters. The formulation for the baseline hazard as two Weibull distributions with a common shape and different scale parameters is similar to the bivariate Burr distribution (Hougaard 2000, p. 235). We use the following functional form to represent the covariate function:

$$(6)\quad \psi(X^*_{ij}, \beta) = e^{\beta_0' X_{i0}} \times e^{\beta_2' X_{i2} \varphi_2} \times e^{\beta_3' X_{i3} \varphi_3},$$

where

X_{i0} = a row vector of customer heterogeneity variables that are constant over the j channel adoption events,

X_{ij} = a row vector of interaction factors associated with the customer's transaction history when shopping in one channel for j = 2 and the customer's transaction history when shopping in two channels versus one channel for j = 3,

φ_j = 1 if the observation represents the jth channel adoption and 0 if otherwise,

β_0 = a row vector of coefficients for customer heterogeneity variables, and

β_j = a row vector of event-specific (i.e., adoption-specific) coefficients for the interaction factors.

We estimate a separate set of coefficients for the second- and third-channel coefficients to accommodate for any differences in customer behavior when shopping in a single channel (used to predict second-channel adoption duration) and when shopping in two channels (used to predict third-channel adoption duration). For each customer i, we model the shared frailty, w_i, as a random draw from a gamma distribution, such that scale and shape parameters are equal to each other (the mean of the gamma distribution is equal to one).[7] We impose this restriction to ensure identification of the model parameters (Hougaard 2000). The gamma distribution is represented as

$$(7)\quad w_i \sim \frac{w_i^{\kappa - 1} e^{-\kappa w_i} \kappa^{\kappa}}{\Gamma(\kappa)},$$

where κ (>0) represents both the scale and the shape parameters. For the duration to adopt a second channel, we calculate the interaction characteristics on the basis of a customer's transaction history when shopping in a single channel. Likewise, for the duration to adopt a third channel, we calculate the interaction characteristics on the basis of a customer's transaction history when shopping in two channels. In the analysis of channel adoption duration, we do not include the customer transactions that are observed after the customers adopt the third channel (i.e., only the first transaction in the third channel), because in this study, we focus only on the time they take to make their first transaction in the new channel. Calculating the interaction characteristics on the basis of customers' transactions before they adopt a new channel enables us to control for the possibility of endogeneity of the drivers of channel adoption. The likelihood function for our model framework is

$$(8)\quad L = \prod_{i=1}^{n} \prod_{j=2}^{3} \Big[(\lambda_j \gamma t_{ij}^{\gamma - 1} w_i e^{\beta_0' X_{i0} + \beta_2' X_{i2} \varphi_2 + \beta_3' X_{i3} \varphi_3})^{\delta_{ij}} \times \exp(-\lambda_j t_{ij}^{\gamma} w_i e^{\beta_0' X_{i0} + \beta_2' X_{i2} \varphi_2 + \beta_3' X_{i3} \varphi_3}) \Big]^{g_{ij}}.$$

The index, i, represents a customer, and the index, j, represents channel adoption (i.e., j = 2 represents the time until adoption of the second channel, and j = 3 represents the time until adoption of the third channel). The censoring indicator, δ_{ij}, is equal to 1 if the customer adopts the jth channel within the analyses time frame and 0 if the customer's adoption of the jth channel is not observed in data (i.e., if the duration for the jth channel adoption is censored). The product of the first (the hazard function) and

[6]We also plotted a histogram of duration for channel adoption across customers and found that a Weibull distribution represents the data best. Compared with the other distributions, the Weibull distribution provided the best fit to the data on the basis of the Anderson–Darling tests.

[7]The gamma distribution is the most commonly used distribution to model the frailty parameter (Hougaard 2000).

second (the survival function) terms in the likelihood function provides the density function for the duration model. For uncensored observations, both the first and the second terms in the likelihood function (i.e., the density function) are applicable, and for censored observations, only the second term (i.e., the survivor function) is applicable. For single-channel shoppers, the duration to adopt the second channel is censored (i.e., $\delta_{i2} = 0$), and the duration to adopt the third channel is not applicable for these customers. Therefore, we set g_{i2} equal to one and g_{i3} equal to zero for these customers. In other words, only the censored duration to adopt the second channel contributes to the likelihood function for single-channel customers. For multichannel customers—that is, for both two-channel (i.e., $\delta_{i2} = 1$, and $\delta_{i3} = 0$) and three-channel (i.e., $\delta_{i2} = 1$, and $\delta_{i3} = 1$) customers—we set g_{i2} and g_{i3} equal to one.

The estimation of Equation 8 using a maximum likelihood–based approach would require integration of the likelihood with respect to w_i (Hougaard 2000). As the Appendix shows, in Markov chain Monte Carlo (MCMC) methods, the model parameters are simulated directly from their posterior distributions, thus avoiding the need to integrate the likelihood over the frailty distribution. We complete the model specification by specifying prior distributions for the model parameters. We assume gamma distributed priors for λ_1, λ_2, γ, and κ and multivariate normal distributions priors for the response coefficients β_0, β_2, and β_3 (for further details on the prior distributions and the estimation methodology, see the Appendix).

Data

We use the transaction history of customers since their first purchase until the end of 2003 for our analyses.[8] The different modes of communication that the firm in this study uses include direct mail and e-mail. All the customers in our population made at least one purchase in the full-price bricks-and-mortar store, 92% made at least one purchase in the discount bricks-and-mortar store, and 55% made at least one purchase from the Web site. Similarly, 65% of the transactions occurred in the full-price bricks-and-mortar store, 26% of the transactions occurred in the discount bricks-and-mortar store, and 9% of the transactions occurred at the Web site. Whenever discounts are offered, on average, the full-price bricks-and-mortar stores offer a 25% discount, the discount bricks-and-mortar stores offer a 35% discount, and the Web site offers a 30% discount. On average, customers obtain discounts on 12% of their purchases from the full-price bricks-and-mortar stores, on 18% of their purchases from the discount bricks-and-mortar store, and on 8% of their purchases from the Web site. We do not find significant differences in the extent of discount offered and the frequency of discounts offered across channels, because the variation in these factors is high within each channel.

Customers seem to shop more in the bricks-and-mortar stores (full-price and discount stores) than at the Web site. The gross profit per transaction is the highest for the full-price bricks-and-mortar stores ($260) and is significantly different ($p < .01$) from the gross profit per transaction for the Web site ($189) and the discount bricks-and-mortar stores ($122). The difference between the number of transactions per quarter a customer makes in two channels and the number of transactions per quarter a customer makes in a single channel is significant and positive (average difference = 3.2, $p < .01$). We observe a similar phenomenon when we compare transaction levels when a customer shops in three channels with transaction levels when a customer shops in two channels. This implies that there is little or no cannibalization in sales from the previous channels when a customer adopts a new channel.

From the population of customers, we randomly sampled 1165 and 379 customers to create the calibration and holdout samples, respectively. Among the 1165 customers in the calibration sample, 250 were three-channel customers (i.e., we observe the duration to adopt both the second and the third channel for these customers), 463 were two-channel customers (i.e., we observe the duration to adopt the second channel, but the duration to adopt the third channel is censored), and 452 were single-channel shoppers (i.e., the duration to adopt both the second and the third channels is censored). For both the two-channel and the three-channel customers, we have two observations per customer—one observation for the duration to adopt the second channel and one observation for the duration to adopt the third channel. For the single-channel customers, we have only one observation per customer—the censored duration to adopt the second channel. The distribution of single-, two-, and three-channel customers in the holdout sample is similar to that of the calibration sample. We use the holdout sample to evaluate the predictive accuracy of the proposed model. Table 2 provides the operationalization of the drivers on channel adoption duration.

Duration to Adopt the Second Channel

We measure basket size as the ratio of the sum of the number of items a customer bought in each transaction to the number of transactions the customer made when shopping in a single channel. Similarly, we measure cross-buying as the ratio of the sum of the number of different product categories a customer bought at each transaction to the total number of transactions the customer made when shopping in a single channel. We measure proportion of returns as the ratio of the number of return occasions to the number of transactions a customer made when shopping in a single channel. We measure frequency of marketing communications as the ratio of the sum of the number of marketing communications sent by the firm between two consecutive customer transactions to the total number of transactions the customer made.

We measured level of price discounts as the product of the probability that a discount would be available for a customer in a given shopping trip (Prob[dis]) and the average

[8]Fewer than 1% of the transactions made by a customer are through the use of cash. Therefore, we have reliable information on when and through which channel the customer made his or her first transaction.

TABLE 2
Operationalization of Drivers

Variable	Operationalization
Drivers of Duration to Adopt Second Channel	
Basket size	Total number of items bought per transaction when shopping in a single channel
Cross-buying	Number of different products categories bought per transaction when shopping in a single channel
Level of price discounts	Product of Prob(dis) and APDS when shopping in a single channel, where Prob(dis) = the ratio of number of transactions when a discount was available to the number of transactions and APDS = average percentage difference between the regular and the purchase price for a product that was bought on discount
Proportion of returns	Ratio of number of returns to number of transactions when shopping in a single channel
Purchase frequency	Reciprocal of the average interpurchase time when shopping in a single channel
Frequency of marketing communications	Number of marketing communications (direct mail or e-mail) between two transactions when shopping in a single channel
Travel cost proportion	Ratio of the distance to the closet store in the current channel to the sum of the distances to the closet store in all available channels
IPA proportion	Ratio of the IPA in the current channel to the number of channels with IPA among all the available channels (equal to 1 if the transaction channel is either discount or full price and 0 if otherwise)
Drivers of Duration to Adopt Third Channel	
Basket size	Total number of items bought per transaction when shopping in two channels
Cross-buying	Number of different products categories bought per transaction when shopping in two channels
Level of price discounts	Product of Prob(dis) and APDS when shopping in two channels, where Prob(dis) = the ratio of number of transactions when a discount was available to the number of transactions and APDS = average percentage difference between the regular and the purchase price for a product that was bought on discount
Proportion of returns	Ratio of number of returns to number of transactions when shopping in two channels
Purchase frequency	Reciprocal of the average interpurchase time when shopping in two channels
Frequency of marketing communications	Number of marketing communications (direct mail or e-mail) between two transactions when shopping in two channels
Travel cost proportion	Ratio of the sum of the distances to the closet stores in each transaction channel (when shopping in two channels) to the sum of the distances to the closet store in all available channels
IPA proportion	Ratio of the IPA in the current channels to the number of channels with IPA among all the available channels (equal to 1 if the transaction channel is either discount or full price and 0 if otherwise)

percentage savings the customer obtains when the discount is available (APDS). We interpret the level of price discounts as the percentage savings a customer obtains in any shopping trip, allowing for the nonavailability of discounts on every customer transaction. We measure frequency of transactions as the reciprocal of the average interpurchase time for the customer when shopping in a single channel. In our data, the offline channels (full-price and discount bricks-and-mortar stores) have higher travel costs than the online channel. Conversely, the online channel has a higher cost related to the nonavailability of IPA, whereas the two offline channels have IPA and, thus, lower interaction costs. Therefore, there is no a priori reason to expect that the channels differ in interaction costs other than their travel costs and IPA. As we explained previously, measuring these variables on a per transaction basis controls for the possibility that customers who have a longer duration for channel adoption can also have higher levels for the cumulative values of basket size, cross-buying, the number of marketing communications, and returns.

Duration to Adopt the Third Channel

We measured the drivers of the third-channel adoption duration similar to the drivers of second-channel adoption duration, except that we used customer transactions when shopping in two channels instead of customer transactions when shopping in a single channel. In Table 3, we provide the descriptive statistics and the correlation matrix of the drivers of channel adoption used in our study. On average, the customers in the calibration sample take approximately 15 months to adopt a second channel. Among the customers who also adopted a third channel, the duration for adopting a third channel is approximately 10 months. The correlation matrix shows that multicollinearity is not a serious threat in our analyses.

Results and Discussion

We estimated four versions of the proportional hazard model (based on the likelihood function in Equation 8) using the customers selected in the calibration sample through MCMC methods (as we explain in the Appendix). Model 1 has no covariates and no frailty, Model 2 has frailty but no covariates, Model 3 has covariates but no frailty, and Model 4 has both covariates and frailty. We used 10,000 iterations for burn-in and 20,000 iterations to form the posterior sample. The line plots of the posterior sample revealed that the algorithm converged satisfactorily. We report the results of our analyses in Table 4.

Model Fit

We use the aggregate log conditional predictive ordinate (CPO) for evaluating the in-sample fit of the four competing models (Gelfand, Dey, and Chang 1992). Similar to the log-likelihood, a higher value of the aggregate log CPO is interpreted as a better model fit. Table 4 shows that Model 4 has the highest aggregate log CPO (–13,383) among the four models. Compared with Model 3, we calculate the psuedo-Bayes factor (PsBF) of Model 1 as the difference between the aggregate log CPO of Model 4 and that of Model 3 (equal to 39); the results indicate strong support for Model 4 over Model 3 and for including the frailty term in our model formulation.[9] The PsBF measures also provide strong support for Model 4 over Models 1 and 2 (see Table 4). Overall, the model comparisons suggest that a proportional hazard model with both the proposed covariates and the frailty term provides the best in-sample fit.

Predictive Accuracy

To evaluate the predictive accuracy of our model, we used the posterior distribution of the parameters obtained from the calibration sample to simulate the predictive distribution of hazard rates for the customers in the holdout sample. We then obtained the duration for channel adoption in the holdout sample from the inverse cumulative distribution function corresponding to the hazard function in Equation 4. For customers in the holdout sample, we obtained the frailty parameter (w_i) through a random draw from the frailty distribution (Equation 7), whose parameters (κ, $1/\kappa$) we estimated using the calibration sample. We then evaluated the mean absolute deviation (MAD) between the predicted duration to adopt a second channel and the predicted duration to adopt a third channel with the observed durations to adopt in the holdout sample. We note that the MAD comparisons could be performed only for the uncensored observations. Approximately 22% and 20% of the customers in the holdout sample had censored observations for the duration to adopt the third channel and the duration to adopt the second channel, respectively.

Similar to the in-sample fit comparisons, we find that Model 4 provides better predictions of the channel adoption duration in the holdout sample (MAD for Event 1 = 5.0 months, and MAD for Event 2 = 4.0 months) than does Model 3 (MAD for Event 1 = 8.1 months, and MAD for Event 2 = 6.0 months).[10] Model 4 also provides better predictions of channel adoption durations than do Models 1 and 2 (see Table 4). We also used the average duration to adopt the second and third channels from the calibration sample as a naive estimate of the duration for adopting the second and third channels, respectively. The MAD of the naive estimate in the holdout sample was 11 months for Event 1 and 10 months for Event 2. Finally, we calculated the hit ratio of the number of customers predicted to have channel adoption durations (second and third) outside the observation window and the number of customers observed to have censored durations in the holdout sample. We find that the predictions from Model 4 match the observations in the holdout sample for 80% of the customers, whereas the predictions from Model 4 match only 69% of the observations in the holdout sample. Thus, we use the results of Model 4 to discuss the parameter estimates.

Baseline Hazard

The shape of the baseline distribution (α = 1.65) is significantly different from 1, implying that an exponential distribution would not be appropriate for modeling the baseline hazard in our context. The scale parameters (λ_2 = 4.8e-05, and λ_3 = 1.8e-04) imply that the customers' baseline hazards vary between the second- and the third-channel adoption (see Figure 2). Although the baseline hazard increases for both the second- and the third-channel adoption durations, it is flatter and has a lower risk (i.e., longer duration) for the second-channel adoption. This implies that similar to the descriptive statistics, the baseline hazards also indicate that, in general, customers take a longer time to adopt the second channel than to adopt the third channel.

Antecedents of Channel Adoption Duration

We discuss the risk ratio to understand the relative impact of a variable on the hazard of channel adoption (the parameter estimates themselves appear in Table 4). We can

[9]When Model 1 is compared with Model 2, PsBF values greater than 20 can be considered a significant support for Model A over Model B (Raftery 1996).

[10]Event 1 is the adoption of the second channel, and Event 2 is the adoption of the third channel.

TABLE 3
Descriptive Statistics and Correlation Matrix

Variable	M	SD	Duration (Days)	Basket Size	Cross-Buying	Level of Price Discounts	Proportion of Returns	Purchase Frequency	Frequency of Marketing Communi-cations	Travel Cost Proportion	IPA Proportion
Duration to Adopt Second Channel											
Duration (days)	489	436	1								
Basket size	48.6	88.3	.06	1							
Cross-buying	1.8	1.5	–.45	–.17	1						
Level of price discounts	.005	.08	–.08	–.001	.07	1					
Proportion of returns	.01	.06	.15	.06	–.15	.02	1				
Purchase frequency	.02	.02	–.31	.13	.008	.12	.08	1			
Frequency of marketing communications	5.5	10.9	–.1	–.14	.16	.02	–.06	–.13	1		
Travel cost proportion	.41	.29	.25	.03	–.03	–.02	.07	–.08	–.37	1	
IPA proportion	.23	.42	–.25	–.15	.05	–.04	–.11	.03	.47	–.67	1
Duration to Adopt Third Channel											
Duration (days)	338	330	1								
Basket size	52.1	78.2	.16	1							
Cross-buying	1.8	.7	–.28	–.1	1						
Level of price discounts	.009	.08	–.12	–.03	.08	1					
Proportion of returns	.02	.08	.16	.09	–.17	.03	1				
Purchase frequency	.02	.04	–.31	.12	–.01	–.02	.03	1			
Frequency of marketing communications	9.2	14.6	.21	–.1	.18	.05	.04	.07	1		
Travel cost proportion	.72	.26	.36	.06	–.005	.07	.04	–.02	–.07	1	
IPA proportion	.43	.49	–.37	–.09	–.1	.06	.09	–.06	–.19	–.6	1

TABLE 4
Results from Model Estimation

	Model 1: Proportional Hazard with No Covariates and No Frailty	Model 2: Proportional Hazard with Frailty and No Covariates	Model 3: Proportional Hazard with Covariates and No Frailty	Model 4: Proportional Hazard with Covariates and Frailty
Baseline Distribution				
λ_1 (second-channel adoption)	1.3E-3***	9.2E-4***	1.8e-4***	4.8e-5***
	(9.2E-4)	(1.8E-4)	(2.9e-05)	(1.2e-05)
λ_2 (third-channel adoption)			5.7e-4***	1.8e-04***
			(8.3e-5)	(5.86e-05)
α	1.5***	1.1***	1.4***	1.6***
	(.06)	(.04)	(.02)	(.06)
κ		4.97***		4.9***
		(2.7)		(2.6)
Customer Heterogeneity				
Income			.04**	.02
			(.02)	(.03)
Gender (female = 1)			.13***	.15***
			(.04)	(.07)
Adoption of Second-Channel Interaction Characteristics				
Purchase-Related Attributes				
Basket size			.33***	.45***
			(.07)	(.09)
Square of basket size			–.13***	–.19***
			(.07)	(.09)
Cross-buying			–.55***	–.72***
			(.03)	(.05)
Level of price discounts			–.04***	–.07***
			(.03)	(.04)
Proportion of returns			–.39***	–.49***
			(.10)	(.13)
Square of proportion of returns			.42***	.51***
			(.09)	(.11)
Frequency-Related Attributes				
Purchase frequency			–.81***	–1.1***
			(.02)	(.09)
Frequency of marketing communications			–.37***	–.62***
			(.09)	(.14)
Square of frequency of marketing communications			.15***	.29***
			(.08)	(.11)
Channel-Related Attributes				
Travel cost proportion			–.19***	–.25***
			(.05)	(.07)
IPA proportion			.17***	.18***
			(.11)	(.10)
Adoption of Third-Channel Interaction Characteristics				
Purchase-Related Attributes				
Basket size			.18***	.26***
			(.07)	(.10)
Square of basket size			–.08*	–.11***
			(.06)	(.07)
Cross-buying			–.35***	–.56***
			(.02)	(.06)
Level of price discounts			–.06*	–.05*
			(.05)	(.04)
Proportion of returns			.48***	.52***
			(.10)	(.15)

TABLE 4
Continued

	Model 1: Proportional Hazard with No Covariates and No Frailty	Model 2: Proportional Hazard with Frailty and No Covariates	Model 3: Proportional Hazard with Covariates and No Frailty	Model 4: Proportional Hazard with Covariates and Frailty
Frequency-Related Attributes				
Purchase frequency			–.68***	–1.13***
			(.02)	(.15)
Frequency of marketing communications			–.85***	–.98***
			(.07)	(.10)
Square of frequency of marketing communications			–.40***	.40***
			(.06)	(.09)
Channel-Related Attributes				
Travel cost proportion			–.60***	–.70***
			(.06)	(.08)
IPA proportion			.20***	.26***
			(.12)	(.17)
Frailty (w)		1.0		1.04
		(.33)		(.22)
Aggregate log CPO[a]	–16,214	–14,278	–13,306	–13,283
Psuedo-Bayes factor (PsBF)[b]	2931	995	39	
MAD for adopting second channel (months)	15.5	14.0	8.1	5.0
MAD for adopting third channel (months)	15.1	12.1	6.0	4.0

*More than 90% of the posterior distribution does not contain zero.
**More than 95% of the posterior distribution does not contain zero.
***More than 99% of the posterior distribution does not contain zero.
[a]The aggregate of the log of the CPO is computed similarly to Gelfand, Dey, and Chang (1992).
[b]Calculated with Model 4 as the base model. The PsBF for Model 1 is equal to the difference between the aggregate log CPO values for Model 4 and Model 1. The PsBF for Models 2 and 3 is calculated similarly.
Notes: The coefficients measure the influence of the covariates on channel adoption duration.

interpret the risk ratio as the percentage change in the hazard for a one-unit increase in the independent variable, after we control for all other independent variables. We calculated the risk ratio as ([exp{β} – 1]100). The risk ratios appear in Table 5.

Interaction Characteristics: Purchase-Related Attributes

Basket size. As hypothesized (H_1), we find that basket size has a nonlinear relationship with both the second- and the third-channel adoption durations. The inverted U-shaped influence of basket size implies that customers who purchase an intermediate number of items on each shopping trip would take longer to adopt an additional channel than customers who purchase either a very small number of items or a very large number of items. The risk ratio for basket size indicates that up to a certain threshold, the second-channel adoption duration is longer by 40%, and beyond the threshold, the second-channel adoption is shorter by 40% for a unit increase in basket size (i.e., purchasing one additional item at each transaction) across single-channel customers. Similarly, up to a certain threshold, the third-channel adoption duration is longer by 19%, and beyond the threshold, the third-channel adoption duration is shorter by 19% for a unit increase in basket size across two-channel customers.

Cross-buying. The results provide support for our hypothesis (H_2) that customers who purchase across product categories (i.e., exhibit a higher level of cross-buying) have shorter channel adoption durations. The risk ratio indicates that the duration for adopting a second channel is shorter by 51% for a unit increase in cross-buying (i.e., purchasing from one additional product category at each transaction) across single-channel customers. Across two-channel customers, the third-channel adoption duration decreases by 51% for a unit increase in cross-buying.

Level of price discounts. As hypothesized (H_3), we find evidence for a negative relationship between an increase in the level of price discounts and channel adoption duration. The risk ratio indicates that the duration to adopt the second channel is shorter by 7% for a unit increase in the level of price discounts (i.e., one additional dollar in the discounts expected during any transaction) across single-channel customers, and the duration to adopt the third channel is shorter by 5% for a unit increase in the level of discounts across two-channel customers. Our results imply that though discounts may be primarily considered a tool for acquiring new customers (Gupta 1988), they can also be effective in growing the relationship with current customers.

Proportion of returns. Our results support the hypothesis that there is a U-shaped relationship between the propor-

FIGURE 2
Baseline Hazard for Second- and Third-Channel Adoption Duration

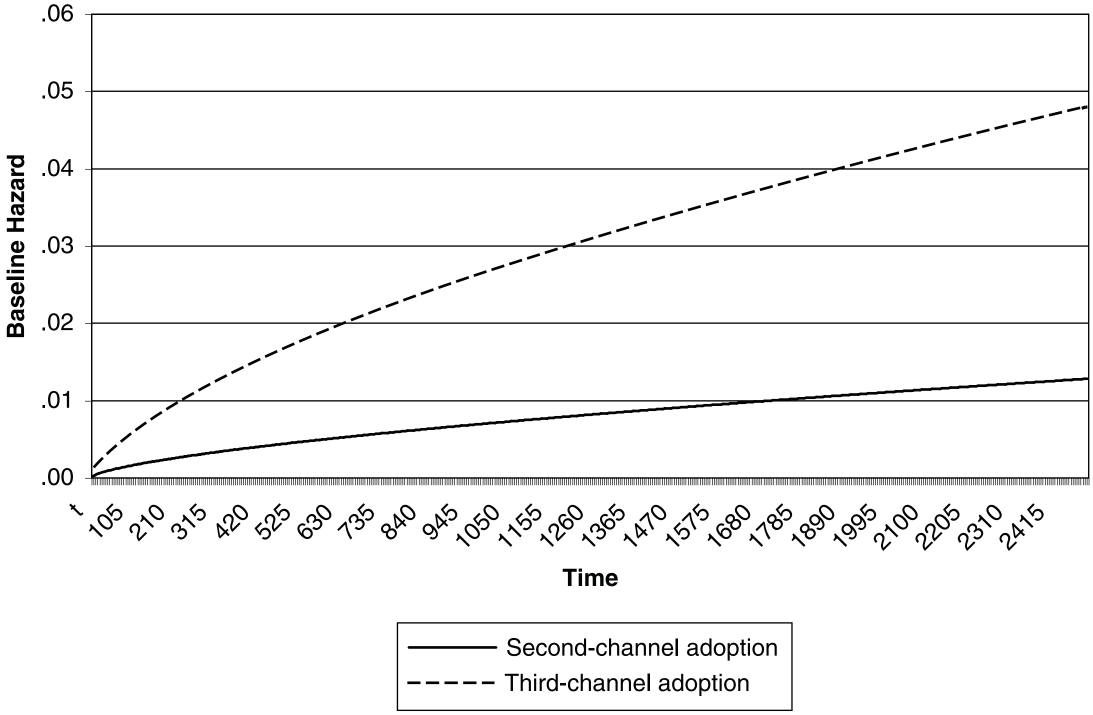


TABLE 5
Risk Ratios for Drivers of Channel Adoption Duration

Driver	Second-Channel Adoption Duration: Risk Ratio (%)	Second-Channel Adoption Duration: Effect on Adoption Duration	Third-Channel Adoption Duration: Risk Ratio (%)	Third-Channel Adoption Duration: Effect on Adoption Duration
Interaction Characteristics: Purchase-Related Attributes				
Basket size (Basket size)^2	40	∩	19	∩
Cross-buying	–51	–	–42	–
Level of price discounts	–7	–	–5	–
Proportion of returns	4	∪	68	+
(Proportion of returns)^2			N.A.	N.A.
Interaction Characteristics: Frequency-Related Attributes				
Purchase frequency	–67	–	–68	–
Frequency of marketing communications (Frequency of marketing communications)^2	12	∪	3	∪
Interaction Characteristics: Channel-Related Attributes				
Travel cost proportion	–22	–	–50	–
IPA proportion	20	+	30	+

Customer Heterogeneity

	Risk Ratio (%)	Expected Effect
Income	N.A.	N.A.
Gender (female = 1)	17	N.A.

Notes: N.A. = not applicable.

tion of returns and a customer's duration for adopting a second channel (H_{4a}). Regarding two-channel customers, we find that customers with a higher proportion of returns have a longer third-channel adoption duration, in support of H_{4b}. The risk ratio indicates that up to a certain threshold, the second-channel adoption duration is shorter by 4%, and beyond the threshold, the second-channel adoption is longer by 4% for a unit increase in the proportion of returns across single-channel customers. Across two-channel customers, the duration to adopt a third channel is longer by 68% for a unit increase in the proportion of returns.

Customer returns provide firms with an opportunity to address concerns about the customer–firm relationship. The U-shaped relationship for single-channel customers indicates that customers who make intermediate levels of returns adopt a second channel faster than customers who make very few or too many returns. However, the higher the number of returns a two-channel customer makes, the longer is the customer's third-channel adoption duration. We infer that allowing a smooth and costless product return process is essential for encouraging customers to shop across multiple channels. Overall, we find that with the exception of the proportion of returns, the product-related interaction attributes (basket size, cross-buying, and level of price discounts) have greater impacts on single-channel customers than on two-channel customers.

Interaction Characteristics: Frequency-Related Attributes

Purchase frequency. As hypothesized (H_5), we find that customers with a higher purchase frequency have shorter channel adoption duration. The risk ratio indicates that across single-channel customers, the duration to adopt a second channel decreases by 67% for a unit increase in purchase frequency. Similarly, across the two-channel customers, the duration to adopt a third channel decreases by 68% for a unit increase in purchase frequency.

Frequency of marketing communication. We find strong support for our hypothesis that there is a U-shaped relationship between the frequency of marketing communication and channel adoption duration (H_6). Up to a certain threshold, the second-channel adoption duration is shorter by 12%, and beyond the threshold, the second-channel adoption is longer by 12% for a unit increase in the frequency of marketing communications (i.e., an additional marketing communication between two transactions) across single-channel customers. Similarly, across two-channel customers, the third-channel adoption duration is shorter by 13% up to a certain threshold and is longer by 13% beyond the threshold for a unit increase in the frequency of marketing communications.

Overall, our results support the notion that higher interaction frequency leads to relationship development and shorter channel adoption duration. We also find that the reciprocal communications from the firm are important in influencing customer channel adoption duration. Although the influence of purchase frequency on channel adoption duration is similar for both single- and two-channel customers, the difference in channel adoption duration for a unit difference in the frequency of marketing communications is higher for two-channel customers than for single-channel customers. This implies that managers should be more cautious about not exceeding the optimal level of marketing communications for two-channel customers and single-channel customers.

Interaction Characteristics: Channel-Related Attributes

Travel cost proportion. As hypothesized (H_7), we find that the proportion of the travel cost in the current channels is negatively related to the duration to adopt for both single-channel and two-channel customers. The risk ratio indicates that the second- (third-) channel adoption duration decreases by 22% (50%) for a unit increase in the travel cost proportion. We find support for the conventional wisdom that travel costs, which increase with distance, influence customers' store choices (Bell, Ho, and Tang 1998). This result has important implications for the location of a new store and for the store format in the new location.

IPA proportion. We find strong support for the notion that (at least for apparel manufacturers) the time lag between when the product is ordered and when the product is available is an important determinant of channel adoption duration. Our results indicate that across single- (two-) channel shoppers, the second- (third-) channel adoption duration is longer by 20% (30%) for a unit increase in IPA proportion. These results imply that managers should try to find alternative ways (e.g., free shipping and handling) to reduce customer costs of shopping in channels without IPA. Our results indicate that the influence of channel-related interaction attributes is greater for two-channel customers than for single-channel customers.

Observed Customer Heterogeneity (Income and Gender)

We find that male customers have shorter channel adoption duration and that income is not related to channel adoption behavior. The adoption duration for female customers is 17% longer than the adoption duration for male customers. The information in customer heterogeneity variables adds explanatory power in the channel adoption duration model beyond the interaction characteristics.

Managerial Implications

Do Customers Provide Higher Profits When They Shop in Multiple Channels?

Our longitudinal analysis implies that managers have the opportunity to grow customer profits by encouraging customers to shop in multiple channels. Overall, providing a multichannel experience to customers has the potential to improve two critical aspects of CRM: customer retention and customer growth. There could be several reasons that customers provide more profits when they shop in multiple channels. One rationale is that firms can provide several add-on services to customers through their multiple channels (e.g., order online, pickup offline). Customers who shop in multiple channels (regardless of their purchase activity) are exposed to the services the firm provides and therefore are expected to be more satisfied with the firm and develop a deeper relationship with the firm. These factors translate into multichannel customers potentially allocating a higher share of wallet to the firm and therefore providing higher profits.

How Do Customer–Firm Interaction Characteristics Affect Channel Adoption Duration?

We find strong support for using the social exchange theory to understand customer channel adoption duration. The importance of the interaction characteristics varies between single- and two-channel customers. Frequency-related interaction characteristics (purchase frequency and frequency of marketing communication) have the greatest influence on second-channel adoption duration. This result adds to recent findings that heavy users (i.e., those with higher purchase frequency and spending levels) have a greater preference for shopping in multiple channels (Gensler, Dekimpe, and Skiera 2007). In contrast, proportion of returns has the highest influence on third-channel adoption duration, followed by the frequency-related attributes. This implies that managers need to take every effort to address product returns from single-channel customers because addressing initial product returns is necessary for relationship development and faster channel adoption. The results also add to the growing belief in the literature that marketing communications are critical in influencing customer channel choices (Neslin et al. 2006). However, our results also urge managers to be aware that there is an optimal frequency of communications for each customer, and overcommunicating to customers can have dysfunctional consequences, such as longer channel adoption durations.

Variation across customers in purchase-related attributes (except proportion of returns) has a greater impact on the duration to adopt the second channel than on the duration to adopt the third channel. In contrast, variation across customers in the channel-related attributes has a greater influence on the third-channel adoption duration than on the second-channel adoption duration. This implies that managers can expect better responses by directing a higher level of discounts to single-channel customers than to two-channel customers. In addition to targeting customers who purchase frequently, the channel adoption campaigns to single-channel customers should also target customers who have either very small or very large basket sizes and who purchase across different categories. Although the influence of customer heterogeneity factors may not be generalizable, our results imply that male customers are more likely to adopt an additional channel faster.

Does Channel Adoption Duration Change on the Basis of a Customer's Current and Future Transaction Channels?

Information about how channel adoption durations vary depending on a customer's current transaction channels would enable managers to target certain channels for multichannel marketing. On the basis of the risk ratios in Table 5, we find that the second-channel adoption duration for customers who first adopt the full-price store is longer than the second-channel adoption duration for customers who first adopt the discount store by 27% and is longer than the second-channel adoption duration for customers who first adopt the Web site by 6%. Customers who adopt the discount store first have shorter second-channel adoption duration than customers who first adopt the Web site by 21%. The third-channel adoption duration for customers who shop either in the discount store or at the Web site is shorter than the third-channel adoption duration of customers who shop in either the full-price store or the discount store by .8% and is shorter than the third-channel adoption duration for customers who shop either in the full-price store or at the Web site by 36%. The third-channel adoption duration for customers who shop in either the full-price store or the discount store is shorter than the third-channel adoption duration of customers who shop either in the full-price store or at the Web site by 35%.[11]

In addition to current transaction channels, channel adoption duration could vary systematically on the basis of the future transaction channels. We assessed the MAD of the model predictions in the holdout sample for each current and future channel combination. Specifically, we split the holdout sample into six subsamples based on the second- and third-channel adoption durations. We found that the MAD of model predictions ranged from 4.2 (3.7) to 5.5 (4.1) months among the six subsamples for the second- (third-) channel adoption durations. This is in line with the MADs of 5 and 4 months for the second- and third-channel adoption durations, respectively, when all the subsamples are pooled. Therefore, there is no reason to believe that the channel-related attributes we included in the conceptual framework fail to capture any systematic variation in channel adoption durations related to a customer's current and future transaction channels.

Managing Multichannel Marketing Resources

In our context, we do not expect that the parameter estimates are biased because we did not model (1) the firm actions related to targeting customers for multichannel shopping (i.e., the supply side) and (2) the customer expectations of incentives that can be obtained from multichannel shopping (Frances 2005). However, managers need to be cautious when adopting our modeling framework for managing multichannel marketing resources. The customer–firm interaction characteristics and their corresponding impact on channel adoption duration are based on a retrospective analysis of customer transactions with a firm, and our modeling framework assumes a constant managerial strategy during the analyses time frame. Prospective actions that are based on the retrospective analyses we presented in this study, such as targeting customers for multichannel shopping when they are ready to adopt another channel, imply changing the managerial strategy, and the impact of

[11]We find similar results when we replace travel cost proportion and IPA proportion with channel-related dummies. The results are available on request.

customer–firm interaction characteristics on channel adoption duration could potentially change after a new strategy is implemented.[12] Thus, we recommend that managers adopt a phased approach for managing multichannel marketing resources.

For illustration, consider a firm that wants to adopt a strategy in which it sends direct mail to single-channel customers to inform them about the multiple channels available for transaction, but only when the single-channel customers are expected to adopt a second channel. Before implementing the new strategy for the entire customer base, we recommend that the firm conduct a field experiment for a sample of the customers. Customers who participate in the field experiment would be selected for the mailing effort through a stratified random sampling process. The weights for the stratified sampling process are proportional to the customer's propensity to adopt a new channel during the experiment time frame. The model we present and the customer–firm interaction characteristics we identify would enable managers to predict a customer's hazard for channel adoption at each period. Customer responses during the experiment could then be used to assess (1) the return on investment of the new strategy and (2) whether the impact of customer–firm interaction characteristics changed after adopting the new strategy. If the firm realized return-on-investment improvements from the new strategy, our model would need to be updated to incorporate explicitly the firm's strategy during the experiment to develop optimal resource allocation guidelines for multichannel marketing. The field experiment would also enable managers to assess the true effectiveness of the model recommendations.

Limitations and Further Research

Our results are based on customer behavior in the apparel product category. We expect that the influence of the drivers at the construct level (i.e., purchase-related, channel-related, and frequency-related attributes of customer–firm interactions) and the shared-frailty model framework for predicting channel adoption duration are generalizable to other product categories. However, further replications in other industries would be required to obtain empirical regularities on the relative influence of the variables, such as basket size on single- and two-channel customers. Such replications would be beneficial for developing theories that can improve the effectiveness of multichannel marketing. Another limitation of our study is that we do not allow for the possibility that a single purchase can be related to two channels. For example, many mail-order-catalog firms also have online channels. This leads to a significant "flowback" issue in which customers receive the catalog in the mail and then go online to place the order. This is not a major restriction in our context, because the retailer we study does not offer a direct mail catalog. The model framework we propose here would need to be suitably modified in instances in which a "dual-channel" purchase process is likely. Further research that explores customer attitudes (motivations and apprehensions) toward shopping in multiple channels would help managers design effective channel migration campaigns.

In the customer database we used, the primary mode of communication with the customers was through direct mail. Thus, we were not able to investigate whether a customer's preferences for modes of communication vary with the transaction channels he or she uses. Given that the cost of communication varies across the different modes (e.g., salespeople, direct mail, telephone sales, e-mail), further research that explores the link between modes of communication and channel adoption rate would be valuable for profitable multichannel customer management.

[12] A reasonable estimate of how the parameter estimates might change can be obtained by comparing the parameter estimates for customers who were (1) touched heavily and (2) touched less in the past. We find that the substantive conclusions of our study are the same for both groups, leading us to believe that the influence of customer–firm interaction characteristics would not change dramatically if a firm adopts our model framework.

Appendix Conditional Distributions and MCMC Estimation Algorithm

Likelihood Function

Let δ_{ij} denote the indicator variable, which is 1 if t_{ij} is an actual observed time to adoption and is 0 if it is a censored observation. Let g_{i2} equal 1 and g_{i3} equal 0 for single-channel customers (i.e., $\delta_{i2} = 0$, and $\delta_{i3} = 0$). For multichannel customers—both two-channel (i.e., $\delta_{i2} = 1$, and $\delta_{i3} = 0$) and three-channel (i.e., $\delta_{i2} = 1$, and $\delta_{i3} = 1$) customers—let g_{i2} and g_{i3} equal 1. The variables (t_{ij}, δ_{ij}, g_{ij}, X^*_{ij}) are observed for channel adoption events j = 2, 3 and customers i = 1, …, n, where X^*_{ij} includes event-specific and common covariates. Let all such factors be denoted as $\tilde{D}$. Let $\tilde{W} = (w_1, \ldots, w_n)$ denote the vector of unobserved frailties. We refer to $(\tilde{D}, \tilde{W})$ as the complete data. The likelihood has the following form:

$$L = \prod_{i=1}^{n} \prod_{j=2}^{3} \left[(\lambda_j \gamma t_{ij}^{\gamma-1} w_i \vartheta_{ij})^{\delta_{ij}} \times \exp(-\lambda_j t_{ij}^{\gamma} w_i \vartheta_{ij}) \right]^{g_{ij}},$$

where $\vartheta_{ij} = e^{\beta_0' X_{i0}} \times e^{\beta_2' X_{i2} \varphi_2} \times e^{\beta_3' X_{i3} \varphi_3}$ and $\varphi_j = 1$ if the observation represents the jth channel adoption and 0 if otherwise.

Prior Specifications

The product prior specifications for the model parameters (assuming independence) are as follows: For the common covariates, we assume that the prior distribution $\pi(\beta_{0s})$ is normal (c_{0s}, d_{0s}) for s = 1, …, p_0; the prior distribution for covariates of second-channel adoption duration (Event 1) $\pi(\beta_{2s})$ is normal (c_{2s}, d_{2s}) for s = 1, …, p_2; and the prior distribution for covariates of third-channel adoption duration (Event 2) $\pi(\beta_{3s})$ is normal (c_{3s}, d_{3s}) for s = 1, …, p_3. The prior distribution for κ is $\pi(\kappa)$ = Gamma (c_k, c_k), for $\pi(\lambda_j)$ is Gamma ($c_{\lambda j}$, $c_{\lambda j}$), and for $\pi(\gamma)$ is Gamma (1, c_γ). The values of the hyperparameters are chosen to correspond to noninformative prior assumptions.

MCMC Algorithm

The MCMC algorithm proceeds by sampling sequentially from the following conditional distributions. Given all other parameters and the data, the complete conditional distribution of λ_j is proportional to a gamma distribution as follows:

$$p(\lambda_j|\gamma, t_{ij}, w_i, \vartheta_{ij})$$

$$\sim \text{gamma}\left(\sum_i \delta_{ij}g_{ij} + c_{\lambda j} - 1, \sum_i vt_{ij}^{\gamma}w_i\vartheta_{ij}g_{ij} + c_{\lambda j}\right).$$

The complete conditional distribution of γ, given all other parameters, is proportional to

$$p(\gamma|\lambda, t_{ij}, w_i, \vartheta_{ij}) \propto \gamma^{\sum_i\sum_j \delta_{ij}*g_{ij}}\left(\prod_{i=1}^{n}\prod_{j=2}^{3} t_{ij}^{\delta_{ij}g_{ij}}\right)^{\gamma}$$

$$\times \exp\left(-\sum_i\sum_j \lambda_j t_{ij}^{\gamma}w_i\vartheta_{ij}g_{ij} - \gamma c_{\gamma}\right).$$

We used the ratio of uniforms method to generate samples. The complete conditional distribution of κ, given all other parameters, is proportional to

$$p(\kappa|w_i) \propto \left(\prod_{i=1}^{n} w_i\right)^{\kappa}\frac{\kappa^{n\kappa + c_{\kappa} - 1}}{\Gamma(\kappa)^n}\exp\left[-\kappa\left(\sum_{i=1}^{n} w_i + c_{\kappa}\right)\right].$$

We use the Metropolis–Hastings algorithm to generate samples. For i = 1, …, n, the complete conditional distribution of w_i, given all other parameters and the data, is proportional to a gamma distribution as follows:

$$p(w_i|\delta_{ij}, \lambda, \gamma, t_{ij}, \vartheta_{ij}, \kappa)$$

$$\sim \text{gamma}\left(\sum_{j=2}^{3}\delta_{ij}g_{ij} + \kappa, \sum_{j=2}^{3}\lambda_j t_{ij}^{\lambda}\vartheta_{ij}g_{ij} + \kappa\right).$$

The complete conditional distributions of β_0 (the common regression parameters) is

$$p(\beta_{0s}|t_{ij}, w_i, \lambda, \gamma) \propto \prod_{i=1}^{n}\prod_{j=2}^{3}\Big[(e^{-\beta_0' X_{i0}})^{\delta_{ij}g_{ij}}$$

$$\times \exp(-\lambda_j t_{ij}^{\gamma}w_i\vartheta_{ij}g_{ij})\Big] \times \prod_{s=1}^{p\_0}\exp\left[\frac{-1}{2d_{0s}}(\beta_{0s} - c_{0s})^2\right].$$

The complete conditional distributions of β_2 (the regression parameters specific to Event 1) and β_3 (the regression parameters specific to Event 2) have the forms

$$p(\beta_{js}|t_{ij}, w_i, \lambda, \gamma) \propto \prod_{i=1}^{n}\prod_{j=2}^{3}\Big[(e^{-\beta_j' X_{ij}\vartheta_{ij}})^{\delta_{ij}g_{ij}}$$

$$\times \exp(-\lambda_j t_{ij}^{\gamma}w_i\vartheta_{ij}g_{ij})\Big] \times \prod_{s=1}^{p\_j}\exp\left[\frac{-1}{2d_{js}}(\beta_{js} - c_{js})^2\right].$$

We use the ratio of uniforms method to generate samples in each case.

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