The Role of Product Line Length for Brands Marketing Horizontally Differentiated Products

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Abstract

Product line extension is pervasive in categories of horizontally differentiated products. Despite the popularity of this marketing strategy, its effects on performance metrics relevant to brand managers remain largely under-studied. Extending a brand's product line can cause product proliferation (i.e., the marketing of seemingly identical products by a brand), which has been identified to incur several costs. This thesis explores the effects of product line length on the following metrics: product sales, product exit, new product trial, and brand preference. It also considers the structure of a product line in order to assess the impacts of product proliferation. Methodologically, the author develops a dynamic path analysis model, a threshold regression model, and a multiple discrete-continuous model. The empirical results from the U.S. potato chip market suggest that a brand's product line length has positive effects on its product sales and the likelihood of consumers' trial of its new products (i.e., products within the first year after launch). However, it also has a positive effect on the hazard of product exit for its new products and negative effects on consumers' preferences for both the brand and its competitors. The author further characterizes the structure of a product line by distinct SKUs (i.e., SKUs with unique configurations) and duplicate SKUs (i.e., SKUs similar to distinct SKUs previously introduced). The results indicate that the number of a brand's duplicate SKUs, which can measure the degree of product proliferation, has no effect on its product sales. Even though it has a positive effect on the likelihood of new product trial, it has a positive effect on the product exit hazard for the brand's mature products (i.e., products surviving more than one year) and a negative effect on consumers' preference for the brand. In contrast, although the number of a brand's distinct SKUs has a negative effect on the likelihood of new product trial, it has negative effects on the product exit hazard for the brand's mature products and consumers' preference for its competitors.

Résumé

L'élargissement de la gamme de produits est omniprésent dans les catégories de produits différenciés horizontalement. Malgré la popularité de cette stratégie de marketing, ses effets sur les indicateurs de performance pertinents pour les gestionnaires de marque restent largement sous-étudiés. L'élargissement de la gamme de produits d'une marque peut entraîner la prolifération des produits (par exemple, la commercialisation de produits apparemment identiques par une marque), ce qui encourt souvent de nombreux coûts. Cette thèse explore les effets de la longueur de la gamme de produits sur les paramètres suivants : les ventes de produits, la fin de vie d'un produit sur le marché, l'essai d'un nouveau produit et la préférence de la marque. Elle examine également la structure d'une gamme de produits afin d'évaluer les impacts de la prolifération des produits. Méthodologiquement, l'auteur développe un modèle d'analyse du parcours dynamique, un modèle du seuil de régression et un modèle multiple discret-continu. Les résultats empiriques du marché des chips de pomme de terre des États-Unis semblent indiquer que la longueur de la gamme de produits d'une marque a des effets positifs sur ses ventes de produits et la probabilité que les consommateurs essaient ses nouveaux produits (à savoir, les produits dans la première année après leur lancement). Cependant, cela contribue aussi au risque de fin de vie d'un produit sur le marché pour les nouveaux produits et a des effets négatifs sur les préférences des consommateurs pour, à la fois, la marque et ses concurrents. De plus, l'auteur caractérise la structure d'une gamme de produits par UGSs (unité de gestion de stock) distinctes (à savoir, les UGSs avec des configurations uniques) et les UGSs dupliquées (par exemple, les UGSs similaires jusqu’aux UGSs distinctes introduites précédemment). Les résultats indiquent que le nombre d'UGS dupliquées d’une marque donnée, qui permet de mesurer le degré de prolifération des produits, n'a aucun effet sur les ventes de produits. Même si ceci a un effet

positif sur la probabilité que les consommateur essaient un nouveau produit, cela contribue aussi au risque de fin de vie d'un produit sur le marché pour les produits matures de la marque (par exemple, les produits survivants plus d'un an) et a un effet négatif sur la préférence des consommateurs pour la marque. En revanche, bien que le nombre d'UGSs d'une marque distincte ait un effet négatif sur la probabilité que les consommateurs essaient un nouveau produit, cela a des effets négatifs sur le risque de fin de vie d'un produit sur le marché pour les produits matures de la marque et la préférence des consommateurs pour ses concurrents.

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Contribution of Authors

Chapter 4 of this dissertation is written in collaboration with Demetrios Vakratsas, who has acted as the advisor of this dissertation and is an associate professor of Marketing in Desautels Faculty of Management at McGill University. Specifically, Wei-Lin Wang developed the main research idea and performed the data analysis. Wei-Lin Wang and Demetrios Vakratsas discussed the revisions of the essay.

Chapter 1

Introduction and Literature Review

1.1 Motivation

Product line extension occurs when a company uses its established brand name to introduce a new item into one of its existing product categories, consequently increasing the product line length or the number of products marketed by the brand. This new product strategy is frequently used by brands managing horizontally differentiated products, such as consumer packaged goods (CPG). In fact, an IRI study suggested that 90% of new product introductions in CPG markets are line extensions (IRI 2010). Although product line extension is pervasive, its effect is inconclusive because contradictory results regarding the influences of product line length on some performance metrics have been reported and because the influences of product line length on many other performance metrics have not been investigated. Moreover, few studies exploring those effects examine the context of horizontally differentiated products (see Section 1.2 for a review of the literature). Therefore, the main objective of this study is to understand the role of product line length for brands with horizontally differentiated products. Specifically, in chapters 2-4, we assess the effects of product line length on product sales, product exit, new product trial, and brand preference for those brands.

Chapter 2 probes the relationships between product line length, product sales, and new product exit. It has been shown that a longer product line increases brand sales (e.g., Ataman et al. 2008; Ataman et al. 2010), suggesting that produce line length may increase product sales and thereby lower the hazard of product exit for the brand. However, a longer product line has been typically shown to increase the hazard of product exit (e.g., de Figueiredo and Kyle 2006). Such seemingly conflicting findings may be explained by the different effects for products at different stages of life, which theoretically emerge from the literature (e.g., Hitsch 2006; Mason and Milne 1994). Chapter 2, hence, explores the dynamic relationships among product line length, product sales, and product lifetime by estimating a dynamic path analysis model. Methodologically, this chapter also extends the application of the dynamic path analysis to include a large number of control variables by estimating the model in a semiparametric approach.

Chapter 3 explores the drivers of new product trial and early product withdrawal. Considering the high product failure rate, CPG managers hope to identify drivers that encourage consumers to try their new products. However, product trial models, such as hazard-based models (e.g., Steenkamp and Gielens 2003), typically ignore early product withdrawal and use data only of SKUs that survive more than one year after their launches. The results from these models, thus, suffer from selection biases. In this chapter, we develop a threshold regression model with a Weiner process and two absorbing thresholds. The Weiner process represents the attractiveness of a new product; the upper threshold represents the threshold of trial by a consumer; and the lower threshold represents the threshold of withdrawal by managers. We further link time-varying marketing variables, such as product line length, to the two thresholds to identify variables that can drive new product trial or early product withdrawal. By incorporating time-varying coefficients into a model with multiple thresholds, we further contribute to the literature of threshold regression models.

Chapter 4 examines the effect of product line length on consumers' brand preferences and their product choices. Most empirical studies on brand preference have used single discrete choice models that assume consumers select only one item. For CPGs, however, consumers may buy multiple items in a product category on one shopping trip, a behavior called multiple discreteness. The work by Harlam and Lodish (1995) is the only exception; it stresses multiple discreteness in studying product choices. However, Harlam and Lodish (1995) do not use a utility-maximizing framework nor consider the satiation effects. This chapter examines the relationship between product line length and brand preference at the individual consumer level using a multiple discrete-continuous choice model that is based on utility maximization and incorporates the satiation effects. This chapter also considers the role of interbrand competition and consumer heterogeneity in terms of variety seeking propensities.

Product line extension often leads to product proliferation (Berman 2011), or the marketing of seemingly identical products by a brand, especially when the brand runs horizontally differentiated products. While researchers have discussed the forces for and against product proliferation (Berman 2011), to the best of our knowledge, no empirical study assesses the effects of product proliferation. Hence, we consider the role of product line structure (Chong et al. 1998) in Chapters 2-4. Specifically, product line length is further separated into two variables: the number of distinct SKUs (i.e., SKUs representing unique combinations of salient product attribute levels to the brand) and the number of duplicate SKUs (i.e., the other SKUs with the same combination as any of the distinct SKUs previously introduced by the brand). Product proliferation leads to more duplicate SKUs; thus, the effect of the number of duplicate SKUs can be viewed as the effect of product proliferation.

1.2 Literature Review

Table 1 provides a brief summary of empirical studies on the effects of product line length. We summarize the effects of product line length without considering product line structure (see panels (a) and (b) of Table 1) and those considering product line structure (see panels (c) and (d) of Table 1). Related experimental studies are not reported here because most of them focus on product assortment or the total number of products from different firms/brands available to consumers. Please refer to Chernev (2012) and Chernev et al. (2015) for detailed reviews of the effects of product assortment. Unlike product assortment, product line length is the number of products marketed by only one firm/brand. The work by Berger et al. (2007) may be the only experimental study addressing the product portfolio of one brand. It shows that consumers tend to view a brand that provides a great variety of compatible options as an expert in the product category; thus, they are more likely to select the brand. Hereafter, we discuss the findings from empirical studies.

1.2.1 Product Line Length

Product line length is, conceptually, the number of products belonging to the same product line; however, the boundary of a product line seems subjective to researchers and depends on the product categories. Researchers emphasizing firm-level strategies tend to measure the number of products marketed by the firm when investigating industrial goods or durable goods (see panel (a) in Table 1). These goods, usually sold under the manufacturers' brands, are mostly vertically differentiated goods that are sold at different prices according to their objective quality. However, in the CPG market, a company may run several brand names in the same product category, and most consumers are aware of only those product brand names. Moreover, most CPGs owned by

Table 1: Empirical Studies on the Effects of Product Line Length

(a) Independent Variable: The number of products marketed by the firm

Dependent Variable	Result	Author (Year)	Product Category
Firm's market share	Positive	Bayus and Putsis (1999)	Personal computer
Firm's average product price	Positive	Bayus and Putsis (1999)	Personal computer
	Positive	Shankar (2006)	Desktop laser printer
Firm's distribution intensity	Positive	Shankar (2006)	Desktop laser printer
Probability of product exit	Positive	Ruebeck (2002); Ruebeck (2005)	Hard disc driver
	Positive	Cottrell and Nault (2004)	Microcomputer software
	Positive	de Figueiredo and Kyle (2006)	Desktop laser printer
Probability of firm exit	Negative	Sorenson (2000)	Computer workstation
	Positive	Cottrell and Nault (2004)	Microcomputer software
	Negative	Dowell (2006)	Bicycle
	Not Significant	Sorenson et al. (2006)	Machine tool and computer workstation
Speed of service elimination decision-reaching process	Positive	Argouslidis (2008)	Financial service
Level of formalization in service elimination decisions	Positive	Argouslidis and Baltas (2007)	Financial service
Proportion of new products in the firm's portfolio	Negative for machine tool; positive for computer workstation	Sorenson et al. (2006)	Machine tool and computer workstation
Proportion of new products expanding to new niche in the firm's portfolio	Negative	Sorenson et al. (2006)	Machine tool and computer workstation
Technological expansions	Negative	Sorenson et al. (2006)	Machine tool and computer workstation

(b) Independent Variable: The number of products marketed by the brand

Dependent Variable	Result	Author (Year)	Product Category
Brand's sales growth	Positive	Ataman et al. (2008)	25 CPG categories
Brand's potential for sales	Positive	Ataman et al. (2008)	25 CPG categories
Brand's Base sales	Positive	Ataman et al. (2010)	25 CPG categories
Brand's Regular price elasticity	Positive	Ataman et al. (2010)	25 CPG categories
Brands' revenue premium	Not Significant	Slotegraaf and Pauwels (2008)	7 CPG categories
Brands' long-term sales elasticity from display	Negative	Slotegraaf and Pauwels (2008)	7 CPG categories
Brands' long-term sales elasticity from feature	Negative	Slotegraaf and Pauwels (2008)	7 CPG categories
Brands' long-term sales elasticity from price promotion	Negative	Slotegraaf and Pauwels (2008)	7 CPG categories
Brand choice/utility	Positive	Chong et al. (1998)	8 food categories
Product choice/utility	Negative	Harlam and Lodish (1995)	Powdered soft drink

(c) Independent Variable: The number of distinct SKUs marketed by the firm

Dependent Variable	Result	Author (Year)	Product Category
Number of retail stores carrying the product	Positive	Bergen et al. (1996)	14 home appliance categories
Level of service for the product	Positive	Bergen et al. (1996)	14 home appliance categories

(d) Independent Variable: The number of distinct SKUs marketed by the brand

Dependent Variable	Result	Author (Year)	Product Category
Brand choice/utility	Positive	Chong et al. (1998)	8 food categories
	Positive (Inverted U)	Draganska and Jain (2005)	Yogurt

the same brand are horizontally differentiated products that are sold at the same price per standard unit and vary in attributes that cannot be objectively ranked, such as colours, styles, shapes, and flavours. Therefore, it is appropriate to measure product line length by the number of products marketed by the brand when studying horizontally differentiated products in the consumer market (see panel (b) in Table 1).

Considering the rapid product turnover in high-tech industries, researchers have examined the effect of internal competition induced by more products marketed by a firm on the probability that the firm's products will exit the market (Cottrell and Nault 2004; de Figueiredo and Kyle 2006; Ruebeck 2002; Ruebeck 2005). They have concluded that a firm's product line length has a positive effect on the probability of product exit. Although CPGs are also called "fast-moving consumer goods" because they are the quickest items to leave retail shelves, the effect of the internal competition driven by a longer product line on the probability of product exit has not been assessed. So far, the literature has shown that a CPG brand's product line length has a positive effect on the brand's sales (Ataman et al. 2008; Ataman et al. 2010) or the utility of the brand (Chong et al. 1998). These findings imply that, to some extent, product line length should have a positive effect on the sales of a brand's products and, hence, a negative indirect effect on the hazard of product exit for those products; the latter indirect effect is contradictory to the direct effect found in high-tech industries. This contradiction motivates us to investigate the relationships among product line length, product sales, and product exit in Chapter 2.

Urged by the high turnover rate of CPG, brand managers are eager to explore the drivers of new product trial in order to expedite product diffusion (Gielens and Steenkamp 2007; Steenkamp and Gielens 2003). However, the effect of product line length on the probability of new product trial is unaddressed in the literature. Moreover, the typical models used to explore individuals' new product trial (e.g., Steenkamp and Gielens 2003) have not been adjusted to account for the fact that many new CPGs leave the retail shelves less than one year after their launches, which is termed "early product withdrawal" in this study. Both the conceptual and methodological gaps motivate us to construct a model that can probe the drivers for both new product trial and early product withdrawal in Chapter 3.

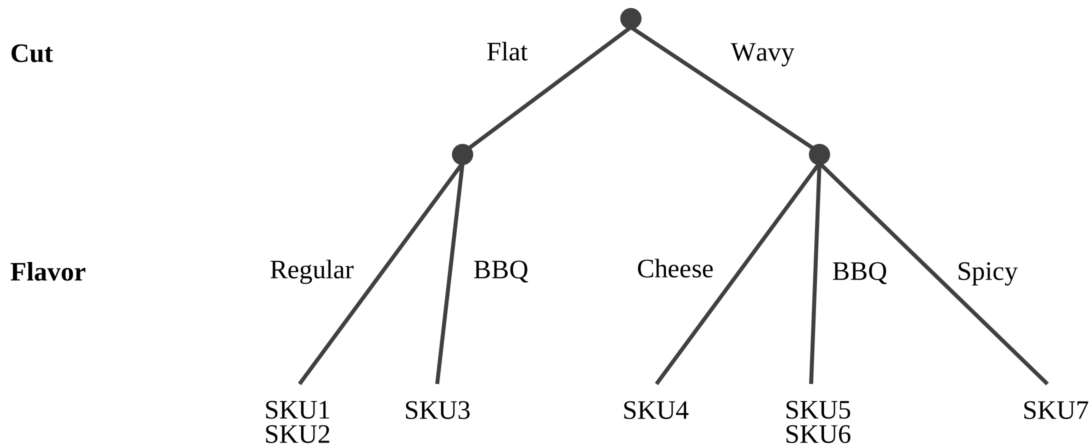
Whether a longer product line can help a brand gain consumer preference for the brand is unclear. While product line length has a positive effect on brand utility/choice (Chong et al. 1998), it also has a negative effect on product utility or decreases the probability that consumers will choose the brand's products (Harlam and Lodish 1995). Furthermore, Chong et al. (1998) did not consider that consumers' multiple discreteness behavior (e.g., Dubé 2004). While Harlam and Lodish (1995) stress the multiple discreteness behavior, they did not use a utility-maximizing model nor deal with the satiation effect when a consumer buys many units of the same item. Therefore, in Chapter 4, we use a multiple discrete model addressing these issues in order to explore the effect of product line length on brand preference.

1.2.2 Product Line Structure

While product line length captures the total number of options a brand makes available to the consumer, not all of these options are differentiated to the same degree. Chong et al. (1998) introduce the concept of product line structure, which distinguishes between distinct SKUs and duplicate SKUs in a brand's product portfolio. Specifically, Chong et al. (1998) use a tree structure to represent a product line by considering salient product attributes $f = 1, \ldots, F$ (e.g., cut and flavor of potato chips) with different level $l = 1, \ldots, L_f$ of each salient product attribute (e.g., wavy is a level of the cut of potato chips). With this, they define a unique combination of salient product attribute levels (e.g., wavy and BBQ chips) to the brand as a distinct SKU. Thus, the numbers of distinct SKUs in a product line indicate how many different combinations of product attribute levels that a brand carries on the market. The difference between product line length and the number of distinct SKUs is the number of duplicate SKUs, which captures the number of products that do not provide additional combinations in the product line. Note that the numbers of distinct and duplicate SKUs do not focus on the role of individual SKUs. Naturally we may like to identify whether an SKU is a distinct or duplicate SKU. For example, one can consider the earliest one introduced among a group of SKUs with the same combination as the distinct SKU. However, an SKU that has the same combination as the other previously introduced SKUs when it is introduced may later become the only one with the combination if the brand deletes those previously introduced SKUs without adding any similar SKU.

Figure 1 provides a simple illustration: A potato chip brand carries seven SKUs in a store, which can be described by five different combinations in terms of cut and flavor levels. Thus, the number of distinct SKUs of this brand is five SKUs, and the number of duplicate SKUs is two SKUs. Note that although SKUs 1 and 2 have the same combination of cut and flavor levels, they are highly similar but not identical products because they are different on some non-salient product attributes[1]. For example, they may be slightly different in terms of the thickness of cut.

[1] Empirically, we consider the cut, flavor, size, and fat content as salient attributes for potato chips because these are the attributes provided by the IRI Academic dataset. Li (2014) studies the same dataset also uses the four attributes. We consider product attributes of potato chips other than the four attributes non-salient attributes.



Product Line Length = **7 SKUs** (7 SKUs offered by the brand)
Number of Distinct SKUs = **5 SKUs** (5 different combinations of cut and flavor offered by the brand)
Number of Duplicate SKUs = **2 SKUs** (product line length – the number of distinct SKUs)

Figure 1: An illustration of the Structure of a Potato Chip Brand's Product Line

Few empirical studies consider product line structure in investigating the effects of product line length (see panels (c) and (d) in Table 1), and all of them focus solely on distinct SKUs. Yet, duplicate SKUs are commonly observed in the CPG market as a result of product proliferation (Berman 2011). Given that the effect of product proliferation has not been empirically examined, we study not only the effects of product line length and the number of distinct SKUs but also the effect of the number of duplicate SKUs in Chapters 2-4. By comparing and contrasting the effects of the three product line length measures, we aim to shed more light on the consequences of product line extension and product proliferation.

Chapter 2

Product Line Length, Product Sales, and Product Exit: A Dynamic Path Analysis

2.1 Introduction

Products in a longer product line are shown to have higher exit rates (Cottrell and Nault 2004; de Figueiredo and Kyle 2006; Ruebeck 2002; Ruebeck 2005). Empirical evidence also supports that product line length can increase the sales and sales-based performance at the brand level (Ataman et al. 2008; Ataman et al. 2010; Chong et al. 1998; Draganska and Jain 2005) or the firm level (Bayus and Putsis 1999; Boulding and Christen 2009; Kekre and Srinivasan 1990). Since the brand-wise or firm-wise sales are the aggregation of the individual products' sales, it is reasonable to infer that, to some extent, product line length has a positive effect on product sales. Product sales, which reflect the future demand for a product, should support the survival of the product (Asplund and Sandin 1999; Carroll et al. 2010). Empirical studies have also revealed that products with higher sales or are more important to the firm's profit have lower exit rates (de Figueiredo and Kyle 2006; Ruebeck 2002). Consequently, by affecting product sales, product line length may also have a negative indirect effect on the hazard of product exit, an understudied effect that contradicts the direct effect. Without considering the indirect effect, therefore, we may not fully understand the total effect of product line length on product exit.

The product line management literature reveals that the effects of product line length on product sales and on the hazard of product exit may vary for products at different stages of product life cycle, but there is no consensus on the signs of the effects. In studying product line extension, most researchers highlight the cannibalization of the existing products' sales by a new product (e.g., Mason and Milne 1994), an intrabrand competition that might drive the existing products out of the market. If product line extension decreases those existing products' sales and, at the same time, increases the brand-wide sales as shown in the literature, the new product's sales must be high enough to compensate for the decrease in the existing products' sales. As a result, product line length may have a positive effect on the sales of a new product and a negative effect on the sales of a mature product, consequently a negative effect on the hazard of product exit for the new product and a positive effect on that for the mature product. Nevertheless, brand managers may introduce several new products to collect market information and keep only those deemed to be profitable (Hitsch 2006). It may be less likely, though, for a new product in a longer product line to generate profitable sales and pass the screen-out phase due to severe intrabrand competition. In contrast, the profitability of a mature product is already proven. Therefore, product line length may have a negative effect on product sales and a positive effect on the hazard of product exit possibly only for a new product.

Consumer choice studies provide yet another speculation on the effects of product line length on product exit rates for products at different stages of product life cycle. Specifically, consumers may use product line length as a quality cue and select the brand with more products that appear compatible (Berger et al. 2007), and they tend to buy the same consumer product goods over time (Harlam and Lodish 1995). For product categories composed of horizontally differentiated products (e.g., consumer packaged goods, CPG), which should be compatible to one another, the findings imply that consumers are inclined to choose a brand with a longer product line and select those mature products that they frequently buy. Therefore, product line length may have a positive effect on product sales and a negative effect on the hazard of product exit for mature products. Overall, considering the different theoretical predictions regarding the effects of product line length on product sales and on the hazard of product exit for a product at different stages of product life cycle, we need an empirical investigation of the possibly dynamic effects.

Consumer choice studies further speculate that the effects of product line length may depend on the structure of the product line. Particularly, Chong et al. (1998) separate product line length into the number of distinct SKUs (i.e., SKUs representing unique combinations of salient product attribute levels to the brand) and the number of duplicate SKUs (i.e., the other SKUs having the same combinations as some of those distinct SKUs in terms of salient product attribute levels), and argue that only the number of distinct SKUs has a positive effect on consumer brand choice. Nowadays, brand managers frequently add duplicate SKUs in their product lines, a practice called “product proliferation” (Berman 2011), rendering it imperative to understanding the influence of duplicate SKUs. However, researchers have not yet considered product line structure in studying the effect of product line length on product sales nor on the hazard of product exit. To fill this gap, we further probe the role of product line structure in examining the potential dynamic effects among the three variables.

In this study, we conduct a dynamic path analysis (Fosen et al. 2006) to explore the time-varying relationships between product line length, product sales, and the hazard of product exit. Our model is mainly composed of an additive hazard regression model (Aalen 1980; Aalen 1989) associated with product exit and regression models related to product sales, product line length, and other marketing variables. We use a semi-parametric approach (Martinussen and Scheike 2006; McKeague and Sasieni 1994) to estimate the model and, hence, expand the application of dynamic path analysis to deal with time-fixed coefficients. By doing so, we can focus on the dynamic relationships among key variables while controlling the others and avoiding too much variance. As a result, this study offers both theoretical and methodological contributions.

We apply the dynamic path analysis model with three-year data on 1,084 new potato chip UPCs[2] introduced in 2002 in the U.S. from the IRI academic dataset (Bronnenberg et al. 2008). The results suggest that, in general, product line length increases product exit rates for only new products (i.e., items in their first year since their launches), and these effect are mitigated when new products have higher sales. However, the direct effect dominates the indirect effect, leading to a total effect highly similar to the direct effect. Further investigations on the influence of product line structure show that for products in the market for less than a year, the number of distinct SKUs increases product exit rates, while the number of duplicate SKUs does not have a significant direct effect; for products surviving more than one year, the number of distinct SKUs decreases product exit rates, whereas the number of duplicate SKUs increases product exit rates. Moreover, the number of distinct SKUs can also increase product sales and consequently lower product exit rates, while the number of duplicate SKUs does not have such an indirect effect on product exit rates. We also consider the inter-brand competition and found that the number of a brand's competing products on the market decreases the brand's product exit rates.

The rest of this paper is organized as follows. Section 2.2 briefly introduces the dynamic path analysis and discusses the specification and estimation of our dynamic path analysis model, including the regression of the hazard of product exit, product sales, and product line length. Section 2.3 then describes data and variables, followed by a discussion of our empirical findings

[2] In this thesis, we use a UPC (universal product code) and an SKU interchangeably to indicate a product.

and insights. We conclude in section 2.4 by identifying avenues for future research.

2.2 Model Development

2.2.1 Dynamic Path Analysis

Dynamic path analysis is an extension of path analysis, a method which has been heavily applied in marketing (e.g., Deshpande and Zaltman 1982). A path analysis model is a set of hierarchical linear regression models in which some covariates in one model will be the dependent variable in another, showing how variables are related to each other. A dynamic path analysis model considers the case that one of the regression models is the regression of a counting process, which can be used to indicate whether an existing product exits the market. The model is fitted each time the information of the model is collected (Fosen et al. 2006). Since the model is fitted successively, the path coefficients are allowed to vary over time. This property is appropriate for exploring the dynamic relationships between product line length, product sales and product exit. For a detailed discussion of dynamic path analysis please refer to Fosen et al. (2006).

Here we consider a counting process $N(t)$, which is one special stochastic process counting the number of events until time t. An additive hazard regression model (Aalen 1980; Aalen 1989) can be used for the regression of $dN(t)$ because the model is linear at time t given covariates $X_1(t)$, …, $X_P(t)$, and thus fit the path analysis framework. Mathematically, by Doob-Meyer decomposition, $N(t)$ can be decomposed into a model part and a random noise part:

$$\begin{aligned} N(t) &= \Lambda(t) + M(t) \\ &= \int_0^t Y(s)\{dB_0(s) + dB_1(s)X_1(s) + \cdots + dB_P(s)X_P(s)\} + M(t), \end{aligned} \tag{1}$$

where $\Lambda(t)$ and $M(t)$ are the compensator (i.e., the model) and the martingale (i.e., the noise) of the counting process; $Y(s)$ is the at-risk indicator being one at time s if neither the event nor the end of the observation period has happened before time s; $dB_j(s) = \beta_j(s)ds$, and the $\beta_j(s)$ is an arbitrary regression function, $j = 1, \ldots, P$. Thus $N(t)$ has intensity in an additive hazards form:

$$\lambda(t) = Y(t)\{\beta_0(t) + \beta_1(t)X_1(t) + \cdots + \beta_P(t)X_P(t)\}, \tag{2}$$

where $\beta_0(s) + \beta_1(s)X_1(s) + \cdots + \beta_P(s)X_P(s)$ is a conditional hazard function (Martinussen and Scheike 2006).

To complete a dynamic path analysis model, we need to specify how the covariates, $X_1(t)$, …, $X_P(t)$, affect one another. We assume that the relationships between these variables are time-invariant. In addition, we order the variables such that $X_j(t)$ does not influence $X_h(t)$ for $h < j$. Thus for any time t, we have P ordered variables where

$$X_j(t) = \sum_{h=1}^{j-1} \beta_{hj}(t)X_h(t) + \varepsilon_j(t), j = 2, \ldots, P, \tag{3}$$

where $\beta_{hj}(t)$ is path coefficient from $X_h(t)$ to $X_j(t)$ at time t. $\varepsilon_j(t)$ are i.i.d. with expectation zero and variance σ^2. We may further assume that one or some $\beta_{hj}(t) = 0$, suggesting that $X_h(t)$ will not influence $X_j(t)$. The ordering of variables and the assumption of zero path coefficients should be made by prior knowledge or by logical considerations.

The dynamic path analysis of Fosen et al. (2006) is very flexible with all coefficients being time-varying. However, when the data is limited, it is necessary and sensible to limit the degree of freedom of the model and to avoid too much variance by specifying time-fixed coefficients. In many practical settings, we may intend to control the influences of certain covariates, of which the effects are not supported by theories nor subject-matter knowledge to be time-varying.

McKeague and Sasieni (1994) consider the semiparametric additive intensity model:

$$\lambda(t) = Y(t)\{X(t)\beta(t) + Z(t)\gamma\} \tag{4}$$

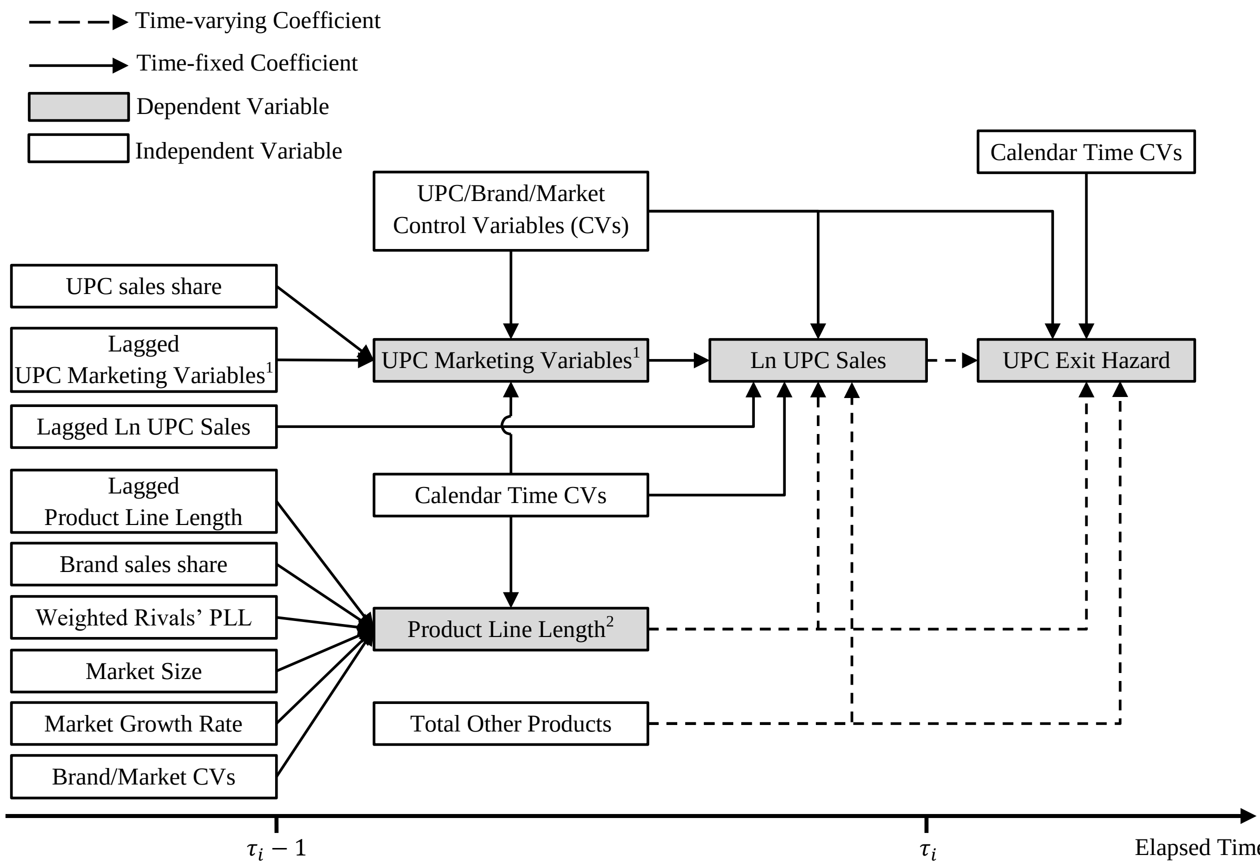
where $X(t)$ and $Z(t)$ are covariate vectors of dimensions p and q, $\beta(t)$ is the p-dimensional locally integrable function, and γ is the q-dimensional time-fixed regression coefficient vector. Similarly, we may replace some $\beta_{hj}(t)$ in Equation (3) with a time-fixed coefficient γ_{hj}, such as,

$$X_j(t) = \sum_{h=i}^{j-1} \beta_{hj}(t)X_h(t) + \sum_{h=1}^{i-1} \gamma_{hj}X_h(t) + \varepsilon_j(t). \tag{5}$$

We consider both time-varying and time-fixed coefficients and, thus, extend the application of dynamic path analysis. The estimation of our path analysis model will be discussed later.

2.2.2 Model Specification

We focus on the influence of a brand's product line length on the exit of its products labeled by universal product codes (UPCs). The influence is allowed to vary over time, and it may be directly from product line length to product exit or indirectly via the sales of the UPC. Thus, our dynamic path analysis model mainly contains regression models of UPC exit, UPC sales, and brand-level product line length. We will also construct regression models of UPC-level marketing variables that are covariates of UPC sales. The regression of UPC exit will be modeled using the semiparametric additive hazard form exhibited in Equation (4), while the other regression models will have forms similar to Equation (5). Just like any standard path analysis model, our dynamic path analysis model can be represented by a path diagram that illustrates the relationships between all variables. We summarize our model in Figure 2 and discuss each regression model in details in the following texts.



Note:

1. UPC-level marketing variables include regular price (in logarithm), price index (in logarithm), feature ad, in-store display, and distribution breadth. Each marketing variable is affected by its own lagged value.
2. To incoporate prodcut line structure, product line length can be further separated into the number of distinct SKUs and the number of duplicate SKUs (i.e., two regression models).

Figure 2: Path Diagram of the Dynamic Path Analysis Model

We denote a UPC by u, $u = 1, \dots, U$; a brand by b, $b = 1, \dots, B$; a market by m, $m = 1, \dots, M$; and the elapsed time from product launch by t, $t \in (0, T]$, where T is the end of observation period. Because each UPC u can be traced back to a particular brand b that offers the UPC, we ignore the subscript b associated with UPC u, unless it is necessary. Our unit of analysis is a specific UPC in a specific market, and a UPC-market pair is denoted by v, $v = 1, \dots, V$. The observation associated with UPC u in market m begins when the UPC is launched in the market, and the observed elapsed product exit time is $T_v \leq T$, if the exit time is not right-censored. Thus,

$N_v(t)$ is the counting process indicating whether UPC u exits market m until time t. Suppose we observe covariates associated with $N_v(t)$ at equally distant elapsed time $\tau_0 = 0 < \tau_1 < \cdots < \tau_{N-1} < \tau_N$, $\tau_{N-1} < T$, and $\tau_N \geq T$, and we assume the covariates observed at τ_i remain the same during $(\tau_i, \tau_{i+1}]$. This assumption can eliminate the concern that $N_v(t)$ will influence any covariate and thus violate the assumption that no feedback loop exists in the model.

2.2.2.1 Regression of Product Exit

In this study, we examine the effects of product line length and product sales on product exit; thus, the former two variables are included to explain the intensity/hazard of product exit. Since product line length can also be used by a brand for the purpose of competition, we also included the total number of products provided by the other brands in the market. All of these effects are allowed to be time-varying. As a result, we incorporate three key determinants of product exit highlighted by de Figueiredo and Kyle (2006): product sales, inter-brand competition, and intra-brand competition or strategic product line decision. We do not consider the direct effects of UPC-level marketing variables on product exit because we assume these variables will influence product exit only indirectly through product sales. Furthermore, we control the time-fixed effects regarding product features, brand, market, and calendar time by using dummy variables. As to the effect of calendar time, we speculate that the existence of special holidays (e.g., Christmas) or events (e.g., NFL Super Bowl) during $(\tau_i, \tau_{i+1}]$, which is predetermined and thus can be observed at τ_i, will have a concomitant effect on product exit during the same period. Specifically, the intensity/hazard rate of exit of UPC u in market m has an additive hazard form:

$$\begin{aligned} \lambda_v(t) = Y_v(t)\{&\beta_{1,1}(t) + \ln\left(Sales_{v,\tau_i}\right)\beta_{1,2}(t) + PLL_{bm,\tau_i}\beta_{1,3}(t) + TOPLL_{bm,\tau_i}\beta_{1,4}(t) \\ &+ \boldsymbol{X_u^T\gamma_{1,1}} + \gamma_{1,2,b} + \gamma_{1,3,m} + \boldsymbol{CTIME_{\tau_{i+1}}^T\gamma_{1,4}}\}, \end{aligned} \tag{6}$$

where

$\lambda_v(t)$ = the intensity/hazard rate of UPC u in market m at elapsed time t, $t \in (\tau_i, \tau_{i+1}]$,

$i = 0, \ldots, N-1$;

$Y_v(t)$ = the at risk indicator for UPC u in market m, which is one as long as the UPC is still on the market;

$\ln\left(Sales_{v,\tau_i}\right)$ = the logarithm of the total sales of UPC u in market m during $(\tau_{i-1}, \tau_i]$;

PLL_{bm,τ_i} = the average product line length of brand b in market m during $(\tau_{i-1}, \tau_i]$;

$TOPLL_{bm,\tau_i}$ = the average number of total competing products provided by brands, except brand b in market m during $(\tau_{i-1}, \tau_i]$;

$\beta_{1,j}(t)$ = time-varying coefficient, $j = 1, \ldots, 4$, where $\beta_{1,1}(t)$ is the hazard when all covariates are equal to zero;

$\boldsymbol{X_u}$ = the vector of the product features of UPC u, such as package size;

$\boldsymbol{\gamma_{1,1}}$ = the time-fixed coefficient vector associated with $\boldsymbol{X_u}$;

$\gamma_{1,2,b}$ = the brand-specific time-fixed coefficient, $b = 1, \ldots, B-1$, where $\gamma_{1,2,B} = 0$ is the coefficient for private label;

$\gamma_{1,3,m}$ = market-specific time-fixed coefficient, $m = 1, \ldots, M-1$;

$\boldsymbol{CTIME_{\tau_{i+1}}}$ = the vector of dummy variables indicating the characteristics of the calendar time during $(\tau_i, \tau_{i+1}]$ that are known at τ_i, such as the existence of a special holiday;

$\boldsymbol{\gamma_{1,4}}$ = the vector of time-fixed coefficients associated with the calendar time.

2.2.2.2 Regression of Product Sales

We formulate a UPC-level product sale regression model similar to that of Macé and Neslin (2004) and the observation equation of Ataman et al. (2010). The sales of UPC u in market m

during $(\tau_{i-1}, \tau_i]$ may be affected by both its brand's product line length and the number of competing products in the market during the same period, and the effects are allowed to be time-varying. Furthermore, marketing variables associated with the UPC in the market during the period should also influence the sales of the UPC. Here we consider five UPC-level marketing variables, including regular (unit) price, price index (i.e., the ratio of actual price to regular price), feature ads of the UPC, in-store display of the UPC, and distribution breadth (i.e., the percentage of store selling the UPC in the market). Since our main focus is on the effect of product line length, we set the coefficients of those UPC-level marketing variables to be time-fixed. We also include the total sales of the UPC in the market during $(\tau_{i-2}, \tau_{i-1}]$ to account for the autoregressive effect. In line with the specification of the regression of product exit, we control the time-fixed effects regarding product features, brand, market, and calendar time.

Mathematically, for any $t \in (\tau_{i-1}, \tau_i]$, the logarithm of sales of UPC u in market m has the form:

$$\begin{aligned}\ln\left(Sales_{v,\tau_i}\right) = {} & PLL_{bm,\tau_i}\beta_{2,1}(t) + TOPLL_{bm,\tau_i}\beta_{2,2}(t) + \gamma_{2,1} + \ln\left(RP_{v,\tau_i}\right)\gamma_{2,2} \\ & + \ln\left(PI_{v,\tau_i}\right)\gamma_{2,3} + FEA_{v,\tau_i}\gamma_{2,4} + DIS_{v,\tau_i}\gamma_{2,5} + DB_{v,\tau_i}\gamma_{2,6} \\ & + \ln\left(Sales_{v,\tau_{i-1}}\right)\gamma_{2,7} + \boldsymbol{X}_{\boldsymbol{u}}^{T}\boldsymbol{\gamma}_{\mathbf{2,8}} + \gamma_{2,9,b} + \gamma_{2,10,m} + \boldsymbol{CTIME}_{\boldsymbol{\tau_i}}^{T}\boldsymbol{\gamma}_{\mathbf{2,11}},\end{aligned} \tag{7}$$

where

$\beta_{2,j}(t)$ = time-varying coefficient, $j = 1,2$;

$\ln\left(RP_{v,\tau_i}\right)$ = the logarithm of average regular unit price of UPC u in market m during $(\tau_{i-1}, \tau_i]$;

$\ln\left(PI_{v,\tau_i}\right)$ = the logarithm of average price index (i.e., the ratio of actual unit price to the regular unit price) of UPC u in market m during $(\tau_{i-1}, \tau_i]$;

FEA_{v,τ_i} = the average percentage that feature ads are used for UPC u in market m during $(\tau_{i-1}, \tau_i]$;

DIS_{v,τ_i} = the average percentage that in-store display is used for UPC u in market m during

$(\tau_{i-1}, \tau_i]$;

DB_{v,τ_i} = the average percentage of store selling UPC u in market m during $(\tau_{i-1}, \tau_i]$;

$\ln(Sales_{v,\tau_{i-1}})$ = the logarithm of total sales of UPC u in market m during $(\tau_{i-2}, \tau_{i-1}]$;

$\gamma_{2,j}$ = time-fixed coefficient, $j = 1, \ldots, 7$, where $\gamma_{2,1}$ is the time-fixed intercept;

$\boldsymbol{CTIME}_{\boldsymbol{\tau_i}}$ = the vector of dummy variables indicating the characteristics of the calendar time during $(\tau_{i-1}, \tau_i]$; and

$\boldsymbol{\gamma}_{\mathbf{2,8}}$, $\gamma_{2,9,b}$, $\gamma_{2,10,m}$, $\boldsymbol{\gamma}_{\mathbf{2,11}}$ = the time-fixed (vectors of) coefficients regarding the product features $\boldsymbol{X_u}$, the brand b, the market m, and the calendar time $\boldsymbol{CTIME}_{\boldsymbol{\tau_i}}$.

Considering that product sales may be highly skewed, we use a logarithmic transformation in order to transform product sales into one variable that is more approximately normal.

2.2.2.3 Regression of Product Line Length

The regression of product line length includes lagged brand-level and market-level covariates considered in the marketing literature. At the brand level, we consider the market share of the focal brand and the weighted number of products offered by all the brand's competitors (Bayus and Putsis 1999). At the market-level, we study the market size of the product category and its growth rate (Shankar 2006). We also include the product line length during $(\tau_{i-2}, \tau_{i-1}]$ to account for the autoregressive effect. All coefficients are considered to be time-fixed. Lastly, we control the effects of the brand, the market, and the calendar time. The regression of product line length, hence, has the form:

$$\begin{aligned} PLL_{bm,\tau_i} = \gamma_{3,1} + Share_{bm,\tau_{i-1}}\gamma_{3,2} + WRPLL_{bm,\tau_{i-1}}\gamma_{3,3} + \ln(Size_{m,\tau_{i-1}})\gamma_{3,4} \\ + MGR_{m,\tau_{i-1}}\gamma_{3,5} + PLL_{bm,\tau_{i-1}}\gamma_{3,6} + \gamma_{3,7,b} + \gamma_{3,8,m} + \boldsymbol{CTIME}^T_{\boldsymbol{\tau_i}}\boldsymbol{\gamma}_{\mathbf{3,9}}, \end{aligned} \tag{8}$$

where

$Share_{bm,\tau_{i-1}}$ = the average market share of brand b in market m in terms of sales revenue during $(\tau_{i-2}, \tau_{i-1}]$;

$WRPLL_{bm,\tau_{i-1}}$ = the average number of UPCs offered by all competitors of brand b in market m during $(\tau_{i-2}, \tau_{i-1}]$ weighted by sales;

$\ln(Size_{m,\tau_{i-1}})$ = the market size or the logarithm of the average sales of all UPCs in the product category in market m during $(\tau_{i-2}, \tau_{i-1}]$;

$MGR_{m,\tau_{i-1}}$ = the growth rate of the market size in market m from $(\tau_{i-3}, \tau_{i-2}]$ to $(\tau_{i-2}, \tau_{i-1}]$;

$PLL_{bm,\tau_{i-1}}$ = the average product line length of brand b in market m during $(\tau_{i-2}, \tau_{i-1}]$;

$\gamma_{3,j}$ = time-fixed coefficient, $j = 1, \ldots, 6$, where $\gamma_{3,1}$ is the time-fixed intercept; and

$\gamma_{3,7,b}, \gamma_{3,8,m}, \boldsymbol{\gamma_{3,9}}$ = the time-fixed (vectors of) coefficients regarding the brand b, the market m, and the calendar time $\boldsymbol{CTIME_{\tau_i}}$.

We can further consider product line structure, and separate product line length into the number of distinct SKUs and the number of duplicate SKUs (Chong et al. 1998). Specifically, we specify two regression models with the form in Equation (8) and replace PLL_{bm,τ_i} with $NDIS_{bm,\tau_i}$ and $NDUP_{bm,\tau_i}$ respectively, where $NDIS_{bm,\tau_i}$ is the average number of distinct SKUs of brand b in market m during $(\tau_{i-1}, \tau_i]$, $NDUP_{bm,\tau_i}$ is the average number of duplicate SKUs of brand b in market m during $(\tau_{i-1}, \tau_i]$, and $PLL_{bm,\tau_i} = NDIS_{bm,\tau_i} + NDUP_{bm,\tau_i}$.

2.2.2.4 Regression of UPC-level Marketing Variables

Other than the three main regression models, we also incorporate into our dynamic path analysis model the regressions of the five UPC-level marketing variables that are covariates in the regression of product sales. In line with Ataman et al. (2008) and Ataman et al. (2010), we consider the effect of performance feedback (i.e., sales gains lead to increased marketing). We assume that the five marketing variables, including $\ln\left(RP_{v,\tau_i}\right)$, $\ln\left(PI_{v,\tau_i}\right)$, FEA_{v,τ_i}, DIS_{v,τ_i}, and DB_{v,τ_i}, are affected by the lagged UPC-level market share in terms of sales, considering that brand managers usually track own-brand market share and may adjust marketing variables based on the performance measure (Horvath et al. 2005), and that market share can summarize the sales performance in a competitive environment. We further include the value of each marketing variable during $(\tau_{i-2}, \tau_{i-1}]$ to account for the autoregressive effect. We also control the effects of the product features, the brand, the market, and the calendar time. All coefficients are assumed to be time-fixed. In brief, the regression model of the marketing variable k has the form:

$$\begin{aligned} MAR_{v,\tau_i,k} = \gamma_{4,1,k} + Share_{v,\tau_{i-1}}\gamma_{4,2,k} + MAR_{v,\tau_{i-1},k}\gamma_{4,3,k} + \boldsymbol{X}_{\boldsymbol{u}}^T\boldsymbol{\gamma}_{\mathbf{4},\mathbf{4},\boldsymbol{k}} + \gamma_{4,5,b,k} \\ + \gamma_{4,6,m,k} + \boldsymbol{CTIME}_{\boldsymbol{\tau_i}}^T\boldsymbol{\gamma}_{\mathbf{4},\mathbf{7},\boldsymbol{k}}, \end{aligned} \tag{9}$$

where

$MAR_{v,\tau_i,k}$ = the marketing variable k associated with UPC u in market m during $(\tau_{i-1}, \tau_i]$,

$k = 1, \dots, 5$;

$Share_{v,\tau_{i-1}}$ = the average market share of UPC u in market m in terms of sales during

$(\tau_{i-2}, \tau_{i-1}]$;

$MAR_{v,\tau_{i-1},k}$ = the marketing variable k associated with UPC u in market m during $(\tau_{i-2}, \tau_{i-1}]$,

$k = 1, \dots, 5$;

$\gamma_{4,j,k}$ = the time-fixed coefficients associated with marketing variable k, $j = 1,2,3$, where $\gamma_{4,1,k}$

is the time-fixed intercept; and

$\boldsymbol{\gamma}_{\mathbf{4},\mathbf{4},\boldsymbol{k}}, \gamma_{4,5,b,k}, \gamma_{4,6,m,k}, \boldsymbol{\gamma}_{\mathbf{4},\mathbf{7},\boldsymbol{k}}$ = the time-fixed (vectors of) coefficients associated with marketing

variable k regarding the product features $\boldsymbol{X}_{\boldsymbol{u}}$, the brand b, the

market m, and the calendar time $\boldsymbol{CTIME}_{\boldsymbol{\tau_i}}$.

2.2.2.5 Endogeneity

To deal with the potential endogeneity issue, we first regress every dependent variable on lagged independent variables, unless the values of the independent variables, such as calendar time, are predetermined. Furthermore, to handle the endogeneity between product sales and UPC-level marketing variables, we use the lagged market share of the product in terms of sales as an independent variable for each product marketing variable. As we discussed, brand managers may use the sales information to decide marketing variables in the next period. The market share summarizes the sales information in a competitive environment; thus, including the variable can help us resolve the issue of endogeneity. Similarly, product sales and product line length might also have an endogeneity issue, even though product line length is operationalized at the brand level. We use the market share of the brand in terms of sales as an independent variable for product line length in order to eliminate the concern.

2.2.3 Estimation

2.2.3.1 Regression of Product Exit

Equation (6) can be rewritten as follows:

$$\lambda_v(t) = Y_v(t)\{\boldsymbol{X_v}(t)d\boldsymbol{B_1}(t) + \boldsymbol{Z_v}(t)\boldsymbol{\gamma_1}\}, \tag{10}$$

where

$\boldsymbol{X_v}(t) = \left[1, ln\left(Sales_{v,\tau_i}\right)(t), PLL_{bm,\tau_i}(t), TOPLL_{bm,\tau_i}(t)\right]$, where $ln\left(Sales_{v,\tau_i}\right)(t)$, $PLL_{bm,\tau_i}(t)$, and $TOPLL_{bm,\tau_i}(t)$ are processes with value $ln\left(Sales_{v,\tau_i}\right)$, PLL_{bm,τ_i}, and $TOPLL_{bm,\tau_i}$ respectively for any $t \in (\tau_i, \tau_{i+1}]$;

$\boldsymbol{B_1}(t) = [B_{1,1}(t), \ldots, B_{1,P}(t)]^T$, where $P = 4$ is the number of columns of $\boldsymbol{X_v}(t)$;

$\boldsymbol{Z_v}(t) = \left[\boldsymbol{X_u}, \boldsymbol{D}_{1,2}, \boldsymbol{D}_{1,3}, \boldsymbol{CTIME}^T_{\boldsymbol{\tau_{i+1}}}(t)\right]$, where $\boldsymbol{D}_{1,2}$ is the vector of brand indicators $d_{1,2,b}$, $\boldsymbol{D}_{1,3}$

is the vector of market indicator $d_{1,3,m}$, and $\boldsymbol{CTIME}^T_{\boldsymbol{\tau_{i+1}}}(t)$ has the values $\boldsymbol{CTIME}^T_{\boldsymbol{\tau_{i+1}}}$ for any $t \in (\tau_i, \tau_{i+1}]$; and

$\boldsymbol{\gamma_1} = [\boldsymbol{\gamma}^T_{\boldsymbol{1,1}}, \gamma_{1,2,1}, \dots, \gamma_{1,2,B-1}, \gamma_{1,3,1}, \dots, \gamma_{1,3,M-1}, \boldsymbol{\gamma}^T_{\boldsymbol{1,4}}]^T$.

Thus the Doob-Meyer decomposition gives:

$$dN_v(t) = Y_v(t)\{\boldsymbol{X_v}(t)d\boldsymbol{B_1}(t) + \boldsymbol{Z_v}(t)\boldsymbol{\gamma_1}dt\} + dM_v(t), \tag{11}$$

where $N_v(t)$ and $M_v(t)$ are the counting process and the martingale process associated with the UPC-market pair v.

We assume that there are V independent copies of $N_v(t)$, $Y_v(t)$, $\boldsymbol{X_v}(t)$, and $\boldsymbol{Z_v}(t)$. We further organize the design vectors into matrixes:

$$\boldsymbol{N}(t) = [N_1(t) \quad \cdots \quad N_V(t)]^T;$$

$$\boldsymbol{W_1}(t) = [\boldsymbol{X_1}(t)^T Y_1(t) \quad \cdots \quad \boldsymbol{X_V}(t)^T Y_V(t)]^T;$$

$$\boldsymbol{W_2}(t) = [\boldsymbol{Z_1}(t)^T Y_1(t) \quad \cdots \quad \boldsymbol{Z_V}(t)^T Y_V(t)]^T;$$

$$\boldsymbol{M}(t) = [M_1(t) \quad \cdots \quad M_V(t)]^T;$$

Thus, we can write the matrix form of Equation (11) as follows:

$$d\boldsymbol{N}(t) = \boldsymbol{\lambda}(t)dt + d\boldsymbol{M}(t) = \boldsymbol{W_1}(t)d\boldsymbol{B_1}(t) + \boldsymbol{W_2}(t)\boldsymbol{\gamma_1}dt + d\boldsymbol{M}(t). \tag{12}$$

Equation (12) has a form of a linear model; hence $d\boldsymbol{B_1}(t)$ and $\boldsymbol{\gamma_1}$ can be estimated from the least square equations:

$$\boldsymbol{W_1}(t)^T(d\boldsymbol{N}(t) - \boldsymbol{\lambda}(t)dt) = \boldsymbol{0}; \tag{13}$$

$$\int \boldsymbol{W_2}(t)^T(d\boldsymbol{N}(t) - \boldsymbol{\lambda}(t)dt) = \boldsymbol{0}. \tag{14}$$

These equations can be solved sequentially. Given $\boldsymbol{\gamma_1}$, we can solve Equation (13) and yield

$$d\widehat{\boldsymbol{B_1}}(t) = \left(\boldsymbol{W_1}(t)^T\boldsymbol{W_1}(t)\right)^{-1}\boldsymbol{W_1}(t)^T(d\boldsymbol{N}(t) - \boldsymbol{W_2}(t)\boldsymbol{\gamma_1}dt), \tag{15}$$

where $\left(W_1(t)^T W_1(t)\right)^{-1} W_1(t)^T = 0$ if the inverse does not exist. Note that if all coefficients are time-varying, and thus γ can be ignored, $d\widehat{\boldsymbol{B}_1}(t) = \left(\boldsymbol{W_1}(t)^{\boldsymbol{T}} \boldsymbol{W_1}(t)\right)^{-1} \boldsymbol{W_1}(t)^{\boldsymbol{T}} d\boldsymbol{N}(t)$ is the estimator of the Aalen's additive hazard regression model (Aalen 1980; Aalen 1989; Fosen et al. 2006). Plugging the solution from Equation (15) into Equation (14) and solving for $\boldsymbol{\gamma_1}$ gives

$$\widehat{\boldsymbol{\gamma_1}} = \left\{\int_0^{\omega} \boldsymbol{W_2}(t)^T \boldsymbol{H}(t) \boldsymbol{W_2}(t) dt\right\}^{-1} \int_0^{\omega} \boldsymbol{W_2}(t)^T \boldsymbol{H}(t) d\boldsymbol{N}(t), \tag{16}$$

where ω is an arbitrary (elapsed) time, $H(t) = \left(I - W_1(t)\left(W_1(t)^T W_1(t)\right)^{-1} W_1(t)^T\right)$, and $H(t) = 0$ if the matrix inverse does not exist. By using Equation (15) and replacing $\boldsymbol{\gamma_1}$ with $\widehat{\boldsymbol{\gamma_1}}$, we get the following estimator of $\boldsymbol{B_1}(t)$:

$$\widehat{\boldsymbol{B_1}}(t) = \int_0^{t} \left(\boldsymbol{W_1}(s)^T \boldsymbol{W_1}(s)\right)^{-1} \boldsymbol{W_1}(s)^T \left(d\boldsymbol{N}(s) - \boldsymbol{W_2}(s)\widehat{\boldsymbol{\gamma_1}} ds\right). \tag{17}$$

The estimators in Equations (16) and (17) are unbiased, consistent, and asymptotically normal (Martinussen and Scheike 2006; McKeague and Sasieni 1994).

In practice, the integral in Equations (16) and (17) cannot be evaluated directly, but must be approximated by a sum. Note that $\boldsymbol{N}(t)$ will only be observed at realized (i.e., uncensored) product exit time T_v. We can order all realized product exit times so that $T^0 \equiv 0 < T^1 \equiv \min(T_v) < T^2 < \cdots < T^j < \cdots < T^M \equiv \max(T_v)$, and we choose ω as the longest realized product exit time T^M. Thus, $\boldsymbol{\gamma_1}$ and $\boldsymbol{B_1}(\mathrm{t})$ can be estimated as follows:

$$\widehat{\boldsymbol{\gamma_1}} = \left\{\sum_{s=1}^{M} \boldsymbol{W_2}(T^s)^T \boldsymbol{H}(T^s) \boldsymbol{W_2}(T^s) \Delta T^s\right\}^{-1} \sum_{s=1}^{M} \boldsymbol{W_2}(T^s)^T \boldsymbol{H}(T^s) \Delta \boldsymbol{N}(T^s), \tag{18}$$

$$\widehat{\boldsymbol{B_1}}(t) = \sum_{s=1}^{j:T^j \le t} \left(\boldsymbol{W_1}(T^s)^T \boldsymbol{W_1}(T^s)\right)^{-1} \boldsymbol{W_1}(T^s)^T (\Delta \boldsymbol{N}(T^s) - \boldsymbol{W_2}(T^s)\widehat{\boldsymbol{\gamma_1}} \Delta T^s), \tag{19}$$

where $\Delta T^s = T^s - T^{s-1}$, and $\Delta \boldsymbol{N}(T^s) = \boldsymbol{N}(T^s) - \boldsymbol{N}(T^{s-1})$.

2.2.3.2 Other Regressions

All other regression models in the dynamic path analysis model are linear models that can also be solved by least square. Here, we introduce the path coefficient estimators, which have a similar form to the estimators in Equations (16) and (17). The matrix form of a regression model with both time-varying and time fixed coefficients can be represented as follows:

$$\boldsymbol{W_j}(t) = \boldsymbol{W^1}_{\boldsymbol{-j}}(t)\boldsymbol{\beta^j}(t) + \boldsymbol{W^2}_{\boldsymbol{-j}}(t)\boldsymbol{\gamma^j} + \boldsymbol{\varepsilon_j}(t), \tag{20}$$

where

$\boldsymbol{W_j}(t) = [Y_1(t)X_{j,1}(t) \quad \cdots \quad Y_V(t)X_{j,V}(t)]^T$, where $X_{j,v}(t)$ is a time-varying covariate associate with the UPC-market pair v;

$\boldsymbol{W^k}_{\boldsymbol{-j}}(t) = \left[Y_1(t)\boldsymbol{X^k}_{\boldsymbol{-j,1}}(t) \quad \cdots \quad Y_V(t)\boldsymbol{X^k}_{\boldsymbol{-j,V}}(t)\right]^T$, where $\boldsymbol{X^k}_{\boldsymbol{-j,v}}(t)$ is a vector of time-varying covariate $X_{i,v}(t)$ that are independent variables of $X_{j,v}(t)$, $i \neq j$; the dimension of $\boldsymbol{X^k}_{\boldsymbol{-j,v}}(t)$ is $p_j \times 1$ if $k = 1$ and $q_j \times 1$ if $k = 2$;

$\boldsymbol{\beta^j}(t) = \left[\beta_1^j(t) \quad \cdots \quad \beta_{p_j}^j(t)\right]^T$, the vector of time-varying coefficients associated with $\boldsymbol{W^1}_{\boldsymbol{-j}}(t)$;

$\boldsymbol{\gamma^j} = \left[\gamma_1^j \quad \cdots \quad \gamma_{q_j}^j\right]^T$, the vector of time-fixed coefficients associates with $\boldsymbol{W^2}_{\boldsymbol{-j}}(t)$; and

$\boldsymbol{\varepsilon_j}(t) = [Y_1(t)\varepsilon_{j,1}(t) \quad \cdots \quad Y_1(t)\varepsilon_{j,V}(t)]^T$, where $\varepsilon_{j,v}(t)$ is the error term associated with the dependent variable $X_{j,v}(t)$ and the UPC-market pair v.

The corresponding least square equations are:

$$\boldsymbol{W}^{\mathbf{1}}_{-\boldsymbol{j}}(t)^T\left(\boldsymbol{W}_{\boldsymbol{j}}(t) - \boldsymbol{W}^{\mathbf{1}}_{-\boldsymbol{j}}(t)\boldsymbol{\beta}^{\boldsymbol{j}}(t) - \boldsymbol{W}^{\mathbf{2}}_{-\boldsymbol{j}}(t)\boldsymbol{\gamma}^{\boldsymbol{j}}\right) = \mathbf{0}, \tag{21}$$

$$\int \boldsymbol{W}^{\mathbf{2}}_{-\boldsymbol{j}}(t)^T\left(\boldsymbol{W}_{\boldsymbol{j}}(t) - \boldsymbol{W}^{\mathbf{1}}_{-\boldsymbol{j}}(t)\boldsymbol{\beta}^{\boldsymbol{j}}(t) - \boldsymbol{W}^{\mathbf{2}}_{-\boldsymbol{j}}(t)\boldsymbol{\gamma}^{\boldsymbol{j}}\right) = \mathbf{0}. \tag{22}$$

Once again, these equations can be solved subsequently, and the estimators $\boldsymbol{\gamma}^{\boldsymbol{j}}$ and $\boldsymbol{\beta}^{\boldsymbol{j}}(t)$ are:

$$\widehat{\boldsymbol{\gamma}}^{\boldsymbol{j}} = \left(\int_{\mathbf{0}}^{\omega} \boldsymbol{W}^{\mathbf{2}}_{-\boldsymbol{j}}(t)^T \boldsymbol{H}_{\boldsymbol{j}}(t) \boldsymbol{W}^{\mathbf{2}}_{-\boldsymbol{j}}(t)\right)^{-1} \int_{\mathbf{0}}^{\omega} \boldsymbol{W}^{\mathbf{2}}_{-\boldsymbol{j}}(t)^T \boldsymbol{H}_{\boldsymbol{j}}(t) \boldsymbol{W}_{\boldsymbol{j}}(t), \tag{23}$$

$$\widehat{\boldsymbol{\beta}}^{\boldsymbol{j}}(t) = \left(\boldsymbol{W}^{\mathbf{1}}_{-\boldsymbol{j}}(t)^T \boldsymbol{W}^{\mathbf{1}}_{-\boldsymbol{j}}(t)\right)^{-1} \boldsymbol{W}^{\mathbf{1}}_{-\boldsymbol{j}}(t)^T\left(\boldsymbol{W}_{\boldsymbol{j}}(t) - \boldsymbol{W}^{\mathbf{2}}_{-\boldsymbol{j}}(t)\widehat{\boldsymbol{\gamma}}^{\boldsymbol{j}}\right), \tag{24}$$

where $\boldsymbol{H}_{\boldsymbol{j}}(t) = \left(\boldsymbol{I}_{\boldsymbol{p}_{\boldsymbol{j}}} - \boldsymbol{W}^{\mathbf{1}}_{-\boldsymbol{j}}(t)\left(\boldsymbol{W}^{\mathbf{1}}_{-\boldsymbol{j}}(t)^T \boldsymbol{W}^{\mathbf{1}}_{-\boldsymbol{j}}(t)\right)^{-1} \boldsymbol{W}^{\mathbf{1}}_{-\boldsymbol{j}}(t)^T\right)$, $\boldsymbol{I}_{\boldsymbol{p}_{\boldsymbol{j}}}$ is a p_j-dimension identity matrix, and $\boldsymbol{H}_{\boldsymbol{j}}(t) = 0$ if the matrix inverse does not exist. Note that if we assume all path coefficients in the regression are time-fixed, as we do for the regressions of product line length and UPC-level marketing variables, $\boldsymbol{W}^{\mathbf{1}}_{-\boldsymbol{j}}(t)$ will be ignored and the estimator $\boldsymbol{\gamma}^{\boldsymbol{j}}$ will be:

$$\widehat{\boldsymbol{\gamma}}^{\boldsymbol{j}} = \left(\int_{\mathbf{0}}^{\omega} \boldsymbol{W}^{\mathbf{2}}_{-\boldsymbol{j}}(t)^T \boldsymbol{W}^{\mathbf{2}}_{-\boldsymbol{j}}(t)\right)^{-1} \int_{\mathbf{0}}^{\omega} \boldsymbol{W}^{\mathbf{2}}_{-\boldsymbol{j}}(t)^T \boldsymbol{W}_{\boldsymbol{j}}(t).$$

Practically, we choose ω as the longest realized product exit time T^M and estimate $\boldsymbol{\gamma}^{\boldsymbol{j}}$ as follows:

$$\widehat{\boldsymbol{\gamma}}^{\boldsymbol{j}} = \left\{\sum_{s=1}^{M} \boldsymbol{W}^{\mathbf{2}}_{-\boldsymbol{j}}(T^s)^T \boldsymbol{H}_{\boldsymbol{j}}(T^s) \boldsymbol{W}^{\mathbf{2}}_{-\boldsymbol{j}}(T^s)\right\}^{-1} \sum_{s=1}^{M} \boldsymbol{W}^{\mathbf{2}}_{-\boldsymbol{j}}(T^s)^T \boldsymbol{H}_{\boldsymbol{j}}(T^s) \boldsymbol{W}_{\boldsymbol{j}}(T^s). \tag{25}$$

2.2.3.3 Direct Effect and Indirect Effect

One of the advantages of the dynamic path analysis is that it preserves the additivity of typical path analysis; hence researchers can evaluate the direct effect and the indirect effect of one covariate on another (Fosen et al. 2006). In this study, we are interested in the effect of product line length on product exit, an effect possibly mediated by product sales. The cumulative direct effect of product line length on product exit is $B_{1,3}(t) = \int_0^t \beta_{1,3}(s)ds$, which can be estimated using Equation (19), where $\beta_{1,3}(s)$ is the coefficient of product line length on product exit in Equation (6). The cumulative indirect effect is $\int_0^t \beta_{2,1}(s)\beta_{1,3}(s)ds$, where $\beta_{2,1}(s)$ is the coefficient of product line length on product sales in Equation (7) and can be estimated using Equation (24). Empirically, the cumulative indirect effect is estimated by

$$\sum_{s=1}^{j:T^j \leq t} \{\hat{\beta}_{2,1}(T^s) d\hat{B}_{1,3}(T^s)\},$$

where $d\hat{B}_{1,3}(T^s)$ can be obtained via Equation (15), where $\boldsymbol{\gamma_1}$ is replaced with $\widehat{\boldsymbol{\gamma_1}}$. The cumulative total effect is simply the summation of the cumulative direct effect and the cumulative indirect effect.

It is difficult to find the large sample distribution of the cumulative indirect effect, which is beyond the scope of this study, because the effect is a sum of highly correlated terms, where each term is a multiplication of a regression function and an additive hazard function. To assess the variability of the cumulative indirect effect, we follow Fosen et al. (2006) to construct bootstrap confidence intervals. Specifically, we adopt a non-parametric bootstrap by randomly sampling with replacement from the set of all UPC-market pairs (Efron 1981). We also use bootstrapping to obtain the piecewise confidence intervals for all the other coefficients, the direct effect, and the total effect. Since many of our control variables are dummy variables, during bootstrapping the inverse of the summation of matrixes in Equations (18) and (25) may not exist. In such a case, we calculate the Moore-Penrose pseudoinverse in computing the estimates.

2.3 Empirical Analysis

2.3.1 Data

We investigate the relationship between product line length, product sales, and product exit by using the IRI academic dataset (Bronnenberg et al. 2008). We focus on the potato chip market, in which most potato chip brands horizontally extend their product line by adding similar items. The IRI dataset includes weekly UPC-store-level scanner data on potato chip purchases in 50 IRI markets. During 2001-2005, the U.S. potato chip market was dominated by Lay's, which on average commands a revenue share of 64.6%, followed by Ruffles (10.0% market share) and Pringles (6.3% market share). No other potato chip brand had a market share of more than 3%, and many of them only marketed their products in regional markets. Moreover, potato chip brands usually exit their products at individual regional markets. Considering these facts, we decided to study at the UPC-market level.

We first determine the product lifetime for each UPC-market pair. The lifetime of a product in a market is measured by the duration between the first and the last sales records of the UPC in any store in the market. A UPC-market pair is included in our analysis if the lifetime of the pair begins during the IRI weeks of 1166 and 1217 (i.e., December 31, 2001-December 29, 2002). Hence, we can ensure that no UPC-market pair in our analysis has sales records during January 1, 2001 and December 30, 2001, mitigating the concern that the first sales record of any pair in our sample is not observed. We also set the end of study on the IRI week 1321 (i.e., December 26, 2004). Thus, any UPC that is considered exiting the market by the end of study has no sales record from December 27, 2004 to December 25, 2005, reducing the possibility that a UPC that is temporarily out of stock in a market is misclassified as a product that exits the market. Overall, our data span three years, which we think is long enough to cover the duration from the introduction stage to the relatively mature stage of a potato chip UPC, considering many new CPGs are dropped during their first year (Gielens and Steenkamp 2007)[3].

While the raw data are collected on a weekly basis, our empirical analysis is conducted on a monthly basis to allow the potential time lag effects of covariates on the hazard of product exit. We operationally define four weeks as a month (i.e., $\tau_{i-1} - \tau_i = 1$ month), and update time-varying covariates for each UPC-market pair on a monthly basis. Note that we keep the information of product exit provided by the weekly data in our analysis. For example, if the last sales record regarding a UPC-market pair occurs in the first week of a certain month, we regard that UPC to be exiting the market at some time point during that week. Since we cannot observe the exact time of product exit, we use a randomly drawn time point during the first-quarter of the month as the product exit time. This approach is frequently used in the software of hazard models (e.g., the "timereg" package distributed by R; see Martinussen and Scheike 2006) and can break the ties among realized product exit times in order to satisfy the assumption that $0 < T^1 < \cdots < T^M$.

We do not include UPC-market pairs that have product lifetimes shorter than three months in our analysis for two reasons. First, we are not interested in products that are only temporarily available, such as a special promotion package. According to the survey of U.S. retailers in 2003 by the U.S. Federal Trade Commission (Federal Trade Commission 2003), if a retailer accepts a new product, the product would be on the shelf for a reasonable amount of time. In this study, we,

[3] We consider a UPC that survives the first year enters a relatively mature stage. We also restrict the interpretation of the findings for a UPC only within the first three years. The restriction is not because we exclude UPCs that survive more than three years (right truncation) but because we have not information on a UPC's survival after the period.

therefore, assume products that survive the first three months are not products developed by the manufacturers specifically for short-term purposes. Second, by focusing on products that survive at least three months, we can estimate the effects from the beginning of the fourth month and avoid missing values. As a result, 1,084 UPCs marketed by 101 brands (including one composite private label that represents all private labels) in 50 markets are included in our analysis, resulting in 4,469 UPC-market pairs and 82,563 UPC-market-month observations. Among the 4,469 UPC-market pairs, 2,551 pairs (57.1%) are observed exiting the market. The plot of Kaplan-Meier estimates of the survival function is presented in Figure 3.

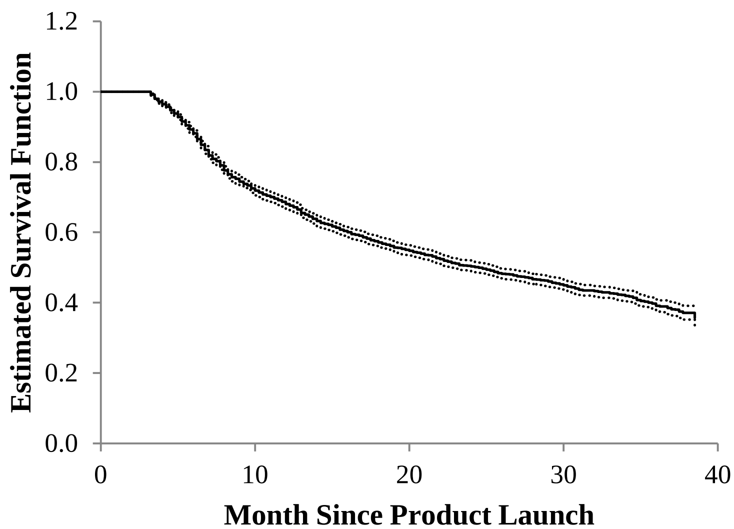


Figure 3: The Kaplan-Meier Estimates of Survival Function with 95% Pointwise Confidence Intervals

2.3.2 Variables

Most covariates are defined in the specification of the dynamic path analysis model. In this section, we focus on those covariates that have not been operationalized (e.g., the product features $\boldsymbol{X_u}$) and discuss how we generate covariates from raw data. After inferring the lifetime of each UPC-market pair, we can compute product line length, PLL_{bm,τ_i}, which is the average number of UPCs marketed by brand b in market m over weeks in $(\tau_{i-1}, \tau_i]$. $TOPLL_{bm,\tau_i}$ is the average number of all products marketed by the other brands in market m over weeks in $(\tau_{i-1}, \tau_i]$. Similarly, $WRPLL_{bm,\tau_i}$ measures the weighted average product line length of all brands, except brand b in market m over weeks. To generate this variable, we follow Bayus and Putsis (1999) to use the total sales of a brand in the market in $(\tau_{i-1}, \tau_i]$ as the weight and average product line lengths over brands. Note that we consider only one (composite) private label in our analysis. Therefore, the product line length of the private label is the number of all private-label UPCs on the shelf in the market.

Regarding the product features, $\boldsymbol{X_u}$, we focus on four salient product attributes of potato chips: cutting type, fat content, package size, and flavor. There are two levels of cut: flat or not (e.g. wavy); two levels of fat content: low-fat/fat-free or regular fat; three levels of package size: small (i.e., weight ≤ 4.8oz), medium (i.e., weight is between 4.8oz and 8oz), or large (i.e., weight > 8oz); and eight levels of flavor[4]: regular, BBQ, cheese, herb and/or ranch, salt and/or vinegar, sour cream, spicy, or the other flavors. Overall, there are 96 unique combinations of the attribute levels. For those chips with flavors missing in the IRI data, we use their UPCs to gather information online, primarily through databases such as Digit-eyes[5] and UPC database[6]. There are eight UPCs (38 UPC-market pairs) that have unknown flavor after data calibration, and we do not include these UPCs in our analysis. Based on the four attributes, which generate 96

[4] We first clustered flavors of all potato chips on the market into different groups. For example, “original” and “classic” are clustered in the same group, “regular”. If an SKU combines different flavors, we considered only the first flavor mentioned in the IRI dataset in clustering. Finally, we identified seven flavor groups that are commonly marketed by brands and regarded all the other flavors as a group. Please see Appendix A for the details.
[5] http://www.digit-eyes.com.
[6] http://www.upcdatabase.com.

possible combinations of attribute levels, we can compute $NDIS_{bm,\tau_i}$, which is the average number of combinations of attribute levels marketed by brand b in market m over weeks in $(\tau_{i-1}, \tau_i]$.

Sometimes, firms may use the same UPC subsequently for different products. This situation is recorded in the IRI data via a generation code. We control the potential difference between a new UPC and a reused UPC by incorporating a dummy variable that indicates whether the code associated with a product item is used for the first time (i.e., the first generation UPC). Moreover, we adopt 12 dummy variables to indicate the calendar month (i.e., four weeks) in which there is the first sales record associated with the UPC in the market. These dummy variables are used to capture potential cohort effects regarding product introduction time.

As to the characteristics of the calendar time associated with the elapsed time duration $(\tau_{i-1}, \tau_i]$, i.e., $\boldsymbol{CTIME}_{\tau_i}$, we control the occurrences of special holidays and major sporting events, considering the purchase occasions of potato chips. Specifically, we create a dummy variable to indicate whether Thanksgiving Day, Christmas Day, or New Year’s Day is observed during $(\tau_{i-1}, \tau_i]$, and another dummy variable to indicate whether any final game of the five professional sport leagues (NFL Super Bowl, NBA finals, MLB World Series, MLS Cup, and NHL Stanley Cup) or the Olympic Games is observed during $(\tau_{i-1}, \tau_i]$.

We consider five UPC-level marketing variables, including regular unit price, price index, feature ads, in-store display, and distribution breadth in our analysis. Information regarding actual retailing price, price discount, feature ads, and in-store display at a week-UPC-store level is recorded in the IRI data set. We first recode feature ads and in-store display by dummy variables, indicating whether feature ads or in-store displays for the UPC are observed in the store during the week. The information of price, feature ads, and in-store display is missing if no one buys the UPC in a specific market during a specific week. We then replace the missing data with the moving averages of the values over the previous four weeks in the market. If the moving average is not available, we replace the missing data with the mean value over the whole observation period in the market. Following Ataman et al. (2008), we aggregate the store-level data to the market-level data by using the stores' estimated annualized sales (ACV-All Commodity Volume) provided by IRI as the weight. We further calculate the actual price per ounce and use the most recent nonpromotion price (Gedenk and Neslin 2000) for weeks involving price promotion. If nonpromotion price cannot be observed, we use the maximum actual price per ounce as the regular unit price. The price index, thus, is the ratio of the actual price to the regular price, which is less or equal to one. Regarding the distribution breadth, we calculate the percentage of stores carrying the UPC in the market, using the estimated ACV as the weight. Finally, we take the average values over weeks in $(\tau_{i-1}, \tau_i]$ to generate the five marketing variables. Key variables in our empirical analysis are summarized in Table 2.

2.3.3 Findings and Discussion

2.3.3.1 Time-Fixed Coefficients

Table 3 lists the estimation results of time-fixed coefficients. We find that product attributes play an important role in influencing both the exit rate and product sales. Specifically, the coefficients regarding cutting type, fat content, and flavor are significant. In general, a product attribute level that generates lower product sales also increases the hazard rate of product exit (i.e., product exit

Table 2: Description of Key Variables in the Dynamic Path Analysis

Variables	Mean	S.D.	Minimum	Maximum
UPC-Market Level (N=4469)				
First generation UPC	0.611	0.488	0.000	1.000
Flat-cut chip	0.744	0.436	0.000	1.000
Low-fat/fat-free chip	0.078	0.268	0.000	1.000
Package size (Base: Small)				
Medium	0.284	0.451	0.000	1.000
Large	0.413	0.492	0.000	1.000
Flavor (Base: Regular)				
BBQ	0.194	0.396	0.000	1.000
Cheese	0.059	0.235	0.000	1.000
Herb/ranch	0.114	0.318	0.000	1.000
Salt/vinegar	0.081	0.273	0.000	1.000
Sour cream	0.082	0.275	0.000	1.000
Spicy	0.101	0.301	0.000	1.000
Other flavors	0.064	0.244	0.000	1.000
UPC-Market-Time Level (N=82563)				
UPC sales, $\ln(Sales_{v,\tau_i})$	6.040	4.099	0.000	18.131
Regular price, $\ln(RP_{v,\tau_i})$	1.557	0.400	-0.945	5.074
Price index, $\ln(RP_{v,\tau_i})$	-0.080	0.114	-2.428	0.000
Feature, FEA_{v,τ_i}	0.081	0.161	0.000	1.000
Display, DIS_{v,τ_i}	0.256	0.302	0.000	1.000
Distribution breadth, DB_{v,τ_i}	0.344	0.354	0.000	1.000
UPC market share, $Share_{v,\tau_{i-1}}$	0.009	0.044	0.000	0.600
Product line length, PLL_{bm,τ_i}	32.058	20.831	1.000	95.250
Number of Distinct SKUs, $NDIS_{bm,\tau_i}$	17.207	9.540	1.000	40.000
Number of Duplicate SKUs, $NDUP_{bm,\tau_i}$	14.852	12.495	0.000	63.250
All other competiting products, $TOPLL_{bm,\tau_i}$	271.688	82.871	99.000	520.250
Weighted rival product line length, $WRPLL_{bm,\tau_i}$	34.529	17.714	0.863	78.250
Brand market share, $Share_{bm,\tau_{i-1}}$	0.209	0.301	0.000	0.968
Market size, $ln(Size_{m,\tau_{i-1}})$	15.250	0.769	12.330	17.437
Market growth rate, $MGR_{m,\tau_{i-1}}$	0.064	0.415	-0.817	4.062

rates). Some exceptions do exist; for example, low-fat potato chips or chips with salt, vinegar, and/or sour cream flavors generate lower product sales but have lower product exit rate. Such exceptions suggest that product sales may be one but not the only driver of product exit. As to the effect of product features on UPC-level marketing variables, the results are generally consistent with our expectations. For instance, compared with small-packaged chips, medium-packaged and large-packaged chips have a lower regular price per ounce, are more likely to be promoted by price discount and feature ads, and are sold in more stores; however, they are less likely to be promoted by in-store display, which may be easier to implement for small-packaged items. Compared with regular-flavored chips, chips with other flavors are more likely to be promoted by price discount and feature ads.

We also report the time-fixed coefficients associated with the top-five brands in terms of nationwide sales. We find that the top-five brands' UPCs tend to generate fewer sales than those of the private label. The relatively lower ability to generate sales does not necessarily increase product exit rates. Only UPCs of the market leaders, such as Lay's and Ruffles, have higher product exit rates than those of the private label. In contrast, UPCs of Pringles have lower product exit rates than those of the private label. Shankar (2006) finds that market leaders in a product category are more likely to adjust their product line lengths in order to respond to product proliferation by their competitors. Frequent adjustments of product line lengths may lead to frequent product replacements or product withdrawals, which might explain our findings regarding higher hazard rates of product exit associated with Lay's and Ruffles. Concerning UPC-level marketing variables, it is shown that the top-five brands tend to charge higher regular prices and, thus, have higher brand values than the private label. Compared with the private label, Pringles, Wise and Utz tend to sell their products more broadly in the market, and Wise and Utz are more likely to promote their products by using in-store display.

Table 3: Estimation Results of Time-Fixed Coefficients of the Dynamic Path Analysis Model

	Hazard of product exit		Product Sales		Regular Price		Price Index		Feature		Display		Distribution Breadth		Product Line Length	
Covariates	**Coef.**	**Sig.**[1]	**Coef.**	**Sig.**	**Coef.**	**Sig.**	**Coef.**	**Sig.**	**Coef.**	**Sig.**	**Coef.**	**Sig.**	**Coef.**	**Sig.**	**Coef.**	**Sig.**
Product Features																
First generation UPC	0.0027		0.0432		-0.0008		-0.0048	*	0.0093	*	0.0032		0.0021	*		
Flat-cut chip	0.0076	*	-0.0935	*	0.0036	*	-0.0003		0.0136	*	-0.0062	*	-0.0023	*		
Low-fat/fat-free chip	-0.0127	*	-0.0997	*	0.0041	*	0.0123	*	-0.0058		-0.0208	*	-0.0049	*		
Package size																
Small (Base)																
Medium	0.0063	*	-0.0459		-0.0032	*	-0.0178	*	0.0247	*	-0.0312	*	0.0033	*		
Large	0.0019		-0.0822	*	-0.0114	*	-0.0311	*	0.0537	*	-0.0290	*	0.0044	*		
Flavor																
Regular (Base)																
BBQ	0.0041	*	-0.1367	*	-0.0005		-0.0048	*	0.0097	*	0.0028		0.0005			
Cheese	0.0279	*	-0.0773	*	-0.0010		-0.0088	*	0.0206	*	0.0080		0.0007			
Herb/ranch	0.0302	*	-0.1619	*	-0.0006		-0.0073	*	0.0131	*	0.0035		-0.0095	*		
Salt/vinegar	-0.0084	*	-0.1030	*	0.0003		-0.0042	*	0.0100	*	-0.0005		0.0026	*		
Sour cream	-0.0044	*	-0.1223	*	-0.0006		-0.0039	*	0.0195	*	0.0080	*	0.0008			
Spicy	0.0061	*	-0.0990	*	0.0010		-0.0004		-0.0030		-0.0027		-0.0028	*		
Other flavors	0.0567	*	-0.3161	*	-0.0032	*	-0.0076	*	0.0214	*	0.0135	*	-0.0085	*		
Brand[2]																
Private label[3] (Base)																
Lay’s	0.0250	*	-0.2796	*	0.0111	*	0.0015		0.0044		0.0058		-0.0012		0.3121	*
Ruffles	0.0487	*	-0.2365	*	0.0140	*	0.0238	*	-0.0234	*	-0.0265	*	0.0003		-0.4461	*
Pringles	-0.0081	*	-0.2010	*	0.0168	*	0.0192	*	-0.0398	*	-0.0379	*	0.0194	*	-0.4003	*
Wise	-0.0057		-0.1405	*	0.0038	*	-0.0030		-0.0335	*	0.0138	*	0.0082	*	-0.0305	
Utz	-0.0058		-0.2473	*	0.0095	*	0.0004		-0.0208	*	0.0234	*	0.0042	*	0.5699	*
Intercept			0.7558	*	0.0385	*	0.0054		-0.0363	*	0.0586	*	0.0034		7.1520	*

Note:

1. The result is tested using a 95% bootstrap percentile confidence interval based on 500 bootstrap replications.
2. The estimates of the top 5 nationwide best-selling brands are reported.
3. Private label is composed of all private labels in the market.

Table 3: Estimation Results of Time-Fixed Coefficients of the Dynamic Path Analysis Model (Con.)

	Hazard of product exit		Product Sales		Regular Price		Price Index		Feature		Display		Distribution Breadth		Product Line Length	
Covariates	**Coef.**	**Sig.[1]**	**Coef.**	**Sig.**	**Coef.**	**Sig.**	**Coef.**	**Sig.**	**Coef.**	**Sig.**	**Coef.**	**Sig.**	**Coef.**	**Sig.**	**Coef.**	**Sig.**
Marketing Variables																
Regular price			-0.2912	*												
Price index			-0.6345	*												
Feature ad			0.9282	*												
In-store display			0.5220	*												
Distribution breadth			1.9412	*												
Lag product sales			0.7746	*												
Lag product share					-0.0087	*	-0.0583	*	0.2107	*	0.3656	*	0.0251	*		
Lag Marketing Var.																
Regular price					0.9724	*										
Price index							0.6415	*								
Feature ad									0.5255	*						
In-store display											0.7640	*				
Distribution breadth													0.9874	*		
Product line length															0.9803	*
Brand market share															-0.7720	*
Weighted rivals' PLL															-0.0149	*
Market size															-0.3587	*
Market growth rate															0.0009	

Note:

1. The result is tested using a 95% bootstrap percentile confidence interval based on 500 bootstrap replications.

As to the time-varying covariates, the signs of most coefficients in the regression of product sales are consistent with our expectations. Specifically, regular price has a negative effect on product sales, suggesting that high regular price results in lower sales. Price index has a negative effect on product sales, while feature, display, and distribution breadth have positive effects. These results suggest that the product sales can be boosted by promotions, including price discount, feature ads, and in-store display, or enhanced by a broader distribution. Regarding the performance feedback effects (Ataman et al. 2008; Ataman et al. 2010; Horvath et al. 2005) at the UPC level, the results show that UPC market share has negative effects on regular price and price index, as well as positive effects on feature ads, in-store display, and distribution breadth. These findings may be because marketers constantly support a UPC with a higher market share by conducting price discount, feature ads and in-store display for the UPC and/or by extending its distribution breadth.

Concerning the regression of product line length, unlike the findings of Bayus and Putsis (1999), our results suggest that brand market share and the weighted average of competitors' product line lengths have negative effects on the focal brand's product line length. The difference may be due to the fact that we control the lagged product line length, brand effects, and other variables. If we exclude the control variables, we find that the two covariates have positive coefficients. We further find that market size also has a negative effect on product line lengths, and market growth rate has no significant effect, findings that are different from those in Shankar (2006). Once again, if we ignore the control variables, we find that market size has a positive effect. Conceptually, product line length only changes when the brand adds or deletes UPCs. Our results support the conclusion that product line length is highly autoregressive (i.e., the coefficient of the autoregressive term is 0.98; see Table 3), which is also found by Ataman et al. (2010).

2.3.3.2 Direct Effects on Product Exit

Figure 4 illustrates the time-varying coefficients of covariates on the hazard of product exit. We depict the estimated cumulative coefficients with 95% bootstrap percentile piecewise confidence intervals based on 500 bootstrap replications. The piecewise confidence intervals can be used to test the null hypothesis that the time-varying coefficient is equal to zero, i.e., $\beta(t) = 0$, or equivalently $B(t) = 0$. In this study, we are more interested in whether the effects of product line length on product sales and on the hazard of product exit are constant for products at the different stages of the lifecycle. That is, we test whether the time-varying coefficients associated with product line length are time-fixed (i.e., $\beta(t) = c$, or equivalently $B(t) = ct$) by using the Kolmogorov-Smirnov test or Cramér-von Mises test. (For more details on the tests, please refer to Martinussen and Scheike 2006, p135-146.). The test results are reported in Figure 4. Note that the largest realized product exit time is nearly 39 months (i.e., 3 years because we consider four weeks a month) after product launch; hence, our interpretation should be limited to the first three years of a UPC.

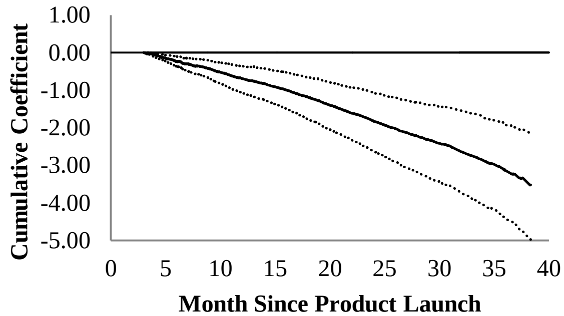
Figure 4-(a) depicts the time-varying coefficient regarding the intercept of the hazard of product exit. The coefficient should be interpreted as the hazard given that all other covariates equal zero or the hazard associated with how long the UPC has been introduced. As shown in the figure, the estimates have negative values and the piecewise confidence intervals in general do not cover the value zero, indicating the coefficient of the intercept is significantly negative. The results imply that, as a UPC becomes mature, the hazard that the UPC will exit the market becomes lower. The

tests of time-fixed effects further reject the null hypothesis that the coefficient is time-fixed. Figure 4-(a) shows that the slopes of the cumulative coefficient become steeper over time, suggesting that the rate of the decrease in the hazard of product exit becomes larger as the UPC becomes more mature.

Figure 4-(b) gives the time-varying coefficient of product sales on the hazard of product exit. The coefficient is significantly negative, indicating that a UPC with higher sales is less likely to exit the market. Moreover, the null hypothesis of the time-fixed effect of product sales is not rejected. In other words, the negative effect of product sales on the hazard of product exit does not significantly change over time. These findings imply that a longer product line might decrease product exit rates, depending on whether it can increase product sales.

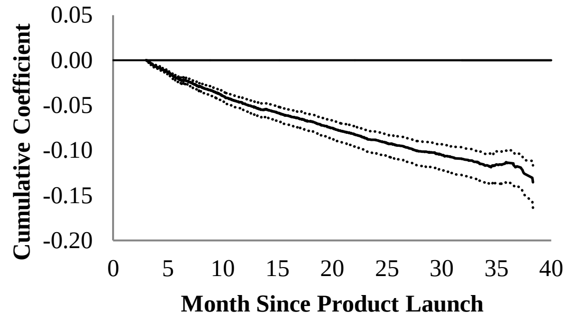
Figure 4-(c) demonstrates the time-varying coefficient of product line length on the hazard of product exit. The results show that the cumulative coefficient is significantly positive, indicating that a UPC in a longer product line is more likely to exit the market. This finding is consistent with those in the literature (Cottrell and Nault 2004; de Figueiredo and Kyle 2006; Ruebeck 2002; Ruebeck 2005). However, the null hypothesis that the coefficient is time-fixed is rejected. The figure also demonstrates that once a UPC has been on the market for 13 months (i.e., one year), the cumulative coefficient of product line length on the hazard of product exit becomes flat, suggesting a longer product line may not affect product exit rates for relatively mature SKUs (i.e., SKUs surviving the first year) but increase product exit rates only for new SKUs (i.e., SKUs in the first year after introduction).

(a) Intercept



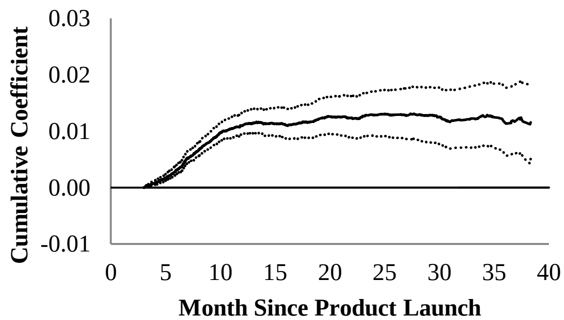
Tests of Time-fixed Effect[1]
Kolmogorov-Smirnov test: 0.312, p-value: 0.010
Cramér-von Mises test: 1.800, p-value: <0.001

(b) Product Sales Effect



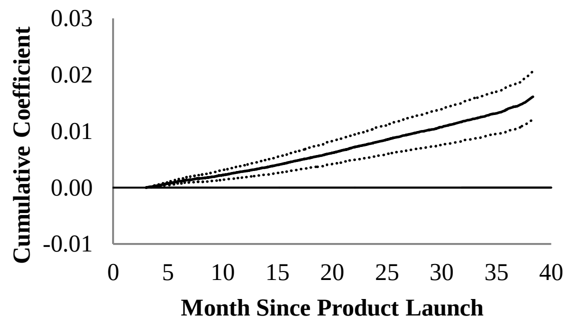
Tests of Time-fixed Effect[1]
Kolmogorov-Smirnov test: 0.015, p-value: 0.244
Cramér-von Mises test: 0.002, p-value: 0.204

(c) Product Line Length Effect



Tests of Time-fixed Effect[1]
Kolmogorov-Smirnov test: 0.008, p-value: <0.001
Cramér-von Mises test: 0.001, p-value: <0.001

(d) Total Number of Competing UPCs Effect



Tests of Time-fixed Effect[1]
Kolmogorov-Smirnov test: 0.002, p-value: 0.002
Cramér-von Mises test: <0.001, p-value: <0.001

Note:

1. The null hypothesis is that the coefficient is a constant term (i.e., $\beta(t) = c$) or $B(t) = ct$.
2. The dotted lines show the 95% bootstrap percentile pointwise confidence intervals based on 500 bootstrap replications.

Figure 4: The Estimated Cumulative Coefficients (Direct Effects) on The Hazard of Product Exit

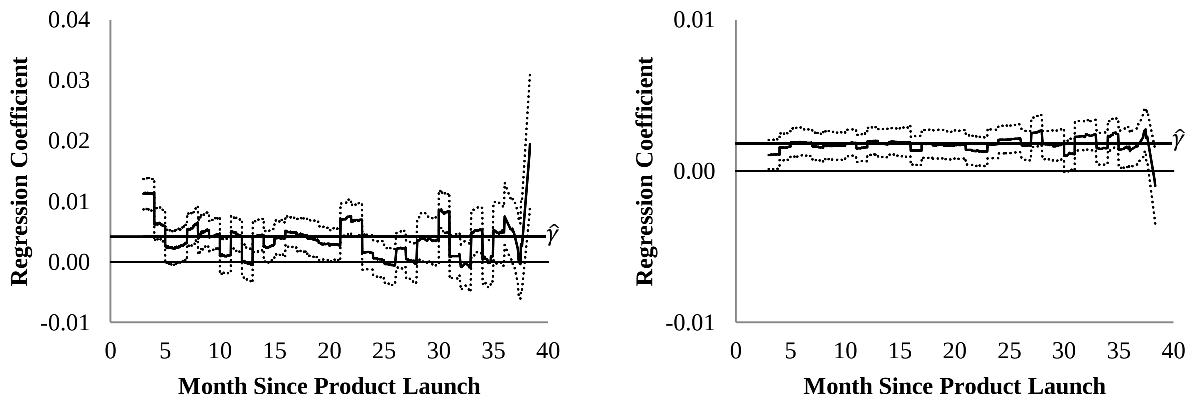
Figure 4-(d) portrays the time-varying coefficient of the number of competing UPCs on the exit hazard of the focal UPC. The coefficient is significantly positive, suggesting a UPC is more likely to exit the market if there are more competing UPCs in the market. Furthermore, the results of the tests of time-fixed effect reject the hypothesis that the coefficient is time-fixed. It seems that the effect of the number of competing UPCs is slightly higher for mature SKUs.

2.3.3.3 Effects on Product Sales

Figure 5-(a) illustrates the coefficient of product line length on product sales. In general, the coefficient is (at least partially) significantly positive based on the piecewise confidence intervals. However, the piecewise confidence intervals frequently cover zero after 23 months since product launch. These findings suggest that, to some extent, product line length has a positive effect (or at least no negative effect) on product sales, providing no strong evidence of cannibalization in this specific product category and an explanation for the findings in the literature that product line length increases brand-level sales (Ataman et al. 2008; Ataman et al. 2010; Chong et al. 1998; Draganska and Jain 2005).

The finding that the coefficient of product line length might be positive at some but not all time points motivates us to test the time-fixed effect. A formal statistical hypothesis test requires the asymptotic distribution of the test statistics and a true time-fixed coefficient, and the test may be conducted through a resampling procedure. In this study, we use a simple approach by assuming the coefficient of product line length on product sales to be constant (i.e., time-fixed) and estimating the dynamic path analysis model again. We then check whether the 95% piecewise confidence interval associated with the time-varying coefficient covers the estimated time-fixed coefficient ($\hat{\gamma}$), depicted in Figure 5-(a). We find that the piecewise confidence interval is higher than $\hat{\gamma}$ in the fourth month since product launch, occasionally lower than $\hat{\gamma}$ after 23 months since product launch, and higher than $\hat{\gamma}$ in the 39 month since product launch. We, thus, conclude that the coefficient is not time-fixed and that product line length might have a stronger positive effect on very new SKUs than on mature SKUs.

(a) Covariate: Product Line Length (b) Covariate: Total Number of Competing UPCs



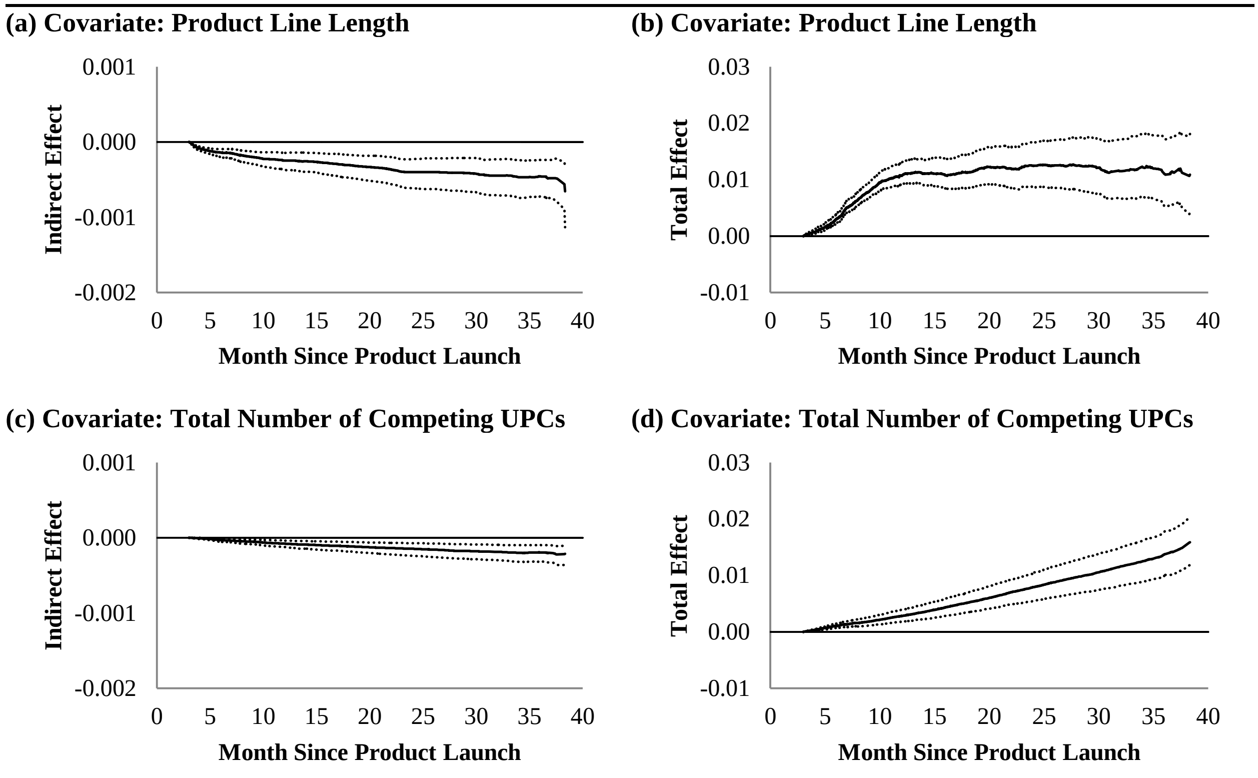
Note: The dotted lines show the 95% bootstrap percentile pointwise confidence intervals based on 500 bootstrap replications.

Figure 5: The Estimated Time-fixed Coefficient on Product Sales ($\hat{\gamma}$) and the Estimated Time-varying Coefficients on Product Sales

Figure 5-(b) demonstrates the time-varying coefficient of the number of competing UPCs on product sales. The results suggest that the coefficient is significantly positive. This finding seems to contradict some empirical results in the literature, and deny the competitive role of product line length. For example, Bayus and Putsis (1999) found that the number of competing products will decrease the market share of the focal brand, implying that a product in a more crowded market may generate lower sales because of inter-brand competition. However, some researchers have argued that, when a firm extends its product line length, it may increase the sales of the other firms and thus benefit its competitors, especially for consumer non-durable goods (Kadiyali et al. 1999) or in horizontally differentiated markets (Thomadsen 2012). Since potato chip UPCs are consumer non-durable goods in a horizontally differentiated market, our findings may provide additional evidence of the win-win consequence of product line extension in this specific context. We also assess whether the coefficient of the number of competing UPCs is time-fixed. Since the time-fixed estimate is almost always covered by the 95% piecewise confidence intervals, we conclude that the effect is constant over time.

2.3.3.4 Indirect Effects and Total Effects on Product Exit

We have found that both product line length and the number of competing UPCs have positive effects on product sales, which further can decrease product exit rates. The cumulative indirect effect of product line length is depicted in Figure 6-(a). The 95% bootstrap percentile piecewise confidence intervals are below zero, suggesting that the indirect effect of product line length on the hazard of product exit is significantly negative, confirming extant literature claims. Since we have found that product sales have a time-fixed effect on the hazard of product exits, and product line length has a time-varying effect on product sales, the indirect effect is expected to be time-varying, depending on how product line length influences product sales.



Note: The dotted lines show the 95% bootstrap percentile pointwise confidence intervals based on 500 bootstrap replications.

Figure 6: The Estimated Indirect Effects (a-b) and Total Effects (c-d) on the Hazard of Product Exit

So far we have found that, in general, product line length has a positive direct effect and a negative indirect effect on the hazard of product exit. The cumulative total effect that combines the two forces is demonstrated in Figure 6-(b). We found that the total effect is highly similar to the direct effect because the indirect effect has a very limited impact. That is, a longer product line is more likely to drive new SKUs (i.e., SKUs in their first year since product launch) out of the market, but has no effect for mature SKUs. It might result from brand managers extending their product lines simply to assess the value of new products (Hitsch 2006), and the fact that profitability of mature products is already proven. However, a further investigation considering product line structure in the following sections suggests that a demand side story regarding consumer preference and product familiarity may also or even better explain the total effect.

Figure 6-(c) illustrates that the indirect effect of the number of competing UPCs on the hazard of product exit is negative. Considering that both the coefficient of the number of competing UPCs on product sales and that of product sales on the hazard of product exit are found to be time-fixed, we expect the indirect effect of the number of competing UPCs on the hazard of product exit to be constant. The total effect of the number of competing UPCs on the hazard of product exit is shown in Figure 6-(d). Similarly, we found that the positive direct effect dominates the negative indirect effect, leading to a significantly positive total effect. In addition, the slope of the total effect slightly increases over time. These findings suggest that a crowded market with more competing UPCs may be more likely to drive mature SKUs out of the market.

2.3.3.5 Time-Fixed Coefficients Considering Product Line Structure

We also consider product line structure in the analysis. Table 4 shows the estimation results of time-fixed coefficients, which are highly similar to those in Table 3, except for the regressions of the numbers of distinct and duplicate SKUs. We found that a longer product line may lead to more distinct SKUs and more duplicate SKUs in the next period. Brand market share and weighted Rivals' Product line length have negative effects on the number of distinct SKUs and positive effects on the number of duplicate SKUs. Shankar (2006) finds that market leaders extend their product line to respond to their competitors' line extensions; our results suggest that they might be inclined to respond to their competitors by adding duplicate SKUs. Another possible explanation is that a brand with high market share may be more likely to exhaust its SKU options and thus be more likely to offer duplicate SKUs.

2.3.3.6 Effects of the Number of Distinct SKUs on Sales and Product Exit

The direct effect of the number of distinct SKUs on product exit rates is reported in Figure 7-(c). Similar to product line length, the number of distinct SKUs has a positive direct effect for new SKUs. A new product in a product line with more distinct SKUs might be more likely to exit the market because current distinct SKUs may have already satisfied consumers with different preferences, or the new product may be positioned too far away from the other SKUs and, thus, become too new for consumers to accept. However, unlike product line length, the number of distinct SKUs has a negative direct effect for relatively mature SKUs (i.e., the cumulative coefficient decreases). Once a product becomes more mature and established, it may be more likely to keep a profitable customer base in the product line with more distinct SKUs because those SKUs' positions are not too close to one another. Figure 8-(a) suggests that the number of distinct SKUs has a marginal and positive effect on product sales, leading to a negative indirect effect on the hazard of product exit as shown in Figure 9-(a). The indirect effect is very limited

Table 4: Estimation Results of Time-Fixed Coefficients Considering Product Line Structure

Dependent Variable	The hazard of product exit		Product Sales		Regular Price		Price Index		Feature		Display		Distribution Breadth		Distinct SKUs		Duplicate SKUs	
Covariates	**Coef.**	**Sig.**[1]	**Coef.**	**Sig.**	**Coef.**	**Sig.**	**Coef.**	**Sig.**	**Coef.**	**Sig.**	**Coef.**	**Sig.**	**Coef.**	**Sig.**	**Coef.**	**Sig.**	**Coef.**	**Sig.**
Product Features																		
First generation UPC	0.0028		0.0421	*	-0.0008		-0.0048	*	0.0093	*	0.0034		0.0021	*				
Flat-cut chip	0.0066	*	-0.0923	*	0.0035	*	-0.0003		0.0136	*	-0.0062	*	-0.0023	*				
Low-fat/fat-free chip	-0.0135	*	-0.0996	*	0.0041	*	0.0124	*	-0.0057		-0.0209	*	-0.0049	*				
Package size																		
Small (Base)																		
Medium	0.0062	*	-0.0396		-0.0032	*	-0.0179	*	0.0246	*	-0.0313	*	0.0034	*				
Large	0.0015		-0.0795	*	-0.0113	*	-0.0311	*	0.0538	*	-0.0290	*	0.0044	*				
Flavor																		
Regular (Base)																		
BBQ	0.0041	*	-0.1376	*	-0.0005		-0.0048	*	0.0097	*	0.0028		0.0005					
Cheese	0.0270	*	-0.0787	*	-0.0010		-0.0087	*	0.0205	*	0.0079		0.0007					
Herb/ranch	0.0295	*	-0.1634	*	-0.0007		-0.0074	*	0.0130	*	0.0036		-0.0097	*				
Salt/vinegar	-0.0081	*	-0.1031	*	0.0003		-0.0042	*	0.0100	*	-0.0005		0.0026	*				
Sour cream	-0.0039	*	-0.1231	*	-0.0006		-0.0039	*	0.0195	*	0.0079	*	0.0008					
Spicy	0.0065	*	-0.0977	*	0.0009		-0.0004		-0.0030		-0.0028		-0.0029	*				
Other flavors	0.0548	*	-0.3214	*	-0.0032	*	-0.0075	*	0.0212	*	0.0133	*	-0.0085	*				
Brand[2]																		
Private label[3] (Base)																		
Lay's	0.0316	*	-0.3416	*	0.0111	*	0.0015		0.0043		0.0056		-0.0010		7.7713	*	-7.4583	*
Ruffles	0.0493	*	-0.2537	*	0.0140	*	0.0239	*	-0.0236	*	-0.0266	*	0.0003		2.2402	*	-2.6869	*
Pringles	-0.0055		-0.2471	*	0.0168	*	0.0193	*	-0.0398	*	-0.0379	*	0.0195	*	5.5475	*	-5.9479	*
Wise	-0.0020		-0.1740	*	0.0038	*	-0.0030		-0.0336	*	0.0138	*	0.0083	*	4.1042	*	-4.1349	*
Utz	-0.0046		-0.2694	*	0.0095	*	0.0004		-0.0208	*	0.0234	*	0.0043	*	3.0054	*	-2.4346	*
Intercept			0.6924	*	0.0385	*	0.0054		-0.0363	*	0.0583	*	0.0032		9.4961	*	-2.3344	*

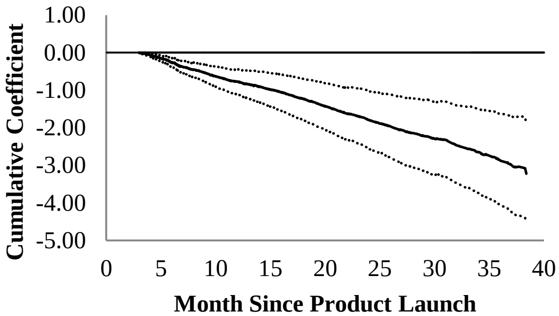
Note: 1. The result is tested using a 95% bootstrap percentile confidence interval based on 500 bootstrap replications.
2. The estimates of the top 5 nationwide best-selling brands are reported.
3. Private label is composed of all private labels in the market.

Table 4: Estimation Results of Time-Fixed Coefficients of the Dynamic Path Analysis Model (Con.)

Dependent Variable	The hazard of product exit		Product Sales		Regular Price		Price Index		Feature		Display		Distribution Breadth		Distinct SKUs		Duplicate SKUs	
Covariates	**Coef.**	**Sig.**[1]	**Coef.**	**Sig.**	**Coef.**	**Sig.**	**Coef.**	**Sig.**	**Coef.**	**Sig.**	**Coef.**	**Sig.**	**Coef.**	**Sig.**	**Coef.**	**Sig.**	**Coef.**	**Sig.**
Marketing Var.																		
Regular price			-0.2937	*														
Price index			-0.6376	*														
Feature ad			0.9196	*														
In-store display			0.5198	*														
Distribution breadth			1.9435	*														
Lag product sales			0.7742	*														
Lag product share					-0.0087	*	-0.0585	*	0.2108	*	0.3650	*	0.0248	*				
Lag Marketing Var.																		
Regular price					0.9724	*												
Price index							0.6411	*										
Feature ad									0.5252	*								
In-store display											0.7642	*						
Distribution breadth													0.9874	*				
Product line length															0.3140	*	0.6663	*
Brand Market Share															-0.9171	*	0.1453	*
Weighted Rivals' PLL															-0.0240	*	0.0091	*
Market Size															-0.2050	*	-0.1542	*
Market Growth Rate															-0.0301		0.0319	

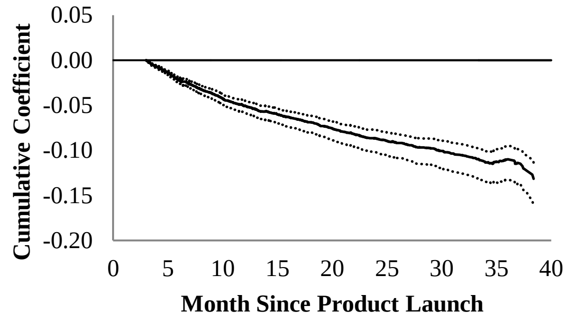
Note: 1. The result is tested using a 95% bootstrap percentile confidence interval based on 500 bootstrap replications.

(a) Covariate: Intercept



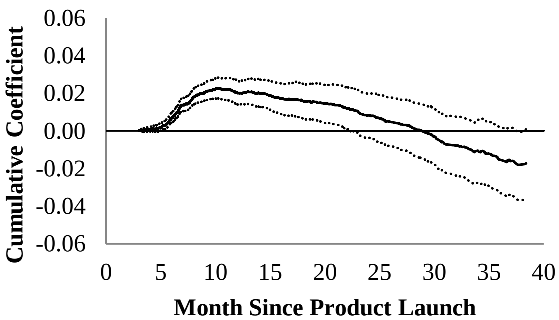
Tests of Time-fixed Effect[1]
Kolmogorov-Smirnov test: 0.238, p-value: 0.136
Cramér-von Mises test: 0.485, p-value: 0.167

(b) Covariate: Product Sales



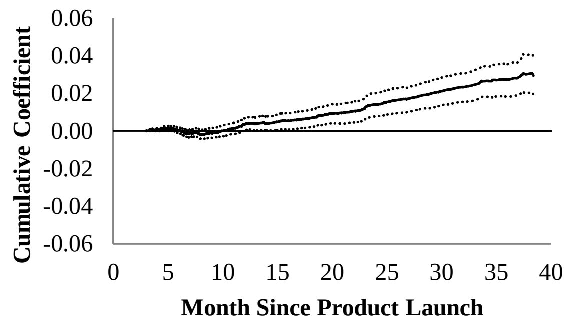
Tests of Time-fixed Effect[1]
Kolmogorov-Smirnov test: 0.017, p-value: 0.175
Cramér-von Mises test: 0.004, p-value: 0.124

(c) Covariate: Number of Distinct SKUs



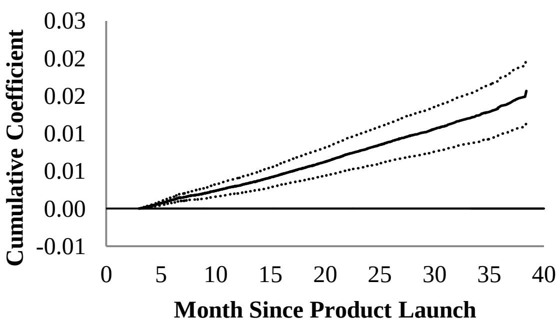
Tests of Time- fixed Effect[1]
Kolmogorov-Smirnov test: 0.026, p-value: <0.001
Cramér-von Mises test: 0.011, p-value: <0.001

(d) Covariate: Number of Duplicate SKUs



Tests of Time- fixed Effect[1]
Kolmogorov-Smirnov test: 0.006, p-value: 0.018
Cramér-von Mises test: <0.001, p-value: 0.039

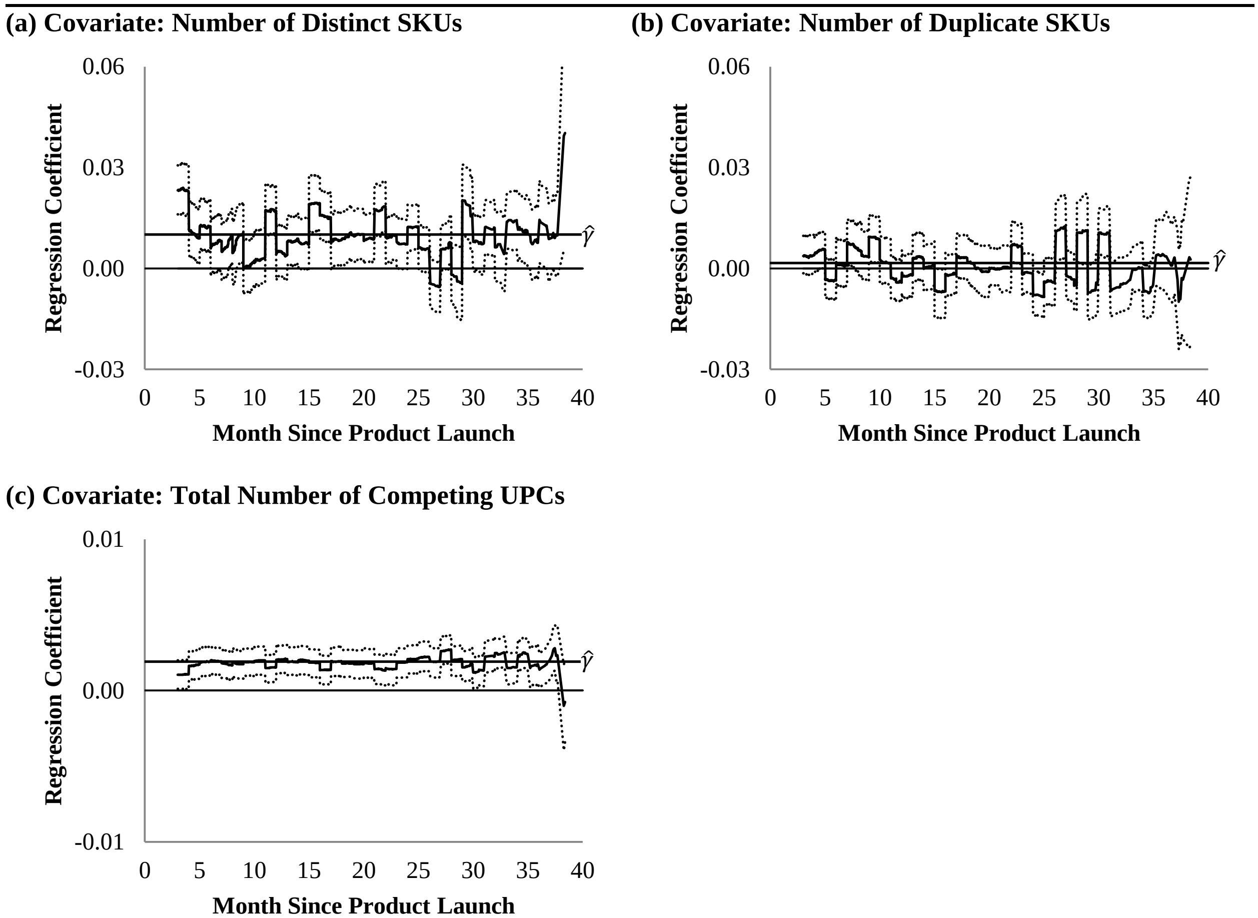
(e) Covariate: Total Number of Competing UPCs



Tests of Time- fixed Effect[1]
Kolmogorov-Smirnov test: 0.002, p-value: 0.012
Cramér-von Mises test: <0.001, p-value: <0.001

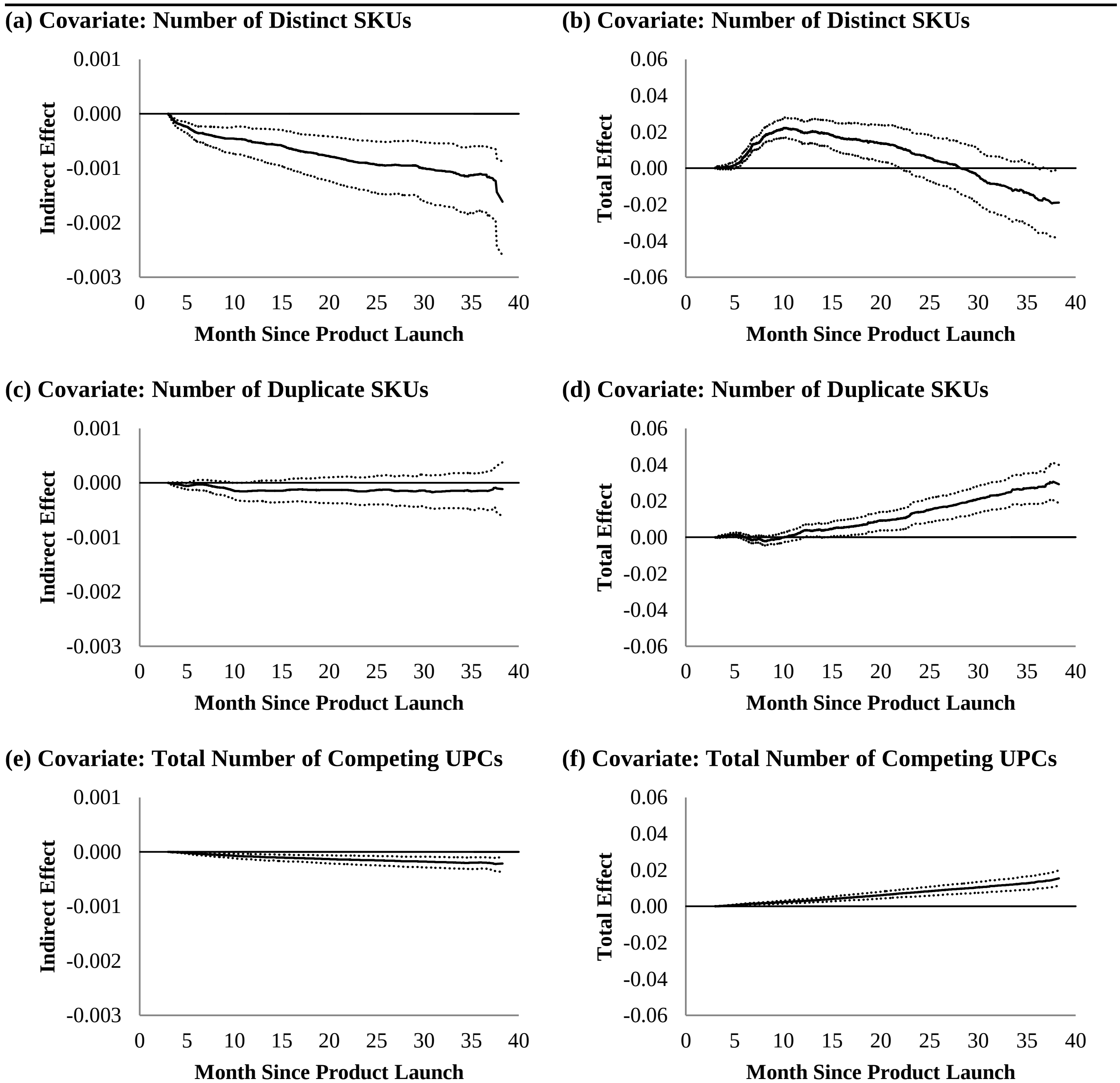
Note:
1. The null hypothesis is that the coefficient is a constant term (i.e., $\beta(t) = c$) or $B(t) = ct$.
2. The dotted lines show the 95% bootstrap percentile pointwise confidence intervals based on 500 bootstrap replications.

Figure 7: The Estimated Cumulative Coefficients (Direct Effects) on the Hazard of Product Exit Considering Product Line Structure



Note: The dotted lines show the 95% bootstrap percentile pointwise confidence intervals based on 500 bootstrap replications.

Figure 8: The Estimated Time-fixed Coefficient on Product Sales ($\hat{\gamma}$) and the Estimated Time-varying Coefficients on Product Sales Considering Product Line Structure



Note: The dotted lines show the 95% bootstrap percentile pointwise confidence intervals based on 500 bootstrap replications.

Figure 9: The Estimated Indirect Effects (a-c) and Total Effects (d-f) on the Hazard of Product Exit Considering Product Line Structure

compared with the direct effect; therefore, the total effect displayed in Figure 9-(b) has a similar pattern to the direct effect.

2.3.3.7 Effects of the Number of Duplicate SKUs on Sales and Product Exit

The direct effect of the number of duplicate SKUs on the hazard of product exit is reported in panel Figure 7-(d). Unlike product line length or the number of distinct SKUs, the number of duplicate SKUs has no direct significant effect for new SKUs. When a brand carries many duplicate SKUs, although consumers might not receive the newness of a new duplicate SKU and, thus, have less interest in it, they are still familiar with the new SKU and, thus, might still be willing to buy it. If the new SKU is a distinct SKU to the brand, it could be a promising extension because of its newness to consumers, but they might think the brand extends too far. These mixing arguments might explain the insignificant effect of the number of duplicate SKUs for a relatively new SKU. Moreover, the number of duplicate SKUs has a positive direct effect for mature SKUs. In a product line with more duplicate SKUs, which may highly overlap in terms of positioning, a mature SKU might be less likely to keep a profitable customer base because of the severe overlap caused by existing or new SKUs. Figure 8-(b) suggests that, unlike the number of distinct SKUs, the number of duplicate SKUs has no effect on product sales and, thus, no indirect effect on the hazard of product exit (see Figure 9-(c)). Figure 9-(d) demonstrates that the total effect regarding the number of duplicate SKUs is basically the direct effect.

Overall, the combination of the two total effects regarding distinct and duplicate SKUs can give us the total effect of product line length. For a new product within the first year, more distinct SKUs in the product line can increase the probability of product exit, while more duplicate SKUs have no effect. Therefore, a longer product line may increase the probability of product exit for a new SKU. However, for a relatively mature product, more distinct SKUs in the line can decrease the probability of product exit, yet more duplicate SKUs can increase that probability. As a result, a longer product line may not affect the probability of product exit for a mature SKU. Although the supply side story of assessing the profitability of new products seems to be able to explain the total effect of product line length alone, it cannot explain the effect that the number of distinct (or duplicate) SKUs has for mature SKUs. Therefore, we believe the effect of product line length on the hazard of product exit might be better explained by the demand side story.

2.4 Chapter Conclusion

Product line length is an important decision in product portfolio management. While the direct effect of product line length on product exit has been evident in empirical studies, the indirect effect of product line length on product exit through product sales has not been examined. The literature on product line management and consumer choice further implies that the effects may vary for products at different stages of the lifecycle and under different product line structures. This paper constructs a dynamic path analysis model to empirically investigate the dynamic relationships between product line length, product sales, and the hazard of product exit. In order to deal with control variables and to avoid much variance, we estimate the dynamic path analysis model in a semiparametric approach, which allows us to estimate not only time-varying covariates but also time-fixed coefficients. Overall, the contributions of this study are twofold: conceptually, this study enhances the understanding of the effects of product line length on product sales and on product exit; methodologically, it expands the application of the dynamic path analysis by estimating time-fixed coefficients.

We study the U.S. potato chip industry and find that a longer product line increases the product exit rate only for a new product in the line (i.e., a product in the first year after launch), and the effect is mitigated when the product generates higher sales. The total effect is highly similar to the direct effect because the indirect effect is very limited. A further investigation concerning product line structure suggests that the number of distinct SKUs has a positive direct effect for new products, a negative direct effect for mature products (i.e., products surviving more than one year), and a marginally negative indirect effect. Moreover, the number of duplicate SKUs has no significant direct effect for new products, a positive direct effect for mature products, and no significant indirect effect. These effects may be explained by consumer preference and product familiarity. We also found that the number of competing UPCs has a positive total effect on the hazard of product exit for the focal product.

Our findings are based on analysis of potato chips SKUs, which are horizontally differentiated consumer nondurable goods. Therefore, the implications of our study may not be generalized to vertically differentiated and/or durable goods. Researchers may investigate these product categories and shed more light on product line management. Furthermore, even though we argue that the demand side story may better explain our findings, we have no intention to rule out the impact of the supply side on product exit. Carroll et al. (2010) identify four inextricably intertwined perspectives, including both the demand and supply sides, which affect product lifetime and thus product exit. Future research may consider all those perspectives and further examine the underlying mechanism regarding product line length, product sales, and product exit.

Chapter 3

A Threshold Regression Model of New Product Trial and Early Product Withdrawal: Application to the Potato Chip Category with a Focus on Product Line Competition

3.1 Introduction

New product introduction is an essential marketing activity. In the consumer packaged goods (CPG) industry, more than 190,000 new SKUs were introduced on the market in 2013 (IRI 2014). Whether to try a new SKU, thus, is a consumer decision important to marketers (Steenkamp and Gielens 2003). It is in marketers' interests to identify drivers of new product trial in order to expedite the penetration of a new product (Toubia et al. 2014). The need for identifying the drivers is even more significant considering the high risk of new product introduction in a fast-changing and uncertain environment. Studies have shown that the average new product failure rate across industries is around 40%, and that of CPG is 45% (Castellion and Markham 2013). Many new CPG fail in their first year (Gielens and Steenkamp 2007). Even products named as the best launches, such as Pepsi Edge, Dr Pepper Berries & Cream, and Colgate Simply White, disappeared within two years (Schneider and Hall 2011). However, early product withdrawal (i.e., product withdrawal within the first year after launch) has not been considered in studies exploring drivers of new product trial. Therefore, empirical findings from these studies are subject to sample selection biases (Shugan 2007). Specifically, the Anna Karenina bias cautions that key drivers of new product trial might exhibit negligible variation among successful products that survive the first year because survivors are necessarily alike. Consequently, the true key drivers might become statistically insignificant in those studies. This caution motivates us to explore the drivers of new product trial without ignoring early withdrawn products.

Many researchers on new product trial have adopted hazard-based models (e.g., Du and Kamakura 2011; Fader et al. 2003; Steenkamp and Gielens 2003). Unlike individual-level diffusion models (Chatterjee and Eliashberg 1990; Horsky 1990; Song and Chintagunta 2003), hazard-based models do not explicitly account for a consumer's new product trial decision process. By modeling the timing of an event, the hazard approach focuses on the outcome (event time) rather than the decision-making process that leads to the outcome. As a result, hazard model applications in marketing rarely provide a theoretical basis for the model specification (Aalen et al. 2008; Lancaster 1990b; Seetharaman 2004; Seetharaman and Chintagunta 2003). In contrast, the individual-level model of Chatterjee and Eliashberg (1990) is a first hitting time (FHT) model that accommodates the new product trial decision process and can be extended to consider early product withdrawal and to incorporate time-varying marketing variables. To the best of our knowledge, it has not been developed as an FHT model with multiple absorbing states that can deal with time-varying covariates. Thus, building such a model has both conceptual and methodological contributions.

The contribution of the new FHT model is further enhanced if it can also explore the drivers of early product withdrawal. Product withdrawal is an important decision that requires managers to recognize and quickly take action when a product launch has failed (Boulding et al. 1997). Product withdrawal may be explained from different theoretical perspectives (Carroll et al. 2010). Marketing researchers in general have adopted a market rationality (e.g., Bayus 1998; Hitsch 2006; Putsis and Bayus 2001), positing that product withdrawal is the outcome of insufficient market support for the existence of the new product, and a firm rationality (e.g., Bayus and Putsis 1999; Putsis and Bayus 2001), postulating that product withdrawal is determined by the

competitive position of the brand/firm. However, few empirical studies examine the effects of both market and brand/firm variables specifically in the context of early product withdrawal. We, hence, link those drivers to early product withdrawal to gain more insights about the event.
In this study, we construct a threshold regression (TR) model (i.e., an FHT model that accommodates covariates in regression forms) based on a Wiener process with two absorbing thresholds. We use the Wiener process to represent the attractiveness of a new SKU to a consumer, of which the utility of the SKU to a consumer can be a subordinate concept, an upper threshold representing the level of the attractiveness that triggers an individual consumer to try the SKU (i.e., the threshold of trial), and a lower threshold representing the level of the attractiveness that prompts managers to withdraw the SKU (i.e., the threshold of withdrawal). A consumer will try the SKU when its attractiveness hits the threshold of trial, and the SKU will be withdrawn when its attractiveness hits the threshold of withdrawal. We further incorporate time-varying covariates into the model and use a hierarchical model specification to deal with consumer heterogeneity.

We apply the TR model to a study of 1000 households' trials of 160 new potato chip SKUs and identify many drivers of new product trial, including household characteristics, product characteristics, marketing strategies, social contagion, and sale performance. Focusing on product line competition, we found that consumers are more likely to try a new SKU of a brand with a longer product line, but they are less likely to try one when there are more competing SKUs provided by other brands. The former effect is insignificant if we fit a simpler TR model that does not account for early product withdrawal. We also explore drivers of early product withdrawal and found that an SKU of a brand with a longer product line is more likely to be withdrawn in the first year, but it is less likely to be withdrawn when there are more competing SKUs on the market. Considering that product line structure (Chong et al. 1998) may alter the effect of product line length on the probability of new product trial, we further explore the roles of distinct SKUs (i.e., SKUs representing unique combinations of salient product attribute levels to the brand) and duplicate SKUs (i.e., the other SKUs with the same combination as any of the distinct SKUs previously introduced by the brand). We find that the number of distinct SKUs has negative effects on the probability of new product trial and that of early product withdrawal, and the number of duplicate SKUs has positive effects on both probabilities.

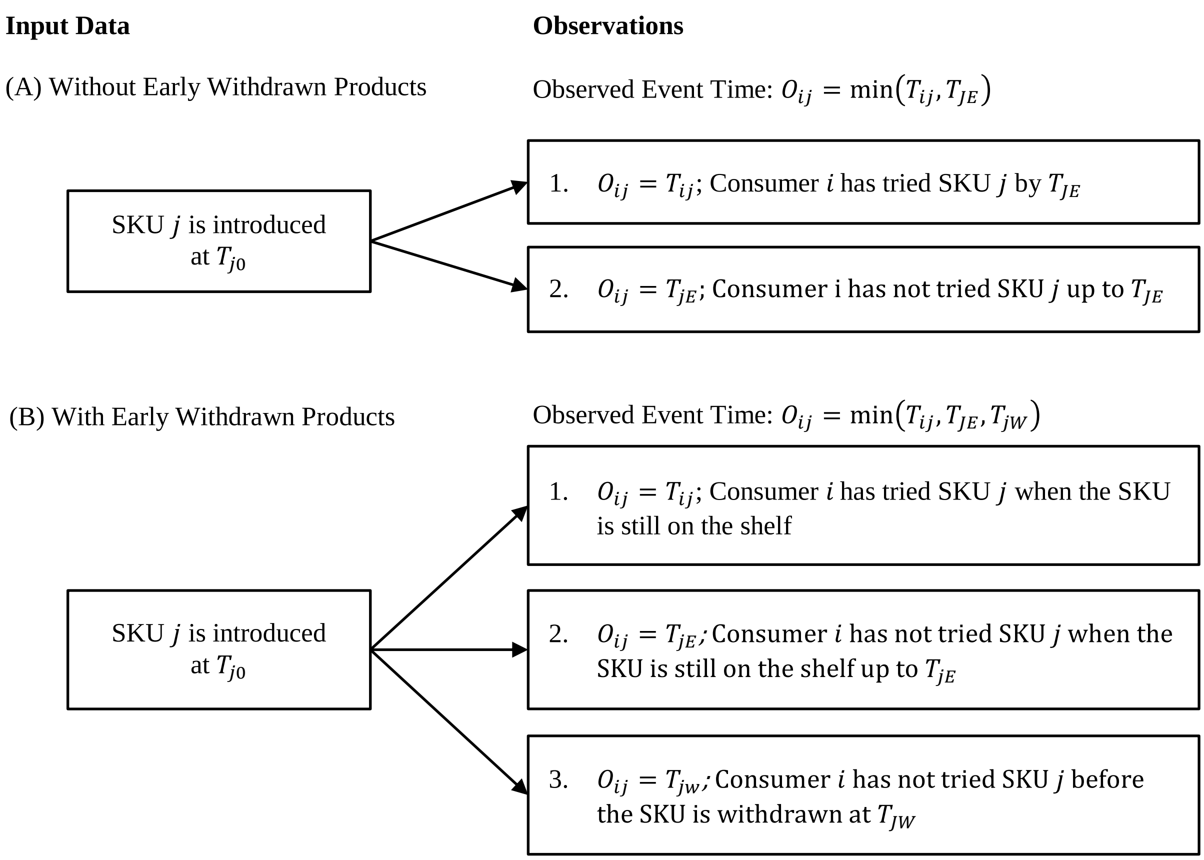
The rest of this chapter is organized as follows. In section 3.2, we briefly review new product trial models and discuss the linkage between these models, early product withdrawal, and our TR model. In section 3.3, we discuss the conceptualization, specification, and estimation of our TR model. We then describe data and the potential drivers of new product trial and early product withdrawal in our application, following a discussion of our findings in section 3.4. Section 3.5 concludes the paper by identifying avenues for future research.

3.2 Literature Review on New Product Trial Models

3.2.1 Individual-Level New Product Trial Model and Early Product Withdrawal

Since the seminal paper of Bass (1969), diffusion or initial purchases of a product have become a main topic in the marketing literature. Because new product trial is a consumer decision affected by individual consumer characteristics (Im et al. 2007; Manning et al. 1995; Steenkamp and Gielens 2003), individual-level models that can describe the decision-making process and can incorporate both product and individual consumer characteristics are preferable. Researchers studying new product diffusion/trial at the individual level have adopted survival analysis models, such as hazard-based models (Du and Kamakura 2011; Fader et al. 2003; Kamakura et al. 2004; Risselada et al. 2014; Sinha and Chandrashekaran 1992; Steenkamp and Gielens 2003) or accelerated failure time models (Chandrashekaran and Sinha 1995). However, to the best of our knowledge, researchers using these models have not considered the influence of early product withdrawal.

The aforementioned individual-level models allow only right-censored data and thus cannot handle the event of early product withdrawal. For example, suppose we observe the introductions of a group of new CPG SKUs. Our goal is to explore drivers of new product trial within the first year after launch because in the CPG industry the first year after launch has been considered critical for the success or failure of a new product (Steenkamp and Gielens 2003). Assume SKU j is introduced at calendar time $T_{j0}, j = 1, \dots, J$, and the end of observation period regarding SKU j is $T_{jE} = T_{j0} + 52$(weeks); SKUs $j = 1, \dots, g < J$ have been withdrawn at some time T_{jW} within the first year after launch, i.e., $T_{j0} < T_{jW} \leq T_{jE}$ for $j = 1, \dots, g$. To explore drivers of new product trial, we may use the data containing only SKUs that survive more than one year after product launch (i.e., SKUs $j = g + 1, \dots, J$) and apply individual-level models used in the literature. The observed event time for consumer i and SKU j is $O_{ij} = \min(T_{ij}, T_{jE})$, where T_{ij} is the time when consumer i tries SKU j (i.e., new product trial; see panel (a) in Figure 10). These models can accommodate for the case when some consumers have tried SKU j by T_{jE} (i.e., $O_{ij} = T_{ij}$) and the others have not (i.e., $O_{ij} = T_{jE}$ or the end of the observation period is observed). However, our findings based on these models are subject to sample selection biases (Shugan 2007) because early withdrawn SKUs are excluded. If we use the complete data, the observed event time becomes $O_{ij} = \min(T_{ij}, T_{jE}, T_{jW})$. (See panel (b) in Figure 10.) Nevertheless, those models are unable to handle the case associated with early product withdrawal: consumers who have not tried SKU j before the SKU is withdrawn shortly after launch (i.e., $O_{ij} = T_{jW}$ or observation (3) of panel (b) in Figure 10).



Notation
T_{j0} = the time when SKU j is introduced
O_{ij} = the observed event time associated with Consumer i and SKU j
T_{ij} = the time when Consumer i tries SKU j
T_{JE} = the ending time point of the observation period; e.g., $T_{JE} = T_{J0} + 52$
T_{jW} = the observed time when SKU j is withdrawn; $T_{JW} \leq T_{JE}$

Figure 10: Input Data of New Product Trial and Observed Events

Readers familiar with survival analysis models may notice that the new product trial data considering early product withdrawal can be analyzed by a competing risk model or a multistate model (Kalbfleisch and Prentice 2002). The two models are suitable to study a process where at least two events are playing a role, among which one event can be the event of interest, such as new product trial in this study, and the other event/s may prevent the event of interest from occurring (Putter et al. 2007), such as right censoring or early product withdrawal in our case. Most often, these models are constructed by using the Cox proportional hazards model, but a hazard-based model does not account for the new product trial decision process. In this study, we extend an FHT model, which can describe the individual-level new product trial decision (Chatterjee and Eliashberg 1990), to establish a competing risk model that can accommodate two absorbing states (i.e., new product trial and early product withdrawal) and time-varying covariates. Before proceeding to the model development, though, we briefly introduce the FHT model and review the linkage between the model and the new product trial decision.

3.2.2 First Hitting Time (FHT) model and New Product Trial

FHT models delineate a multidimensional stochastic process, $X(t)$, and study the FHT of the process to an absorbing boundary set, $\mathcal{B}$, that incurs an event of interest (Whitmore 1986). The time when the process first hits the boundary set is a random variable, defined as $T = \inf\{t: X(t) \in \mathcal{B}\}$. The stochastic process is typically unobserved by the researcher. In the context of new product trial, the process may represent the utility of a new product perceived by a consumer over time. When the utility is high enough to hit an upper threshold implicitly set by a consumer for the first time, the consumer will try the new product.

Mathematically, the stochastic process can be any Markovian diffusion process (Aalen et al. 2008). One well-known Markovian diffusion process is the Wiener diffusion process with drift: $X(t) = \mu t + \sigma W(t)$, and $X(0) = -x_0$, $x_0 > 0$, where μ is the drift coefficient, σ is the diffusion coefficient, $\sigma > 0$, and $W(t)$ is a standard Brownian motion. Without loss of generality, we can assume the threshold to be zero, which is usually assumed to be the utility of no purchase. The initial state of the process is lower than the threshold, and the process may conceptually describe the utility of a new product. A utility-maximizing consumer is expected to try the new product when the utility of the new product hits and passes the utility of no purchase (i.e., the threshold). Note that the sign of μ is not constrained. If $\mu \geq 0$, the Wiener process will eventually hit the threshold with probability one (i.e., the consumer eventually will try the new product). If $\mu < 0$, the probability that the FHT equals infinity is given by $\Pr[T = \infty] = 1 - \exp(-2x_0\mu/\sigma^2)$. In other words, the process with unconstrained μ can accommodate for the possibility that some consumers may never try a new product. The corresponding first hitting time T follows an inverse Gaussian distribution with density:

$$f(t) = \frac{x_0}{\sigma\sqrt{2\pi}} t^{-\frac{3}{2}} exp\left[-\frac{(x_0 - \mu t)^2}{2\sigma^2 t}\right]. \tag{26}$$

If $\mu < 0$, the probability density function is improper. The survival function associated with Equation (26) is:

$$S(t) = \Phi\left(\frac{x_0 - \mu t}{\sigma\sqrt{t}}\right) - \exp\left(\frac{2x_0\mu}{\sigma^2}\right)\Phi\left(\frac{-x_0 - \mu t}{\sigma\sqrt{t}}\right), \tag{27}$$

where $\Phi(\quad)$ is the standard normal cumulative density function.

The FHT model has been used to describe the individual-level innovation adoption process. Specifically, Chatterjee and Eliashberg (1990) propose a new product trial decision process for a consumer who is risk averse and unclear about the true quality of a high involvement durable good. The process $X(i)$ describes the utility of the product perceived by the consumer considering the risk, price, and expected performance associated with a new product, where i is a continuous variable indicating the cumulative amount of information about the product. As more information comes in, the utility changes. The consumer will not try the new product until the utility, net of the impact of price, crosses a threshold equal to zero, which can be viewed as the utility of no purchase. If we assume that the amount of information increases uniformly over time (i.e., $i = t$), we can rewrite Equation (15) in Chatterjee and Eliashberg (1990), which gives the p.d.f. of the amount of information (i.e., the time) required for new product trial, as Equation (26) in this study, given $x_0 \equiv \alpha$, $\mu \equiv \mu - \beta$, and $\sigma \equiv \delta$.

So far, we have assumed that the initial state of the stochastic process, $-x_0$, is a random variable and the threshold is a given constant value (i.e., zero). Instead of assuming that the threshold is a constant term, some researchers prefer to treat the threshold as a random variable and fix the initial state (e.g., Abbring 2012; Whitmore 1986). Note that x_0 measures the distance between the initial state and the threshold zero, and it is this distance that affects the first hitting time. The closer the initial state and the threshold are, the higher the probability that the event of interest (e.g., new product trial) will occur. If we set the initial state equal to zero and consider the threshold to be a random variable x_0, $x_0 > 0$, we can obtain the same p.d.f. for the FHT as that shown in Equation (26). Thus, it is entirely at the researcher's discretion to specify the initial state and the threshold. It should also be noted that there are three parameters in the inverse Gaussian distribution shown in Equation (26), namely x_0, μ, and σ, but the distribution only depends on these through the transformations, x_0/σ and μ/σ. Hence, in order to make the distribution identifiable, one of the three parameters is usually fixed, depending on which is of less interest in the application context.

3.2.3 FHT model and Competing Risks

The FHT model with one threshold can be used to analyze the right-censored data associated with only one event, such as new product trial. Such a model has been extended to analyze competing risks data by specifying multiple thresholds along with a stochastic process. For instance, researchers have used a Weiner process with two absorbing thresholds to study the length of stay in hospital (Horrocks and Thompson 2004; Whitmore 1986). A patient will keep staying in a hospital until the patient is discharged or until the patient dies in the hospital. The stochastic process fluctuating between two thresholds represents the health status of the patient, while the upper (lower) threshold captures the critical health status of recovery (death). When the patient's health status is above (below) the upper (lower) threshold, he is discharged (dies); otherwise, he remains in the hospital. The model setting has also been adopted in studying memory retrieval (Ratcliff 1978; Ratcliff and Tuerlinckx 2002). In the following section, we will demonstrate that an FHT model with two thresholds is also suitable for studying new product trial considering early product withdrawal. Moreover, we will further incorporate time-varying covariates into the model so that the model can be used to explore the effects of both time-fixed and time-varying variables on the two events.

3.2.4 FHT model and Time-varying Covariates

An FHT model with covariates is called a threshold regression (TR) model. One advantage of TR models is that they do not require the proportional hazards assumption. Furthermore, TR models with one threshold have recently been extended to accommodate time-varying covariates (Lee et al. 2010). As a result, TR models can serve as an appealing alternative to proportional hazards models for studying new product trial. A detailed review of FHT and TR models can be found in the work of Aalen et al. (2008) and Lee and Whitmore (2006).

Researchers have shown that an FHT model with multiple thresholds can incorporate time-fixed variables (e.g., Whitmore 1986) or time-varying covariates for a discrete-state, discrete-time process (Stettler 2015); however, the model has not been extended to deal with time-varying covariates for a continuous-state, continuous-time process. Many marketing variables that may influence a consumer's product trial decision are time-varying covariates, such as price, feature ad, and in-store display. Therefore, we develop a TR model with a continuous-state, continuous-time process and two absorbing thresholds that can accommodate two different sets of time-varying covariates. By doing so, we contribute not only to the literature on new product trial and early product withdrawal but also to the literature on TR models. The details of the proposed model are discussed in the following section.

3.3 Model Development

3.3.1 The Conceptual Background of the Proposed TR Model

In our empirical application, we deal with weekly data that contain the information on when a CPG SKU j is introduced (T_{j0}), when an individual household i tries the SKU (T_{ij}), and when the SKU is withdrawn from the market (T_{jW}). The exact time of trial and withdrawal are not observed; only the week in which a certain event happens is known. Suppose a stochastic process associated with SKU j, $X_j(t)$, describes the attractiveness of SKU j. The attractiveness is the ability of the SKU to successfully drive individual households to move through stages of an adoption process, and product trial is one important stage of the process. We use the term attractiveness because the adoption process consists of many stages, and the utility of a product may not be relevant at early stages, such as the awareness stage (Horsky 1990). By definition, the attractiveness of an SKU affects individual households at all stages through the adoption process, and thus it is a superordinate concept that can contain the utility of the product.

We assume an individual household i intrinsically has a threshold of trial for SKU j that may fluctuate over time t. The threshold of trial, TT_{ijt}, describes the level of attractiveness provided by SKU j to trigger the household to try SKU j at time t. The concept has been adopted in the literature. Chatterjee and Eliashberg (1990) implicitly regard the utility of no purchase (i.e., zero) as the threshold of trial. Studying threshold models of diffusion, Granovetter and his colleague assign each person a threshold of adoption, defined as the number or proportion of people in a network that have made the decision (e.g., to try an innovation) that one person must see before she makes the decision (Granovetter 1978; Granovetter and Soong 1983). This concept has been well accepted in the literature on social networks (e.g., Valente 1996). Wejnert (2002) also suggests that studies concerning the relationship between individual-level thresholds and individual characteristics can benefit the area of diffusion. We argue that the threshold of trial may be affected by multiple and possibly time-varying drivers, including the social network influence, product characteristics, household characteristics, and/or simply time. A household will try an SKU when the SKU's attractiveness hits the household's threshold of trial for the first time. At the time when SKU j is introduced, T_{j0}, the threshold of trial is assumed to be higher than the SKU's attractiveness; otherwise, the household will try the SKU right at T_{j0}.

We further assume that the manufacturer of SKU j, together with its retailers, have a threshold of withdrawal for the SKU. The threshold of withdrawal, TW_{jt}, is the minimum amount of SKU j's attractiveness required by the supply side at time t. The higher the attractiveness an SKU has, the higher the possibility that consumers will purchase and repurchase the SKU, and the larger the revenue that the firm and its channel partners can expect from the SKU. It is very common that the manufacturer and/or the retailers set criteria or objectives for a new SKU, constantly evaluate the performance of the SKU against those criteria or objectives, and withdraw the SKU if it is unlikely to meet those criteria or objectives (e.g., Broniarczyk et al. 1998; Dupre and Gruen 2004; Hitsch 2006). The threshold of withdrawal can represent the overall criterion that may contain several sub-criteria. If an SKU cannot meet the minimum requirement by providing enough attractiveness in a competitive environment, the SKU will be withdrawn. We assume that the threshold of withdrawal is below the SKU's attractiveness when the SKU is launched; otherwise, the firm would not introduce the SKU. Moreover, the threshold of withdrawal may fluctuate over time. For example, as the manufacturer and/or the retailers collect more information about the profitability of the SKU, they may adjust the threshold of withdrawal (Hitsch 2006). Some companies may also consider the competition structure in determining their threshold of withdrawal (Chisholm and Norman 2006; Ruebeck 2002).

In order to explore influential drivers of new product trial and early product withdrawal, we model the two types of thresholds as functions of time-varying covariates, of which time-fixed covariates are special cases. These thresholds, hence, can be viewed as the systematic component of our model. We assume that the covariate values remain constant within a week but may change from week to week. This type of time-varying covariate is very common in practice. For example, product price, feature ad, and in-store display are usually adjusted on a weekly basis. Given the function form and the corresponding parameters, the two thresholds will have constant values within a week; their values may vary over weeks, depending on the value of the time-varying covariates. Note that it is the distance between the threshold and the initial state of the attractiveness of SKU j that matters. Because the observed covariates are linked to the two thresholds, at the beginning of each week, we fix the initial states of the SKU's attractiveness to be zero for those households that have not tried SKU j in order to identify the distances between the initial state and the two thresholds. As a result, $X_j(t)$ is the rescaled attractiveness of SKU j. Note that for a product, the attractiveness varies among consumers, so it seems improbable that the attractiveness will hit the threshold of withdrawal simultaneously for all consumers. However, by adjusting the level of the attractiveness at the beginning of each week and letting the threshold of withdrawal fluctuate over time, we allow the threshold of withdrawal to jump to a level that is very close to the adjusted attractiveness for all consumers. Thus, the adjusted attractiveness can hit the threshold of withdrawal almost simultaneously.

The concept of our model can be illustrated in Figure 11. Suppose there are two SKUs introduced at calendar time 0, and there are three households in the market. For simplicity, we set the end of observation period as the end of the fourth week after the product launch. Panel (A) of Figure 11 demonstrates the sample path of the adjusted attractiveness of SKU 1 (the dot line), the threshold of trial of household i, i =1,2,3, with a distance to the initial state U_{i1t} over time t, and the threshold of withdrawal for the SKU with a distance to the initial state L_{1t} over time t. At time 0, the initial state of the attractiveness of SKU 1, $X_1(0)$, is below all the thresholds of trial and above the threshold of withdrawal in the first week. The level of all the thresholds in the first week are determined by the time-varying covariates observed at time 0. Over time, $X_1(t)$ fluctuates because of unobserved random terms. At the end of the first week, $X_1(t)$ does not cross any thresholds, indicating that none of the three households has tried the new SKU and that the SKU is still on the market. At time 1, the values of time-varying covariates are updated; thus, the values of all thresholds may change, and $X_1(1)$ is reset to zero. In the second week after SKU 1 is introduced, $X_1(t)$ crosses household 2's threshold of trial and, thus, the household tries the SKU in that week. At the end of the fourth week after introduction, both households 1 and 3 have not yet tried SKU 1, while the SKU is still on the market.

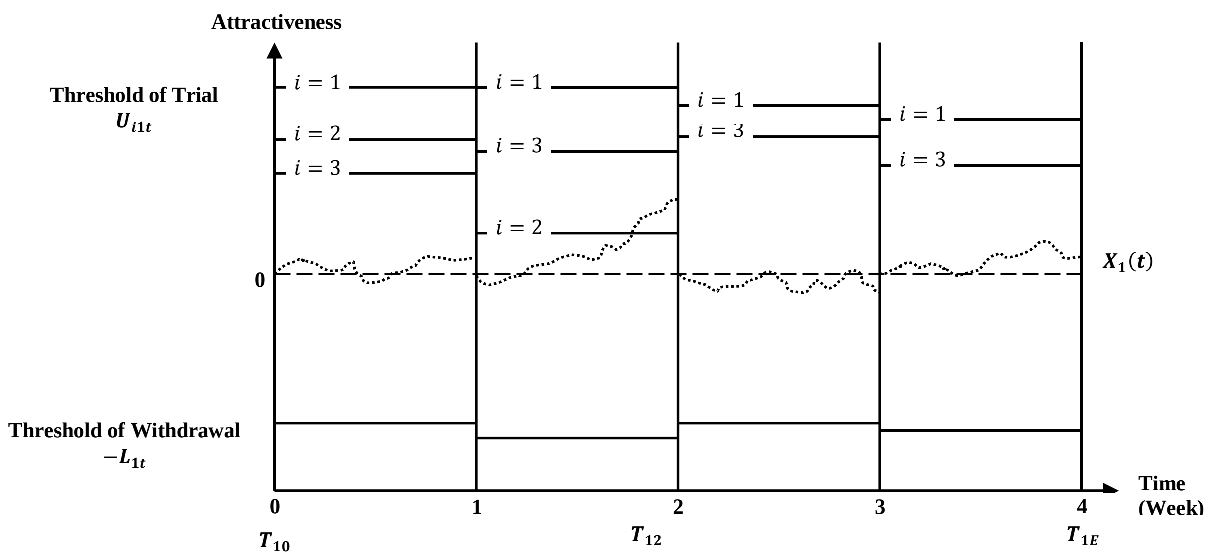
Panel (B) of Figure 11 depicts the case of SKU 2, which is an early withdrawn product. In the first week after the SKU is introduced, household 3 tries the new SKU. The other two households have not yet tried the SKU by the end of the third week, in which SKU 2's attractiveness hits the threshold of withdrawal, and hence the SKU is withdrawn before the end of the predetermined observation period. Note that one threshold of trial may not always be higher than another because of the heterogeneity in the households' responses to certain time-varying variables. One example can be found in panel (A) of Figure 11 where Household 2 has a higher threshold of trial than Household 3 does in the first week but not in the second week.

3.3.2 Model Specification

We mathematically specify our TR model in this section. To begin with, we denote a sequence of fixed calendar time points at which observations are available regarding household i and SKU j by $w_{ij0} \leq w_{ij1} \leq \cdots w_{ijm} \leq \cdots \leq w_{ijM}$, where $w_{ij0} = T_{j0}$ is the time when SKU j is introduced, and $w_{ijM} \equiv O_{ij} = \min\left(T_{ij}, T_{jE}, T_{jW}\right)$ is the observed event time for household i regarding SKU j.

Conceptually, the duration between any two time points can be unequal. Empirically, we consider w_{ijm} the end of the m^{th} week after the launch of SKU j; thus $w_{ijm} = T_{j0} + m$ and $w_{ijm} - w_{ijm-1} = 1$ (week). We emphasize the first year after product launch and, thus, set the end of observation for the SKU $T_{jE} = T_{j0} + 52$ (weeks).

(A) SKU 1 is still on the retail shelves four weeks after introduction.



(B) SKU 2 is withdrawn in the third week after introduction.

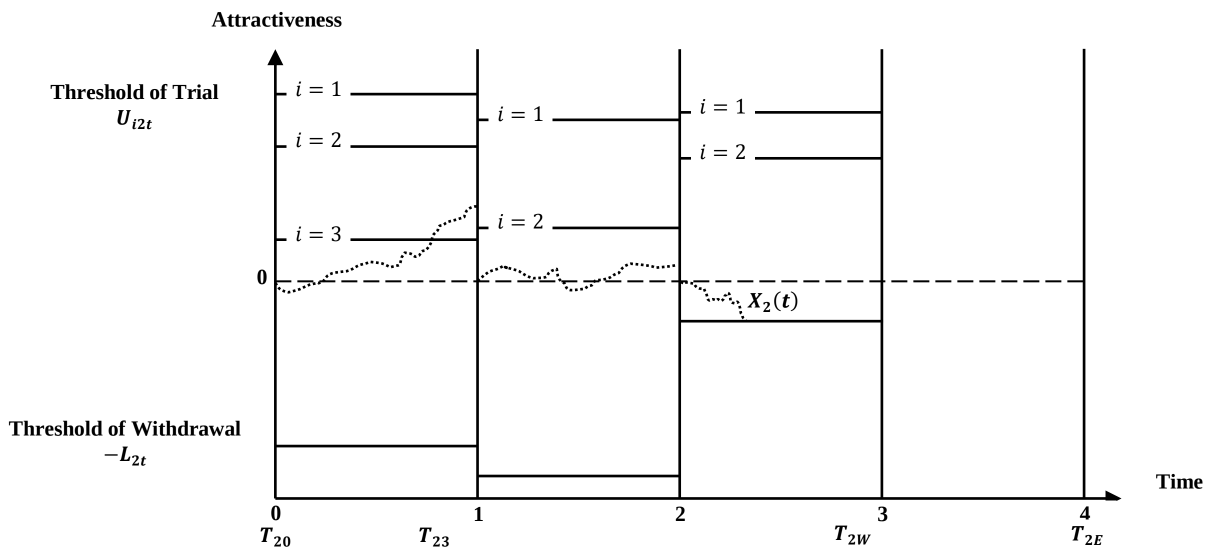


Figure 11: Illustrations of the Adjusted Attractiveness of an SKU, Thresholds of Trial, and Threshold of Withdrawal

To link time-varying covariates to the two thresholds, we follow Lee et al. (2010) and assume a Markov property to decompose $X_j(t)$ into a series of single records. We first assume that the process $X_j(t)$ is observable at each time point. Specifically, we denote events as $A_{ij,t} = (x_{j,t}, \boldsymbol{y}_{ij,t}, u_{ij,t}, l_{j,t}, c_{ij,t})$, where $t = w_{ij0}, w_{ij1}, \ldots, w_{jiM}$, $x_{j,t}$ is the level of $X_j(t)$ at time t; $\boldsymbol{y}_{ij,t}$ is the time-varying covariate vector regarding household i and SKU j at time t; $u_{ij,t}$ is a trial indicator that equals 1 if $t = T_{ij}$; $l_{j,t}$ is a withdrawal indicator that equals 1 if $t = T_{jW}$; and $c_{ij,t}$ is a right-censored indicator that equals 1 if $t = T_{jE}$. We assume that the stochastic process $\{A_{ij,t}\}$ is a Markov process. For household i with respect to SKU j, the probability of the observation sequence can be represented as a product of conditional probabilities:

$$\Pr\left(A_{ij,w_{ij0}}, A_{ij,w_{ij1}}, \ldots, A_{ij,w_{ijM}}\right) = \Pr\left(A_{ij,w_{ij0}}\right) \prod_{m=1}^{M} \Pr\left(A_{ij,w_{ijm}} \middle| A_{ij,w_{ijm-1}}\right), \tag{28}$$

where $\Pr\left(A_{ij,w_{ijm}} \middle| A_{ij,w_{ijm-1}}\right)$ can be factored into the product of two conditional probabilities:

$$\Pr\left(B_{ij,w_{ijm}} \middle| C_{ij,w_{ijm-1}}\right) \times \Pr\left(\boldsymbol{y}_{ij,w_{ijm}}, c_{ij,w_{ijm}} \middle| B_{ij,w_{ijm}}, C_{ij,w_{ijm-1}}\right), \tag{29}$$

where $B_{ij,t} = \{x_{j,t}, u_{ij,t}, l_{j,t}\}$, $C_{ij,t} = \{x_{j,t}, \boldsymbol{y}_{ij,t}, u_{ij,t} = 0, l_{j,t} = 0, c_{ij,t} = 0\}$. Note that our main interest is in the parameters $\boldsymbol{\theta}$ that govern the process $X_j(t)$ and the two thresholds. These parameters involve only the first term of (29). The partial likelihood, thus, can serve as a basis for estimating the parameters of interest. Given that $\Pr\left(A_{ij,w_{ij0}}\right) = 1$, the contribution of a single observation sequence regarding household i and SKU j to the sample partial likelihood is:

$$L_{ij}(\boldsymbol{\theta}) = \prod_{m=1}^{M} \Pr\left(B_{ij,w_{ijm}} \middle| C_{ij,w_{ijm-1}}\right). \tag{30}$$

Considering that the process $X_j(t)$ is, in fact, unobservable and that the independent censoring assumption is adopted, Equation (30) can be rewritten as

$$L_{ij}(\boldsymbol{\theta}) = \prod_{m=1}^{M} \Pr\left(u_{ij,w_{ijm}}, l_{ij,w_{ijm}} \middle| \boldsymbol{y}_{ij,w_{ijm-1}}, u_{ij,w_{ijm-1}} = 0, l_{j,w_{ijm-1}} = 0\right). \tag{31}$$

The partial likelihood over households and SKUs, thus, has the form

$$L(\boldsymbol{\theta}) = \prod_{i=1}^{I} \prod_{j=1}^{J} L_{ij}(\boldsymbol{\theta}). \tag{32}$$

So far we have not specified $X_j(t)$ nor the two thresholds, so the conditional probability on the right-hand side of Equation (31) remains unknown. We assume that for each week $X_j(t)$ is a standard Brownian motion, $t \in (w_{ijm-1}, w_{ijm}]$, and $X_j(w_{ijm-1}) = 0$. The standard Brownian motion is used to account for the error component of the model. For an individual household that has not tried SKU j that is still on the market, the initial state (i.e., 0) falls between the lower threshold of withdrawal, $TW_{jt} \equiv -L_{jt}$, and the upper threshold of trial, $TT_{ijt} \equiv U_{ijt}$, so that $-L_{jt} < 0 < U_{ijt}$. The two thresholds can be connected to time-varying covariates via logarithm link functions that ensure $L_{jt} > 0$ and $U_{ijt} > 0$:

$$\ln(U_{ijt}) = \alpha_m + \boldsymbol{v}_{1ij}^T \boldsymbol{\gamma}_1 + \boldsymbol{v}_{2ij,w_{ijm-1}}^T \boldsymbol{\gamma}_{2i}, \tag{33}$$

$$\ln(L_{jt}) = \beta_m + \boldsymbol{z}_{j,w_{ijm-1}}^T \boldsymbol{\lambda}, \tag{34}$$

where α_m and β_m are the baseline thresholds that are constant during $(w_{ijm-1}, w_{ijm}]$ regarding the threshold of trial and threshold of withdrawal respectively, and the baseline thresholds for one period are set to be zero for identification; $\boldsymbol{v}_{1ij}$ is a vector of time-fixed covariates that might influence the trial of SKU j by household i, and $\boldsymbol{\gamma}_1$ is the corresponding coefficient vector; $\boldsymbol{v}_{2ij,w_{ijm-1}}$ is a vector of time-varying covariates (including an intercept term) that might influence the trial of SKU j by household i, and $\boldsymbol{\gamma}_{2i}$ is the corresponding coefficient vector for household i; $\boldsymbol{z}_{j,w_{ijm-1}}^T$ is a vector of time-varying covariates (including an intercept term) that might influence the withdrawal of SKU j, and $\boldsymbol{\lambda}$ is the corresponding coefficient vector. Covariates for the two thresholds examined in our empirical application will be discussed in detail in the following section. Regarding the household-level coefficient vector, $\boldsymbol{\gamma}_{2i}$, we account for the heterogeneity among households by assuming that

$$\boldsymbol{\gamma}_{2i} \sim \text{Normal}\left(\overline{\boldsymbol{\gamma}}_2, \boldsymbol{\Sigma}_{\boldsymbol{\gamma}_2}\right), \tag{35}$$

where $\overline{\boldsymbol{\gamma}}_2$ and $\boldsymbol{\Sigma}_{\boldsymbol{\gamma}_2}$ are the mean vector and variance-covariance matrix of the prior distribution respectively.

Note that L_{jt} measures the distance between the initial state (i.e., 0) and the threshold of withdrawal, which is invariant over households, whereas U_{ijt} measures the distance between the initial state and the upper threshold associated with individual household i. The smaller L_{jt} is, the closer the attractiveness of SKU j and the threshold of withdrawal at w_{ijm-1}, and the more likely the SKU will be withdrawn in the week. Similarly, the smaller U_{ijt} is, the more likely the household will try the SKU during the week.

Based on the specification of $X_j(t)$ and the two thresholds, we can derive the conditional probability in Equation (31). Let $F\left(t|U_{ijm}, L_{jm}\right)$ denote the cumulative distribution function of the random variable T which represents the time $X_j(t)$ first hits either U_{ijm} or $-L_{jm}$. In other words, $F\left(t|U_{ijm}, L_{jm}\right)$ is the probability that either new product trial or early product withdrawal occurs by time t, conditional on U_{ijm} and L_{jm}. Let $F_U(t)$ be the conditional probability that the process first hits U_{ijm} (i.e., the household tries the SKU) by time t, and $F_L(t)$ be the conditional probability that the process first hits L_{jm} (i.e., the SKU is withdrawn) by time t. It is clear that, by definition, $F\left(t|U_{ijm}, L_{jm}\right) = F_U(t) + F_L(t)$, and the survival function $S\left(t|U_{ijm}, L_{jm}\right) = 1 - F\left(t|U_{ijm}, L_{jm}\right)$. Both $F_U(t)$ and $F_L(t)$ are defective cumulative probabilities and do not fully integrate to one because the absorption of the attractiveness can occur at both the upper and the lower thresholds. The two cumulative probabilities can be represented in the following forms (Blurton et al. 2012; Ratcliff and Tuerlinckx 2002):

$$F_U(t) = p_{ijm} - \frac{\pi}{{q_{ijm}}^2} \times \sum_{k=1}^{\infty} \frac{2k \sin\left(\pi k\left(1 - p_{ijm}\right)\right) exp\left(-\frac{1}{2}\left(\frac{\pi^2 k^2}{{q_{ijm}}^2}\right) t\right)}{\frac{\pi^2 k^2}{{q_{ijm}}^2}}, \tag{36}$$

$$F_L(t) = 1 - p_{ijm} - \frac{\pi}{{q_{ijm}}^2} \times \sum_{k=1}^{\infty} \frac{2k \sin\left(\pi k p_{ijm}\right) exp\left(-\frac{1}{2}\left(\frac{\pi^2 k^2}{{q_{ijm}}^2}\right) t\right)}{\frac{\pi^2 k^2}{{q_{ijm}}^2}}, \tag{37}$$

where $p_{ijm} = L_{jm}/\left(U_{ijm} + L_{jm}\right)$ and $q_{ijm} = \left(U_{ijm} + L_{jm}\right)$. The corresponding defective densities $f_U(t)\ and\ f_L(t)$ are (Feller 1968; Navarro and Fuss 2009):

$$f_U(t) = \frac{\pi}{{q_{ijm}}^2} \times \sum_{k=1}^{\infty} k \sin\left(\frac{\pi k U_{ijm}}{q_{ijm}}\right) exp\left(-\frac{1}{2} \frac{\pi^2 k^2}{{q_{ijm}}^2} t\right), \tag{38}$$

$$f_L(t) = \frac{\pi}{{q_{ijm}}^2} \times \sum_{k=1}^{\infty} k \sin\left(\frac{\pi k L_{jm}}{q_{ijm}}\right) exp\left(-\frac{1}{2} \frac{\pi^2 k^2}{{q_{ijm}}^2} t\right). \tag{39}$$

By a defective density, we mean one that does not integrate to one (Feller 1968).

The defective cumulative probabilities and densities in Equations (36) – (39) involve the evaluation of infinite sums and, thus, must be truncated at some point. Note that Equations (36) and (37) can be represented by the following equations (Horrocks 1999):

$$F_U(t) = 2\sum_{k=0}^{K}\left\{\Phi\left(\frac{-(2k+1)U_{ijm} - 2kL_{jm}}{\sqrt{t}}\right) - \Phi\left(\frac{-(2k+1)U_{ijm} - (2k+2)L_{jm}}{\sqrt{t}}\right)\right\}, \tag{40}$$

$$F_L(t) = 2\sum_{k=0}^{K}\left\{\Phi\left(\frac{-2kU_{ijm} - (2k+1)L_{jm}}{\sqrt{t}}\right) - \Phi\left(\frac{-(2k+2)U_{ijm} - (2k+1)L_{jm}}{\sqrt{t}}\right)\right\}, \tag{41}$$

where $\Phi(\quad)$ is the standard normal cumulative density function. Blurton et al. (2012) show that if K satisfies the following condition, it is guaranteed that the truncation error at K is below ε:

$$K \geq \begin{cases} \frac{1-p_{ijm}}{2} - \frac{\sqrt{t}}{2q_{ijm}}\Phi^{-1}\left(\frac{\varepsilon}{2p_{ijm}}\right), for\ F_U(t), \\ \frac{p_{ijm}}{2} - \frac{\sqrt{t}}{2q_{ijm}}\Phi^{-1}\left(\frac{\varepsilon}{2-2p_{ijm}}\right), for\ F_L(t). \end{cases} \tag{42}$$

We truncate the infinite sum at $K = 3$, and the truncation error is guaranteed below 10^{-4} given $\mathrm{t} = 1$ if $U_{ijm} + L_{jm} \geq 0.7$. Since our data for empirical analysis are interval censored, we use the defective cumulative probabilities in Equations (40) and (41) to construct the partial likelihood. The partial likelihood function contributed by household i regarding SKU j have the following form:

$$L_{ij}(\boldsymbol{\theta}) = \prod_{m=1}^{M}\left(1 - F_U(\Delta t) - F_L(\Delta t)\right)^{1-u_{ij,w_{ijm}}-l_{j,w_{ijm}}} F_U(\Delta t)^{u_{ij,w_{ijm}}} F_L(\Delta t)^{l_{j,w_{ijm}}}, \tag{43}$$

where $1 - F_U(t) - F_L(t) = S\left(t|U_{ijt}, L_{jt}\right)$, and $\Delta t \equiv w_{ijm} - w_{ijm-1} = 1$. For some applications, it is reasonable to assume that the first hitting time can be exactly observed. In this case, the defective cumulative probabilities should be replaced by defective densities in Equations (38) and (39). Please refer to Navarro and Fuss (2009) for the representations of the defective densities and the conditions regarding the finite truncation error. The specification of the partial likelihood is complete, and the model can be estimated in a Bayesian fashion. The details of the prior and posterior distributions are given in Appendix B.

3.4 Empirical Application

3.4.1 Data

The proposed model is used to analyze the trial of new potato chip SKUs. We use the data provided by the IRI academic dataset (Bronnenberg et al. 2008), which includes weekly SKU-store-level scanner data and consumer panel data from January 1, 2001 to December 25, 2005. We explore the drivers for panel households to try new potato chip SKUs in Pittsfield, MA. In order to identify early withdrawn products, we need to determine the product lifetime of each SKU. The lifetime of a product is inferred from its sales records. The starting point of the lifetime is operationalized as the first week in which the SKU is sold in any chain store in the Pittsfield market covered by the IRI dataset. As to the end point of the lifetime, if there is no sales record of the SKU in the market in 2005, we determine that the SKU is withdrawn from the market and consider the last week with sales records as the end point of its lifetime.

We include all 160 new potato chip SKUs launched during IRI weeks 1166-1269 (Dec. 31, 2001 – Dec. 28, 2003) in Pittsfield. Industry analysts consider the first year after launch critical for a product to succeed in the CPG industry (Steenkamp and Gielens 2003). The survival status of those SKUs in the first year is depicted in Figure 12, showing that 71 of the 160 SKUs (44.38%) exited the market within the first year after launch. We gathered the trials of these new products in the first year by 1,000 randomly selected panel households, resulting in 6,172,415 household-

SKU-week observations. The frequencies of trials of these new potato chip SKUs are illustrated in Figure 13. Among the 160 SKUs, 58 SKUs tried by less than 10 (of the 1,000) households in the first year still survive after the first year, while 56 SKUs tried by less than 10 households were withdrawn within the first year. One SKU, which was still on the market after its first year, had been tried by 383 households in the first year.

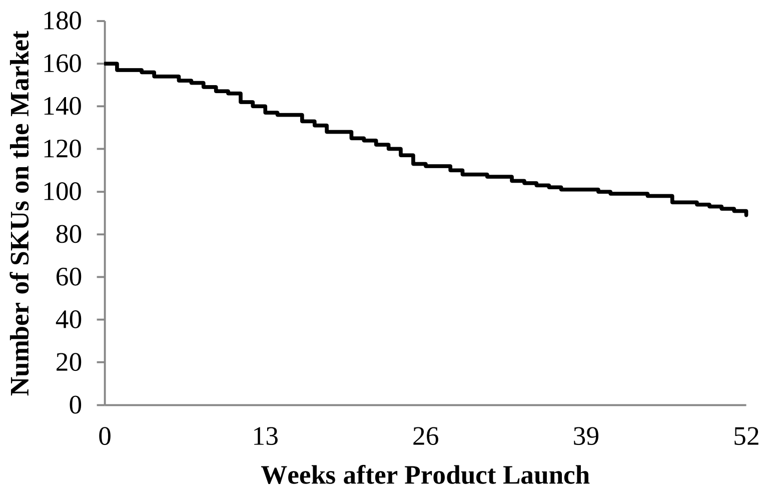


Figure 12: The Survival Status of New Potato Chip SKUs in the First Year

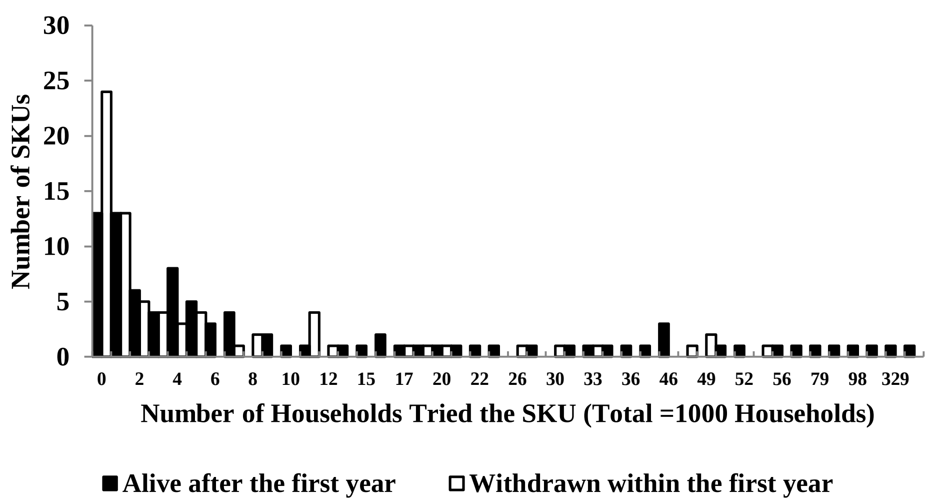


Figure 13: New Potato Chip SKU Trial in the First Year

3.4.2 Potential Drivers of New Product Trial

We consulted the literature on new product trial (Gielens and Steenkamp 2007; Steenkamp and Gielens 2003) and product lifetime (Carroll et al. 2010) to select potential drivers of new product trial in the context of CPGs. These potential drivers include household characteristics, product characteristics, marketing strategies, social contagion, and product sales performance. The measures and descriptive statistics of these variables are reported in Table 5 and Table 6.

3.4.2.1 Household Characteristics

Household characteristics are time-fixed covariates in Equation (33). We considered both demographic and behavioral variables. Regarding the demographic variables, we included ***family size***, and the ***income*** of the household, whether at least one family member is a ***child***, and whether the heads of the household are ***married***. Concerning the behavioral variables, we focused on the purchase behavior and households' propensities of variety seeking. Following Steenkamp and Gielens (2003), we included ***usage intensity***, determined by the amount of potato chips bought by the household in the past year counted in ounces. In addition, we tracked the brand of the new SKU and measured ***brand usage ratio*** as the percentage of the weight of the brand's SKUs bought by the household to the amount of potato chips bought by the household. A household that frequently purchases a brand are more likely to be aware of the new product introduced by the brand. Finally, since some households may never try any salty snacks, we also included the variable ***nonuser*** and expect that those nonusers are less likely to try a new SKU.

Table 5: Explanatory Variables for New Product Trial and Early Product Withdrawal

Variable	Measure
Household Characteristics	
Demographic Variables	
Family Size	Head counts of household *i*
Low Income	Dummy variable, 1 if the combined pre-tax income of the heads of household *I* is below US$25,000
Medium Income	Dummy variable, 1 if the combined pre-tax income of the heads of household *I* is above US$24,999 and below US$55,000
Child	Dummy variable, 1 if household *I* has at least one child under 18 years old
Married	Dummy variable, 1 if the heads of household *I* are married
Behavioral Variables	
Usage Intensity	The volume of potato chips household *I* bought over the past 12 months before the introduction of SKU *j* (16oz/unit)
Brand Usage Ratio	The percentage of the volume of brand *b*'s potato chips bought by household *I* over the past 12 months before the introduction of SKU *j* to the usage intensity; SKU *j* is introduced by brand *b*
Nonuser	Dummy variable, 1 if household *I* had not bought any salty snack SKU during the past 12 months before the introduction of SKU *j*
Within-Trip Variety Seeking	Household *i*'s propensity to purchase multiple salty snack SKUs on one shopping trip during the past 12 months before the introduction of SKU *j*
Across-Trip Variety Seeking	Household *i*'s propensity to purchase different salty snack SKUs over shopping trips during the past 12 months before the introduction of SKU *j*
Product Characteristics	
Brand (Base: Private Label)	
Cape Cod	Dummy variable, 1 if SKU *j* is introduced by Cape Cod
Lay's	Dummy variable, 1 if SKU *j* is introduced by Lay's
Lay's Sub-brand	Dummy variable, 1 if SKU *j* is introduced by any of Lay's sub-brands
Pringles	Dummy variable, 1 if SKU *j* is introduced by Pringles
Ruffles	Dummy variable, 1 if SKU *j* is introduced by Ruffles
Utz	Dummy variable, 1 if SKU *j* is introduced by Utz
Wise	Dummy variable, 1 if SKU *j* is introduced by Wise
Other Brands	Dummy variable, 1 if SKU *j* is introduced by Other brands that are not private labels
Salient Attribute	
Flat-Cut	Dummy variable, 1 if SKU *j* is flat-cut
Low-Fat	Dummy variable, 1 if SKU *j* is reduced-fat or fat free
Flavor (Base: Original)	
BBQ	Dummy variable, 1 if SKU *j* is barbecue flavored
Cheese	Dummy variable, 1 if SKU *j* is cheese flavored
Herb/Ranch	Dummy variable, 1 if SKU *j* is herb-and/or-ranch flavored
Salt/Vinegar	Dummy variable, 1 if SKU *j* is salt-and/or-vinegar flavored
Sour Cream	Dummy variable, 1 if SKU *j* is sour cream flavored
Spicy	Dummy variable, 1 if SKU *j* is spicy flavored
Other Flavors	Dummy variable, 1 if SKU *j* does not have any of the above flavors
Package Size (Base: Small)	
Medium	Dummy variable, 1 if SKU *j* is between 4.8oz and 8oz
Large	Dummy variable, 1 if SKU *j* is more than 8oz

Table 5: Explanatory Variables for New Product Trial and Early Product Withdrawal (Con.)

Variable	Measure
Launch Season	
02 Summer	Dummy variable, 1 if SKU *j* is introduced in Summer, 2002
02 Fall	Dummy variable, 1 if SKU *j* is introduced in Fall, 2002
02 Winter	Dummy variable, 1 if SKU *j* is introduced in Winter, 2002
03 Spring	Dummy variable, 1 if SKU *j* is introduced in Spring, 2003
03 Summer	Dummy variable, 1 if SKU *j* is introduced in Summer, 2003
03 Fall	Dummy variable, 1 if SKU *j* is introduced in Fall, 2003
03 Winter	Dummy variable, 1 if SKU *j* is introduced in Winter, 2003
Marketing Strategy	
Product	
Product Line Length	Number of potato chip SKUs offered by brand *b* (20 SKUs/unit)
Number of Distinct SKUs	Number of unique combinations of salient attribute levels offered by brand *b* (10 SKUs/unit)
Number of Duplicate SKUs	Product line length of brand *b* – number of distinct SKUs of brand *b* (10 SKUs/unit)
Competing SKUs	Number of potato chip SKUs offered by other brands (20 SKUs/unit)
Price	Price of SKU *j* per 16oz in week *t*, weighted by estimate ACV
Promotion	
Feature	Dummy variable, 1 if SKU *j* is featured in week *t*; the variable is weighted by estimate ACV
Display	Dummy variable, 1 if SKU *j* is displayed in week *t*; the variable is weighted by estimate ACV
Distribution	
Local Breadth	The percentage of retailers in the market selling SKU *j* in week *t*, weighted by estimate ACV
National Coverage	Number of markets where SKU *j* is sold in week *t* (20 markets/unit)
Social Contagion	
Trial Ratio	The percentage of households that have tried SKU *j* at the end of week *t*-1. We consider the percentage of all 3,202 panel households in the market.
Sales Performance	
Weekly Sales	The sales of SKU *j* in week *t*-1 (US$100,000/unit)
Cumulative Sales	The cumulative sales of SKU *j* up to the end of week *t*-1 (US$3,000,000/unit)

Table 6: Description of Explanatory Variables for New Product Trial and Early Product Withdrawal

Variables	Mean	S.D.	Minimum	Maximum
Household Characteristics				
Demographic Variables		*(Sample size = 1,000 Households)*		
Family Size	2.459	1.255	1.000	6.000
Low Income	0.279	0.449	0.000	1.000
Medium Income	0.381	0.486	0.000	1.000
Child	0.255	0.436	0.000	1.000
Married	0.628	0.484	0.000	1.000
Behavioral Variables		*(Sample size = 160,000 Household-SKUs)*		
Usage Intensity	9.031	10.182	0.000	86.375
Brand Usage Ratio	0.175	0.287	0.000	1.000
Nonuser	0.035	0.185	0.000	1.000
Within-Trip Variety Seeking	1.513	0.568	0.000	6.600
Across-Trip Variety Seeking	0.631	0.246	0.000	1.000
Product Characteristics		*(Sample size = 160 SKUs)*		
Cape Cod	0.075	0.264	0.000	1.000
Lay's	0.213	0.410	0.000	1.000
Lay's Sub-brand	0.113	0.317	0.000	1.000
Pringles	0.044	0.205	0.000	1.000
Ruffles	0.094	0.292	0.000	1.000
Utz	0.088	0.283	0.000	1.000
Wise	0.125	0.332	0.000	1.000
Other Brands	0.169	0.376	0.000	1.000
Flat-Cut	0.619	0.487	0.000	1.000
Low-Fat	0.069	0.254	0.000	1.000
BBQ	0.206	0.406	0.000	1.000
Cheese	0.069	0.254	0.000	1.000
Herb/Ranch	0.119	0.325	0.000	1.000
Salt/Vinegar	0.075	0.264	0.000	1.000
Sour Cream	0.106	0.309	0.000	1.000
Spicy	0.031	0.175	0.000	1.000
Other Flavors	0.063	0.243	0.000	1.000
Medium	0.319	0.467	0.000	1.000
Large	0.419	0.495	0.000	1.000
02 Summer	0.106	0.309	0.000	1.000
02 Fall	0.063	0.243	0.000	1.000
02 Winter	0.144	0.352	0.000	1.000
03 Spring	0.113	0.317	0.000	1.000
03 Summer	0.163	0.370	0.000	1.000
03 Fall	0.244	0.431	0.000	1.000
03 Winter	0.050	0.219	0.000	1.000
Marketing Strategy		*(Sample size = 6,249 SKU-weeks)*		
Product Line Length (20 SKUs/unit)	1.797	1.011	0.050	3.400
# of Distinct SKUs (10 SKUs/unit)	1.961	0.985	0.100	3.400
# of Duplicate SKUs (10 SKUs/unit)	1.632	1.081	0.000	3.700
Competing SKUs (20 SKUs/unit)	11.630	1.169	9.500	14.600
Price	1.909	1.078	0.100	6.810
Feature	0.092	0.247	0.000	1.000
Display	0.198	0.334	0.000	1.000
Local Breadth	0.357	0.344	0.000	1.000
National Coverage	1.200	0.902	0.050	2.500
Social Contagion		*(Sample size = 6,249 SKU-weeks)*		
Trial Ratio	0.013	0.038	0.000	0.411
Sales Performance		*(Sample size = 6,249 SKU-weeks)*		
Weekly Sales	0.138	1.345	0.000	40.793
Cumulative Sales	0.124	0.988	0.000	15.315

Considering that variety seekers may be more likely to try new products, we computed households' propensities of variety seeking (Kahn 1995) within a shopping trip (i.e., propensity to buy multiple SKUs on one trip) and across shopping trips (i.e., propensity to buy different SKUs over trips) using their purchase history by the following two measures:

$$WTVS_{ij} = \frac{NSKU_{ij}}{NTRIP_{ij}}, \tag{44}$$

$$ATVS_{ij} = \frac{NDIFSKU_{ij}}{NTRIP_{ij}} \div WTVS_{ij} = \frac{NDIFSKU_{ij}}{NSKU_{ij}}, \tag{45}$$

where $WTVS_{ij}$ is Household i's ***within-trip variety seeking*** propensity; $NSKU_{ij}$ is the number of salty snack SKUs bought by household i during the 52 weeks before the introduction of SKU j; $NTRIP_{ij}$ is the number of shopping trips on which those SKUs are bought by household i; $ATVS_{ij}$ is Household i's ***across-trip variety seeking*** propensity; and $NDIFSKU_{ij}$ is the number of different salty snack SKUs bought by household i during the period.

3.4.2.2 Product Features

Product features represent the main attributes of the product and, hence, and are expected to influence its trial. One important product characteristic is the brand of the product. We regard private labels as a benchmark and estimate fixed effects for the following brands: ***Cape Cod***, ***Lay's***, ***Pringles***, ***Ruffles***, ***Utz***, ***Wise***, and ***Other Brands***. Since the market leader, Lay's, introduced many new SKUs with sub-brands (e.g., "Wow" is a sub brand used by Lay's), we include one more brand indicator, ***Lay's Sub-brand***, to indicate these new SKUs. We further control four salient attributes of potato chips (Li 2014), including cut (***flat-cut*** or others), fat content (***low-fat*** or others), package size (small, ***medium***, or ***large***), and flavor (original, ***BBQ***, ***cheese***, ***herb/ranch***, ***salt/vinegar***, ***sour cream***, ***spicy***, and ***the other flavors***). We also control the cohort effects by considering the launch season of each SKU.

3.4.2.3 Marketing Strategies

Marketing strategies play important roles in influencing new product trial. We first consider the product strategies other than product characteristics. Specifically, we focus on the ***product line length,*** i.e., the number of potato chip SKUs of each brand. This variable reflects the effect of product line extension, which occurs intensively in the CPG industry (Berman 2011). Product line extension may attract new consumers via legitimization. As the number of similar product variants of a brand increases, customers start to take the brand for granted and are more willing to buy it and use it (Ingram and Roberts 1999). Consumers perceive brands offering more similar options as having greater expertise in the category, which consequently enhances their perceived quality and purchase likelihood (Berger et al. 2007). Product line extension, however, inevitably increases the degree of internal competition or cannibalization. Consumers may be confused and delay the purchase decision as the number of similar products increases. The effect of product line length may vary depending on the structure of the product line (Chong et al. 1998). We, thus, also separate product line length into the ***number of distinct SKUs*** and the ***number of duplicate SKUs*** to assess the role of product line structure. Furthermore, product line length has been considered as a competitive tool (e.g., Bayus and Putsis 1999; Draganska and Jain 2005). Other things being equal, a new SKU in a crowded market with more competing SKUs may be less likely to capture consumers' attention. We, hence, include the ***number of competing SKUs***.

Price may also affect new product trial. Economic theory posits that, other being equal, rational consumers will choose the cheapest product. Price discount is also a strategic tool frequently used by CPG managers to stimulate short-term sales and, thus, may induce new product trial. Like price discount, any forms of SKU-level promotions may also urge consumers to try a new SKU (Steenkamp and Gielens 2003). Common practices of SKU-level promotions in the CPG industry are ***feature*** ads and in-store ***display***; both are considered in our analysis.

As to the distribution of an SKU, we investigate the effects of both within-market and across-market distribution. In a specific market, a product entering more stores provides more opportunities for consumers to be aware of its existence and to buy the product. We, hence, consider the ***local breadth*** of the distribution of an SKU (Ataman et al. 2008). Firms may launch the same product in many markets, especially after the product has been proven to succeed in some markets. We, therefore, expect that consumers may be more likely to try a product with a higher ***national coverage*** (i.e., a product that enters more markets).

3.4.2.4 Social Contagion and Sales Performance

Social contagion has been viewed as a key driver in the diffusion theory (e.g., Granovetter 1978; Granovetter and Soong 1983) and has been captured by empirical models (Du and Kamakura 2011). The bandwagon effect suggests that consumers tend to try a new product once it becomes popular (Leibenstein 1950). We account for such an effect by incorporating ***trial ratio***, which is measured by the percentage of panel households that had tried the SKU up to last week. The trial ratio, however, does not capture consumers' repurchasing behavior frequently observed in the CPG industry, which are mostly reflected on product sales. We, thus, tested the effect of product sales on new product trial by considering its flow (***weekly sales***) and its stock (***cumulative sales***).

3.4.3 Potential Drivers of Early Product Withdrawal

While, to the best of our knowledge, there is no literature focusing on early product withdrawal, the literature on product lifetime (Carroll et al. 2010) suggests that product withdrawal may be due to lacking market support (e.g., Bayus 1998; Hitsch 2006; Putsis and Bayus 2001) or competition (e.g., Bayus and Putsis 1999; Putsis and Bayus 2001). Regarding the market support, managers usually evaluate the profitability of a product and decide whether to withdraw it. A product with a higher ***trial ratio*** or ***cumulative sales*** may be less likely to exit the market. We do not consider ***weekly sales*** because managers usually monitor and evaluate a new product's profitability over a longer period of time. It should also be noted that we estimate brand-level fixed effects since each brand may set different criteria for its new SKUs.

As to the effect of competition, we focus on it through product line length. Managers may withdraw some products in a long product line in order to mitigate the internal competition. Researchers have shown that ***product line length*** has a positive effect on the likelihood of product withdrawal (e.g., de Figueiredo and Kyle 2006). Yet the degree of internal competition may depend on the structure of the product line and thus depend on the ***number of distinct SKUs*** and the ***number of duplicate SKUs***. Managers may also infer the demand or the profitability of a product from the crowdedness of a market. When there is a greater ***number of competing SKUs*** on the market, a single product may bring lower returns. However, firms may strategically enter a crowded market (Bayus and Putsis 1999; Connor 1981) and keep products with zero or negative profits thereon (Ruebeck 2002), possibly as part of their strategy against existing competitors (Chisholm and Norman 2006). In this study, we explore how product line length, product line structure, and the number of competing SKUs affect early product withdrawal.

3.4.4 Findings and Discussion

The estimation results of the models with or without product line structure are displayed in Table 7. We control the baseline thresholds α_m and β_m for the two events respectively. The baseline is assumed to be constant over a period of four weeks, and the level of each period (i.e., weeks 5-8 to weeks 49-52 after product introduction) is estimated. Our model's dependent variable is the distance from the threshold of trial (or the threshold of withdrawal) to the initial state zero. Therefore, a significantly positive coefficient suggests that the corresponding variable has a positive effect on the distance and, hence, is less likely to drive or accelerate new product trial (or early product withdrawal). We compare the two models (i.e., with or without product line structure) by using the log pseudo marginal likelihood (LPML,Geisser and Eddy 1979) and the deviance information criterion (DIC, Spiegelhalter et al. 2002). According to the two criteria, the model without product line structure outperforms the other. However, conceptually product line structure is an important element of a product line, and empirically the number of distinct SKUs and the number of duplicate SKUs do have significant effects. Thus, we focus on the significant coefficients with the same sign in both models.

3.4.4.1 New Product Trial

We start with the influence of household characteristics on new product trial. Regarding the demographic variables, we find that a household with a married couple is more likely to try new potato chip SKUs. Moreover, compared with households with high income, households with medium income are more likely to try new potato chip SKUs. As to the behavioral variables, we do not find any significant effect consistently suggested by both models. However, we do obtain evidence of social contagion, as trial ratio has a significantly positive effect on the probability of

Table 7: Estimation Results from the Two-threshold Models

	Model without Product Line Structure						Model with Product Line Structure					
	New Product Trial (U_{ijm})			Early Product Withdrawal (L_{jm})			New Product Trial (U_{ijm})			Early Product Withdrawal (L_{jm})		
	Mean	**S.E.**	**Sig.[1]**	**Mean**	**S.E.**	**Sig.[1]**	**Mean**	**S.E.**	**Sig.[1]**	**Mean**	**S.E.**	**Sig.[1]**
Household Characteristics												
Demographic Variables												
Size	0.120	0.043	**				0.043	0.030				
Low Income	0.104	0.045	**				-0.271	0.039	**			
Medium Income	0.195	0.026	**				0.212	0.080	**			
Child	-0.085	0.023	**				0.079	0.039	**			
Married	-0.181	0.046	**				-0.165	0.049	**			
Behavioral Variables												
Usage Intensity	0.005	0.013					0.009	0.010				
Brand Usage Ratio	0.058	0.043					-0.030	0.031				
Within-Trip Variety Seeking	0.005	0.035					-0.063	0.044				
Across-Trip Variety Seeking	0.274	0.086	**				-0.014	0.020				
Nonuser	0.065	0.050					0.118	0.032	**			
Social Contagion												
Trial Ratio	-0.313	0.066	**	0.020	0.033		-0.261	0.031	**	-0.043	0.031	
Product Characteristics												
Brand (Base: Private Label)												
Cape Cod	0.269	0.050	**	0.025	0.020		0.190	0.030	**	-0.060	0.025	**
Lay's	0.086	0.030	**	0.134	0.026	**	-0.021	0.027		0.046	0.030	
Lay's Sub-brand	0.322	0.026	**	-0.076	0.017	**	0.245	0.040	**	-0.124	0.025	**
Pringles	0.235	0.030	**	-0.290	0.016	**	0.021	0.025		-0.308	0.030	**
Ruffles	-0.046	0.020	**	-0.076	0.014	**	-0.195	0.036	**	-0.134	0.027	**
Utz	0.150	0.021	**	-0.101	0.018	**	0.075	0.032	**	-0.184	0.023	**
Wise	0.335	0.050	**	-0.352	0.019	**	0.259	0.027	**	-0.328	0.040	**
Other Brands	0.278	0.029	**	0.108	0.030	**	0.223	0.024	**	-0.049	0.053	
Salient Attribute												
Flat-Cut	0.163	0.024	**				0.166	0.021	**			
Low-Fat	0.507	0.021	**				0.592	0.040	**			
Flavor (Base: Original)												
BBQ	0.248	0.020	**				0.283	0.021	**			
Cheese	0.274	0.027	**				0.303	0.028	**			
Herb/Ranch	0.283	0.039	**				0.287	0.043	**			
Salt/Vinegar	0.277	0.024	**				0.279	0.036	**			
Sour Cream	0.127	0.024	**				0.149	0.029	**			
Spicy	0.296	0.048	**				0.275	0.038	**			
Other Flavors	0.410	0.019	**				0.431	0.024	**			
Package Size (Base: Small)												
Medium	-0.434	0.049	**				-0.472	0.030	**			
Large	-0.586	0.041	**				-0.626	0.033	**			
Marketing Strategy												
Product												
Product Line Length	-0.082	0.016	**	-0.045	0.010	**						
Number of Distinct SKUs							0.105	0.024	**	0.074	0.019	**
Number of Duplicate SKUs							-0.114	0.015	**	-0.068	0.013	**
Number of Competing SKUs	0.216	0.017	**	0.089	0.003	**	0.268	0.011	**	0.095	0.006	**
Price	0.146	0.016	**				0.125	0.018	**			
Promotion												
Feature	-0.095	0.018	**				-0.083	0.025	**			
Display	-0.136	0.016	**				-0.184	0.025	**			
Distribution												
Local Breadth	-0.631	0.031	**				-0.634	0.018	**			
National Coverage	0.025	0.013	*				0.033	0.022				

Note:
1. = significant at the 0.1 level; ** = significant at the 0.05 level

Table 7: Estimation Results from the Two-threshold Models (Con.)

	Model without Product Line Structure						Model with Product Line Structure					
	New Product Trial (U_{ijm})			Early Product Withdrawal (L_{jm})			New Product Trial (U_{ijm})			Early Product Withdrawal (L_{jm})		
	Mean	**S.E.**	**Sig.[1]**	**Mean**	**S.E.**	**Sig.[1]**	**Mean**	**S.E.**	**Sig.[1]**	**Mean**	**S.E.**	**Sig.[1]**
Sales Performance												
Sales	0.060	0.007	**				0.061	0.007	**			
Cumulative Sales	0.038	0.011	**	0.672	0.092	**	0.043	0.011	**	0.457	0.049	**
Product Launch Season												
(Base: 2002 Spring)												
2002 Summer	0.152	0.021	**				0.084	0.021	**			
2002 Fall	0.108	0.023	**				0.112	0.021	**			
2002 Winter	-0.105	0.022	**				-0.166	0.018	**			
2003 Spring	0.287	0.027	**				0.173	0.017	**			
2003 Summer	0.026	0.018					-0.074	0.028	**			
2003 Fall	0.016	0.027					-0.103	0.033	**			
2003 Winter	0.090	0.025	**				-0.076	0.030	**			
Baseline Effect												
(Base: Weeks 1-4)												
Weeks 5-8	-0.069	0.056		0.036	0.017	**	-0.106	0.029	**	0.056	0.015	**
Weeks 9-12	-0.078	0.045	*	-0.060	0.018	**	-0.093	0.033	**	-0.043	0.018	**
Weeks 13-16	0.127	0.039	**	-0.049	0.016	**	-0.114	0.025	**	-0.023	0.019	
Weeks 17-20	-0.035	0.025		-0.079	0.019	**	0.036	0.041		-0.062	0.016	**
Weeks 21-24	0.049	0.023	**	-0.083	0.018	**	0.118	0.083		-0.070	0.015	**
Weeks 25-28	-0.115	0.050	**	-0.087	0.024	**	-0.176	0.028	**	-0.066	0.016	**
Weeks 29-32	0.087	0.030	**	-0.008	0.019		-0.032	0.044		0.010	0.021	
Weeks 33-36	0.303	0.045	**	-0.073	0.015	**	-0.210	0.045	**	-0.043	0.019	**
Weeks 37-40	0.053	0.036		0.024	0.018		0.122	0.047	**	0.038	0.020	*
Weeks 41-44	0.011	0.051		0.016	0.026		-0.080	0.036	**	0.046	0.028	*
Weeks 45-48	-0.016	0.059		-0.077	0.021	**	-0.282	0.054	**	-0.048	0.027	*
Weeks 49-52	0.161	0.035	**	-0.100	0.019	**	-0.123	0.030	**	-0.083	0.024	**
Intercept	0.077	0.032	**	-0.085	0.015	**	0.191	0.037	**	-0.086	0.028	**
Information Criteria												
LPML[2]	-386,759.438						-388,476.752					
DIC[3]	761,282.554						761,856.801					

Note:

1. * = significant at the 0.1 level; ** = significant at the 0.05 level
2. We select the model that maximizes log marginal pseudo likelihood (LMPL).
3. We select the model that minimizes deviance information criterion (DIC).

new product trial. Regarding the influence of product characteristics, our findings suggest brands and salient product attributes can affect new product trial. Specifically, households are more likely to try new SKUs of Ruffles. Furthermore, households are more likely to try non-flat-cut, regular-fat, original-flavored, and/or medium/large-size potato chips.

We also find that households are more likely to try the new product from a brand with a longer product line, which may be explained by legitimization or the expert image created by the brand

(Berger et al. 2007; Ingram and Roberts 1999). A further investigation shows that households are less (more) likely to try a new product from a brand with more distinct (duplicate) SKUs. A new product from a brand with more distinct SKUs may be less likely to attract consumers because those existing SKUs may have already satisfied a greater number of segments. In addition, if the new product tries to differentiate itself from the other products in the already diversified product line, consumers may think it is too new and feel too risky to try it. However, a new product from a brand with more duplicate SKUs may be more likely to attract a new segment of consumers, given most of those existing products are highly similar. If the new product is also similar to the previously introduced products in the product line, consumers may feel familiar with it and perceive less risk to try it. Moreover, households are less likely to try a new potato chip SKU when there are more SKUs from competing brands, possibly because it is relatively hard for the new SKU to capture consumers' attention in a more crowded market.

The effects of price, promotion, and distribution are generally in line with our expectation. Households are less likely to try a new SKU at a higher price and more likely to try it when it is promoted by feature ads or in-store display or carried by more stores. Finally, we find that households are less likely to try a new SKU when its weekly sales or cumulative sales are higher. While the result regarding the trial ratio is in line with our expectation, the results concerning product sales are unexpected. These may be due to the high correlations between trial ratio, weekly sales, and cumulative sales, among which the lowest Pearson's correlation is already 0.58.

3.4.4.2 Early Product Withdrawal

The market rationality suggests that a product earning more market support is less likely to exit the market. We find that new potato chip SKUs that accumulate more sales soon after introduction are less likely to be withdrawn in the first year. In addition, we do not find a significant effect of the trial ratio. These findings may be due to the high correlation between the trial ratio and cumulative sales or due to the fact that managers care mainly about the bottom line that reflects not only trial but also repeat purchases. Furthermore, we find that, except for Lay's, most top-selling brands are more likely to withdraw their new SKUs. One possible reason is that other brands are mainly local brands that have few SKUs and seldom introduce new SKUs. Once they introduce a new SKU, they may grant it more time to develop.

Considering the competition in product line length, we find that the new potato chip SKU introduced by a brand with a longer product line is more likely to be withdrawn, which may be the outcome of the internal competition. However, when there are more competing SKUs, the new SKU is less likely to be withdrawn, implying that brand managers may actively engage in brand competition. An investigation into the role of product line structure further suggests that a new product is less likely to be withdrawn when the brand has more distinct (or less duplicate) SKUs, possibly because when there are more distinct (or less duplicate) SKUs, the internal competition or cannibalization is less severe.

3.4.4.3 New Product Trial Using Data without Early Withdrawn SKUs

In order to demonstrate the differences when early product withdrawal is considered, we run another, simpler TR model using data of only SKUs that survive more than one year. Since there is no SKU withdrawn in the first year, the threshold of withdrawal is dropped, and the model essentially becomes the one discussed by Chatterjee and Eliashberg (1990) and developed by

Lee et al. (2010). Specifically, we fit the simpler TR model discussed in Appendix A with data regarding only the 89 SKUs that were still on the retail shelves one year after their launches in our sample; such contain 4,560,566 household-SKU-week observations. The estimation results are given in Table 8. A significantly positive coefficient suggests that the corresponding variable is less likely to drive new product trial. We also use LPML and DIC to compare the models with and without considering product line structure, and the two information criteria do not reach a consensus regarding which model performs better. Therefore, we focus on the significant coefficients with the same sign from both models and highlight the findings different from those shown in Table 7.

Regarding the effect of household characteristics on new product trial, the model using data without early-withdrawn SKUs suggests that, compared with households with high income level, households with low income level are more likely to try new products. However, the model considering early product withdrawal suggests that households with low income level are not significantly more likely to try new products, but households with medium income level are significantly less likely to try new products. In addition, the model using data without early-withdrawn SKUs indicates that some behavioral variables, such as brand usage and across-trip variety seeking are significant, while the model considering early product withdrawal suggests that no behavioral variable is significant. As to the brand fixed effect, unlike the model using data without early-withdrawn SKUs, the model considering early product withdrawal suggests that households are more likely to try Ruffle's new products and less likely to try Utz's new products. Concerning marketing variables, the model using data without early-withdrawn SKUs shows that product line length has no significant effect on new product trial, while the model considering early product withdrawal reveals that product line length has a positive effect on new product trial. Lastly, the model using data without early-withdrawn SKUs indicates that households are more likely to try a product sold in more markets, yet the model considering early product withdrawal does not support this effect. Overall, considering early product withdrawal does change our understanding about several potential drivers of new product trial.

3.4.4.4 Results Using Data without Temporarily Available SKUs

Temporarily available SKUs, such as special promotion packages, have lifetimes predetermined by managers before their introductions. Hence, the withdrawal decision regarding these products, which may not be associated with the threshold of withdrawal, is different from that regarding the other new products. Unfortunately, the information of temporarily available SKUs is not provided by the IRI Academic dataset. In order to alleviate the concern of including those SKUs, in this section, we assume that products surviving the first three months are not temporarily available SKUs. Therefore, we exclude 20 SKUs that have product lifetimes shorter than three months in our analysis and drop 144,921 household-SKU-week observations. Table 9 shows that the model considering product line structure outperforms the other model according to both LPML and DIC, a result different from that using all SKUs. Moreover, the effects of product line length metrics remain the same. In particular, product line length and the number of duplicate SKUs have negative effects on the probability of new product trial and that of early product withdrawal, while the number of distinct SKUs has positive effects on both probabilities.

Table 8: Estimation Results of New Product Trial Using Only SKUs Surviving More than One Year

	Model without Product Line Structure			Model with Product Line Structure		
	Mean	S.E.	Sig.[1]	Mean	S.E.	Sig.[1]
Household Characteristics						
Demographic Variables						
Size	0.025	0.016		-0.020	0.009	**
Low Income	0.082	0.032	**	0.023	0.009	**
Medium Income	-0.006	0.012		0.048	0.017	**
Child	0.016	0.016		0.003	0.016	
Married	-0.046	0.009	**	-0.054	0.011	**
Behavioral Variables						
Usage Intensity	0.000	0.003		0.004	0.001	**
Brand Usage Ratio	-0.255	0.026	**	-0.189	0.024	**
Within-Trip Variety Seeking	0.007	0.009		0.031	0.012	**
Across-Trip Variety Seeking	0.088	0.024	**	0.076	0.033	**
Nonuser	0.003	0.015		0.069	0.029	**
Social Contagion						
Trial Ratio	-0.354	0.046	**	-0.338	0.043	**
Product Characteristics						
Brand (Base: Private Label)						
Cape Cod	0.168	0.039	**	0.137	0.025	**
Lay’s	-0.034	0.035		-0.038	0.033	
Lay’s Sub-brand	0.326	0.064	**	0.231	0.033	**
Pringles	0.079	0.063		0.129	0.043	**
Ruffles	-0.033	0.065		-0.021	0.035	
Utz	0.033	0.031		0.077	0.047	
Wise	0.062	0.022	**	0.110	0.036	**
Other Brands	0.368	0.038	**	0.317	0.031	**
Salient Attribute						
Flat-Cut	0.248	0.041	**	0.202	0.032	**
Low-Fat	0.347	0.026	**	0.377	0.027	**
Flavor (Base: Original)						
BBQ	0.411	0.051	**	0.377	0.036	**
Cheese	0.314	0.052	**	0.229	0.029	**
Herb/Ranch	0.281	0.074	**	0.198	0.051	**
Salt/Vinegar	0.287	0.033	**	0.275	0.063	**
Sour Cream	0.237	0.045	**	0.123	0.031	**
Spicy	0.251	0.048	**	-0.057	0.031	*
Other Flavors	0.187	0.039	**	0.429	0.030	**
Package Size (Base: Small)						
Medium	-0.257	0.044	**	-0.270	0.060	**
Large	-0.654	0.079	**	-0.718	0.069	**
Marketing Strategy						
Product						
Product Line Length	-0.018	0.027				
Number of Distinct SKUs				0.163	0.031	**
Number of Duplicate SKUs				-0.121	0.032	**
Number of Competing SKUs	0.348	0.013	**	0.362	0.009	**
Price	0.196	0.020	**	0.215	0.025	**
Promotion						
Feature	-0.129	0.023	**	-0.080	0.031	**
Display	-0.193	0.025	**	-0.200	0.028	**
Distribution						
Local Breadth	-0.841	0.047	**	-0.900	0.062	**
National Coverage	-0.098	0.021	**	-0.106	0.031	**

Note:
1. = significant at the 0.1 level; ** = significant at the 0.05 level

Table 8: Estimation Results of New Product Trial Using Only SKUs Surviving More than One Year (Con.)

	Model without Product Line Structure			Model with Product Line Structure		
	Mean	**S.E.**	**Sig.[1]**	**Mean**	**S.E.**	**Sig.[1]**
Sales Performance						
Sales	0.069	0.008	**	0.069	0.008	**
Cumulative Sales	0.057	0.012	**	0.045	0.012	**
Product Launch Season						
(Base: 2002 Spring)						
2002 Summer	0.133	0.031	**	0.114	0.039	**
2002 Fall	0.049	0.025	*	0.059	0.050	
2002 Winter	-0.295	0.026	**	-0.289	0.026	**
2003 Spring	0.315	0.056	**	0.298	0.059	**
2003 Summer	0.113	0.052	**	-0.037	0.028	
2003 Fall	-0.113	0.040	**	-0.151	0.043	**
2003 Winter	0.278	0.027	**	0.021	0.037	
Baseline Effect						
(Base: Weeks 1-4)						
Weeks 5-8	0.022	0.011	**	-0.012	0.023	
Weeks 9-12	0.034	0.010	**	-0.002	0.014	
Weeks 13-16	-0.023	0.009	**	-0.054	0.013	**
Weeks 17-20	0.056	0.008	**	0.026	0.020	
Weeks 21-24	0.013	0.011		-0.039	0.020	**
Weeks 25-28	-0.050	0.014	**	-0.068	0.016	**
Weeks 29-32	-0.087	0.013	**	-0.129	0.028	**
Weeks 33-36	-0.068	0.019	**	-0.101	0.021	**
Weeks 37-40	0.035	0.012	**	0.030	0.025	
Weeks 41-44	-0.008	0.009		-0.050	0.036	
Weeks 45-48	0.039	0.017	**	0.030	0.031	
Weeks 49-52	-0.079	0.026	**	-0.107	0.034	**
Intercept	0.189	0.036	**	0.147	0.048	**
Information Criteria						
LPML[2]		-9,869.697			-9,949.868	
DIC[3]		18,892.842			18,743.651	

Note:

1. * = significant at the 0.1 level; ** = significant at the 0.05 level
2. We select the model that maximizes log marginal pseudo likelihood (LMPL).
3. We select the model that minimizes deviance information criterion (DIC).

Table 9: Estimation Results from the Two-threshold Models Using SKUs Surviving the First 12 Weeks

	Model without Product Line Structure						Model with Product Line Structure					
	New Product Trial (U_{ijm})			Early Product Withdrawal (L_{jm})			New Product Trial (U_{ijm})			Early Product Withdrawal (L_{jm})		
	Mean	S.E.	Sig.[1]	Mean	S.E.	Sig.[1]	Mean	S.E.	Sig.[1]	Mean	S.E.	Sig.[1]
Household Characteristics												
Demographic Variables												
Size	0.086	0.019	**				0.036	0.011	**			
Low Income	0.107	0.017	**				0.101	0.009	**			
Medium Income	0.046	0.024	*				-0.166	0.008	**			
Child	-0.165	0.029	**				0.133	0.018	**			
Married	0.028	0.009	**				0.018	0.018				
Behavioral Variables												
Usage Intensity	0.011	0.007					0.004	0.004				
Brand Usage Ratio	0.068	0.012	**				0.012	0.013				
Within-Trip Variety Seeking	0.008	0.022					0.026	0.023				
Across-Trip Variety Seeking	0.081	0.013	**				0.080	0.020	**			
Nonuser	0.051	0.011	**				0.106	0.009	**			
Social Contagion												
Trial Ratio	-0.216	0.023	**	-0.152	0.008	**	-0.124	0.012	**	0.079	0.015	**
Product Characteristics												
Brand (Base: Private Label)												
Cape Cod	0.150	0.023	**	0.006	0.018		0.113	0.023	**	-0.144	0.013	**
Lay's	0.027	0.014	*	0.128	0.009	**	0.014	0.012		-0.013	0.007	*
Lay's Sub-brand	0.233	0.014	**	0.109	0.009	**	0.211	0.013	**	-0.132	0.012	**
Pringles	0.080	0.012	**	-0.211	0.011	**	0.064	0.016	**	-0.270	0.011	**
Ruffles	-0.027	0.017		0.018	0.014		-0.078	0.021	**	-0.115	0.007	**
Utz	0.062	0.015	**	-0.022	0.009	**	0.002	0.017		-0.162	0.014	**
Wise	0.229	0.016	**	-0.231	0.014	**	0.112	0.016	**	-0.213	0.014	**
Other Brands	0.147	0.014	**	0.224	0.016	**	0.145	0.013	**	0.181	0.051	**
Salient Attribute												
Flat-Cut	0.172	0.013	**				0.134	0.015	**			
Low-Fat	0.420	0.017	**				0.410	0.016	**			
Flavor (Base: Original)												
BBQ	0.212	0.017	**				0.207	0.015	**			
Cheese	0.180	0.018	**				0.194	0.014	**			
Herb/Ranch	0.171	0.017	**				0.235	0.018	**			
Salt/Vinegar	0.204	0.019	**				0.242	0.020	**			
Sour Cream	0.083	0.020	**				0.099	0.013	**			
Spicy	0.185	0.013	**				0.195	0.012	**			
Other Flavors	0.278	0.012	**				0.322	0.013	**			
Package Size (Base: Small)												
Medium	-0.276	0.016	**				-0.302	0.012	**			
Large	-0.454	0.016	**				-0.442	0.025	**			
Marketing Strategy												
Product												
Product Line Length	-0.041	0.010	**	-0.017	0.010	*						
Number of Distinct SKUs							0.060	0.013	**	0.173	0.010	**
Number of Duplicate SKUs							-0.086	0.010	**	-0.124	0.011	**
Number of Competing SKUs	0.232	0.007	**	0.088	0.001	**	0.244	0.006	**	0.088	0.002	**
Price	0.121	0.010	**				0.128	0.013	**			
Promotion												
Feature	-0.125	0.014	**				-0.103	0.013	**			
Display	-0.163	0.015	**				-0.166	0.012	**			
Distribution												
Local Breadth	-0.585	0.016	**				-0.613	0.013	**			
National Coverage	0.011	0.008					0.000	0.010				

Note:
1. = significant at the 0.1 level; ** = significant at the 0.05 level

Table 9: Estimation Results from the Two-threshold Models Using SKUs Surviving the First 12 Weeks (Con.)

	Model without Product Line Structure						Model with Product Line Structure					
	New Product Trial (U_{ijm})			Early Product Withdrawal (L_{jm})			New Product Trial (U_{ijm})			Early Product Withdrawal (L_{jm})		
	Mean	**S.E.**	**Sig.**[1]	**Mean**	**S.E.**	**Sig.**[1]	**Mean**	**S.E.**	**Sig.**[1]	**Mean**	**S.E.**	**Sig.**[1]
Sales Performance												
Sales	0.055	0.008	**				0.054	0.006	**			
Cumulative Sales	0.045	0.009	**	0.395	0.014	**	0.040	0.009	**	0.305	0.009	**
Product Launch Season												
(Base: 2002 Spring)												
2002 Summer	0.158	0.016	**				0.089	0.013	**			
2002 Fall	0.101	0.013	**				0.084	0.013	**			
2002 Winter	-0.165	0.016	**				-0.164	0.013	**			
2003 Spring	0.177	0.018	**				0.169	0.014	**			
2003 Summer	-0.040	0.023	*				-0.022	0.015				
2003 Fall	-0.077	0.017	**				-0.066	0.015	**			
2003 Winter	0.068	0.012	**				0.043	0.013	**			
Baseline Effect												
(Base: Weeks 1-4 for Trial; Weeks 1-12 for Withdrawal)												
Weeks 5-8	-0.051	0.014	**				0.058	0.011	**			
Weeks 9-12	-0.041	0.018	**				-0.020	0.006	**			
Weeks 13-16	0.061	0.012	**	-0.230	0.014	**	0.030	0.017	*	-0.284	0.021	**
Weeks 17-20	-0.024	0.014	*	-0.260	0.011	**	0.031	0.012	**	-0.309	0.019	**
Weeks 21-24	0.022	0.006	**	-0.263	0.013	**	-0.036	0.010	**	-0.301	0.024	**
Weeks 25-28	-0.038	0.013	**	-0.271	0.015	**	-0.134	0.019	**	-0.318	0.012	**
Weeks 29-32	-0.024	0.023		-0.169	0.013	**	0.077	0.010	**	-0.205	0.023	**
Weeks 33-36	0.079	0.014	**	-0.239	0.026	**	-0.021	0.011	*	-0.271	0.012	**
Weeks 37-40	0.041	0.014	**	-0.164	0.024	**	0.168	0.007	**	-0.187	0.019	**
Weeks 41-44	0.033	0.021		-0.172	0.015	**	-0.070	0.010	**	-0.185	0.008	**
Weeks 45-48	-0.061	0.011	**	-0.279	0.010	**	-0.026	0.009	**	-0.303	0.020	**
Weeks 49-52	0.022	0.014		-0.304	0.012	**	0.080	0.019	**	-0.368	0.012	**
Intercept	-0.024	0.013	*	-0.015	0.009		0.081	0.013	**	-0.014	0.009	
Information Criteria												
LPML[2]	-278,981.096						-276,406.207					
DIC[3]	556,825.673						551,672.484					

Note:

1. * = significant at the 0.1 level; ** = significant at the 0.05 level
2. We select the model that maximizes log marginal pseudo likelihood (LMPL).
3. We select the model that minimizes deviance information criterion (DIC).

3.5 Chapter Conclusion

While new product failure rate is high and early product withdrawal is a common phenomenon in many industries, especially in the CPG industry, individual-level new product trial models typically do not account for product withdrawal. Therefore, the results from those models suffer from sample selection bias. We propose a model that can explore the drivers of both new product trial and early product withdrawal. The proposed TR models are rooted in the FHT model of a Weiner process with two absorbing thresholds. The Weiner process can be connected to the attractiveness of a product, the upper threshold represents the threshold of trial, and the lower threshold represents the threshold of withdrawal. The model also accommodates time-varying covariates and accounts for heterogeneity in consumers' responses to possible drivers of new product trial. We apply the model to explore the trials of new potato chip SKUs using household panel data. Many drivers of new product trial are identified, including household characteristics, product characteristics, marketing strategies, social contagion, and sale performance. Focusing on product line competition, we find that product line length has a positive effect on the probability of new product trial, and the number of competing SKUs has a negative effect on the probability. However, the effect of product line length also depends on the structure of the product line. Specifically, the number of distinct SKUs has a negative effect on the probability of new product trial, while the number of duplicate SKUs has a positive effect on the probability. We also explore drivers of new product withdrawal and find that product line length has a positive effect on the probability of early product withdrawal, and the number of competing SKUs has a negative effect on the probability. Moreover, the number of distinct SKUs has a negative effect on the probability of early product withdrawal, whereas the number of duplicate SKUs has a positive effect on the probability.

We apply our TR model only to the potato chip category; thus, the generalizability of our findings may be restricted to the related product categories. Future research can investigate other industries by using the proposed models to validate the generalizability of our findings. In addition, we cannot directly observe product withdrawal but can only infer the occurrence of the event based on sales records. Therefore, although our main interest is in new product trial, we encourage researchers whose main interest is in product withdrawal to validate the generalizability of our findings by using data containing product lifetime directly measured as the time between product introduction and product withdrawal. Moreover, our model captures only the main effect of each potential driver. Researchers interested in the interaction effects among potential drivers or the moderating effects can modify our model and further the understanding of the mechanism of new product trial or early product withdrawal. Lastly, we focus on the trials of new products. Future research may extend our model to accommodate repeat purchases, possibly by assuming the Wiener process in our model as an ordinary renewal process. The repeat purchase context may provide more insights on new product trial and early product withdrawal.

Chapter 4

Investigating Product Line Length Effects on Brand Preference in a Multiple Discreteness Modeling Framework

4.1 Introduction

Product portfolio expansion via line extensions is a pervasive marketing strategy. An IRI study suggested that 90% of new product introductions in consumer packaged goods (CPG) markets are line extensions (IRI 2010). Despite the ubiquity of this type of strategy, much remains to be learned about the effects of product line length on brand preference. For example, brands with longer product lines are in a better position to satisfy consumers who seek variety (Chong et al. 1998; Lancaster 1990a), a behavior often demonstrated through multiple discreteness, i.e., the purchasing of multiple items on a single shopping trip (Dubé 2004; Harlam and Lodish 1995; Kim et al. 2002; Simonson 1990). Yet, to the best of our knowledge, Harlam and Lodish (1995) is the only study examining product line length effects in the context of multiple-SKU purchase. They found that product line length has a negative effect on SKU choice, in contrast to previous studies conducted at the brand/firm level which found such an effect to be positive. However, Harlam and Lodish (1995) do not use a utility-maximizing framework which can allow for the possibility of satiation effects. Moreover, they do not account for SKU similarity within a product line, competition, and consumer variety seeking propensities, all of which can critically influence product line length effects on consumer preference.

In this paper we offer the first, to our knowledge, comprehensive investigation of product line length effects in a multiple discreteness modeling framework. Our analysis considers the role of product line structure, defined by Chong et al. (1998) in terms of distinct and duplicate SKUs, competition through product line length and interbrand variant overlap (Aribarg and Arora 2008), and consumer variety seeking propensities. We employ a hierarchical Bayesian multiple discrete-continuous extreme value (HBMDCEV) model of SKU choice and apply it to household panel data on purchases of potato chips and other salty snacks from the IRI Academic dataset (Bronnenberg et al. 2008).

We find that the number of a brand's distinct SKUs, i.e., SKUs representing unique combinations of salient product attribute levels to the brand, has no significant effect on its own brand preference but a significantly negative effect on its competitors' brand preferences. In contrast, the number of a brand's duplicate SKUs, i.e., the other SKUs with the same combination as any of the distinct SKUs previously introduced by the brand, has a significantly negative own effect and no significant cross effect. Overall, the net effect of the number of distinct (duplicate) SKUs is positive (negative). The negative net effect of duplicate SKUs is even more pronounced for households with high variety seeking propensities. In addition, we find a high satiation effect in the presence of multiple SKU purchases which provides validation for our utility-maximizing framework. Hence, our findings refine and extend those of Harlam and Lodish (1995): we are able to trace the negative product line length (net) effects on SKU choice to duplicate SKUs, whereas we find positive (net) effects for distinct SKUs. Furthermore, we find that the negative effects of duplicate SKUs are more pronounced for consumers with stronger variety seeking propensities.

We explore the implications of our findings on the brand share level by conducting a simulation, which finds that even the addition of a duplicate SKU can increase the focal brand's share. However, such a strategy could also lower the collective share of the top four brands, suggesting that adding duplicate SKUs might lead to choice overload. The simulation shows the richness and complexity of our findings and the associated product line strategies.

The rest of this paper is organized as follows. Section 4.2 discusses the development of the HBMDCEV model. Sections 4.3 and 4.4 demonstrate the empirical analysis and implications respectively. Section 4.5 concludes the paper by identifying avenues for future research.

4.2 Model Development

4.2.1 Utility Function Specification for Multiple-discrete SKU Choices

Considering that individual households may purchase multiple SKUs in the same category and many units of each SKU on a shopping trip, we specify an HBMDCEV model to investigate the effect of product line length on brand preference. Our model is based on the MDCEV model of Bhat (2005, 2008), which is a general form of the conditional or multinomial logit models; the former model collapses to the latter two in the case of single discreteness. We choose this model framework because it has a compact likelihood form, which does not require the GHK simulator used by the similar model of Kim et al. (2002, 2007). It also provides a natural setting to deal with varying numbers of choice options (i.e. SKUs) faced by consumers on different shopping trips and to incorporate the correlation among those SKUs. For more details about the MDCEV model, the interested reader may refer to Bhat (2005, 2008).

We assume that for time $t = 1, \ldots, T$, $\bar{K}$ SKUs of a product category (e.g., salty snacks) have been offered on the market. SKU k is marketed by brand b in a sub product category (e.g., potato chips) through the parent brand (e.g., Lay's) and possibly with a sub-brand (e.g., "Wow" is a sub brand used by Lay's); $b = 1, \ldots, B$. Suppose brand b is one of the B_1brands that are key competitors with one another (e.g., Lay's and Pringles), and there are also B_2 $(= B - B_1)$ other brands competing within the subcategory (e.g., private labels). We focus on the B_1brands that have marketed SKU k during the period; $k = 1, \ldots, K < \bar{K}$. For simplicity, we ignore the brand subscript b with respect to SKU k unless necessary. Assume K_{st} is a subset of the K SKUs marketed by the B_1brands in store s at time t; $s = 1, \ldots, S$, and the set K_{st} contains N_{st} SKUs. We further assume household i, $i = 1, \ldots, I$, exogenously decides to enter store s at time t to shop for the product category. We formulate a translated utility function (Bhat 2008; Bhat 2005) for household i over all SKUs in the set K_{st} and one outside good on a shopping trip in store s at time t as follows:

$$U(\boldsymbol{q_{ist}}) = \sum_{k \in K_{st} \cup O} \frac{\gamma_k}{\alpha_k} \psi_{ist,k} \left[\left(\frac{q_{ist,k}}{\gamma_k} + 1 \right)^{\alpha_k} - 1 \right], \tag{46}$$

where $U(\quad)$ is a quasi-concave, increasing, and continuously differentiable function with respect to the $(N_{st} + 1) \times 1$ purchase quantity vector, $\boldsymbol{q_{ist}}$, of which the elements are $q_{ist,k}$, the unit of SKU k purchased by household i in store s at time t, and $q_{ist,k} \geq 0 \; \forall k$; O is a set contains only the outside good that consists of all other SKUs in the product category; $\psi_{ist,k}$, γ_k, and α_k are parameters. The utility function is valid if $\psi_{ist,k} > 0$ and $\alpha_k \leq 1$, $\forall k$. Note that

$$\frac{\partial U(\boldsymbol{q_{ist}})}{\partial q_{ist,k}} = \psi_{ist,k} \left(\frac{q_{ist,k}}{\gamma_k} + 1 \right)^{\alpha_k - 1}. \tag{47}$$

$\psi_{ist,k}$ hence captures the baseline marginal utility of SKU k in store s at time t for household i, or the marginal utility when $q_{ist,k} = 0$. This parameter is our main focus, and we will discuss the baseline marginal utility in detail later.

γ_k is the translation parameter corresponding to SKU k, a parameter that determines the possibility of no purchase of SKU k. If $\gamma_k \neq 0$, it is allowed that a customer does not buy SKU k. α_k is the satiation parameter associated with SKU k, a parameter that reduces the marginal utility with increasing purchase of SKU k. If $\alpha_k = 1$ for all k, the utility function collapses to $\sum_{k \in K_{st} \cup O} \psi_{ist,k} q_{ist,k}$, a function form that assumes constant marginal utility and perfect substitutes, which has been used by many marketing researchers (Arora et al. 1998; Chiang 1991; Chintagunta 1993) If $\alpha_k \to 0$, the utility function collapses to $\sum_{k \in K_{st} \cup O} \gamma_k \psi_{ist,k} ln\left(\frac{q_{ist,k}}{\gamma_k} + 1\right)$, which is first used by Hanemann (1978). If $\alpha_\mathrm{k} \to -\infty$, the utility function indicates immediate and full satiation.

Since $q_{ist,k} = e_{ist,k}/p_{st,k}$, where $e_{ist,k}$ is the purchase amount of SKU k made by household i in store s at time t, and $p_{st,k}$ the price of per unit SKU k in store s at time t, the utility function in Equation (46) is equivalent to:

$$U(\boldsymbol{e_{ist}}) = \sum_{k \in K_{st} \cup O} \frac{\gamma_k}{\alpha_k} \psi_{ist,k} \left[\left(\frac{e_{ist,k}}{\gamma_k p_{st,k}} + 1 \right)^{\alpha_k} - 1 \right], \tag{48}$$

where $\boldsymbol{e_{ist}}$ is the purchase amount vector with elements $e_{ist,k}$. The household's choices are subject to the budget constraint:

$$\sum_{k \in K_{st} \cup O} e_{ist,k} = E_{ist}, \tag{49}$$

where E_{ist} is household i's budget for shopping for the product category in store s at time t.

4.2.2 Baseline Marginal Utility of an Inside SKU

We now focus on the specification of the baseline marginal utility $\psi_{ist,k}$ that can incorporate brand preference. For any one of the K_{st} inside SKUs, we assume a random baseline marginal utility and relate it to explanatory variables in the following form:

$$\psi_{ist,k} = exp\left(\boldsymbol{\beta}_{\boldsymbol{i}}^{\mathbf{T}}\boldsymbol{x}_{\boldsymbol{ist,k}} + \xi_{t,k} + \varepsilon_{ist,k}\right), \tag{50}$$

where $\boldsymbol{x}_{\boldsymbol{ist,k}}$ is a vector of variables associated with household i and SKU k in store s at time t, a vector that we will discuss in details later; $\boldsymbol{\beta}_{\boldsymbol{i}}$ is the household-level coefficient vector associated with $\boldsymbol{x}_{\boldsymbol{ist,k}}$; $\xi_{t,k}$ captures the random common shocks regarding SKU k over time that are observed by consumers but not by researchers (e.g., advertising), of which the variance-covariance matrix which will be discussed in Section 4.2.5 can allow the correlation among SKUs; and $\varepsilon_{ist,k}$ represents the unobserved idiosyncratic random term. An exponential function is used so that the baseline marginal utility takes a positive value. For the outside good, the baseline marginal utility contains only the idiosyncratic random term for identification.

Hereafter we discuss our specification of the first term in the exponential function of the right-hand side of Equation (50), which has the following form:

$$\boldsymbol{\beta}_{\boldsymbol{i}}^{\mathbf{T}}\boldsymbol{x}_{\boldsymbol{ist,k}} = \beta_{i0} + \boldsymbol{\beta}_{\boldsymbol{i1}}^{\mathbf{T}}\boldsymbol{x}_{\boldsymbol{k}} + \beta_{i2}FOD_{st,k} + \beta_{i3}RP_{it-1,k} + \beta_{ist,b}. \tag{51}$$

We include the household-level intercept, β_{i0}, because individual households may have different preferences for the inside goods compared with the outside good. This parameter is identifiable because each household made multiple purchases of the product category. Since consumers may be attracted by certain product attributes, we include a vector of dummy variables, $\boldsymbol{x}_{\boldsymbol{k}}$, indicating the salient product attribute levels of SKU k. Empirically, we study potato chips and consider the levels of four salient product attributes, including flavor, cut, fat content, and package size (Li

2014). Household i's preference for each product attribute level will thus be shown in the coefficient vector $\boldsymbol{\beta_{i1}}$. The utility of SKU k for household i may also be affected by SKU-level marketing variables for the SKU in store s at time t. Specifically, we focus on whether there is a feature ad and/or in-store display for SKU k in store s at time t by using a dummy variable $FOD_{st,k}$, of which the effect on household i will be reflected on β_{i2}. Note that product price is not included in the baseline marginal utility because it has been considered in the utility function in Equation (48). Some consumers may repurchase the same SKU(s) over time because of loyalty or inertia. To deal with this repurchase behavior, we use a dummy variable, $RP_{it-1,k}$, that equals one when household i bought the same SKU k on the pervious shopping trip. β_{i3} thus captures the loyalty or inertia since $\beta_{i3} > 0$ suggests that the household tends to select the same SKU over time. β_{i3} can also be interpreted as an indicator of variety seeking in the sense of SKU switching over time because $\beta_{i3} < 0$ suggests that the household prefers something different than the previously chosen SKU (Osborne 2011). Finally, the baseline marginal utility of SKU k may be influenced by the brand-level variables of brand b and of its competing brands in store s at time t. The overall influence of the brand-level variables, $\beta_{ist,b}$, is defined as household i's brand preference for brand b in store s at time t.

4.2.3 Brand Preference Specification and Operationalization

We are interested in how product line length influences brand preference in a competitive environment considering the product line structure as well as the interbrand variant overlap (Aribarg and Arora 2008). Therefore, brand preference is formulated as follows:

$$\beta_{ist,b} = \overbrace{\beta_{i4,b} + \beta_{i5,b} SB_k}^{Brand\ Fixed\ Effect} + \overbrace{\beta_{i6} NDIS_{st,b} + \beta_{i7} NDUP_{st,b}}^{Own\ Effect\ of\ Product\ Line\ Length}$$

$$+ \overbrace{\beta_{i8} \sum_{\bar{b} \neq b}^{B1} NDIS_{st,\bar{b}} + \beta_{i9} \sum_{\bar{b} \neq b}^{B1} NDUP_{st,\bar{b}} + \beta_{i10} TOCPL_{st,b}}^{Cross\ Effect\ of\ Product\ Line\ Length} \tag{52}$$

$$+ \overbrace{\sum_{\bar{b} \neq b}^{B1} \beta_{b,\bar{b}} VO_{st,b,\bar{b}}}^{Effect\ of\ Variant\ Overlap},$$

where $\beta_{i4,b}$ is the brand-level intercept that captures the fixed effect of the parent brand b for household i, and the intercept for one brand is set to be zero for identification; SB_k is a dummy variable that equals one when SKU k is marketed through a sub-brand (e.g., Lay's Wow), and $\beta_{i5,b}$ is the incremental effect of the use of sub-brands by brand b for household i, $b = 1, \dots, B_1$; $NDIS_{st,b}$ and $NDUP_{st,b}$ are the numbers of distinct and duplicate SKUs of brand b in store s at time t respectively, and β_{i6} as well as β_{i7} indicate the corresponding own effects on the brand preference; $NDIS_{st,\bar{b}}$ and $NDUP_{st,\bar{b}}$ are the numbers of distinct and duplicate SKUs of the key competing brand $\bar{b}$ in store s at time t respectively; $TOCPL_{st,b}$ is the total number of SKUs offered by all the other B_2 competitors of brand b in the subcategory in store s at time t, and β_{i8}, β_{i9}, and β_{i10} capture the corresponding cross effects on the brand preference; $VO_{st,b,\bar{b}}$ is the interbrand variant overlap between brands b and $\bar{b}$ in store s at time t, and $\beta_{b,\bar{b}}$ accounts for the effect of the variant overlap with brand $\bar{b}$ for brand b.

Interbrand variant overlap measures the degree of overlap between two competing brands' product lines. We operationalize the variant overlap by extending the Aribarg and Arora (2008) measure to include duplicate SKUs. The attribute-based variant overlap between Brands A and B in store s at time t, $VO_{A,B}$, has the form (time and store subscripts are dropped for simplicity):

$$VO_{A,B} = \sum_{f=1}^{F} \phi_f \left[\frac{\sum_{l=1}^{L_f} (n_{fl,A} + n_{fl,B}) I_{fl}(A,B)}{(n_A + n_B)} \right], \tag{53}$$

where ϕ_f is the weight associated with the salient product attribute f (e.g., cut and flavor of potato chips), $f = 1, \dots, F$; $n_{fl,A}$ and $n_{fl,B}$ are the numbers of SKUs that have level l of attribute f for Brands A and B respectively, $l = 1, \dots, L_f$; n_A and n_B are the product line lengths of Brands A and B respectively; and $I_{fl}(A,B)$ is an indicator that takes a value one if both Brands A and B offer level l of attribute f and zero otherwise. According to Aribarg and Arora (2008), the weight ϕ_f can be determined based on the variance of variant overlaps across all brand pairs. Let $\sigma^f = \sum \left(VO^f_{A,B} - \overline{VO}_f \right)^2 / P$ be the variance, where $VO^f_{A,B}$ is the variant overlap based on attribute f (i.e., the bracket on the right-hand side of Equation (53)), $\overline{VO}_f$ is the mean of variant overlap based on attribute f across all P brand pairs. Thus, $\phi_f = \sigma^f / \sum_f \sigma^f$. Table 10 exhibits the calculation of the variant overlap and provides two cases regarding product line extension by Brand B. Case A shows the variant overlaps after adding one duplicate SKU, whereas Case B shows the variant overlaps after adding one distinct SKU. Both cases can increase or decrease the interbrand variant overlap. Note that even though the value of $VO_{st,b,\bar{b}}$ is the same for both brands b and $\bar{b}$, the effects of the variant overlap for the two brands, $\beta_{b,\bar{b}}$ and $\beta_{\bar{b},b}$, may differ. Thus, when any of the B_1 brands adjusts its product line length, the impacts on the other key competing brands can vary because of the effects of variant overlaps. Considering that the effects of variant overlaps may not be identifiable at the household level[7], we follow Aribarg and Arora (2008) and estimate the coefficients of variant overlaps at the aggregate level.

[7] $VO_{st,b,\bar{b}}$ is constant over inside SKUs for a household on a shopping trip, and there may be no variation of this variable for a household over shopping trips.

Table 10: Example of Number of Distinct/Duplicate SKUs and Variant Overlap Calculation

Brand	Product Line Length	SKU Configuration based on Cut and Flavor	Product Line Length Considering Product Line Structure: Number of Distinct SKUs	Number of Duplicate SKUs	Cut Overlap (CO)	Flavor Overlap (FO)	Attribute-based Variant Overlap (equal weights)
A	7 SKUs	Flat Regular (x2)[1] Flat BBQ Wavy Cheese Wavy BBQ (x2)[1] Wavy Spicy	5 SKUs	2 SKUs	6/10 = 0.60	7/10 = 0.70	0.5×CO+0.5×FO = 0.65
B	3 SKUs	Flat Regular Flat BBQ Flat Sour Cream	3 SKUs	0 SKU			
Case A-(1): If Brand B adds a duplicate SKU (Flat Sour Cream)							
B	4 SKUs		3 SKUs	1 SKU	7/11 = 0.64	7/11 =0.64	0.5×CO+0.5×FO = 0.64
Case A-(2): If Brand B adds a duplicate SKU (Flat Regular)							
B	4 SKUs		3 SKUs	1 SKU	7/11 = 0.64	8/11 =0.73	0.5×CO+0.5×FO = 0.68
Case B-(1): If Brand B adds one distinct SKU (Flat Vinegar)							
B	4 SKUs		4 SKUs	0 SKU	7/11 = 0.64	7/11 =0.64	0.5×CO+0.5×FO = 0.64
Case B-(2): If Brand B adds one distinct SKU (Wavy BBQ)							
B	4 SKUs		4 SKUs	0 SKU	11/11 =1.00	8/11 =0.73	0.5×CO+0.5×FO = 0.86

Note:
1. There are two SKUs with the same combination of cut and flavor.

4.2.4 Moderating Effects of Variety Seeking Propensity

One simple measure of a consumers' variety seeking propensity on a choice occasion is the number of different options chosen by the consumer on that occasion (e.g., Fishbach et al. 2011; Maimaran and Wheeler 2008; Simonson 1990). Similarly, we operationalize variety seeking as the average number of different SKUs in a product category household i bought per trip when shopping for the product category in the past, which we call "within-trip variety seeking," $WTVS_i$. By definition, $WTVS_i \geq 1$. The higher the propensity, the more different SKUs per shopping trip the household tends to buy.

To assess the moderating effects of the variety seeking propensity, we model the household-level coefficient vector, $\widetilde{\boldsymbol{\beta}}_{\boldsymbol{i}} = [\beta_{i0} \quad \dots \quad \beta_{i10}]^{\mathrm{T}}$, as a function of household i's propensities of variety seeking in purchase with a hierarchical structure:

$$\widetilde{\boldsymbol{\beta}}_{\boldsymbol{i}} \sim MND\left(\boldsymbol{\Gamma z_i}, \boldsymbol{\Sigma_\beta}\right), \tag{54}$$

$$\boldsymbol{\Gamma z_i} = \boldsymbol{\gamma_0} + \boldsymbol{\gamma_1} WTVS_i, \tag{55}$$

where $MND\left(\boldsymbol{\Gamma z_i}, \boldsymbol{\Sigma_\beta}\right)$ is a multivariate normal distribution with mean vector $\boldsymbol{\Gamma z_i}$ and variance-covariance matrix $\boldsymbol{\Sigma_\beta}$; $WTVS_i$ is the within-trip variety seeking propensity of household i; $\boldsymbol{z_i} = [1 \quad WTVS_i]^{\mathrm{T}}$; $\boldsymbol{\Gamma} = [\boldsymbol{\gamma_0} \quad \boldsymbol{\gamma_1}]$ is the coefficient matrix corresponding to $\boldsymbol{z_i}$. If $WTVS_i$ is mean-centered, $\boldsymbol{\gamma_0}$ can be interpreted as the main effects for an average household, and $\boldsymbol{\gamma_1}$ captures the moderating effects of $WTVS_i$.

4.2.5 Model Estimation

In this section, we show the likelihood function can be constructed based on a compact expression of the probability of a household's SKU choice on one shopping trip. The proposed model thus can be estimated in a Bayesian fashion. The utility function in Equation (48) subject to the budget constraint in Equation (49) can be maximized by forming a Lagrangian function:

$$\mathcal{L} = \sum_{k \in K_{st} \cup O} \frac{\gamma_k}{\alpha_k} \psi_{ist,k} \left[\left(\frac{e_{ist,k}}{\gamma_k p_{st,k}} + 1\right)^{\alpha_k} - 1\right] - \lambda \left(\sum_{k \in K_{st} \cup O} e_{ist,k} - E_{ist}\right), \tag{56}$$

where λ is the Largrangian multiplier. Note that in general γ_k and α_k are empirically unidentifiable because γ_k can also capture the satiation effect. Following Bhat (2005) and Kim et al. (2002), we assume that $\gamma_k = 1$. We further replace $\psi_{ist,k}$ with the function in Equation (50) and apply the Kuhn-Tucker (KT) conditions. The logarithm forms of the KT first-order conditions thus are given by:

$$\begin{aligned}\boldsymbol{\beta}_{\boldsymbol{i}}^{\mathbf{T}}\boldsymbol{x}_{\boldsymbol{ist,k}} + \xi_{t,k} + \varepsilon_{ist,k} - ln(p_{st,k}) + (\alpha_k - 1)ln\left(\frac{e_{ist,k}^{*}}{p_{st,k}} + 1\right) = ln(\lambda), \ \ if e_{ist,k}^{*} > 0,\\ \boldsymbol{\beta}_{\boldsymbol{i}}^{\mathbf{T}}\boldsymbol{x}_{\boldsymbol{ist,k}} + \xi_{t,k} + \varepsilon_{ist,k} - ln(p_{st,k}) + (\alpha_k - 1)ln\left(\frac{e_{ist,k}^{*}}{p_{st,k}} + 1\right) < ln(\lambda), \ \ if e_{ist,k}^{*} = 0,\end{aligned} \tag{57}$$

where $k \in K_{st} \cup O$ and $e_{ist,k}^{*}$ is the optimal expenditure allocate to SKU k by household i in store s at time t. We assume that $E_{ist} > 0$, so household i has to buy at least one SKU, possibly the outside good, in store s at time t. Without loss of generalizability, we suppose SKU 1 is purchased. Based on the KT conditions, $ln(\lambda)$ can be represented as follows:

$$ln(\lambda) = \boldsymbol{\beta}_{\boldsymbol{i}}^{\mathbf{T}}\boldsymbol{x}_{\boldsymbol{ist,1}} + \xi_{t,1} + \varepsilon_{ist,1} - ln(p_{st,1}) + (\alpha_1 - 1)ln\left(\frac{e_{ist,1}^{*}}{p_{st,1}} + 1\right), \tag{58}$$

And the KT conditions can be written as:

$$\begin{aligned}V_{ist,k} + \varepsilon_{ist,k} = V_{ist,1} + \varepsilon_{ist,1}, \ \ if e_{ist,k}^{*} > 0,\\ V_{ist,k} + \varepsilon_{ist,k} < V_{ist,1} + \varepsilon_{ist,1}, \ \ if e_{ist,k}^{*} = 0,\end{aligned} \tag{59}$$

where $k \in K_{st} \cup O$ and $k \neq 1$, $V_{ist,k} = \boldsymbol{\beta}_{\boldsymbol{i}}^{\mathbf{T}}\boldsymbol{x}_{\boldsymbol{ist,k}} + \xi_{t,k} - ln(p_{st,k}) + (\alpha_k - 1)ln\left(\frac{e_{ist,k}^{*}}{p_{st,k}} + 1\right)$ for $k \in K_{st}$ and $k \neq 1$, and $V_{ist,k} = (\alpha_k - 1)ln(e_{ist,k}^{*} + 1)$ for $k \in O$. Note that the outside good has a unit price of one. We do not assume the outside good is always purchased, so $V_{ist,k}$ for the outside good is not set to be $(\alpha_1 - 1)ln(e_{ist,k}^{*})$.

Following Bhat (2008), we assume $\varepsilon_{ist,k}$ to be independent of $\boldsymbol{x}_{\boldsymbol{ist,k}}$ and to be independently and identically standard Gumbel distributed. The first assumption is reasonable since endogeneity in our model may be less of a concern. In line with Yang et al. (2003), we incorporate the common random shock $\xi_{t,k}$ and estimate its variance-covariance matrix which allows the correlations among SKUs, hence alleviating the concern of endogeneity. Regarding the second assumption, although we can observe the price variance among SKUs so that the scale parameter σ of the

Gumbel distribution is identifiable, we set $\sigma = 1$ since we have already included the unobserved random component $\xi_{t,k}$.

Based on the aforementioned assumptions, the conditional probability that household i allocates its budget to at least two SKUs in store s at time t has a compact form (Bhat 2008):

$$P\left(\boldsymbol{e}_{\boldsymbol{ist}}^{*} | \boldsymbol{\beta}_{\boldsymbol{i}}, \{\alpha_k; k \in K_{st} \cup O\}, \{\xi_{t,k}; k \in K_{st}\}\right) = \left(\prod_{j \in M_{ist}} \frac{1-\alpha_j}{e_{ist,j}^{*} + p_{st,j}}\right)\left(\sum_{j \in M_{ist}} \frac{e_{ist,j}^{*} + p_{st,j}}{1-\alpha_j}\right) \frac{\prod_{j \in M_{ist}} exp(V_{ist,j})}{\left(\sum_{k \in K_{st} \cup O} exp(V_{ist,k})\right)^{R_{ist}}} (R_{ist} - 1)!, \tag{60}$$

where $\boldsymbol{e}_{\boldsymbol{ist}}^{*}$ is the vector of $e_{ist,j}^{*}$, M_{ist} is the set of R_{ist} SKUs with nonzero purchase amount chosen by household i in store s at time t, R_{ist} is an integer larger or equal to two, and the product of the first terms of the right-hand side is the Jacobian component. When only one SKU is chosen (i.e., $R_{ist} = 1$), there is no satiation effect (i.e., $\alpha_k = 1, \forall k$), and the Jacobian term drops out. Equation (60) hence collapses to that from a standard conditional or multinomial logit model: $\frac{exp(V_{ist,p})}{\sum_{k \in K_{st} \cup O} exp(V_{ist,k})}$, if SKU p is chosen. Let $c_{ist,j} = \frac{1-\alpha_j}{e_{ist,j}{}^{*} + p_{ist,j}}$. Based on Equation (60), the log-likelihood function can be represented as follows:

$$LL\left(\{\boldsymbol{\beta}_{\boldsymbol{i}}, i = 1, \dots, I\}, \{\alpha_k; k \in K_{st} \cup O\}, \{\xi_{t,k}; t = 1, \dots, T, k \in K_{st}\} \middle| Data\right) = \sum_{i} \left\{ \sum_{\substack{(s,t) \in ST_i \\ R_{ist} > 1}} ln\left\{\left(\prod_{j \in M_{ist}} c_{ist,j}\right)\left(\sum_{j \in M_{ist}} \frac{1}{c_{ist,j}}\right) \frac{\prod_{j \in M_{ist}} exp(V_{ist,j})}{\left(\sum_{k \in K_{st} \cup O} exp(V_{ist,k})\right)^{R_{ist}}} (R_{ist} - 1)!\right\} + \sum_{\substack{(s,t) \in ST_i \\ R_{ist} = 1, e_{ist,p}{}^{*} > 0}} ln\left\{\frac{exp(V_{ist,p})}{\sum_{k \in K_{st} \cup O} exp(V_{ist,k})}\right\}\right\}. \tag{61}$$

We adopt a hierarchical structure and estimate the model through a hybrid MCMC approach involving Gibbs sampling and Metropolis-Hastings algorithm. Specifically, α_k is usually restricted to take a value in the interval $[0,1]$ in order to provide stability in estimation (Bhat 2008). We thus reformulate $\alpha_k = 1/[1 + \exp(\delta_k)]$ and assume that

$$\boldsymbol{\delta} = [\delta_1 \quad \dots \quad \delta_K]^{\mathrm{T}} \sim MND(\boldsymbol{\delta_0}, \boldsymbol{\Sigma_\delta}), \tag{62}$$

where $\boldsymbol{\delta_0}$ and $\boldsymbol{\Sigma_\delta}$ are the prior mean vector and variance-covariance matrix of the multivariate normal distribution. The identification of α_k requires that SKU k is chosen in the case of multiple discreteness. Empirically, some unpopular SKUs might not be chosen by any consumer, and some SKUs might be chosen only in the case of single discreteness. To overcome this data limitation that we encounter in the empirical analysis, we follow Kim et al. (2002) to estimate one satiation parameter for the outside good and one for all inside SKUs. Although in this setting all inside SKUs share the same satiation parameter, the rate of satiation, $\partial^2 U(\boldsymbol{q_{ist}})/\partial {q_{ist,k}}^2$, may differ among inside SKUs because it depends not only on the satiation parameters but also on the baseline marginal utility of each SKU (Kim et al. 2002).

In addition, let K_t be a subset of the K SKUs in the sub product category, and K_t contains N_t SKUs on the market at time t; $K_{st} \subseteq K_t$. We follow Yang et al. (2003) and assume that the unobserved common shock vector has the form:

$$\boldsymbol{\xi_t} \sim MND(\mathbf{0}, \boldsymbol{\Sigma_t}), \tag{63}$$

Where $\mathbf{0}$ is a $N_t \times 1$ zero vector, $\boldsymbol{\Sigma_t}$ is the prior variance-covariance matrix, $\xi_{t,k} \in \boldsymbol{\xi_t}$ if and only if $k \in K_t$, and $t = 1, \dots, T$. $\boldsymbol{\Sigma_t}$ allows the correlations among $\xi_{t,k}$ and thus among SKUs. We further define a vector $\boldsymbol{\phi}$ of which the elements are the coefficients of variant overlap, $\beta_{b,\bar{b}}$, and assume

$$\boldsymbol{\phi} \sim MND(\boldsymbol{\phi_0}, \boldsymbol{\Sigma_\phi}), \tag{64}$$

where $\boldsymbol{\phi_0}$ and $\boldsymbol{\Sigma_\phi}$ are the prior mean vector and variance-covariance matrix. We report the prior and posterior distributions of parameters and the sampling procedure in Appendix C.

4.3 Empirical Analysis

4.3.1 Data

We use household panel data on salty snacks purchases and store-level data from the IRI Academic dataset (Bronnenberg et al. 2008). Our choice of the potato chip category is because consumers often purchase multiple SKUs for snacks such as potato chips and because most potato chip brands horizontally differentiate their products. The estimation data contain a random sample of 182 households in Pittsfield, Massachusetts. We focus on those panelists' purchases of potato chip SKUs of the top four brands, including Lay's, Pringles, Ruffles, and Wise, in this specific market in 2002. Households that bought SKU(s) of the top four brands at most three times in 2002 were eliminated from the data before drawing the 182 panelists. Lay's is the market leader in the potato chip category in 2002, with 74.22% market share in Pittsfield in terms of sales revenue. The corresponding shares of the other two national brands, Pringles and Ruffles, are 2.91% and 1.37%. Wise, a regional brand for eastern seaboard states, has 6.66% share. The composite outside good consists of the other salty snack SKUs, including potato chip SKUs offered by other brands. We assume that each household made at most one trip for salty snacks in a store in a week, so all SKUs bought by a household in the same store in the same week are regarded as the SKUs selected by the household on the single trip. On average, a household is faced with a choice among 81.94 SKUs of potato chips (with a range from 23 to 144 SKUs), of which 60.71 SKUs are marketed by the top four brands (with a range from 23 to

82 SKUs) on a given shopping trip. The 182 households made 6,391 SKU purchases (see Table 11), including 3,399 purchases for the outside good, on 4,692 shopping trips (see Table 12). 26.02% of shopping trips involve multiple discreteness.

Table 11: Salty Snack Purchases Made by the Panel Households

	Number of SKU Purchases[1]	%	Purchase Amount	%
Inside Goods				
Lay's				
Parent Brand	1,294	20.25%	2,791.41	15.26%
Sub-brands	588	9.20%	1,626.59	8.89%
Pringles				
Parent Brand	430	6.73%	765.53	4.18%
Sub-brands	86	1.35%	192.46	1.05%
Ruffles				
Parent Brand	92	1.44%	328.71	1.80%
Sub-brands	79	1.24%	211.33	1.16%
Wise				
Parent Brand	374	5.85%	592.07	3.24%
Sub-brands	49	0.77%	117.36	0.64%
Outside Good[2]	3,399	53.18%	11,669.83	63.79%
Total	6,391	100.00%	18,295.29	100.00%

Note:

1. A purchase of multiple units of the same SKU in one shopping trip is counted as one SKU purchase.
2. The outside good is a composite SKU including the other salty snack SKUs.

Table 12: Shopping Trips Made By the Panel Households

Number of SKUs Bought per Trip (NSBT)	Number of Trips Involving Purchases of			Total Trips (TT)	% of Total Trips	Number of SKU Purchase (NSBT×TT)
	Only the Outside Good[1]	Only the Inside Goods	Both Goods			
Single Discreteness						
1	2,576	895	0	3,471	73.98%	3,471
Multiple Discreteness						
2	0	325	535	860	18.33%	1,720
3	0	52	221	273	5.82%	819
4	0	17	49	66	1.41%	264
5	0	4	14	18	0.38%	90
6	0	0	1	1	0.02%	6
7	0	0	3	3	0.06%	21
Total	2,576	1,293	823	4,692	100.00%	6,391

Note:

1. The outside good is a composite SKU and thus is considered only one SKU.

4.3.2 Variables

The descriptive statistics of variables are listed in Table 13 to Table 15. Following Li (2014), we consider four salient product attributes provided in the IRI dataset: cut, fat content, package size, and flavor. There are two levels of cut: flat or not; two levels of fat content: low-fat/fat-free or regular fat; three levels of package size: small (i.e. weight ≤ 4.8oz), medium (i.e. weight is between 4.8oz and 8oz), or large (i.e., weight > 8oz); and eight levels of flavor[8]: regular, BBQ, cheese, herb and/or ranch, salt and/or vinegar, sour cream, spicy, or others. Overall, there are 96 unique combinations of the attribute levels.

The weekly feature, display, and price information for each SKU in each store over weeks were also available from the IRI dataset. The values of $FOD_{st,k}$ and $p_{st,k}$ are missing if none purchases SKU k in store s in week t. We replace the missing data with the moving averages of the values over the previous three weeks in the store. If the moving average is not available, we replace the missing data with the mean value over the whole observation period. Following Ataman et al. (2008), we replace $FOD_{st,k}$ with a value zero when the price discount for SKU k is larger than 5% in order to purify the effect of feature and/or display. As to the variety seeking propensities, we calculate $WTVS_i$ by using each household's purchases of all salty snacks in 2001 (i.e., the previous year); thus, it is an exogenous variable. We mean center $WTVS_i$ so that the $\boldsymbol{\gamma_0}$ captures the main effects for an average household. Table 15 reports the variant overlaps between the four brands for all shopping trips (see panel a), those for trips in stores where both brands were available (see panel b), and the weights for the four salient product attributes (see

[8] We first clustered flavors of all potato chips on the market into different groups. For example, "original" and "classic" are clustered in the same group, "regular". If an SKU combines different flavors, we considered only the first flavor mentioned in the IRI dataset in clustering. Finally we identified seven flavor groups that are commonly marketed by brands and regarded all the other flavors as a group.

Table 13: Description of Input Data for the MDCEV Model

Variables (N = 336,287)[1]	**Mean**	**S.D.**	**Minimum**	**Maximum**
Product Attribute				
Flat-cut	0.713	0.452	0.000	1.000
Low-fat	0.200	0.400	0.000	1.000
Package Size (base: Small)				
Medium	0.525	0.499	0.000	1.000
Large	0.395	0.489	0.000	1.000
Flavor (base: Regular)				
BBQ	0.142	0.350	0.000	1.000
Cheese	0.093	0.290	0.000	1.000
Herb/Ranch	0.079	0.270	0.000	1.000
Salt/Vinegar	0.067	0.250	0.000	1.000
Sour Cream	0.136	0.343	0.000	1.000
Spicy	0.029	0.167	0.000	1.000
Other Flavors	0.029	0.167	0.000	1.000
Feature or Display	0.070	0.236	0.000	1.000
Recent Purchase	0.009	0.097	0.000	1.000
Brand (base: Lay's)				
Pringles	0.215	0.411	0.000	1.000
Ruffles	0.150	0.357	0.000	1.000
Wise	0.209	0.407	0.000	1.000
Sub-brand				
Sub-brands of Lay's	0.225	0.417	0.000	1.000
Sub-brands of Pringles	0.048	0.214	0.000	1.000
Sub-brands of Ruffles	0.086	0.280	0.000	1.000
Sub-brands of Wise	0.081	0.273	0.000	1.000
Price Paid per Unit ($p_{st,k}$)[2]	2.032	0.849	0.170	4.290
Consumer Characteristics (N = 182)[3]				
Within-Trip Variety Seeking Propensity[4]	1.680	0.466	1.000	3.364

Note:
1. N = number of SKU observations.
2. The sale price of outside SKU is set to be one.
3. N = number of households.
4. In our empirical analysis, we mean center the variable so that the intercept vector, $\boldsymbol{r_0}$, can capture the main effect for an average household.

Table 14: Marketing Variables of Potato Chip Brands

Variables (N = 4,692)[1]	Mean	S.D.	Minimum	Maximum
Brand: Lay's				
Average Price Paid per Unit over SKUs	2.033	0.329	0.763	2.481
Average Price Paid per 16 Ounces over SKUs	4.432	0.287	3.111	5.728
Average Feature or Display over SKUs	0.103	0.087	0.000	0.500
Product Line Length[2]	29.549	4.842	6.000	37.000
Number of Distinct SKUs ($NDIS$)[2]	21.311	2.715	6.000	24.000
Number of Duplicate SKUs ($NDUP$)[2]	8.239	2.942	0.000	14.000
Brand: Pringles				
Average Price Paid per Unit over SKUs	1.778	0.248	0.898	2.067
Average Price Paid per 16 Ounces over SKUs	4.489	0.493	3.328	5.241
Average Feature or Display over SKUs	0.025	0.068	0.000	0.500
Product Line Length	15.380	2.548	11.000	24.000
Number of Distinct SKUs	11.784	2.264	8.000	18.000
Number of Duplicate SKUs	3.596	1.262	1.000	8.000
Brand: Ruffles (N = 4621)[3]				
Average Price Paid per Unit over SKUs	2.486	0.264	0.990	2.800
Average Price Paid per 16 Ounces over SKUs	5.187	0.239	4.240	7.968
Average Feature or Display over SKUs	0.042	0.064	0.000	0.312
Product Line Length	10.926	2.899	1.000	15.000
Number of Distinct SKUs	7.913	1.921	1.000	11.000
Number of Duplicate SKUs	3.013	1.257	0.000	5.000
Brand: Wise (N = 4611)[4]				
Average Price Paid per Unit over SKUs	1.906	0.246	0.908	2.242
Average Price Paid per 16 Ounces over SKUs	4.028	0.384	3.040	4.693
Average Feature or Display over SKUs	0.073	0.141	0.000	0.763
Product Line Length	15.246	2.053	10.000	21.000
Number of Distinct SKUs	10.658	1.380	7.000	18.000
Number of Duplicate SKUs	4.588	1.471	2.000	7.000
Number of All the Other SKUs ($TOCPL$)[5]	44.238	14.135	0.000	64.000

Note:

1. N = number of shopping trips.
2. In our empirical analysis, we take 10 SKUs as a unit.
3. Two of the 14 stores did not carry SKUs of Ruffles in 2002.
4. Three of the 14 stores did not carry SKUs of Wise in 2002.
5. In our empirical analysis, we take 20 SKUs as a unit.

Table 15: Interbrand Variant Overlap of Potato Chip Brands

(a) Attribute-based Overlap: All Shopping Trips (N = 4,692)[1]

		Mean (S.D.) of Overlap[2]			
		Lay's	Pringles	Ruffles	Wise
[Min, Max] of Overlap[4]	Lay's		0.835 (0.030)	0.527 (0.089)	0.962 (0.128)
	Pringles	[0.768, 0.906]		0.325 (0.058)	0.845 (0.115)
	Ruffles	[0.000, 0.656]	[0.000, 0.392]		0.671 (0.129)
	Wise	[0.000, 0.991]	[0.000, 0.939]	[0.000, 0.779]	

(b) Attribute-based Overlap: Shopping Trips in Stores That Sell SKUs of Both Brands

		Mean (S.D.) of Overlap[2]			
		Lay's	Pringles	Ruffles	Wise
[Min, Max] of Overlap[3]	Lay's		0.835 (0.030)	0.535 (0.061)[4]	0.978 (0.008)[5]
	Pringles	[0.768, 0.906]		0.330 (0.042)[4]	0.859 (0.025)[5]
	Ruffles	[0.217, 0.656]	[0.058, 0.392]		0.691 (0.060)[6]
	Wise	[0.935, 0.991]	[0.800, 0.939]	[0.253, 0.779]	

(c) Weight of Attribute-based Overlap

	Salient Product Attributes			
	Cut	Flavor	Package Size	Fat Content
Weight	0.575	0.289	0.089	0.046

Note:
1. N = number of shopping trips.
2. Mean (S.D.) = mean (standard deviation) of interbrand variant overlap.
3. [Min, Max] = [minimum, maximum] of interbrand variant overlap.
4. N = 4,621 shopping trips.
5. N = 4,611 shopping trips.
6. N = 4,558 shopping trips.

panel c). Note that some of the 14 stores in our study did not carry all the four brands; we make sure every panelist shopped in at least one of the stores carrying all four brands. We can only infer the retail assortment from the IRI dataset. Our inference is based on the sales of each SKU in each store. We assume that an SKU entered a store in the week in which the SKU was sold in the store for the first time since the beginning of 2001. We determine that an SKU exited the store if there was no sales record of the SKU in 2005, and the last week with sales records is the last week that the SKU was available. Hence, we can infer product line length and interbrand variant overlap based on those SKUs that are deemed available in the store in 2002. For simplicity, we assume that there was no stock-out event and that consumers were exposed to all available inside SKUs in the store.

4.3.3 Findings and Discussion

Table 16 shows the estimation results of the aggregate-level parameter matrix concerning the baseline marginal utility, $\mathbf{\Gamma}$, from the proposed HBMDCEV model. The first column, $\hat{\boldsymbol{\gamma}}_{\mathbf{0}}$, can be interpreted as $\hat{\boldsymbol{\beta}}$ or the main effect for an average household. The second column, $\hat{\boldsymbol{\gamma}}_{\mathbf{1}}$, captures the moderating effect of the within-trip variety seeking propensity. The main effect of within-trip variety seeking propensity (i.e., the moderating effect of $WTVS_i$ on the household-level intercept) is significantly positive, suggesting that the utility of the top four brand's potato chips is higher for households with higher $WTVS_i$. As to the salient product attributes of potato chips, in general, the utility of a flat-cut potato chip SKU is significantly lower than that of a non-flat-cut SKU, especially for households with high within-trip variety seeking propensities. Moreover, the utility of a low-fat or fat-free potato chip SKU typically is lower than that of an SKU with regular fat. Compared with the utility of a small-size potato chip SKU, that of a medium-size or large-size SKU is higher. Concerning the flavor of potato chips, normally the utility of a regular-flavored SKU is the highest. The utility of an SKU with any other flavor, however, may increase for households that tend to seek variety on one shopping trip.

Feature and display increase an SKU utility regardless of households' variety seeking propensities. In addition, consistent with Harlam and Lodish (1995), households tend to repurchase the SKU(s) bought on the previous trip. However, this effect is moderated by the variety seeking propensity which tends to dampen the recently purchased SKU effect, suggesting that households with higher variety within-trip variety seeking propensities are also more likely to engage in SKU switching over time. The results of the brand-level fixed effects indicate that in general the preference for Pringles is higher than that for Lay's, which in turn is higher than

Table 16: Posterior Estimates of Aggregate-level Coefficients and Satiation Parameters

Variable	Intercept[1] $\hat{\gamma}_0$ Mean	SD	Sig.[2]	Within-Trip Variety Seeking $\hat{\gamma}_1$ Mean	SD	Sig.[2]
Household-Level Intercept	-3.923	0.359	**	2.315	1.156	**
Product Feature						
Flat-cut	-2.195	0.197	**	-0.882	0.347	**
Low-fat	-1.018	0.232	**	0.039	0.397	
Package Size						
Small	0.000			0.000		
Medium	4.168	0.214	**	-0.307	0.442	
Large	4.769	0.249	**	-0.275	0.483	
Flavor						
Regular	0.000			0.000		
BBQ	-2.188	0.188	**	1.282	0.322	**
Cheese	-2.216	0.282	**	0.935	0.364	**
Herb/Ranch	-2.187	0.202	**	1.016	0.349	**
Salt/Vinegar	-2.094	0.220	**	1.341	0.403	**
Sour Cream	-1.164	0.133	**	0.862	0.271	**
Spicy	-2.624	0.400	**	0.403	0.543	
Other Flavors	-1.483	0.223	**	1.357	0.405	**
Feature or Display	0.751	0.098	**	0.197	0.183	
Recent Purchase (RP)	0.916	0.093	**	-0.572	0.188	**
Brand						
Lay's	0.000			0.000		
Pringles	1.696	0.387	**	1.180	0.378	**
Ruffles	-3.767	0.509	**	-1.294	0.671	*
Wise	-2.351	0.405	**	-0.451	0.376	
Sub-brand						
Sub-brands of Lay's	-2.755	0.214	**	-0.556	0.373	
Sub-brands of Pringles	-0.304	0.202		-0.736	0.420	*
Sub-brands of Ruffles	-0.628	0.268	**	1.113	0.562	**
Sub-brands of Wise	-3.348	0.305	**	-0.521	0.435	
Product Line Length						
Number of Distinct SKUs	0.304	0.258		0.016	0.295	
Number of Duplicate SKUs	-1.252	0.191	**	-0.631	0.383	*
Number of Key Rivals' SKUs						
Number of Distinct SKUs	-0.401	0.122	**	-0.254	0.234	
Number of Duplicate SKUs	-0.329	0.203		-0.402	0.283	
Number of all the other SKUs	-0.366	0.116	**	0.029	0.212	
	$\hat{\delta}_k$ Mean	SD	Sig.[2]	Satiation Parameter $\hat{\alpha}_k = 1/\left[1+\exp\left(\hat{\delta}_k\right)\right]$ using Mean $\hat{\delta}_k$		
The Inside Goods	2.433	0.340	**	0.081		
The Outside Goods	8.147	2.118	**	<0.001		

Note:

1. The estimates of the coefficients in this column can be regarded as the results for an average household.
2. * = significant at the 0.1 level, ** = significant at the 0.05 level.

those for Ruffles and Wise. One possible reason is that Pringles had differentiated itself by packaging its chips in cans, while all the others packaged their chips in bags in 2002. Since we did not consider product package as a salient attribute, the brand fixed effect may thus capture the differentiation. It is worth noting that the satiation parameter, $\alpha_k = 1/[1 + \exp(\delta_k)]$, is significantly less than one for the inside goods (posterior mean of $\hat{\delta}_k = 2.433$, yielding $\hat{\alpha}_k = 0.081$, see Table 16). On the other hand, and consistent with Bhat (2008), the satiation parameter for the outside good is almost zero (posterior mean of $\hat{\delta}_k = 8.147$, yielding $\hat{\alpha}_k < 0.001$).

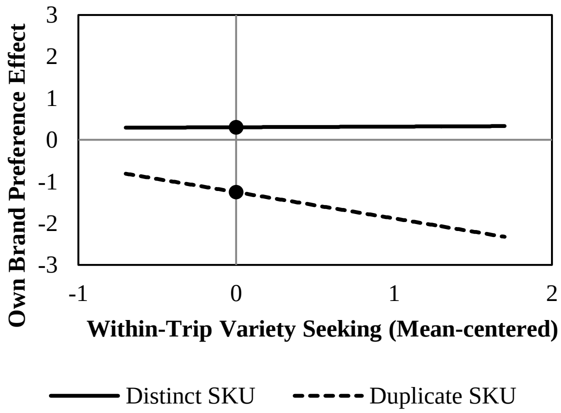
4.3.3.1 Own Effect of Product Line Length

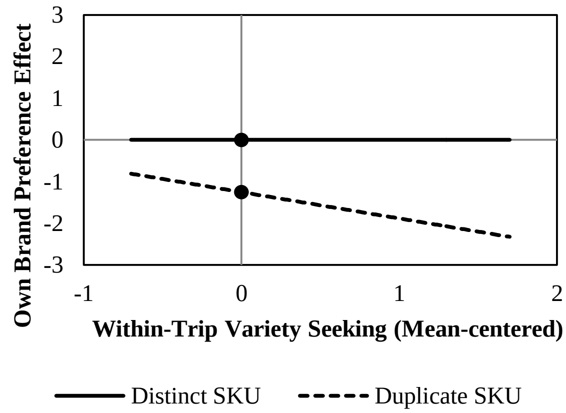
Own brand effects are illustrated in panel (a) of Figure 14[9]. In general, the number of a brand's distinct SKUs has no significant own effect, while the number of a brand's duplicate SKUs has a significantly negative own effect. In contrast to Harlam and Lodish (1995), who found that a brand's overall product line length has a negative effect on the utility of its SKUs, our findings suggest that the negative effect applies only for duplicate SKUs. This result could be attributed to the perceived high similarity of duplicate SKUs, which may increase the cognitive effort consumers make to discern differences among SKUs of this type. For households with high within-trip variety seeking propensities, the number of duplicate SKUs has an even stronger negative own effect. In other words, a product line with more duplicate SKUs is less attractive for households which, uncertain about their future preferences (e.g., Chernev 2012; Kahn 1995), seek a wider assortment of products on one shopping trip.

[9] The left column of Figure 14 shows the results using all posterior mean estimates, which are usually used for policy simulation in practice. The right column displays the results using only significant posterior mean estimates.

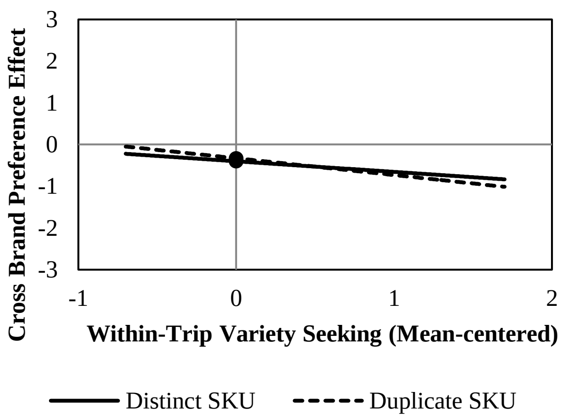
Using Posterior Mean Estimates	Using Only Significant Posterior Mean Estimates

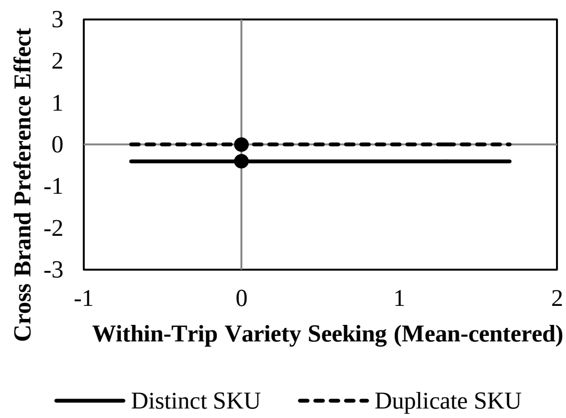
(a) Effect on Own Brand Preference[1]



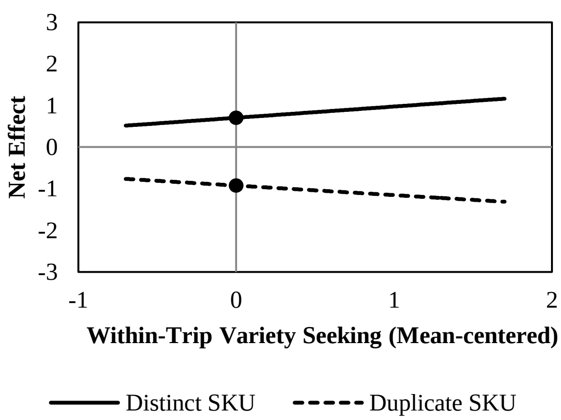


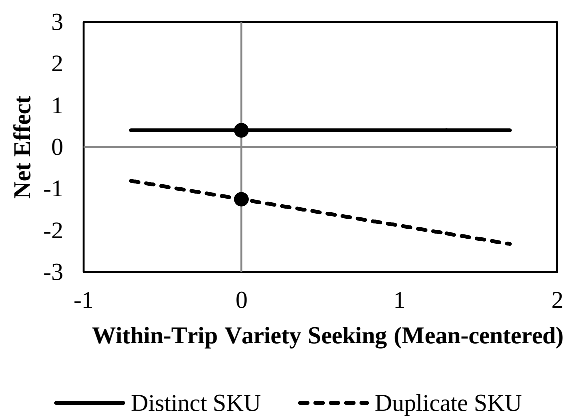
(b) Effect on Cross Brand Preference[1]





(c) Net Effect = (a) – (b)





Note:
1. When the mean-centered $WTVS_i = 0$ (the dot), it is the main effect for a typical household.

Figure 14: Own, Cross, and Net Effect of Numbers of Distinct/Duplicate SKUs

4.3.3.2 Cross Effect of Product Line Length

The cross effects are displayed in panel (b) of Figure 14. Only the number of distinct SKUs offered by key competitors has a significantly negative effect on consumer preference for the focal brand. This finding supports the competitive role of product line length (e.g., Bayus and Putsis 1999) but limits the role only to distinct SKUs. This effect could be attributed to higher shelf exposure gained, and thus “eyeball” share, via extended product lines with distinct products (Berman 2011; Kadiyali et al. 1999; Quelch and Kenny 1994). The number of all SKUs provided by other competitors also has a significantly negative cross effect (see Table 16). Note that in our empirical analysis the units of $NDUP_{st,\bar{b}}$ and $TOCPL_{st,b}$ are 10 and 20 SKUs respectively; thus, the cross effect per SKU of the other competitors is much weaker than those associated with key competitors, mainly because the competition among the key competing brands is stronger.

4.3.3.3 The Net Effect of Product Line Length

Given the differential effects of distinct and duplicate SKUs on own and cross brand preferences, it is of interest to understand the net effects associated with the two types of SKUs for the focal brand. We measure the net effect simply as the difference between the own effect and the cross effect, depicted in panel (c) of Figure 14. In general, the number of distinct (duplicate) SKUs has a positive (negative) net effect. For households with higher within-trip variety seeking propensities, the gap between the two net effects becomes larger. These findings suggest that adding distinct SKUs may help a brand increase consumer preference for the focal brand. However, we have already shown that extending a product line may change the interbrand variant overlap, which may also affect the brand preference.

4.3.3.4 Variant Overlap Effects

Our findings in Table 17 suggest that the effects of variant overlaps depend on the pair of competing brands and are frequently asymmetric. For example, the overlap between Lay's and Pringles deteriorates consumers' preferences for both brands, and the negative effect is much stronger for Pringles. This reveals a "rivalry" between the two brands, marketed by PepsiCo and P&G respectively, with the former being the beneficiary of the asymmetry in the overlap effects possibly due to the strength of its market share. The lack of significant overlap effects between Lay's and Ruffles could be attributed to positioning and coordination since both brands are owned by PepsiCo. Moreover, the variant overlap between any one of the three national brands and the regional brand (i.e., Wise) has a positive effect for the national brand, implying that national brands might benefit from matching their regional competitor's products.

Table 17: Posterior Mean (S.D.) of Coefficient of Interbrand Variant Overlap

		Competing Brands			
		Lay's	**Pringles**	**Ruffles**	**Wise**
Focal Brand	**Lay's**	Mean (S.D.)[1,2]	-1.843 (0.889)**	0.411 (1.215)	2.540 (0.891)**
	Pringles	-4.508 (1.140)**		-1.465 (1.901)	2.725 (1.194)**
	Ruffles	-2.993 (2.157)	-2.017 (1.475)		3.444 (1.603)**
	Wise	-1.142 (1.035)	3.123 (1.601)*	0.382 (1.440)	

Note:
1. Mean (S.D.) = posterior mean (standard deviation) of the coefficient of interbrand variant overlap. In our analysis, the input data are 10 times the values of the interbrand variant overlaps.
2. * = significant at the 0.1 level, ** = significant at the 0.05 level.

4.3.4 Validation

We compare the full MDCEV model (i.e., M1 in Table 18) with sub-models (M2 to M6) by using log pseudo marginal likelihood (LPML, Geisser and Eddy 1979) and Deviance Information Criterion (DIC, Spiegelhalter et al., 2002). Table 18 reports the comparison results and the main effects (i.e., the intercept $\hat{\boldsymbol{\gamma}}_{\mathbf{0}}$) concerning product line length measures for each

Table 18: Model Fit and Comparison

	M1: Full Model	**M2: No Product Line Length**	**M3: No Product Line Structure**	**M4: No Variety Seeking**	**M5: No Cross Effect**	**M6: No Inter-brand Variant Overlap**	**M7: Replace Variety Seeking with Family Size**	**M8: Full Model with Family Size**	**M9: Full Model with Inventory**
Product Line Length									
No Effect		✓							
Main Effect Only			✓						
Product Line Structure (Distinct/Duplicate SKUs)	✓			✓	✓	✓	✓	✓	✓
Variety Seeking									
Within-Trip Variety Seeking	✓	✓	✓		✓	✓		✓	✓
Brand Competition									
Cross Effect	✓		✓	✓		✓	✓	✓	✓
Variant Overlap	✓	✓	✓	✓	✓		✓	✓	✓
Family Size							✓	✓	
Inventory									✓
No Satiation (Single-discrete)[1]									
Main Effect (Intercept)[2]									
Product Line Length			**-0.534**						
			(0.183)						
Number of Distinct SKUs	0.304			0.565	0.147	**0.544**	0.305	0.260	0.253
	(0.258)			(0.350)	(0.265)	(0.126)	(0.232)	(0.237)	(0.241)
Number of Duplicate SKUs	**-1.252**			**-1.205**	**-1.301**	**-0.957**	**-1.086**	**-1.123**	**-1.138**
	(0.191)			(0.192)	(0.182)	(0.190)	(0.192)	(0.182)	(0.184)
Number of All Competing SKUs			**-0.469**						
			(0.105)						
Number of Key Rivals' SKUs									
Number of Distinct SKUs	**-0.401**			**-0.373**		**-0.228**	**-0.422**	-0.194	**-0.446**
	(0.122)			(0.156)		(0.107)	(0.120)	(0.151)	(0.156)
Number of Duplicate SKUs	-0.329			**-0.267**		-0.318	**-0.383**	-0.155	-0.338
	(0.203)			(0.145)		(0.166)	(0.155)	(0.154)	(0.176)
Number of All the Other SKUs	**-0.366**		**-0.342**	**-0.291**		**-0.259**	**-0.233**	**-0.363**	**-0.351**
	(0.116)		(0.102)	(0.117)		(0.117)	(0.113)	(0.092)	(0.106)
LMPL[3]	**-13916.1**	-14001.4	-13926.6	-13934.7	-13936.8	-13925.9	-13931.7	-13949.3	-13940.5
DIC[4]	**27430.3**	27691.9	27459.6	27491.2	27533.5	27462.4	27466.0	27500.2	27453.0

Note:

1. M10 assumes $\alpha_k = 1$ for all SKUs and regards a trip involves multiple discreteness as many conditionally independent single-discrete purchases. We hence transform the multiple-discrete data into a single-discrete data.
2. The estimates in bold are significant at the 0.05 level. The standard errors are in the parentheses.
3. We select the model that maximizes log marginal pseudo likelihood (LMPL).
4. We select the model that minimizes deviance information criterion (DIC).

model. Both criteria suggest that the full (proposed) model provides the best fit among M1 to M6. Notably, the estimates of the own effects of product line length measures are similar regardless of whether the model considers cross effects (i.e., M1) or not (i.e., M5).

We further check whether family size or inventory affects the main findings of the proposed model. A larger household might buy more different SKUs on one trip to accommodate different family members. Thus, we replace $WTVS_i$ with family size (i.e., M7) or add the moderating effect of family size (i.e., M8) through Equation (55). We found that family size has no significant moderating effect regarding product line length measures on brand preference in M7 and M8. Further, the utility of the inside SKUs might be affected by the inventory of the top four brands' SKUs owned by each household[10], if consumers tend to stockpile potato chips. Thus, we include the inventory variable as an element of $\boldsymbol{x}_{ist,k}$. In M9, we found that although the main effect of inventory is significantly negative, it does not change the coefficients concerning product line length measures. Lastly, M1 outperforms M7 to M9 in terms of LMPL and DIC.

4.4 Managerial Implications

In this section, we conduct a model simulation to demonstrate how to decide whether a brand should add or drop an SKU and identify which SKU should be the optimal candidate for product introduction or elimination by calculating the choice share of the brand's SKUs based on our results. We consider Ruffles, the brand with the lowest market share, as the brand of interest. Ruffles is available in nine out of 14 stores in Pittsfield; the nine stores accounted for 98% of salty snacks sales in 2002 in the market. Therefore, we assume that Ruffles will not enter new

[10] We use the inventory of all inside SKUs rather that of each SKU, because the latter is highly correlated to the recent purchase variable. The inventory is generated in line with Ailawadi and Neslin (1998) and Gupta (1988).

stores and calculate brand-level shares in the nine stores. We consider the assortment in each store in the IRI Week 1217 (i.e. the last week in 2002) and assume that there is neither price discount nor feature ad or in-store display for any SKU. We regard an average household as a representative consumer (i.e., using posterior mean estimates of $\boldsymbol{\gamma_0}$ in Table 16 and Table 17), who did not buy any inside goods on the last trip (i.e., $RP_{it-1,k} = 0$). We compute the deterministic part of the baseline marginal utility and the choice probability of each SKU in each store. Finally, we average brand shares (i.e., the sum of choice probabilities of the brand's SKUs) over stores by using the sales of salty snacks in each store in 2002 as weights.

We assume that Ruffles' objective is to maximize its share either by dropping any one of its existing SKUs out of the nine stores or by adding one SKU with any of the 96 combinations of attribute levels in all of the nine stores. The price is assumed to be 0.99/1.99/3.29 for a new small/medium/large-size SKU. The prices are determined according to the average list prices of Ruffles' SKUs in the specific size. Since Ruffles did not offer any small-size SKU, the price is determined based on the average list price of a small-size SKU charged by the other three key competitors. The new SKU will be introduced by using only the parent brand because using a sub-brand has no positive effect according to our findings.

The average household may select: (a) one SKU (single discreteness) or (b) more than one SKU (multiple discreteness). For the single discreteness case, we can calculate the choice probability for each SKU by using the special case of the probability in Equation (60) with no Jacobian term, $\alpha_k = 1$ for all k, and $R_{ist} = 1$. For the multiple discreteness case, we further assume the budget of buying salty snack is \$3.90[11], which is the mean level of the total purchase amount of salty snacks per shopping trip in 2002. Ideally, we should enumerate all possible combinations of choices that can use up the budget and compute the choice probability of each combination through Equation (15). However, the budget cannot buy many SKUs and/or many units of each SKU. Instead of searching all possible combinations, we only consider the possible combinations in following scenarios of multiple discreteness: (1) (up to two units of) one inside SKU and the outside good (of which the unit is the budget minus the purchase amount of the inside SKU); (2) two different inside SKUs of the same brand, one unit for each; (3) two different inside SKUs of different brands, one unit for each; (4) two different inside SKUs of the same brand (one unit for each) and the outside good (of which the unit is the budget minus the purchase amount of the two inside SKUs); and (5) two different inside SKUs of different brands (one unit for each) and the outside good (of which the unit is the budget minus the purchase amount of the two inside SKUs).

To allocate the choice probability of a combination to a brand's choice share, we further use the total units of the brand's SKU(s) in the combination as the weight. If the household buys the outside good, we assume the unit of the outside good is one in computing the weight. For example, the weight for the outside good is 1/3 in case (4). Since in our data 26.02% of shopping trips involving multiple discreteness, we use this percentage as a weight for the multiple discreteness case when averaging the choice share of the two cases.

[11] In the single discreteness case, the choice probability is independent from the budget because purchase amount does not enter the probability. In the multiple discreteness case, however, purchase amount and thus purchase quantity will affect the choice probability, and thus the budget is needed. We consider the integer constraint regarding purchase quantity for inside SKUs in simulation, even though the constraint is not specified in the model.

The simulation results suggest that Ruffles should add a non-flat-cut, regular-fat, medium-size, and regular-flavored SKU. This SKU will be a duplicate SKU for Ruffles in six out of the nine stores. Table 19 shows the changes in the choice shares of the four brands if Ruffles adds the recommended SKU. While Ruffles' brand share will increase after adding the duplicate SKU, the collective share of the four brands will decrease in all cases. Ruffles' new extension will lower the utility of most SKUs, except for the outside good, through product line length and interbrand variant overlap. For Ruffles, the decrease in the total choice probability of its existing SKUs due to the negative effect induced by the new extension will be compensated by the gain in choice probability from the new extension, which has every salient product attribute level that an average household prefers, thus leading to an increase in Ruffle's brand share. However, the gain from Ruffle's new extension is not big enough to offset the decrease in the other three brands' brand shares due to the negative effect induced by the new extension, thus decreasing the collective share of the four brands. These simulation results imply that the representative household is less likely to buy any of the four brand's SKUs after the introduction of the SKU. In other words, adding the duplicate SKU might cause choice overload and lower the total share of the top four brands.

4.5 Chapter Conclusion

We construct a hierarchical Bayesian multiple discrete-continuous extreme value (HBMDCEV) model to examine the effect of product line length on brand preference in the context of multiple discreteness. We consider the role of product line structure, competition, and household variety seeking propensity. The results of our empirical analysis using household panel data on purchases of salty snacks including potato chips suggest that the number of duplicate SKUs has a

Table 19: Effects of the introduction of Ruffles' SKU on Brand Shares

	Choice Shares				
	Lay's	Pringles	Ruffles	Wise	Total
Single Discreteness					
Before Introduction[1]	8.007%	1.185%	0.196%	1.010%	10.399%
After Introduction[2]	7.802%	1.138%	0.238%	0.984%	10.162%
After – Before	-0.206%	-0.047%	0.042%	-0.026%	-0.236%
Multiple Discreteness					
Before Introduction	0.560%	0.047%	0.006%	0.044%	0.656%
After Introduction	0.549%	0.045%	0.007%	0.043%	0.644%
After – Before	-0.011%	-0.002%	0.001%	-0.001%	-0.012%
Overall (Weighted Average[3])					
Before Introduction	6.069%	0.889%	0.146%	0.759%	7.863%
After Introduction	5.915%	0.854%	0.178%	0.739%	7.685%
After – Before	-0.155%	-0.035%	0.031%	-0.019%	-0.178%

Note:
1. The status quo before Ruffles adjusts it product line.
2. The case after Ruffles introduces a non-flat-cut, regular-fat, medium-size, regular-flavored SKU.
3. The weight for the single (multiple) discreteness is 73.98% (26.02%) listed in Table 12.

negative effect on a brand's own preference, especially for households with high within-trip variety seeking propensities, but no significant effect on its key competitors' preference. In contrast, the number of distinct SKUs has no significant own effect but a negative cross effect. Overall, the net effect of product line length is positive for distinct SKUs and negative for duplicate SKUs, especially for households with high within-trip variety seeking propensities. Furthermore, product line length may affect interbrand variant overlap, which also affects the choice share of the brand's SKUs. Our findings refine and extend those of Harlam and Lodish (1995), the only other study on the effects of product line length on SKU choice. However, the latter did not use a utility-maximizing framework which can allow for satiation effects. The significant satiation effects estimated in our study provide validation for the proposed framework.

Our findings indicate that brand managers should finely balance own and cross-brand effects of product line length when considering line extensions since they may result in lower utilities for all inside SKUs in the market. Indeed, a simulation using the HBMDCEV model for Ruffles' product line decision shows that adding a duplicate SKU can be the optimal strategy for Ruffles in terms of maximizing choice share of its SKUs. However, this strategy will also lead to a loss in the total choice share for the top four brands and a shift in preference to the outside good. These findings imply that adding a duplicate SKU may lead to choice overload. This illustrates the complexity of the product line extension decision.

We only study one product category with horizontally differentiated SKUs. Future research should consider other contexts such as vertically differentiated markets and other product categories. Moreover, product line structure is captured using certain salient product attributes because of data limitations. While we argue that distinct/duplicate SKUs may have different contributions to the perceived variety of a product line, product packaging, which can affect the perceived variety and might be operationalized by several attributes, is unobserved in our data. Researchers may investigate how product packaging affects the perceived variety of an assortment of duplicate SKUs or distinct SKUs and shed more light on product line management. Finally, we assume that all active SKUs are always available and that consumers are exposed to them in store. Further modeling the out-of-stock events and consideration sets may lead to more, much-needed insights in this interesting field.

Chapter 5

Conclusion

5.1 Summary of Findings

Product line extension is a pervasive marketing strategy frequently used by brands managing horizontally differentiated products, a strategy that increases product line length and leads to product proliferation or the marketing of seemingly identical products by a brand. This study investigates the effects of product line length on product sales, product exit, new product trial, and brand preference. More specifically, it uses data on potato chip purchases to better understand the effects of product line extension for brands managing horizontally differentiated products in a competitive market. We also consider the role of product line structure in order to evaluate the effects of product proliferation. The key findings are summarized in Table 20.

Table 20: The Effects of Product Line Length, Distinct SKUs, and Duplicate SKUs

	Chapter 2				Chapter 3		Chapter 4	
	Product Sales		Hazard of Product Exit				Brand Preference	
	Within One Year	After One Year	Within One Year	After One Year	Prob. of New Product Trial	Prob. of Early Product Withdrawal	Own Brand Effect	Cross Brand Effect
Product Line Length[1,2]	+	N.S.	+	N.S.	+	+	–	–
# of Distinct SKUs[1,2]	+ (Partial)	+ (Partial)	+	–	–	–	N.S.	–
# of Duplicate SKUs[1,2]	N.S.	N.S.	N.S.	+	+	+	–	N.S.
# of Competing SKUs[3]	+	+	+	+	–	–		–

Note:

1. + = positive effect; + (Partial) = partially positive effect; – = negative effect; N.S. = not significant effect.
2. The cross brand effect in Chapter 4 is the effect of the sum of key competitors' (distinct/duplicate) SKUs on the preference for the focal brand.
3. In Chapters 2 and 3, this variable is the number of SKUs marketed by all competitors, whereas in Chapter 4, this variable is the number of SKUs marketed by all competitors, except key competitors.

Chapter 2 shows that product line length has dynamic effects on both product sales and the hazard of product exit. Specifically, product line length has positive effects on product sales and the hazard of product exit only for products within the first year after their launches; it has no significant effects on either of these two variables for products surviving more than one year. Chapter 3 further suggests that a longer product line may increase the probability of new product trial as well as that of early product withdrawal. The finding regarding early product withdrawal is consistent with that regarding product exit for products within the first year as shown in Chapter 2. Moreover, Chapter 4 demonstrates that product line length has a negative own effect on brand preference. Overall, a longer product line may accelerate new product trial and increase product sales within the first year after launch; yet, it may also drive more new products in the line out of the market, and the effect of product line length may become insignificant for relatively mature products. These findings reveal that simply having a longer product line without consistently adding products may not contribute to higher brand sales. Moreover, a longer product line may even decrease consumer preference for the brand. As a result, a longer product line seems to have limited effects and may even harm brands with horizontally differentiated products.

However, product line length may be an effective tool to shape the competition. Chapter 4 examines the effect of key competitors' product line length on consumer preference for the focal brand and finds that product line length has a negative cross effect. In addition, the number of products marketed by the other competing brands (excluding the key competitors) also has a negative cross effect. Chapter 2 shows that the number of competing products has positive effects on product sales and the hazard of product exit for the focal brand's products, no matter the stage of product life cycle. Furthermore, Chapter 3 suggests that the number of competing products has negative effects on the probability that consumers will try the focal brand's new products and the probability that those products will exit the market within the first year. Therefore, while a brand with a longer product line composed of horizontally differentiated products may help its competitors increase product sales, it may also decrease the probability that consumers will try its competitors' products, increase the probability of product exit for its competitors' products that survive less than one year, and decrease consumer preference for its competing brands.

We also found that the effects of product line length depend on the structure of the product line. Specifically, Chapter 2 shows that the number of distinct SKUs marketed by a brand has a marginally positive effect on the brand's product sales, a positive effect on the hazard of product exit for the brand's products within their first year, and a negative effect on the hazard of product exit for the brand's products surviving more than one year. Chapter 3 indicates that the number of distinct SKUs marketed by a brand has a negative effect on the probability that consumers will try the brand's new products, and a negative effect on the probability that the brand's new products will be withdrawn within their first year. Chapter 4 suggests that the number of distinct SKUs marketed by a brand has no significant effect on consumer preference for the brand but a negative effect on consumer preference for its key competitors' brands. In brief, a brand with more distinct SKUs may have higher sales; even though consumers may be less likely to try its new products within their first year, its products are less likely to exit the market once they survive that period. Moreover, more distinct SKUs may lower consumer preference for its competitors' brands without sacrificing its own brand preference.

In stark contrast to distinct SKUs, duplicate SKUs are less valuable for a brand managing horizontally differentiated products in a competitive environment. Chapter 2 reveals that the number of duplicate SKUs marketed by a brand has no significant effect on the brand's product sales and a positive effect on the hazard of product exit for the brand's products surviving more than one year. Chapter 3 suggests that the number of duplicate SKUs marketed by a brand has positive effects on the probability that consumers will try the brand's new products and the probability that those products will be withdrawn within their first year. Chapter 4 shows that the number of duplicate SKUs marketed by a brand has a negative effect on consumer preference for that brand, and no significant effect on consumer preference for its key competitors' brands. Overall, while more duplicate SKUs may help a brand to accelerate the new product trial, they may also be more likely to drive the brand's products, particularly those surviving more than one year, out of the market as well as lower consumer preference for it but not for its competitors.

Note that the findings regarding the hazard of product exit within the first year in Chapter 2 and those regarding early product withdrawal in Chapter 3 are different for the number of distinct SKUs, the number of duplicate SKUs, and the number of competing SKUs. One possible reason for the difference is that Chapter 2 uses monthly aggregate data across 50 markets, but Chapter 3 uses weekly panel data in one market. In addition, the different findings might result from the use of different models. As a result, more studies on early product withdrawal are needed in order to identify a general pattern.

5.2 Managerial Implications

This study has many implications for brands managing horizontally differentiated products.

Firstly, stretching a brand's product line may increase the sales of the brand's individual products, leading to higher brand sales. However, the effect of a longer product line on a product's sales may end once the product has been on the shelves for one year. This implies that simply maintaining a long product line full of mature products will not help a brand further increase brand sales. Continuously adding new products, however, may be a possible avenue to maintain or even enhance the brand sales. In other words, this study may justify the positive financial impact of product line extension frequently used by managers. Nevertheless, frequently adding new products without retiring existing ones may lead brand managers to a dilemma. That is, while new products may contribute to an increase in brand sales, these new products are more likely to exit the market within the first year after their launches, and, even worse, consumers may prefer the brand less. Therefore, brand managers have to carefully implement product line pruning, in addition to product line extension, in order to optimize the effect of product line length.

Product line length is an effective tool to shape the competition in order to achieve strategic goals. Product line length is mostly effective in helping a brand deteriorate its competitors' competiveness by decelerating new product trial, increasing the hazard of product exit for its competitors' mature products, and by lowering consumer preference for the competition brands. As a result, no matter whether a brand manager is in a position of attack or defense, he or she has to carefully consider the competitive situation in making product line length decisions. For example, this study shows the positive spillover effect of a brand's product line length on its competitors' product sale, which suggests more products in the same category may increase the primary demand for the product category. However, more products in the same category may decrease consumer preference for all brands in the category and lower the total choice share (which results in market share) of the product category; this is evident from the simulation analysis in Chapter 4. Consequently, frequently adding new products without retiring existing ones may not be in the best interest of brands in the same category. Ultimately, collaboration between competing brands in terms of product line length may be a viable strategy to benefit all competitors in this case.

Compared with product line length, product line structure may be an even more important feature of a product portfolio for brand managers. While product proliferation is ubiquitous in markets characterized by horizontally differentiated products, this study shows that a great number of duplicate SKUs marketed by a brand, resulting from product proliferation, may do more harm than good for the brand. Specifically, marketing more duplicate SKUs may not help the brand generate more sales and may even lower consumer preference for the brand, suggesting product proliferation may not be a profitable strategy. In contrast, marketing more distinct SKUs is more likely to help a brand increase its product sales and lower consumer preference for its competitors, even though consumers may be less likely to try its new products. Therefore, in general, adding distinct SKUs in its portfolio should benefit a brand more than adding duplicate SKUs. Yet when consumers have a strong preference for certain existing products in a product line, to add a duplicate SKU that is highly similar to one of those products may still be a brand's optimal strategy to maximize its choice share, as demonstrated in the simulation analysis in Chapter 4. Thus, when making product line length decisions, brand managers should consider not only the structure of the product line but also the extent to which consumers prefer certain product attribute levels, as well as the existence of ideal products.

Finally, this study does not consider the costs associated with product line extension, such as costs of developing and producing new products or slotting fees for new product space, because of data limitation. We believe the cost information is available for brand managers. Hence, after understanding the demand side effects of product line length discussed in this study, brand managers can further conduct a cost-benefit analysis in making product line length decisions.

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Appendix A

Table 21. Classification of Flavors of Potato Chips

Category	Flavor recoded by IRI
REGULAR	Au Naturel, Classic Russets, Dark Russet, Golden, Golden Russet, Russet, Traditional, Robust Russet, Bistro Classic, Classic, Natural, Original, Plain, Regular, Baked Potato
BBQ	Bbq, Bbq Ranch, Backyard Bar-B-Que, Bold Bahama Barbecue, Carolina Style Bar-B-Q Flavored, Classic Barbecue, Firecracker Bbq, Hickory Honey Barbeque, Hot 'N Spicy Bbq, Smoky Barbeque Chedr, Smokin' Sweet Bbq, Smoky Barbecue, Southwest Sweet Barbeque, Sweet Honey Bbq, Sweet Mesquite Bbq, Alder Smoke Barbecue, Aplewd Bbq Smkd Chdr, Barbecue, Barbecue Rib, Barbeque, Barbeque And Cheddar, Boomin Barbecue, Bulls Eye Barbecue, Classic Barbeque, Coastal Barbeque, Country Bbq, Fre Swt Mesqute Bbq, Hickory Barbecue, Honey Barbecue, Hot Barbecue, Hot Bbq, Hot Spicy, Barbecue, Kansas City Barbecue, Kc Masterpiece Barbc, Kc Mastrpc Msqt Brbc, Kc Style Barbecue, Laredo Mesquite Brbc, Luau Bbq, Memphis Barbecue, Mesquite Barbecue, Mesquite Smoked Brbq, Red Hot Bbq, Regular Bbq, Smkhs Barbeque, Smoked Barbecue, Smokey Barbeque, Smokin Barbecue, Smoky Mountain Barbq, Southwestern Barbecu, Spicy Barbeque, Summer Barbecue, Sweet Barbecue, Swet Bby Rays Bbq, Swet N Sasy Barbecue, Swet Potato Barbecue, Zesty Barbecue, Mesquite, Mesquite Smk Bacon, Roast Chicken, Roasted Chicken, Salsa Mesquite, Smokin Grill, Smoky Bacon, Sweet Mesquite, Texas Mesquite, Baby Back Ribs, Bacon Horseradish, Chicago Steakhouse, Steak & Worcestershire
CHEESE	Chedar Chs Sprng Onn, Cheese & Onion, Cheese Onion, Ny Cheddar With Herb, Bacon & Cheddar, Bacon & Cheese, Blue Cheese, Bufalo Wing Blue Chs, Cheddar, Cheddar Bacon, Cheddar Cheese, Cheese, Crackr Brl Shrp Chdr, Fiesta Cheddar Salsa, Mozzarella, New York Cheddar, Salsa Cheese, Sharp Cheddar, Smokehouse Bacn&Chdr, Smokehouse Cheddar, Sour Sweet Cheddar, Tangy Cheese, Tex Mex With Cheese, Ultimate Chedar Sals, White Cheddar, Chargin Chedr Sr Crm, Cheddar & Sour Cream, Cheesy Red Hot, Aged White Cheddar, Buffalo Bleu, Cheddar Jack, Cheddar Beer, Cheddar Cheese With Jalapeno, Cheesy Fries, Electric Blue, Monterey Pepper Jack Ea, Philly Cheese Steak, Sizzlin Cheddar, Sweet Cheesy Chipotle, Three Cheese Jalapeno, Tuscan Three Cheese, White Cheddar Cheese, Wisconsin Cheddar
HERB/RANCH	Bacon Ranch, Creamy French Onion, Crisps Ranch, Four Onion, French Onion & Chive, Fresh Garden Herb, Garlic Pesto, Garden Herb Ranch, Green Onion & Roasted Garli, Herb, Lemon Pepper, Lime, Lime & Black Pepper, Lime & Cracked Black Pepper, Olive Oil & Fine Herbs, Roasted Garlic & Parmesan, Select Parmesan Garlic, Sweet Herb, Black Pepper, Cajun Dill, California Cool Dill, Cracked Pepper, Cracked Peppercorn, Creme Fraich Grn Onn, Creme Fraiche Dill, California Cool Dill, Deli Ranch, Dill, Dill Pickle, Fine Herb, French Onion, Garlic, Garlic & Dill, Garlic & Herb, Garlic & Parmesan, Green Onion, Grilled Stk & Onion, Garlic & Herb, Hidden Valley Ranch, Hawaiian Sweet Onion, Kosher Dill, Maui Onion, Old Bay Seasoning, Onion & Garlic, Onion Garlic Parsley, Original And Ranch, Original French Onin, Parmesan & Pepper, Parmesan Peppercorn, Pepper Jack Cheese, Peppercorn Ranch, Ranch, Roasted Garlic, Rosemary, Santa Fe Ranch, Scr & Green Onion, Sour And Dill, Steak & Onion, Sweet Maui Onion, Toasted Onion Che, Tomato Basil, Wild Wings & Ranch, Yogurt & Green Onion, Yogurt & Onion, Zesty Ranch, Lemon, Limon, Touch Of Lime
SALT/VINEGAR	Salt And Pepper, Balsamic Vinegar & Sea Salt, Crckd Ppr Blsmc Vngr, Salt And Sour Cream, Salt & Cracked Pepper, Salt & Pepper, Sea Salt & Pepper, Sea Salt + Black Pepper, Vinegar Dill, Vinegar & Sea Salt, Salt'n Sour, Salt & Sour, Salt & Vinegar, Salt Malt Vinegar, Salt N Sour, Sea Salt, Sea Salt & Vinegar, Sea Salt Cracked Ppr, Sea Slt And Mlt Vngr, Sizzlin Salt N Sour, Stormy Salt Vinegar, Vinegar
SOUR CREAM	Roasted Garlc Sr Crm, Sc&O Chive, Sour Cream & Chive, Sour Cream & Dill, Sour Cream & Onion, Sourcream And Clam, Sr Crm & Creole Onn, Vidalia Onion&Sr Crm, Wi Cheddar&Sourcream, Wild Sour Cream Onin, Zesty Sour Cream&Onn
SPICY	Honey Dijon, Honey Mustard, Thai, Chipotle Bbq, Chipotle Ranch, Chipotle Smoked Jalapeno, Fiery Hot, Flaming Hot, Hot Chili Cheese, Hot Dill Pickle, Hotter 'N Hot Jalapeno, Jalapeno & Aged Cheddar, Jalapeno Cheddar, Jalapeno With Tequila & Lime, Lips Hot, Roasted Red, Pepper And Goat Cheese, Spicy Mexican, Spicy, Spicy Cajun, Cajun, Cajun Creole, Quakin Cajun, Spicy Creole Tomato, Spicy Thai, Sweet Chili & Sour Cream, Sweet Wasabi Mustard, Tangy Hot Sauce, Thai Sweet Chili, Tomato & Chili, Red Hot Cheddar, Buffalo Wing, Chile Limon, Chili, Chili & Cheese, Chili & Lime, Chili And Spice, Chili Cheese, Chili Limon, Chili Picante, Cholula Hot Sauce, Extra Hot, Extra Red Hot, Flamin Hot, Good N Hot, Habanero, Hearty Chili Cheese, Hot, Hot & Spicy, Hot & Spicy Jalapeno, Hot & Wild, Hot Buffalo Wing, Hot Cajun, Hot Cajun Grill, Hot Jalapeno, Hot Pepperoni Pizza, Hot Picante, Hot Ranch, Hot Stuff, Howlin Hot And Spicy, Habanero, Hot, Hot Buffalo Wing, Jalapeno, Jalapeno & Cheddar, Jalapeno & Cheese, Jalapeno Fiesta, Jalapeno Pepper, Jalapeno, Louisiana Hot Sauce, Red Chile, Red Hot, San Antonio Habanero, San Antonio Jalapeno, Sharp Chedar Jalapen, Smoked Jalapeno, Southwest Spice, Spicy Cajun, Stuffed Jalapeno, Wasabi, Zesty Jalapeno, Buffalo Style
OTHERS	Au Gratin, Burger N Fixins, Cnnm Sweet Potato, Coney Island, Crab, Dark, German, Gourmet, Guacamole, Hawaiian, Ketchup, Milk Chocolate, Nantucket, Pesto, Pizza, Pizza Licious, Salsa, Snd Tmt Bls Vngolvol, Spiced Sweet Potato, Sweet, Sweet Potato, Swet Potat Cnmn Ntmg, The Works, Trio, Bruschetta, Coney Island Hot Dog With Mustard, Gourmet Medley, Italian, Loaded Spud, Mediterranean, Mambo Madness, Nantucket Spice, Open Pit Flavored, Quesadilla, Salsa Verde, Seasoned, Shrimp, Sundried Tomato, Sweet & Sour, San Antonio Salsa, Sweet & Sassy, Sweet Island Style, Taco Fiesta!, Zesty Italian

Appendix B

Model of New Product Trail and Early Product Withdrawal

We adopt a hybrid Markov chain Monte Carlo (MCMC) methodology consisting of Gibbs sampling and Metropolis-Hasting algorithm for model estimation. We assume the reader is familiar with Bayesian estimation techniques and thus only provides the prior and posterior distributions. We first made the following assumptions regarding the prior distributions:

$$\boldsymbol{\gamma} \sim Normal(\overline{\boldsymbol{\gamma}}, \boldsymbol{\Sigma}_{\boldsymbol{\gamma}}), \tag{A1}$$

$$\overline{\boldsymbol{\gamma}} \sim Normal(A_1, B_1), \tag{A2}$$

$$\boldsymbol{\Sigma}_{\boldsymbol{\gamma}} \sim Inverse\ Wishart(c_1, D_1), \tag{A3}$$

$$\overline{\boldsymbol{\gamma}}_2 \sim Normal(A_2, B_2), \tag{A4}$$

$$\boldsymbol{\Sigma}_{\boldsymbol{\gamma}_2} \sim Inverse\ Wishart(c_2, D_2), \tag{A5}$$

$$\boldsymbol{\lambda}_3 \sim Normal(\overline{\boldsymbol{\lambda}}, \boldsymbol{\Sigma}_{\boldsymbol{\lambda}}), \tag{A6}$$

$$\overline{\boldsymbol{\lambda}} \sim Normal(A_3, B_3), \tag{A7}$$

$$\boldsymbol{\Sigma}_{\boldsymbol{\lambda}} \sim Inverse\ Wishart(c_3, D_3), \tag{A8}$$

where $\boldsymbol{\gamma} = [\boldsymbol{\alpha}^T \quad \boldsymbol{\gamma}_1{}^T]^T$, $\boldsymbol{\alpha} = [\alpha_2 \quad \cdots \quad \alpha_M]^T$, $\boldsymbol{\lambda}_3 = [\boldsymbol{\beta}^T \quad \boldsymbol{\lambda}^T]^T$, $\boldsymbol{\beta} = [\beta_2 \quad \cdots \quad \beta_M]^T$, A_l, B_l, c_l, and D_l are hyperparameters, $l = 1,2,3$. The ranks of $\boldsymbol{\gamma}$, $\boldsymbol{\gamma}_2$, and $\boldsymbol{\lambda}_3$ are n_1, n_2, and n_3 respectively. The posterior distributions, as well as the updating mechanism, are given as follows:

(1) Update $\boldsymbol{\gamma}_{2i}$, $i = 1, \ldots, I$

The conditional posterior distribution of $\boldsymbol{\gamma}_{2i}$ given all other parameters has the form:

$$\xi(\boldsymbol{\gamma}_{2i} | \cdot) \propto \prod_{j=1}^{J} L_{ij}(\boldsymbol{\theta}) \times exp\left[-\frac{1}{2}(\boldsymbol{\gamma}_{2i} - \overline{\boldsymbol{\gamma}}_2)^T \boldsymbol{\Sigma}_{\boldsymbol{\gamma}_2}{}^{-1}(\boldsymbol{\gamma}_{2i} - \overline{\boldsymbol{\gamma}}_2)\right]. \tag{A9}$$

Metropolis-Hasting algorithm is used to for updating.

(2) Update $\boldsymbol{\alpha}$, $\boldsymbol{\gamma}_1$, $\boldsymbol{\beta}$, and $\boldsymbol{\lambda}$

The conditional posterior distribution of $\boldsymbol{\alpha}$, $\boldsymbol{\gamma}_1$, $\boldsymbol{\beta}$, and $\boldsymbol{\lambda}$ given all other parameters has the form:

$$\begin{aligned}\xi(\boldsymbol{\gamma}, \boldsymbol{\lambda}_3 | \cdot) \propto L(\boldsymbol{\theta}) \times exp\left[-\frac{1}{2}(\boldsymbol{\gamma} - \overline{\boldsymbol{\gamma}})^T \boldsymbol{\Sigma}_{\boldsymbol{\gamma}}{}^{-1}(\boldsymbol{\gamma} - \overline{\boldsymbol{\gamma}})\right] \\ \times exp\left[-\frac{1}{2}\left(\boldsymbol{\lambda}_3 - \overline{\boldsymbol{\lambda}}\right)^T \boldsymbol{\Sigma}_{\boldsymbol{\lambda}}{}^{-1}\left(\boldsymbol{\lambda}_3 - \overline{\boldsymbol{\lambda}}\right)\right].\end{aligned} \tag{A10}$$

The Metropolis-Hasting algorithm is used to for updating.

Regarding others parameters, the conditional posterior distributions are well-known distributions of which random variables are easy to draw:

$$\xi(\overline{\boldsymbol{\gamma}} | \cdot) \sim Normal\left(\left(B_1{}^{-1} + \boldsymbol{\Sigma}_{\boldsymbol{\gamma}}{}^{-1}\right)^{-1}\left(B_1{}^{-1}A_1 + \boldsymbol{\Sigma}_{\boldsymbol{\gamma}}{}^{-1}\boldsymbol{\gamma}\right), \left(B_1{}^{-1} + \boldsymbol{\Sigma}_{\boldsymbol{\gamma}}{}^{-1}\right)^{-1}\right), \tag{A11}$$

$$\begin{aligned}\xi(\overline{\boldsymbol{\gamma}}_2 | \cdot) \sim Normal\Bigg(\left(B_2{}^{-1} + I\boldsymbol{\Sigma}_{\boldsymbol{\gamma}_2}{}^{-1}\right)^{-1}\Bigg(B_2{}^{-1}A_2 \\ + \boldsymbol{\Sigma}_{\boldsymbol{\gamma}}{}^{-1}\sum_i \boldsymbol{\gamma}_{2i}\Bigg), \left(B_1{}^{-1} + I\boldsymbol{\Sigma}_{\boldsymbol{\gamma}_2}{}^{-1}\right)^{-1}\Bigg),\end{aligned} \tag{A12}$$

$$\xi(\overline{\boldsymbol{\lambda}} | \cdot) \sim Normal\left(\left(B_3{}^{-1} + \boldsymbol{\Sigma}_{\boldsymbol{\lambda}}{}^{-1}\right)^{-1}\left(B_3{}^{-1}A_3 + \boldsymbol{\Sigma}_{\boldsymbol{\lambda}}{}^{-1}\boldsymbol{\lambda}_3\right), \left(B_3{}^{-1} + \boldsymbol{\Sigma}_{\boldsymbol{\lambda}}{}^{-1}\right)^{-1}\right), \tag{A13}$$

$$\xi\left(\boldsymbol{\Sigma}_{\boldsymbol{\gamma}} | \cdot\right) \sim Inverse\ Wishart\ (1 + c_1, (\boldsymbol{\gamma} - \overline{\boldsymbol{\gamma}})(\boldsymbol{\gamma} - \overline{\boldsymbol{\gamma}})^T + D_1), \tag{A14}$$

$$\xi\left(\boldsymbol{\Sigma}_{\boldsymbol{\gamma}_2} | \cdot\right) \sim Inverse\ Wishart\ \left(I + c_2, \sum_i (\boldsymbol{\gamma}_{2i} - \overline{\boldsymbol{\gamma}}_2)(\boldsymbol{\gamma}_{2i} - \overline{\boldsymbol{\gamma}}_2)^T + D_2\right), \tag{A15}$$

$$\xi(\boldsymbol{\Sigma}_{\boldsymbol{\lambda}} | \cdot) \sim Inverse\ Wishart\ \left(1 + c_3, \left(\boldsymbol{\lambda}_3 - \overline{\boldsymbol{\lambda}}\right)\left(\boldsymbol{\lambda}_3 - \overline{\boldsymbol{\lambda}}\right)^T + D_3\right). \tag{A16}$$

We specified the hyperparameters as follows: $A_l = \mathbf{0}_{n_l}$, $B_l = D_l = 10\boldsymbol{I}_{n_l}$, and $c_l = n_l + 1$, where $\mathbf{0}_{n_l}$ is a $n_l \times 1$ zero vector, and $\boldsymbol{I}_{n_l}$ is the identity matrix with rank n_l. We sampled from the conditional posterior distributions for 50,000 iterations following a burn-in of 50,000 iterations to ensure convergence.

Model of Only New Product Trial

In the model of only new product trial, we first construct the contribution of a single observation sequence regarding household i and SKU j to the sample partial likelihood by using Equation (27), assuming $\mu = 0$ and $\sigma = 1$, and replacing x_0 with $x_{0,ik-1} = U_{ijm} = exp\left(\alpha_m + \boldsymbol{v}_{1ij}^T \boldsymbol{\gamma}_1 + \boldsymbol{v}_{2ij,w_{ijm-1}}^T \boldsymbol{\gamma}_{2i}\right)$. Therefore,

$$F\left(\Delta t_{ik} \middle| 0, x_{0,ik-1}\right) = 1 - S\left(\Delta t_{ik} \middle| 0, x_{0,ik-1}\right) = 2\Phi\left(-\frac{x_{0,ik-1}}{\sqrt{\Delta t}}\right), \qquad \text{(A17)}$$

and the contribution of a single observation sequence regarding household i and SKU j to the sample partial likelihood is:

$$L_{ij}(\boldsymbol{\theta}) = \prod_{m=1}^{M} \left(1 - F\left(\Delta t_{ik} \middle| 0, x_{0,ik-1}\right)\right)^{1-u_{ij,w_{ijm}}} F\left(\Delta t_{ik} \middle| 0, x_{0,ik-1}\right)^{u_{ij,w_{ijm}}} \qquad \text{(A18)}$$

(1) Update $\boldsymbol{\gamma}_{2i}$, $i = 1, \dots, I$

The conditional posterior distribution of $\boldsymbol{\gamma}_{2i}$ given all other parameters has the form in Equation (A9). The Metropolis-Hasting algorithm is used to for updating.

(2) Update $\boldsymbol{\alpha}$ and $\boldsymbol{\gamma}_1$

The conditional posterior distribution of $\boldsymbol{\alpha}$ and $\boldsymbol{\gamma}_1$ given all other parameters has the form:

$$\xi(\boldsymbol{\gamma}, \boldsymbol{\lambda}_3 | \cdot) \propto L(\boldsymbol{\theta}) \times exp\left[-\frac{1}{2}(\boldsymbol{\gamma} - \overline{\boldsymbol{\gamma}})^T \boldsymbol{\Sigma}_{\gamma}{}^{-1}(\boldsymbol{\gamma} - \overline{\boldsymbol{\gamma}})\right]. \qquad \text{(A19)}$$

The Metropolis-Hasting algorithm is used to for updating.

Regarding the other prior variables, the conditional posterior distributions are listed in Equations (A11), (A12), (A14), and (A15).

Appendix C

Inference proceeds using a hybrid Markov chain Monte Carlo (MCMC) method consisting of Gibbs sampling and Metropolis-Hasting algorithm. We assume that readers are familiar with the method and thus report mainly the conditional posterior distributions of parameters. For each model, we sample from the conditional posterior distributions by using every tenth sample of 50,000 iterations following a burn-in of 150,000 iterations to ensure convergence.

Posterior Distribution of $\widetilde{\boldsymbol{\beta}}_{\boldsymbol{i}}$, $i = 1, \ldots, I$

Based on Equation (54), $\widetilde{\boldsymbol{\beta}}_{\boldsymbol{i}} \sim MND\left(\boldsymbol{\Gamma z_i}, \boldsymbol{\Sigma_\beta}\right)$. Let LL be the log-likelihood function in Equation (61), and LL_i be the contribution of LL of household i. The logarithm of the posterior conditional distribution of $\widetilde{\boldsymbol{\beta}}_{\boldsymbol{i}}$ thus has the form:

$$ln\left[g\left(\widetilde{\boldsymbol{\beta}}_{\boldsymbol{i}} \middle| \cdot\right)\right] \propto LL_i - \frac{1}{2}\left(\widetilde{\boldsymbol{\beta}}_{\boldsymbol{i}} - \boldsymbol{\Gamma}\mathbf{z}_i\right)^T \boldsymbol{\Sigma_\beta}^{-1}\left(\widetilde{\boldsymbol{\beta}}_{\boldsymbol{i}} - \boldsymbol{\Gamma z_i}\right), \quad \text{(B1)}$$

where $g(\theta| \cdot)$ is the posterior conditional probability. The Metropolis-Hastings algorithm with a random walk chain is used to generate draws of $\widetilde{\boldsymbol{\beta}}_{\boldsymbol{i}}$.

Posterior Distribution of $\boldsymbol{\delta}$

Based on Equation (62), $\boldsymbol{\delta} \sim MND(\boldsymbol{\delta_0}, \boldsymbol{\Sigma_\delta})$**.** The logarithm of the posterior conditional distribution of $\boldsymbol{\delta}$ thus has the form:

$$ln[g(\boldsymbol{\delta}| \cdot)] \propto LL - \frac{1}{2}(\boldsymbol{\delta} - \boldsymbol{\delta_0})^T \boldsymbol{\Sigma_\delta}^{-1}(\boldsymbol{\delta} - \boldsymbol{\delta_0}), \quad \text{(B2)}$$

The Metropolis-Hastings algorithm with a random walk chain is used to generate draws of $\boldsymbol{\delta}$.

Posterior Distribution of $\{\boldsymbol{\xi_t}, t = 1, \ldots, T\}$

Based on Equation (63), $\boldsymbol{\xi_t} \sim MND(\mathbf{0}, \boldsymbol{\Sigma_t})$**.** The logarithm of the posterior conditional distribution of $\{\boldsymbol{\xi_t}, t = 1, \ldots, T\}$ thus has the form:

$$ln[g(\{\boldsymbol{\xi_t}\}|\cdot)] \propto LL - \sum_t \frac{1}{2} \boldsymbol{\xi_t}^T \boldsymbol{\Sigma_t}^{-1} \boldsymbol{\xi_t}. \tag{B3}$$

The Metropolis-Hastings algorithm with a random walk chain is used to generate draws of $\{\boldsymbol{\xi_t}\}$.

Posterior Distribution of $\boldsymbol{\phi}$

Based on Equation (64), $\boldsymbol{\phi} \sim MND(\boldsymbol{\phi_0}, \boldsymbol{\Sigma_\phi})$. The logarithm of the posterior conditional distribution of $\boldsymbol{\phi}$ thus has the form:

$$ln[g(\boldsymbol{\phi}|\cdot)] \propto LL - \frac{1}{2}(\boldsymbol{\phi} - \boldsymbol{\phi_0})^T \boldsymbol{\Sigma_\phi}^{-1}(\boldsymbol{\phi} - \boldsymbol{\phi_0}). \tag{B4}$$

The Metropolis-Hastings algorithm with a random walk chain is used to generate draws of $\boldsymbol{\phi}$.

Posterior Distribution of Γ

We assume the prior distribution of the vectorization of $\boldsymbol{\Gamma}$ is a multivariate normal distribution: $\mathrm{vec}(\boldsymbol{\Gamma}) \sim MND(\boldsymbol{r_0}, \boldsymbol{V_0})$, where $\boldsymbol{r_0}$ and $\boldsymbol{V_0}$ are hyperparameters equal to $\mathbf{0}_{2P}$ and $10 \times \boldsymbol{I}_{2P}$ respectively, $\mathbf{0}_{2P}$ is a $2P \times 1$ zero vector, P is the rank of $\widetilde{\boldsymbol{\beta}}_{\boldsymbol{i}}$, and $\boldsymbol{I}_{2P}$ is a $2P \times 2P$ identity matrix. Let $\mathbf{B}^* = \begin{bmatrix} \widetilde{\boldsymbol{\beta}}_{\boldsymbol{1}} \\ \vdots \\ \widetilde{\boldsymbol{\beta}}_{\boldsymbol{I}} \end{bmatrix}$ and $\mathbf{Z} = \begin{bmatrix} \boldsymbol{z_1} \\ \vdots \\ \boldsymbol{z_I} \end{bmatrix}$. The posterior distributions of $\boldsymbol{\Gamma}$ thus has the form:

$$g(\mathrm{vec}(\boldsymbol{\Gamma^T})|\cdot) \sim MND(\boldsymbol{r_b}, \boldsymbol{V_b}), \tag{B5}$$

where $\boldsymbol{V_b} = \left[(\boldsymbol{Z}^T\boldsymbol{Z}) \otimes \boldsymbol{\Sigma_\beta}^{-1} + \boldsymbol{V_0}^{-1}\right]^{-1}$, and $\boldsymbol{r_b} = \boldsymbol{V_b}\left[\left(\boldsymbol{Z}^T \otimes \boldsymbol{\Sigma_\beta}^{-1}\right)\mathbf{B}^* + \boldsymbol{V_0}^{-1}\boldsymbol{r_0}\right]$.

Posterior Distribution of $\boldsymbol{\Sigma_\beta}$

We assume the prior distribution of $\boldsymbol{\Sigma_\beta}$ is an inverse-Wishart distribution: $\boldsymbol{\Sigma_\beta} \sim IW\left(c_\beta, \boldsymbol{D_\beta}\right)$, where c_β and $\boldsymbol{D_\beta}$ are hyperparameters equal to $P+1$ and $10 \times \boldsymbol{I}_P$ respectively, and $\boldsymbol{I}_P$ is a $P \times P$ identity matrix. The posterior distributions of $\boldsymbol{\Sigma_\beta}$ thus has the form:

$$g\left(\boldsymbol{\Sigma_\beta} \mid \cdot\right) \sim IW\ (c_b, \boldsymbol{D}_{\boldsymbol{b}}^*), \tag{B6}$$

where $c_b = I + c_\beta$, $\boldsymbol{D}_{\boldsymbol{b}}^* = \sum_i \left(\widetilde{\boldsymbol{\beta}}_{\boldsymbol{i}} - \boldsymbol{\Gamma} \boldsymbol{z}_{\boldsymbol{i}}\right)\left(\widetilde{\boldsymbol{\beta}}_{\boldsymbol{i}} - \boldsymbol{\Gamma} \boldsymbol{z}_{\boldsymbol{i}}\right)^T + \boldsymbol{D_\beta}$.

Posterior Distribution of $\boldsymbol{\phi_0}$

We assume the prior distribution of $\boldsymbol{\phi_0}$ is an multivariate normal distribution: $\boldsymbol{\phi_0} \sim MND\left(\boldsymbol{A_\phi}, \boldsymbol{B_\phi}\right)$, where $\boldsymbol{A_\phi}$ and $\boldsymbol{B_\phi}$ are hyperparameters equal to $\boldsymbol{0}_K$ and $10 \times \boldsymbol{I}_K$ respectively, $\boldsymbol{0}_K$ is a $K \times 1$ zero vector, $\boldsymbol{I}_K$ is a $K \times K$ identity matrix, and $K = B_1(B_1 - 1)$. The posterior distributions of $\boldsymbol{\phi_0}$ thus has the form:

$$g(\boldsymbol{\phi_0} \mid \cdot) \sim MND\left(\boldsymbol{m_f}, \mathbf{v}_{\boldsymbol{f}}\right), \tag{B7}$$

where $\boldsymbol{m_f} = \mathbf{v}_{\boldsymbol{f}}\left(\boldsymbol{\Sigma_\phi}^{-1}\boldsymbol{\phi} + \boldsymbol{B_\phi}^{-1}\boldsymbol{A_\phi}\right)$, and $\mathbf{v}_{\boldsymbol{f}} = \left(\boldsymbol{\Sigma_\phi}^{-1} + \boldsymbol{B_\phi}^{-1}\right)^{-1}$.

Posterior Distribution of $\boldsymbol{\Sigma_\phi}$

We assume the prior distribution of $\boldsymbol{\Sigma_\phi}$ is an inverse-Wishart distribution: $\boldsymbol{\Sigma_\phi} \sim IW\left(c_\phi, \boldsymbol{D_\phi}\right)$, where c_ϕ and $\boldsymbol{D_\phi}$ are hyperparameters equal to $K+1$ and $10 \times \boldsymbol{I}_K$ respectively. The posterior distributions of $\boldsymbol{\Sigma_\phi}$ thus has the form:

$$g\left(\boldsymbol{\Sigma_\phi} \mid \cdot\right) \sim IW\left(c_f, \boldsymbol{D_f}\right), \tag{B8}$$

Where $c_f = 1 + c_\phi$ and $\boldsymbol{D_f} = (\boldsymbol{\phi} - \boldsymbol{\phi_0})(\boldsymbol{\phi} - \boldsymbol{\phi_0})^T + \boldsymbol{D_\phi}$.

Posterior Distribution of $\boldsymbol{\Sigma_t}$, $t = 1, \ldots, T$

We assume the prior distribution of $\boldsymbol{\Sigma_t}$ is an inverse-Wishart distribution: $\boldsymbol{\Sigma_t} \sim IW\left(c_\xi, \boldsymbol{D}_{\xi t}\right)\ \forall t$, where c_ξ and $\boldsymbol{D}_{\xi t}$ are hyperparameters equal to $max(N_t) + 1$ and $\boldsymbol{I}_{N_t}$ respectively, $max(N_t) = 145$ is the maximum number of SKUs on shelves at a time point in our data, and $\boldsymbol{I}_{N_t}$ is a $N_t \times N_t$ identity matrix at time t. The posterior distribution of $\boldsymbol{\Sigma_t}$ at time t thus has the form:

$$g(\boldsymbol{\Sigma_t} |\ \cdot) \sim IWishart\ (c_x, \boldsymbol{D_{xt}}), \tag{B9}$$

where $c_x = 1 + c_\xi$, and $\boldsymbol{D_{xt}} = \boldsymbol{\xi_t} \boldsymbol{\xi_t}^T + \boldsymbol{D}_{\xi t}$.

Posterior Distribution of $\boldsymbol{\delta_0}$

We assume the prior distribution of $\boldsymbol{\delta_0}$ is a multivariate normal distribution: $\boldsymbol{\delta_0} \sim MND(\boldsymbol{A_\delta}, \boldsymbol{B_\delta})$, where $\boldsymbol{A_\delta}$ and $\boldsymbol{B_\delta}$ are hyperparameters equal to $\mathbf{0}_2$ and $10 \times \boldsymbol{I}_2$ respectively, $\mathbf{0}_2$ is a 2×1 zero vector, and $\boldsymbol{I}_2$ is a 2×2 identity matrix. The posterior distributions of $\boldsymbol{\delta_0}$ thus has the form:

$$g(\boldsymbol{\delta_0} |\ \cdot) \sim MND(\boldsymbol{m_d}, \mathbf{v}_{\boldsymbol{d}}), \tag{B10}$$

where $\boldsymbol{m_d} = \mathbf{v}_{\boldsymbol{d}}\left(\boldsymbol{\Sigma}_{\boldsymbol{\delta}}{}^{-1}\boldsymbol{\delta} + \boldsymbol{B_\delta}{}^{-1}\boldsymbol{A_\delta}\right)$, and $\mathbf{v}_{\boldsymbol{d}} = \left(\boldsymbol{\Sigma}_{\boldsymbol{\delta}}{}^{-1} + \boldsymbol{B_\delta}{}^{-1}\right)^{-1}$.

Posterior Distribution of $\boldsymbol{\Sigma_\delta}$

We assume the prior distribution of $\boldsymbol{\Sigma_\delta}$ is an inverse-Wishart distribution: $\boldsymbol{\Sigma_\delta} \sim IW(c_\delta, \boldsymbol{D_\delta})$, where c_δ and $\boldsymbol{D_\delta}$ are hyperparameters equal to 3 and $10 \times \boldsymbol{I}_2$ respectively. The posterior distributions of $\boldsymbol{\Sigma_\delta}$ thus has the form:

$$g(\boldsymbol{\Sigma_\delta} |\ \cdot) \sim IW(c_d, \boldsymbol{D_d}), \tag{B11}$$

Where $c_d = 1 + c_\delta$ and $\boldsymbol{D_d} = (\boldsymbol{\delta} - \boldsymbol{\delta_0})(\boldsymbol{\delta} - \boldsymbol{\delta_0})^T + \boldsymbol{D_\delta}$.