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Product Structure, Brand Width and Brand Share

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Abstract

Most brand managers believe that a brand that has more products should have a higher brand share because it offers more options to customers. We utilize the underlying structure of the products (within a brand) to develop three measures of brand width: the number of stock keeping units (SKUs), the number of distinct feature levels, and the number of distinct products. To examine the impact of brand width on brand share, we develop a logit model and estimate the sensitivities of brand share to our brand width measures using panel data of eight food product categories. Our logit model suggests that the brand width measures provide explanatory and predictive power. In addition, our latent-class analysis implies that different segments have different (brand choice) responses to different measures of brand width. We also use the estimated model to simulate the impact of stock-out and delayed new product introduction on brand share. Our simulation results suggest: (1) stock-out will lower the brand share in a long run and its impact is more severe when the stock-out duration lengthens; and (2) delayed new product introduction will lower the brand share initially but has minimal impact on the brand share in a long run.

Keywords: Brand Share, Brand Choice, Product Variety, Logit Model.

1 Introduction

Does wider product selection in a brand yield higher brand share? Apparently, a lot of brand managers think it does. To compete for higher brand share, many firms expand their brands by launching more products[1]. The following arguments justify why a proliferating brand might be beneficial.

- Heterogeneous Market Segments. Different market segments may have different preference for different products in the same category (see Kamukura and Russell (1989) and Grover and Srinivasan (1987), among others). Thus, a brand with a wider selection serves different market segments better.
- Variety Seeking. Due to satiation (Coombs and Avrunin (1977), McAlister(1982)), consumers may change their preference over time (Kahn, Kalwani and Morrison (1986)). Consequently, a brand with a wider selection is an effectively way to meet the consumers' changing needs.
- Uncertain Preference In a single shopping trip, a consumer might shop for multiple consumption occasions. Because of uncertain preference in future consumption occasions, he may diversify his purchase by buying a selection rather than multiple units of the same product (Simonson, 1990). Hence, a brand with a wider selection allows consumers to diversify their purchase so as to hedge against their uncertain future preference.

While a brand with wider product selection should have a higher brand share, not much empirical work focus on how brand width can be measured and used to predict brand share. This observation has motivated us to obtain a better understanding about how product options affect brand share. In this paper, we consider the case in which the products within a brand can be represented as a tree, where each end node represents a SKU (stock keeping unit).[2] Based on the tree structure, we develop three different brand width measures of a brand: the number of SKUs, the number of distinct feature levels, and the number of distinct products.

To examine the impact of different measures of brand width on brand share, we develop a logit model and estimate the model parameters by using panel data that capture consumers' response to brand width. Specifically, the database contains information on purchases made at 5 stores by 548 households over a two-year period (June 1991 - June 1993). Over the two-year period, the width of each brand changes over time because of frequent product additions

[1] For instance, the number of stock keeping units (SKUs) in consumer packaged goods has been increasing at a rate of 16% every year between 1985 and 1992 (Quelch and Kenny, 1994).

[2] The use of tree structure in representing product is prevalent in marketing literature (e.g. Tversky and Sattath(1979), Moore, Pessemier and Lehmann(1986), Kannan and Wright(1991)).

and deletions[3]. The changing brand widths enable us to examine how brand width affects brand choice. In our logit model, we control for the impact of marketing mix variables such as *price, advertising, promotion* on the *brand choice* of consumers (see, for example, Chintagunta(1993), Gupta(1988), Kamakura and Russell(1989)). Our logit model suggests that those brand width measures provide explanatory and predictive power. In addition, our latent-class analysis implies that different market segments have different (brand choice) response to different measures of brand width.

Our logit model enables us to simulate the impact of stock-out and delayed new product introduction on brand share. Our simulation results have the following implications: (1) stock-out will lower the brand share in a long run and its impact is more severe when the stock-out duration lengthens; and (2) delayed new product introduction will lower the brand share initially but will have minimal impact on the brand share in a long run.

This paper is organized as follows. In section 2, we first present the underlying product tree structure of a brand. Then we introduce three different measures of brand width. Section 3 presents the logit model that is intended to examine the impact of brand width on brand share. We present the model estimation result and discuss its implications in section 4. In section 5, we conduct a simulation experiment to evaluate the long-term impact of stock-out duration and delayed new product introduction on brand share. We conclude in section 6 with suggestions for future research.

2 Product Structure and Measures of Brand Width

2.1 Product Tree

Consider a product category that has several salient features and subtle features. For example, in the ice cream category, flavor and package size are salient features while fruit bits and swirls are considered as subtle features. In general, the salient features are the features that customers care for and that are common to all brands within the product category. To examine how brand width affects brand share, we shall focus on the salient features. In addition, to simplify the exposition, we shall restrict our attention to the case in which there are only 2 salient features: flavor and package size. However, we can apply the same approach for the case when there are more than 2 salient features.

Consider the case in which the product category consists of J brands, where each brand j is comprised of N_j SKUs, where $j = 1, ..., J$. Since most consumer products have discrete number of levels for each feature, we can represent the product structure of each brand j as a tree T_j. Since there are only 2 salient

[3]The number of product additions and product deletions that occurred over a 2-year period are documented in Table 1.

features for the product category, the tree T_j has only 2 levels and each level represent a feature. At each level, different branches correspond to different levels of a feature that the brand possesses. Since each SKU can be specified by a combination of different levels of different features, we can represent each SKU as an end node of the tree, where the path between the root node and the end node specifies the combination of different levels of different features that the SKU possesses. Since there are some subtle features that are not captured by the tree, different SKUs of the same brand may share the same path.

Let us consider a hypothetical example in which the ice cream category has 2 brands: Haagen Dazs and Dreyer's. The product structure of the Haagen Dazs brand is depicted by the tree $T_{HaagenDazs}$ in Figure 1.

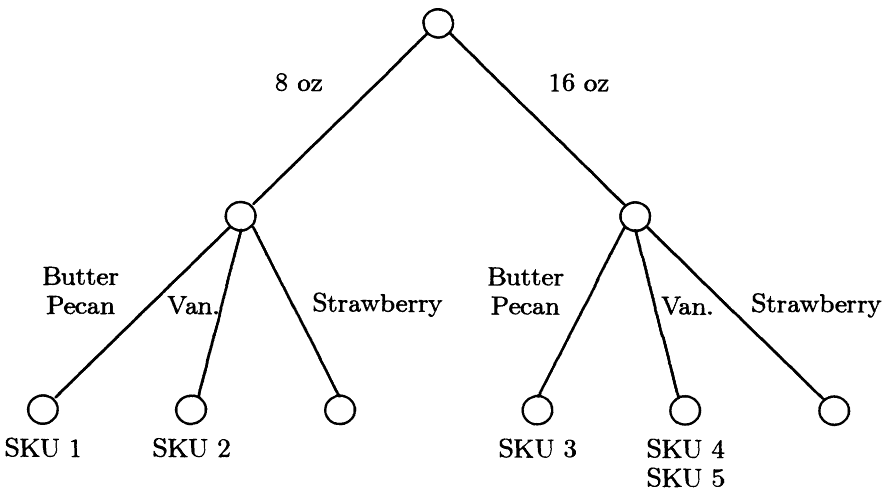

Figure 1: The Product Tree for Haagen Dazs Ice Cream

As shown in Figure 1, the tree $T_{HaagenDazs}$ has 2 levels. Level 1 highlights 2 levels of the package size feature: 8 oz. and 16 oz., and level 2 shows that Haagen Dazs makes only 2 distinct flavors: Butter Pecan and Vanilla. In addition, the Haagen Dazs brand consists of 5 SKUs, where SKU 4 and SKU 5 possess the same level for different salient features but possess different levels of subtle features. For instance, SKU 4 represents the 16 oz. plain vanilla ice cream, while SKU 5 represents the 16 oz. vanilla ice cream (with ground vanilla beans).

By viewing each brand j as a tree T_j, we can define the product options associated with each brand j. Let S_j be the number of 'distinct' package sizes that brand j possesses, F_j be the number of 'distinct' flavors that brand j

possesses, O_j be the number of distinct SKUs (i.e., the number of end nodes that are occupied by at least one SKU) in brand j, and N_j be the number of SKUs in brand j. By examining the tree $T_{HaagenDazs}$ depicted in Figure 1, we have $S_{HaagenDazs} = 2$, $F_{HaagenDazs} = 2$, $O_{HaagenDazs} = 4$, and $N_{HaagenDazs} = 5$.

2.2 Measures of Brand Width

By viewing a brand of products as a tree and by utilizing the definition of S_j, F_j, O_j and N_j, we now develop the following measures of brand width for brand j.

- **Number of SKUs** (N_j)**.** This is a common measure for the width of brand j (see, for example, Chiang and Wilcox(1997)). However, this measure implicitly assumes that all SKUs have identical effect on brand share, which may not be true in general. For instance, consider the tree $T_{HaagenDazs}$ depicted in Figure 1. The impact of SKU 5 on brand share should be relatively low because it has the same level of different salient features as SKU 4. However, if we change SKU 5 to 16 oz. strawberry ice cream, then the new SKU 5 would have a higher impact on brand share because the new SKU 5 provides a new flavor. Since N_j does not capture this phenomenon, we introduce a different measure that deals with this issue.

- **Number of distinct SKUs** (O_j)**.** This measure counts for the number of distinct SKUs in the product tree (or the number of non-redundant SKUs). This measure implicitly assumes that SKUs (with the same level of different salient features) have no impact on brand share. For instance, this measure assumes that SKU 5 in Figure 1 has no impact on brand share of Haagen Dazs, and hence, SKU 5 should not be included in the measure of brand width. This measure, however, does not account for the impact of the number of distinct levels of different features on brand share. To elaborate, suppose we eliminate SKU 5 from the product tree depicted in Figure 1. In this case, $O_j = 4$. Suppose we change SKU 4 to 16 oz. strawberry ice cream. Then F_j increases from 2 to 3. This new change should affect the brand share, but it is not captured by O_j. For this reason, we introduce a different measure.

- **Number of distinct sizes and Number of distinct flavors:** (S_j) **and** (F_j)**.** These two measures assume that the number of distinct sizes and the number of distinct flavors have direct impact on brand share.

The above measures of brand width capture the product options of a brand. However, in order to compare how different brands compete for the sales within a product category, we scale the above brand width measures relative to the category width measures S, F, O, and N, where the category width measures

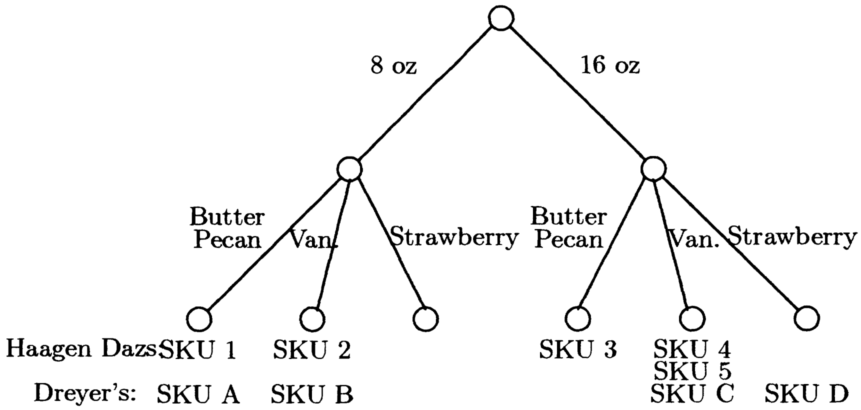

Figure 2: The Product Tree for the Ice Cream Category

are analogous to the brand width measures. To elaborate, consider the case in which there are only two brands within the ice cream category: Haagen Dazs and Dreyer's. Each brand has it own product tree, where $T_{HaagenDazs}$ is given in Figure 1 and $T_{Dreyer's}$ is not shown. Suppose we superimpose both trees. Then this superimposed tree represents the product structure of the ice cream category. Figure 2 depicts the product tree associated with the ice cream category.

It follows from Figure 2, the brand width measures associated with Dreyer's ice cream are given as: $S_{Dreyer's} = 2$, $F_{Dreyer's} = 3$, $O_{Dreyer's} = 4$, and $N_{Dreyer's} = 4$.

Similarly, one can determine the category width measures, that is analogous to the brand width, for the ice cream category as follows: $S = 2$, $F = 3$, $O = 5$ and $N = 9$. It follows from Figure 2, we can scale the brand width measures for brand j according to the category width measures as follows: $\frac{S_j}{S}$, $\frac{F_j}{F}$, $\frac{O_j}{O}$ and $\frac{N_j}{N}$. Notice that these scaled measures are bounded between zero and one.

3 The Model

Given the scaled measures of brand width presented in the last section, we now develop an empirical model that allows us to examine the following questions: Will all SKUs of a brand have the identical impact on the brand share? Will SKUs that occupied the same end node have any effect on brand share? Do the number of package sizes and the number of flavors of a brand affect brand share? In preparation, let us consider the following choice model.

Consider the case in which consumer i goes to store s to purchase ice cream during trip t. There are J brands of ice cream available at store s during trip t, and consumer i has to select one of the J brands. Each brand j is perceived to offer an utility U_{ijt} during trip t, where:

$$U_{ijt} = V_{ijt} + \epsilon_{ijt},$$

V_{ijt} is consumer i's expected utility obtained from buying brand j during trip t; and ϵ_{ijt} is the error term of consumer i's utility that has $E(\epsilon_{ijt}) = 0$. If we assume that consumer i would select the brand that maximizes his utility value and if we assume that the error terms $\epsilon_{ijt}, \forall i, j, t$ are independent and identically distributed with a double exponential (Gumbel) distribution (i.e., $F(\epsilon_{ijt}) = exp(e^{-\epsilon_{ijt}}), \ \forall i, j, t)$, then it can be shown (McFadden 1974, Ben-Akiva and Lehman 1985) that consumer i will select brand j with probability Pr_{ijt}, where:

$$Pr_{ijt} = Prob(U_{ijt} > U_{ij't}, \forall j' \neq j, j' \in \mathcal{J}_{it}) = \frac{e^{V_{ijt}}}{\sum_{j' \in \mathcal{J}_{it}} e^{V_{ij't}}}, \tag{1}$$

where $\mathcal{J}_{it}$ corresponds to the set of brands available in the store s during trip t.

3.1 Model Specifications

To examine the issue of how different brand width measures affect brand share, we develop 4 different models that are based on 4 different specifications of V_{ijt}. The first model is the base model that is based on the work of Guadagni and Little (1983), while the remaining three models incorporate the brand width measures presented in section 2. These 4 models are now specified:
Model 1. The Guadagni and Little Model (GL): In this model, we consider the case in which the expected utility V_{ijt} is specified as:

$$V_{ijt} = \alpha_j + \beta_L L_{ijt} + \beta_P P_{jt} + \beta_D D_{jt} + \beta_{AD} AD_{jt},$$

where α_j is an intercept term that is specific to brand j. We shall assume that α_j is stationary over time and constant across all consumers. In addition, L_{ijt} represents the consumption experience of brand j to consumer i up to trip t and β_L is the corresponding parameter. According to Guadagni and Little, this consumption experience corresponds to *brand loyalty* that can be expressed as the exponentially weighted average of past purchases[4]:

$$L_{ijt} = \phi L_{ij,t-1} + \begin{cases} (1-\phi) & \text{if consumer } i \text{ bought brand } j \text{ at time } t-1, \\ 0 & \text{otherwise.} \end{cases} \tag{2}$$

where $L_{ij,t-1}$ is the loyalty of consumer i towards brand j on trip $t-1$, ϕ is a smoothing constant bounded between zero and one. The above specification

[4]Hence, the brand loyalty variable is bounded between 0 and 1

of consumption experience implies that a brand j that is frequently bought in the past will have a higher value of L_{ijt}. Next, P_{jt}, D_{jt}, AD_{jt} represent the price, display and advertising feature of brand j during trip t, respectively. In addition, $\beta_P, \beta_D, \beta_{AD}$ are the corresponding parameters. Hence, the term $\beta_P P_{jt} + \beta_D D_{jt} + \beta_{AD} AD_{jt}$ captures the marketing environment, such as price, display and advertising feature, that varies over time.

Model 2. The Number of SKUs Model (GL + N): In this model, we augment the (GL) model by adding an additional variable N_{jt}, where $\frac{N_{jt}}{N_t}$ represents the relative number of SKUs in brand j (with respect to the whole product category) observed by consumer i on trip t[5]. Hence, the complete specification for the model becomes:

$$V_{ijt} = \alpha_j + \beta_L L_{ijt} + \beta_P P_{jt} + \beta_D D_{jt} + \beta_{AD} AD_{jt} + \beta_N \frac{N_{jt}}{N_t}.$$

If the number of SKUs of a brand has significant impact on brand share, then the (GL + N) model should outperform the (GL) model.

Model 3. The Number of Distinct SKUs Model (GL + O): In contrast to model (GL + N), we eliminate those 'redundant' SKUs that have the same level of different salient features (i.e., those SKUs that share the same end nodes). In this model, we replace the term $\frac{N_{jt}}{N_t}$ by $\frac{O_{jt}}{O_t}$. The (GL + O) model specification is given as:

$$V_{ijt} = \alpha_j + \beta_L L_{ijt} + \beta_P P_{jt} + \beta_D D_{jt} + \beta_{AD} AD_{jt} + \beta_O \frac{O_{jt}}{O_t}.$$

If those redundant SKUs (i.e., those SKUs that occupied the same end nodes have no effect on brand share, then the (GL + O) model would outperform the (GL + N) model.

Model 4. The Combined Model (GL + SFO): This model is intended to capture the impact of the number of distinct levels of each feature on brand share. Specifically, we examine the impact of the number of distinct package sizes and the number of distinct flavors on brand share. By introducing additional variables $\frac{S_{jt}}{S_t}$ and $\frac{F_{jt}}{F_t}$ to the (GL + O) model, we can specify the (GL + SFO) model as follows:

$$V_{ijt} = \alpha_j + \beta_L L_{ijt} + \beta_P P_{jt} + \beta_D D_{jt} + \beta_{AD} AD_{jt} + \beta_S \frac{S_{jt}}{S_t} + \beta_F \frac{F_{jt}}{F_t} + \beta_O \frac{O_{jt}}{O_t}.$$

Note that the (GL + SFO) model enables us to examine the impact of the number of distinct levels of different features on brand share.

In this section, we present 4 different model specifications for the logit model that are intended to examine the effect of different measures of brand width on

[5]We extend the term N_j and N to include a time index because the number of SKUs is generally different for different shopping trips. We also extend the term S_j, F_j, O_j, S, F, and O by including the time index

brand share. In the next section, we discuss the estimation of the parameters of the model; i.e., α, β and ϕ, where ϕ is bounded between zero and one. We estimate these parameters by fitting our panel data to the proposed models and using maximum likelihood estimation to derive the parameters. We expect the parameter estimates for price, β_P to be negative and we expect other parameter estimates, such as $\beta_D, \beta_{AD}, \beta_N, \beta_S, \beta_F$ and β_O, to be positive. Besides estimating the parameters for each of the 4 model specifications, we also extend our model specification to a two-segment model by using the finite mixture approach (e.g. Kamakura and Russell, 1989)[6].

4 Estimation and Results

In this section, we first describe the data set and discuss briefly the estimation methodology. Then we present the empirical results.

4.1 Data Description

The scanner panel data is drawn from a single IRI market in a metropolitan area in United States[7]. It contains information on household level shopping trips taken over a 2-year period (June 1991 - June 1993) by 548 households. In addition, the database contains purchasing information of 8 food categories at 5 stores located in the same area. These 8 food categories are: Regular Cereal, Yogurt, Ice Cream, Frozen Pizza, Potato Chips, Coffee, Spaghetti Sauce and Hot Dogs.[8] The data set also contains information regarding product availability at each store on a weekly basis. As well as marketing information such as price of SKUs at each stores, advertising features, and in-store display on a weekly basis.

The input variables for our logit model are defined as follows. First, the price of each SKU is computed according to the price per basic unit (e.g., price per oz.). To compute P_{jt}, the price of a brand j in week t, we compute the average price of all SKUs that belong to the brand.[9] In addition, the variable AD_{jt} (the advertising feature) and the variable D_{jt} (the in-store display) are treated as zero-one variables. Next, for different measures of brand width, we utilize the data description files to identify the corresponding brand name, package size, and flavor of each SKU[10]. Due to stock-out, product addition, or product

[6] We do not extend to more than two segments. Extension to more than two segments results in too many parameters for our data sample size.

[7] We are grateful to Professor David Bell for providing us with the data. The data used here represents a portion of the "Basket" data from Information Resources, Inc.

[8] We choose to estimate the parameters on food products because the phenomena of market segmentation, variety seeking and portfolio purchasing are more prevalent in food products (e.g. McAlister, 1982).

[9] Chiang (1991), and Wagner and Taudes (1986) used the same approach to compute the weekly price of a brand

[10] Examples of the different package sizes and flavors for each category are given in Table 1.

deletion, the product tree structure associated with each brand may vary from week to week because the set of SKUs associated with each brand varies from week to week. By specifying the product tree structure associated with each brand j in week t, we can compute those brand width measures N_{jt}, S_{jt}, F_{jt} and O_{jt}. In addition, by superimposing those product trees of different brands that belong to the same category, we can compute those category width measures N_t, S_t, F_t and O_t.

4.2 Estimation of Parameters

To estimate the parameters for our single-segment model, we use the maximum likelihood estimation for the following reasons. First, the maximum likelihood estimation method is asymptotically efficient[11] and it generates normally distributed parameter estimates. Second, the maximum likelihood estimation method enables us to compare the effectiveness of different models. Our maximum likelihood estimation for our model is based on the log-likelihood function $\mathcal{LL} = \sum_i \sum_j \sum_t I_{ijt} \ln Pr_{ijt}$, where Pr_{ijt} (given in (1)) represents the choice probability of consumer i choosing brand j at time t, and I_{ijt} is the indicator variable for consumers i choosing brand j at time t. For the two-segment model, we extend the single-segment log-likelihood function to $\mathcal{LL} = \sum_i \sum_j \sum_t I_{ijt} \ln(\pi^1 Pr^1_{ijt} + \pi^2 Pr^2_{ijt})$, where π^k denotes the probability of having consumer i belonging to segment k, $k = 1, 2$, and Pr^k_{ijt} is the corresponding choice probability of consumer i. For the single-segment and the two-segment models, we have to avoid singularity in our estimation of the α_j's. To do so, we omit α_J, where brand J is the brand that has the lowest brand share. In addition, we use a non-linear optimization routine with analytical gradient to perform the maximization.

4.3 Calibration and Validation Results

To estimate the parameters and to validate our logit model, we divide the data over 104 weeks (2 years) as follows. The first 13 weeks of data are used for initialization, the next 65 weeks are reserved for calibration, and the last 26 weeks are used for validation purposes[12]. By focusing on single-segment, we now report the estimated parameters for the four models presented in section 3. Using the (GL) model as a benchmark, the log-likelihood ratios[13] for the (GL + N), the (GL + O), and the (GL + SFO) models are given in Table 2. The validation results (in terms of the hit rate and the mean squared deviation)

[11] In most product categories, our data set have in excess of 3000 observations. Hence, we should have a sufficient sample size to benefit from the asymptotic property

[12] A detailed breakdown of the sample size for all categories is given in Table 1.

[13] The log-likelihood ratio is given by ($\mathcal{LR} = -2(\mathcal{LL}_M - \mathcal{LL}_{GL})$ where $\mathcal{LL}_M$ refers to the log-likelihood of a model that incorporate the brand width measures and $\mathcal{LL}_{GL}$ refers to the log-likelihood of the (GL) model

are reported in Table 3, and the estimated parameters of our logit models are summarized in Table 4.

The results reported in Tables 2 and 3 have the following implications:

- **The brand width measures have significant impact on brand share.** This implication is derived from Table 2 and Table 3. First, consider the log-likelihood ratios reported in Table 2 that use the (GL) model as the base model. By noting that the log-likelihood ratios for the (GL + N), the (GL + O), and the (GL + SFO) models are significant for 7 categories at 0.1% significant level (except Spaghetti Sauce)[14], we can conclude that the logit models that include various brand width measures outperform the (GL) model. Next, observe from Table 3 that the (GL + N), the (GL + O), and the (GL + SFO) models have better predictive power than the (GL) model in terms of hit rate and mean squared deviation. Therefore, we can conclude that the brand width measures such as N_j, O_j, S_j and F_j have significant impact on brand share.

- **Duplicate SKUs have little impact on brand share.** This implication is deduced from Table 2 and Table 3. In Table 2, we observe that the (GL + O) model outperforms the (GL + N) model in terms of log-likelihood ratio for 6 categories (except Hot Dogs and Spaghetti Sauce). Then in Table 3, we notice that the (GL + O) model has similar predictive performance as the (GL + N) model in terms of hit rate and mean squared deviation. Thus, the (GL + N) model does not provide improvement over the (GL + O) model, and hence, we conclude that SKUs that possess same level of different salient features have little impact on brand share.

- **The number of distinct package sizes and the number of distinct flavors have significant impact on brand share.** This implication is deduced from Table 2 and Table 3. Specifically, we observe that the (GL + SFO) model outperforms the (GL), the (GL + N) and the (GL + O) models in terms of log-likelihood ratios in Table 2 and the (GL + SFO) model has slightly better predictive performance than the other models. Hence, we can conclude that the number of distinct levels of each salient feature that a brand possesses has significant impact on brand share.

The implications generated from Tables 2 and 3 provide the following insight: brand width measures have significant impact on brand share; however, certain measures of brand width (such as the number of distinct flavors) have higher impact on brand share. We now examine the magnitude of the impact

[14]For the spaghetti sauce category, only the (GL + N) model shows significant log-likelihood ratio over the (GL) model at 0.1% significant level.

of different brand width measures on brand share. To do so, let us examine the parameter estimates reported in Tables 4a.

Table 4a has the following implication:

- **The impact of the number of distinct feature levels on brand share depends on product type.** This implication is generated from Table 4a. Specifically, observe that the impact of number of distinct flavors on brand share for products such as pizza, ice cream, yogurt and spaghetti sauce is substantially higher than the impact of the number of distinct package sizes. For example, note that $\beta_F = 4.1262$ and $\beta_S = 0.9402$ for the pizza category[15]. On the contrary, the impact of number of distinct package sizes on brand share for products such as potato chips, regular cereal, coffee and hot dogs, is substantially higher than the impact of the number of distinct flavors. For example, note that $\beta_S = 2.6964$ and $\beta_F = 1.1364$ for the regular cereal category.

The implication generated from Table 4a provides the following managerial insight. When a firm is planning to increase the number of SKUs as a mechanism to increase brand share, it is important for the brand manager to have a good understanding about how consumers respond to different measures of brand width.

We now discuss our estimation results for the two-segment model. Since the (GL) model is the base model and since (GL + SFO) model outperforms all other models in the single segment analysis, we shall consider these two models only in our two-segment analysis. In the two-segment analysis, the (GL2) model and the (GL2 + SFO2) model are analogous to the (GL) model and the (GL + SFO) model in the single-segment analysis, respectively. The calibration results, the validation results, and the estimated parameters for each category are reported in Tables 2, 3, and 4b, respectively.

Observe the likelihood ratios from Table 2 that the (GL2 + SFO2) model provides a better fit (at 0.1% significant level) than the (GL2) model and the single-segment (GL + SFO) model for all eight categories. Next, by examining the hit rate and the mean squared deviation from Table 3, we can conclude that the superior performance of the (GL2 + SFO2) model in the two-segment analysis is not due to over-fitting. In addition, by comparing the validation results (i.e., the log-likelihood, the hit rate and the mean squared deviation)[16]

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[15]Note that the two estimates are comparable because both are coefficients to scale measures that are bounded between zero and one

[16]The best values for the three predictive measures in each category are highlighted in bold face in Table 3.

associated with the (GL2 + SFO2) model and the other models for the single-segment analysis as well as the (GL2) model for the two-segment analysis, it is easy to check that the (GL2 + SFO2) model outperforms all other models in seven out of eight categories. Hence, we can conclude that there exists some heterogeneity in the consumer response to different measures of brand width.

To examine how different segments react to different measures of brand width, let us examine the estimated parameters of β_O, β_F, and β_S for the (GL2 + SFO2) model from Table 4b. Notice that in coffee, potato chips and yogurt, the two segments have different response to the number of distinct flavors F_j, and the number of distinct package sizes S_j. Specifically, notice that the consumers in segment 1 a higher value of β_F while the consumers in segment 2 a higher value of β_S. Segment 1 is more responsive to selection in flavor while segment 2 is more responsive to selection in package size. Frozen pizza, ice cream, and spaghetti sauce are more responsive to selection in flavor for both segments while regular cereal and hot dogs are more responsive to selection in package size for both segments.

5 Impact of Stock-Out and Delayed New Production Introduction

Observed the number of product additions and deletions in Table 1, the number of SKUs associated with a brand could vary from week to week. This variation could be caused by different assortment plans at different stores in different weeks. However, stock-outs and new product introductions at the stores could also cause this variation. Specifically, stock-out reduces the number of SKUs over the duration of the stock-out, while new product introduction increases the number of SKUs over the product life cycle. Hence, stock-outs and new product introduction affect different brand width measures, which in turns affect brand share. In this section, we utilize our (GL + SFO) model for the single-segment to simulate the long term impact of stock-out and delayed new product introduction on brand share. The reason for adopting a simulation methodology is that we can isolate the impact of a stock-out or a new product introduction without the interference from a changing market environment.

In our simulation experiment, we consider the frozen pizza category in which brand 1 encounters a stock-out over 1 week, 5 weeks, and 15 weeks. To simulate delayed new product introduction, we consider the case in which a frozen pizza, that belongs to brand 1, is actually introduced in week 51, week 55, and week 65 (instead of week 50). For both simulation experiments, we consider the SKU (that runs out or being introduced) is a distinct SKU within the brand and it possesses a distinct flavor as well as a distinct package size. This implies that we can adjust the values of O_1, F_1, and S_1 for the (GL + SFO) model as follows. For the stock-out simulation, we reduce these values by 1 over the stock-out duration. Similarly, for the delayed new product introduction simulation, we increase these values by 1 from the actual product introduction week onwards.

We conduct our simulation experiments as follows. We include all consumers (337 in total) who purchase frozen pizzas over the calibration phase (65 weeks) in our simulation experiments. We use the estimated parameters for the (GL + SFO) model obtained from the calibration phase (including the brand loyalty variables from the consumers' last purchase in the calibration phase), to simulate the choice behavior of these 337 consumers over 1000 (simulated) consecutive purchases that occur over 1000 consecutive weeks (from week 0 to week 999). The market environment is held constant throughout the 1000 purchases. We simulate the choice behavior under 6 different market environments[17]. For each of the six market environments, we generate 40 random replications of the 1000 consecutive purchases for each consumer that occur over 1000 consecutive weeks.

In each week, we compute the choice probabilities for each consumer and we simulate a choice by a random draw based on these choice probabilities. This simulated choice is then used to update the brand loyalty variable[18] and the choice probabilities for the next purchase. Hence, for each purchase that occurs in each week, we generate 13,480 random purchases because 13,480 = 337 (number of consumers) x 40 (random replication for each purchase). To compute the brand share of brand 1 in each week, we can simply compute the proportion of those 13,480 purchases that belongs to brand 1. Figure 3 presents the simulated brand share of brand 1 when there is a stock-out for 1 week (from week 0 to week 1), 5 weeks, and 15 weeks. In addition, Figure 4 presents the simulated brand share of brand 1 when a new pizza is actually introduced in week 51, week 55, and week 65 (instead of week 50).

Observe from Figure 3 that the brand share will reduce when a distinct SKU runs out. In addition, the brand share will suffer in a long run if the duration of the stock-out lengthens. This phenomenon can be explained as follows. When the stock-out duration is short, some consumers may switch to other brands temporarily and may switch back when the SKU becomes available

[17]We consider two pricing scenarios. In the first pricing scenario, the price of each brand is the same as the average price of the brand observed in calibration phase. In the second pricing scenario, the price of each brand fluctuates between the maximum and minimum prices observed in the calibration phase. In addition, we consider four display and advertising scenarios that are resulted from whether the leading brand has display and advertising at the store and whether all competitive brands have display and advertising at the store. However, the scenario, which has both the leading brand and all competitive brands display and advertise their products concurrently, is redundant. This is because the promotional effects cancel out. Thus, this scenario has the same effect as the scenario in which there is no display or advertising for any brand. Coupling the three display and advertising scenarios with the two pricing scenarios, we have 6 market environments to consider.

[18]Note that brand loyalty variable is the only variable that changes from one purchase to the next since the variable is affected by past purchases.

again. However, when the stock-out duration is long, the chance for those consumers who switch to other brands and become loyal to other brands is much higher. Consequently, the brand share will suffer in a long run. Next, observe from Figure 4 that delayed new product introduction reduces the brand share over the delayed periods. However, it has very mild impact on the brand share in a long run. This is primarily because delayed new production introduction would not cause the loyal consumer to switch to other brands[19].

6 Concluding Remarks and Future Research

To examine the impact of brand width on brand share, we have utilized the product tree structure to develop different measures of brand width and the corresponding logit models in this paper. Our empirical results confirm that a brand with wider brand width should have a higher brand share. In addition, we found that the impact of the number of distinct package sizes and the number of distinct flavors on brand share is significant and the magnitude of this impact depends heavily on the type of product. Moreover, our logit model enables us to construct simulation experiments that are intended to examine the impact of stock-out and delayed new product introduction. Our simulation experiments have the following implications. First, the brand share will suffer during the stock-out periods and the brand share could continue to suffer in a long run if the stock-out duration is long. Second, when the introduction of a new product is delayed, the brand share will suffer during the delayed periods. However, delayed new product introduction has very little impact on the brand share in a long run.

Although our model indicates that increasing the number of distinct flavors or distinct package sizes (i.e., the number of levels of a salient feature) will increase brand share, it does not identify which new feature level should be added to the existing products of a brand. To identify an effective feature level, one needs to model the consumers' response to a specific configuration of the product tree as depicted in Figure 1[20]. We pursue this modeling effort in the next chapter.

There are several other issues of interests that have not been addressed in this paper. We have not derived the "optimal" assortment of products at the brand level as well as at the category level. At the category level, this issue has been well addressed in the economic literature (The reader is referred to Lancaster(1990) and Bailey and Friedlaender(1982) for a survey). At the brand level, such analysis requires a proper understanding of the cost and ben-

[19] This conclusion is based on the assumption that no new products are introduced by other brands.

[20] Kannan and Wright(1991) and Fader and Hardie(1996) represent two attempts in this direction.

efit elements[21]. Given that the cost and benefit elements, there are several prescriptive/optimization models that deal with composing an optimal product portfolio (see Green and Krieger (1985), Dobson and Kalish(1988), and McBride and Zufryden(1988)). In any event, the brand choice model presented in this paper represents a step towards a better understanding of the benefit of a bigger assortment of products within a brand.

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[21] Quelch and Kenny(1994) discussed the cost associated with different assortments of products within a brand. Kekre and Srinivasan(1988) concluded that increase in production costs is not empirically supported.

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Table 1: Basic Data Description

Category	Coffee	Frozen Pizza	Hotdogs	IceCream	Potato Chips	Regular Cereal	Spaghetti Sauce	Yogurt
Sample Size	6584	5312	4114	6984	7023	12978	4226	12602
Initialization	707	503	607	1004	930	1676	440	1457
Calibration	4363	3397	2580	4356	4395	8262	2701	7955
Validation	1514	1412	927	1624	1698	3040	1085	3190
Total No of Brands over 5 store	47	40	38	37	29	35	41	15
Average No of Brands observed per Visit	22.22	15.34	14.54	15.07	12.09	14.34	17.57	5.63
Total No of SKUs over 5 store	391	337	128	421	285	242	194	288
No. of Products added over 2 years	113	109	47	129	93	114	70	107
No. of Products removed over 2 years	135	96	32	118	77	75	36	51
Feature Description								
Package Size								
Total Number	49	145	11	9	32	73	30	7
Example	26 oz 8 oz 24 oz	22 oz 20 oz 17 oz	16 oz 12 oz 40 oz	64 oz 16 oz 32 oz	6.5 oz 7 oz 6 oz	12 oz 18 oz 15 oz	30 oz 26 oz 14 oz	6 oz 8 oz 32 oz
Flavor/Ingredient								
Total Number	90	71	15	145	31	45	31	74
Example	Regular Columbian Kenya	Sausage Cheese Deluxe	Beef Chicken&Pork Pork&Turkey	Vanilla Neapolitan Chocolate	Regular BBQ SourCream& Onion	Corn Wheat Bran Rice	Plain Italian Garden Tomato & Herb	Plain Strawberry Raspberry

Table 2: Calibration Result
-- Log-Likelihood and Log-Likelihood Ratio

Category	Coffee	Frozen Pizza	Hotdogs	IceCream	Potato Chips	Regular Cereal	Spaghetti Sauce	Yogurt
1-Segment Models								
Quadagni & Little(GL)								
LL	-6305.80	-5053.65	-3768.0384	-5940.67	-6430.32	-11050.18	-2835.40	-5256.03
No fo SKUs(GL+N)								
LL	-6284.03	-5016.38	-3711.05	-5895.76	-6396.79	-10997.80	-2826.95	-5222.12
LR(GL), (d.o.f.)	43.54 (1)	74.53 (1)	113.98 (1)	89.82 (1)	67.07 (1)	104.76 (1)	16.91 (1)	67.82 (1)
No of Distinct SKUs(GL+O)								
LL	-6269.76	-5014.21	-3724.05	-5873.24	-6388.62	-10993.67	-2832.70	-5210.23
LR(GL), (d.o.f.)	72.08 (1)	78.88 (1)	87.98 (1)	134.86 (1)	83.42 (1)	113.02 (1)	5.40 (1)	91.59 (1)
LR(GL+N), (d.o.f.)	28.53 (0)	4.35 (0)	-26.01 (0)	45.04 (0)	16.35 (0)	8.26 (0)	-11.51 (0)	23.77 (0)
No of Dinstinct Feature Levels(GL+SFO)								
LL	-6250.04	-4936.35	-3715.51	-5825.19	-6317.86	-10934.84	-2828.78	-5198.19
LR(GL), (d.o.f.)	111.52 (3)	234.60 (3)	105.06 (3)	230.96 (3)	224.94 (3)	230.68 (3)	13.23 (3)	115.67 (3)
LR(GL+N), (d.o.f.)	67.98 (2)	160.07 (2)	-8.93 (2)	141.13 (2)	157.87 (2)	125.91 (2)	-3.67 (2)	47.84 (2)
LR(GL+O), (d.o.f.)	39.44 (2)	155.72 (2)	17.08 (2)	96.09 (2)	141.52 (2)	117.65 (2)	7.83 (2)	24.07 (2)
2-Segment Models								
Quadagni and Little (GL2)								
LL	-6175.52	-4927.52	-3732.74	-5853.98	-6310.78	-10667.81	-2718.29	-4942.75
No of Dinstinct Feature Levels(GL2+SFO2)								
LL	-5975.48	-4740.85	-3647.68	-5718.34	-6121.66	-10579.82	-2706.19	-4835.85
LR(GL2), (d.o.f.)	400.09 (6)	373.33 (6)	170.13 (6)	271.29 (6)	378.23 (6)	175.98 (6)	24.20 (6)	213.80 (6)
LR(GL+SFO), (d.o.f.)	549.13 (55	390.99 (48	135.66 (46	213.71 (45	392.39 (37)	710.04 (43)	245.20 (49)	724.68 (23)

Note 1: LR(M) is the log-likelihood ratio with model M as a benchmark with the degree of freedom (d.o.f.) indicated

Note 2: The following table provide the chi-sq value at 0.1% significant level

d.f.	Chi-Sq
1	10.83
2	13.82
3	16.27
6	22.46
23	49.73
37	69.35
43	77.42
46	81.40
47	82.72
48	84.04
49	85.35
55	93.17

Table 3: Valibration Result
-- Log-Likelihood and Mean Squared Deviation

Category	Coffee	Frozen Pizza	Hotdogs	IceCream	Potato Chips	Regular Cereal	Spaghetti Sauce	Yogurt
1-Segment Models								
Quadagni & Little(GL)								
LL	-2156.13	-2044.91	-1385.39	-2213.88	-2466.27	-4260.44	-1226.86	-2141.45
MSD	0.0259	0.0353	0.0352	0.0360	0.0459	0.0459	0.0264	0.0629
No fo SKUs(GL+N)								
LL	-2147.57	-2030.04	-1369.22	-2188.21	-2447.45	-4240.92	-1217.94	-2126.51
MSD	0.0259	0.0351	0.0348	0.0357	0.0456	0.0458	0.0262	0.0626
No of Distinct SKUs(GL+O)								
LL	-2141.35	-2028.58	-1371.54	-2178.37	-2439.34	-4239.77	-1223.50	-2119.78
MSD	0.0259	0.0351	0.0349	0.0356	0.0454	0.0458	0.0264	0.0624
No of Dinstinct Feature Levels(GL+SFO)								
LL	-2138.24	-2011.75	-1371.72	-2155.13	-2378.54	-4210.23	-1221.77	-2109.44
MSD	0.0260	0.0349	0.0349	0.0353	0.0448	0.0457	0.0263	0.0621
2-Segment Models								
Quadagni and Little (GL2)								
LL	-2156.33	-1971.89	-1384.49	-2185.83	-2460.14	-4113.56	**-1193.76**	-2038.27
MSD	0.0260	0.0342	0.0352	0.0357	0.0464	0.0447	**0.0256**	0.0603
No of Dinstinct Feature Levels(GL2+SFO2)								
LL	**-2060.70**	**-1942.96**	**-1355.88**	**-2125.89**	**-2342.61**	**-4066.27**	-1195.96	**-1998.20**
MSD	**0.0250**	**0.0340**	**0.0347**	**0.0350**	**0.0446**	**0.0446**	**0.0256**	**0.0595**

Note 1: Bold-faced values indicate the best value observed for the category

Table 4a: Parameter Estimates for One-Segment Models

Category	Coffee	Frozen Pizza	Hotdogs	IceCream	Potato Chips	Regular Cereal	Spaghetti Sauce	Yogurt
Guadagni & Little(GL)								
$\alpha_{max} - \alpha_{min}$	2.5227	2.7649	2.5691	2.7603	4.4064	3.1435	2.8314	2.9585
β_L	6.5934 *	4.6056 *	5.3021 *	5.3022 *	4.5819 *	4.3884 *	4.6065 *	2.9745 *
ϕ	0.7767 *	0.6760 *	0.7521 *	0.7310 *	0.7967 *	0.8615 *	0.7006 *	0.5224 *
β_P	0.0000	-0.4113 *	-0.5545 *	-0.9568 *	-1.1078 *	-0.0270	-0.1793	-1.8890 *
β_D	0.2529 *	0.4710 *	0.8082 *	1.0115 *	0.4907 *	0.0459	0.2824 **	0.5580 *
β_{AD}	1.0515 *	0.5196 *	0.7345 *	1.2097 *	0.7441 *	0.2409 *	1.2378 *	0.6366 *
No fo SKUs(GL+N)								
$\alpha_{max} - \alpha_{min}$	2.5452	3.4270	4.5627	2.9130	4.8387	3.1812	2.6432	2.6893
β_L	6.5934 *	4.5248 *	5.2215 *	5.2189 *	4.5807 *	4.3423 *	4.5805 *	2.9421 *
ϕ	0.7767 *	0.6734 *	0.7526 *	0.7296 *	0.7980 *	0.8624 *	0.7011 *	0.5197 *
β_P	0.0000	-0.4890 *	-0.9436 *	-1.0647 *	-1.1933 *	-0.1619 **	-0.1620	-2.1800 *
β_D	0.2682 *	0.4443 *	0.8166 *	1.0160 *	0.4830 *	0.0470	0.2684 **	0.5307 *
β_{AD}	1.0348 *	0.5016 *	0.5779 *	1.1616 *	0.6959 *	0.2055 *	1.2205 *	0.5971 *
β_N	1.4491 *	1.9213 *	6.4264 *	1.9195 *	1.7606 *	1.6430 *	1.6711 *	1.8154 *
No of Distinct SKUs(GL+O)								
$\alpha_{max} - \alpha_{min}$	2.5996	3.4283	3.9411	2.8312	4.6400	3.1931	2.6988	2.6757
β_L	5.7789 *	4.5219 *	5.2873 *	5.1892 *	4.5997 *	4.3435 *	4.5951 *	2.9169 *
ϕ	0.7770 *	0.6733 *	0.7550 *	0.7294 *	0.7994 *	0.8626 *	0.7007 *	0.5160 *
β_P	0.0000	-0.4904 *	-0.8575 *	-1.0989 *	-1.1930 *	-0.1703 **	-0.1677	-2.3277 *
β_D	0.2780 *	0.4419 *	0.8436 *	1.0208 *	0.4759 *	0.0576	0.2678 **	0.4810 *
β_{AD}	1.0218 *	0.5016 *	0.5929 *	1.1399 *	0.6947 *	0.2006 *	1.2270 *	0.5883 *
β_O	2.0477 *	2.0129 *	3.5097 *	2.4478 *	2.2377 *	1.8247 *	0.9144 *	2.0526 *
No of Dinstinct Feature Levels(GL+SFO)								
$\alpha_{max} - \alpha_{min}$	2.4389	9.1202	4.2097	3.2127	9.3811	4.0592	2.9338	3.3194
β_L	5.7687 *	4.4749 *	5.2364 *	5.1171 *	4.6689 *	4.3490 *	4.5723 *	2.9183 *
ϕ	0.7778 *	0.6711 *	0.7534 *	0.7285 *	0.8043 *	0.8656 *	0.7000 *	0 5177 *
β_P	-0.1718 **	-1.1865 *	-0.9347 *	-1.3415 *	-1.7150 *	-0.6814 *	-0.1571	-2.7697 *
β_D	0.3053 *	0.3313 *	0.8198 *	1.0222 *	0.4362 *	0.1610 **	0.2491	0.3977 **
β_{AD}	0.9758 *	0.3137 *	0.5810 *	1.0438 *	0.4351 *	0.0824	1.2138 *	0.5093 *
β_S	1.8019 *	0.9402 *	1.5777 *	0.4070 **	1.1266 **	2.6964 *	0.0000	0.1180
β_F	1.1914 *	4.1262 *	0.0000	2.3480 *	0.0000	1.1364 *	1.0543 **	1.1202 **
β_O	1.5594 *	0.0000 *	1.4422 *	2.1892 *	3.5492 *	0.8521 *	0.6133 *	1.5418 *

Note 1: * indicates parameter is significant at 1% and ** indicates parameter is significant at 5%

Note 2: α_{max} is the maximum of brand intercepts α_j α_{min} is the minimum of brand intercepts α_j.

Table 4b: Parameter Estimates for Two-Segment Models

Category	Coffee	Frozen Pizza	Hotdogs	IceCream	Potato Chips	Regular Cereal	Spaghetti Sauce	Yogurt
Guadagni and Little (GL2)								
Segment 1								
$\alpha_{max}-\alpha_{min}$	2.6465	2.5148	2.4206	1.5728	1.9928	3.8711	3.8135	2.0596
β_L	39.6639 *	4.1054 *	4.1538 *	6.5833 *	6.4933 *	6.4746 *	7.5169 *	4.9862 *
ϕ	0.9643 *	0.1549 *	0.5142 *	0.5064 *	0.5400 *	0.8605 *	0.8052 *	0.9349 *
β_P	0.0000	-0.1618 *	-0.5872 *	-0.5240 *	-0.3451 *	-0.2706 *	-0.0329	-1.1033 *
β_D	0.3153	0.7566 *	1.0073 *	0.8066 *	0.5770	0.0645	0.0000	0.4344 *
β_{AD}	1.2557 *	0.9743 *	0.8145 *	1.3983 *	0.3981	0.5211 *	1.0560 *	0.7568 *
π_1	32.64% *	41.78% *	49.75% *	41.76% *	35.00% *	44.36% *	48.91%	39.92% *
Segment 2								
$\alpha_{max}-\alpha_{min}$	2.9530	2.2860	2.0667	2.2618	3.5118	2.8710	3.0885	2.9122
β_L	4.7402 *	6.9259 *	10.5309 *	6.2913 *	7.3996 *	6.1241 *	5.1746 *	3.4435 *
ϕ	0.6894 *	0.8826 *	0.9013 *	0.8946 *	0.9532 *	0.8477 *	0.5561 *	0.1199 *
β_P	-0.0129	-0.4101 *	-0.3568 *	-0.8649 *	-1.1860 *	0.0000	-0.6610 *	-1.0104 *
β_D	0.3100	0.4299 *	0.6098	1.0785 *	0.4741 *	0.2131	0.5415 **	0.4195 *
β_{AD}	1.0309 *	0.3741 *	0.8204 *	1.3060 *	1.0205 *	0.1096	1.5644 *	0.8551 *
π_2	67.36% *	58.22% *	50.25% *	58.24% *	65.00% *	55.64% *	51.09%	60.08% *
No of Distinct Feature Levels(GL2+SFO2)								
Segment 1								
$\alpha_{max}-\alpha_{min}$	7.0705	9.5740	3.4462	2.1517	4.6315	3.2860	3.5562	2.7211
β_L	10.7602 *	5.6837 *	6.1244 *	6.1997 *	7.8446 *	5.8497 *	5.6136 *	4.1344 *
ϕ	0.7056 *	0.1334 *	0.4823 *	0.4707 *	0.5450 *	0.8596 *	0.5290 *	0.9226 *
β_P	0.0000	-0.4625 *	-0.5629 *	-0.6287 *	-0.8013 *	-1.3334 *	-0.4925 *	-2.6176 *
β_D	0.5375	0.5281 *	2.1282 *	1.1044 *	1.2578 *	0.0807	0.4419 **	0.6223 *
β_{AD}	0.7156 *	0.3267 *	0.9664 *	1.4348 *	0.0000	0.3224 **	1.6330 *	0.7249 *
β_S	0.2085	1.1110 *	1.8193	0.2016 *	0.0577	3.1286 *	0.0000	0.2399 *
β_F	0.9206	1.8334 *	0.0000	1.0866 *	0.7963	1.2129 *	0.7414	1.2227 *
β_C	0.6606	0.0000	0.6047	0.9665 **	1.2253	0.5321	0 1556	0.8297 *
π_1	39.34% *	39.61% *	31.98% *	40.71% *	30.95% *	49.32% *	46.85%	46.23% *
Segment 2								
$\alpha_{max}-\alpha_{min}$	3.5733	10.9134	3.8909	3.0608	9.8041	3.5282	3.5643	2.4251
β_L	5.9676 *	5.8665 *	6.3676 *	6.1568 *	6.8663 *	6.7066 *	6 9352 *	4.5085 *
ϕ	0.8393 *	0.8697 *	0.8610 *	0.8890 *	0.9454 *	0.8548 *	0.8085 *	0 0000 *
β_P	-0.8453 *	-1.4992 *	-1.1216 *	-1.3769 *	-2.1361 *	-0.0362	-0.0474	-2.0513 *
β_D	0.3359	0.4122 *	0.2022	1.1535 *	0.1988	0.4088 **	0.1464	0.4604 *
β_{AD}	1.0773 *	0.3661 *	0.4961 *	1.0857 *	0.6358 *	0.0000	1.1886 *	0.4871 *
β_S	2.2206 *	2.0880 *	1.7363 *	0.6871 **	2.5675 *	2.5371 *	0.0000	1.3100 *
β_F	1.8931 *	5.3989 *	0.2988	2.1537 *	0.0000	1.7013 *	0.9366	1 0684 *
β_C	2.2794 *	1.0779 *	1.3215 *	2.0428 *	4.1494 *	1.1503 *	1.0758 *	0.9060 *
π_2	60.66% *	60.39% *	68.02% *	59.29% *	69.05% *	50.68% *	53.15%	53.77% *

Note 1: * indicates parameter is significant at 1% and ** indicates parameter is significant at 5%

Note 2: α_{max} is the maximum of brand intercepts α_j. α_{min} is the minimum of brand intercepts α_j

Figure 3: The Impact of Stock-Out Duration on Long Run Brand Share

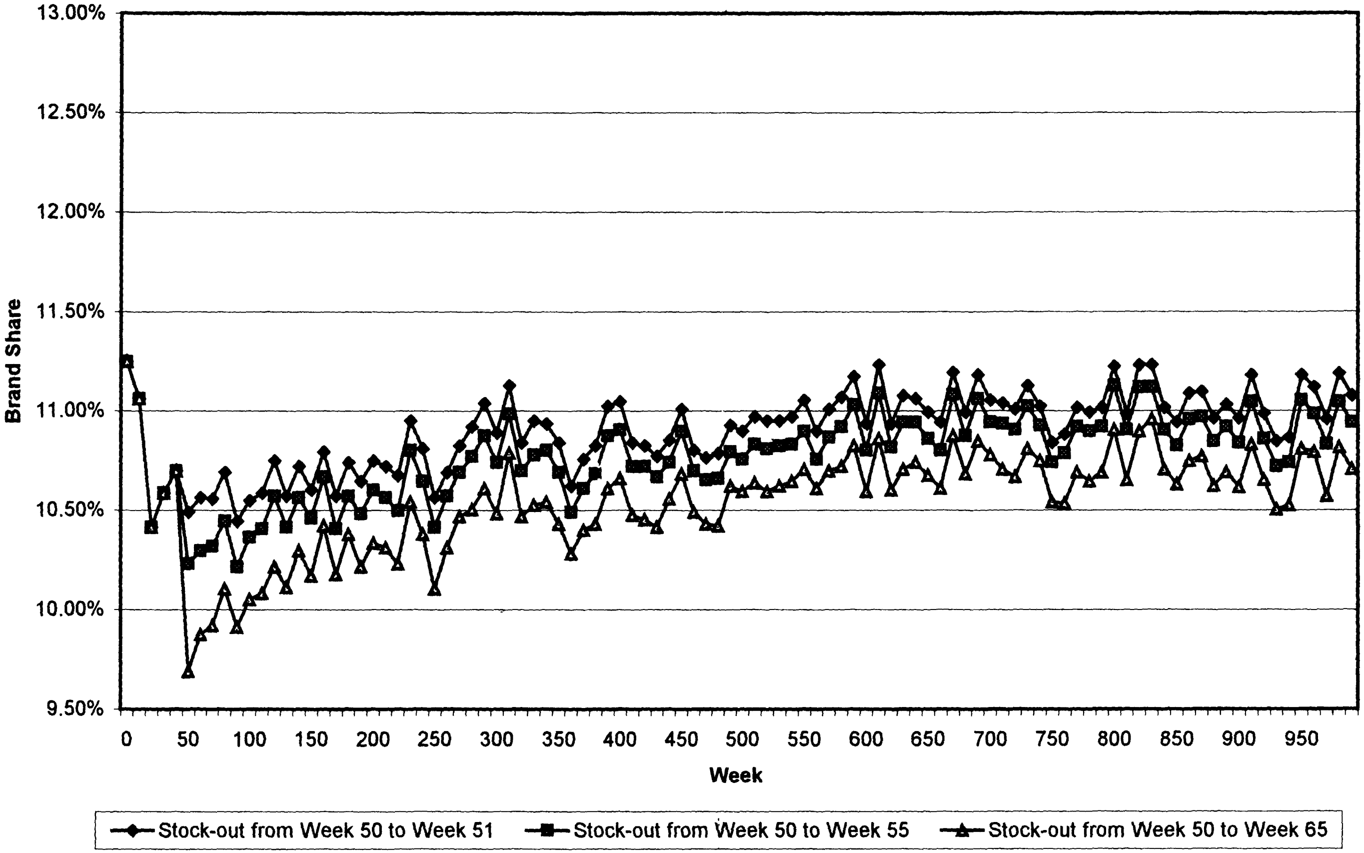

Figure 4: The Impact of Timing of New Product Introduction on Long Run Brand Share