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Effects of Brand Preference, Product Attributes, and Marketing Mix Variables in Technology Product Markets

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We develop a demand model for technology products that captures the effect of changes in the portfolio of models offered by a brand as well as the influence of the dynamics in its intrinsic preference on that brand's performance. To account for the potential correlation in the preferences of models offered by a particular brand, we use a nested logit model with the brand (e.g., Sony) at the upper level and its various models (e.g., Mavica, FD, DSC, etc.) at the lower level of the nest. Relative model preferences are captured via their attributes and prices. We allow for heterogeneity across consumers in their preferences for these attributes and in their price sensitivities in addition to heterogeneity in consumers' intrinsic brand preferences. Together with the nested logit assumption, this allows for a flexible substitution pattern across models at the aggregate level. The attractiveness of a brand's product line changes over time with entry and exit of new models and with changes in attribute and price levels. To allow for time-varying intrinsic brand preferences, we use a state-space model based on the Kalman filter, which captures the influence of marketing actions such as brand-level advertising on the dynamics of intrinsic brand preferences. Hence, the proposed model accounts for the effects of brand preferences, model attributes and marketing mix variables on consumer choice. First, we carry out a simulation study to ensure that our estimation procedure is able to recover the true parameters generating the data. Then, we estimate our model parameters on data for the U.S. digital camera market. Overall, we find that the effect of dynamics in the intrinsic brand preference is greater than the corresponding effect of the dynamics in the brand's product line attractiveness. Assuming plausible profit margins, we evaluate the effect of increasing the advertising expenditures for the largest and the smallest brands in this category and find that these brands can increase their profitability by increasing their advertising expenditures. We also analyze the impact of modifying a camera model's attributes on its profits. Such an analysis could potentially be used to evaluate if product development efforts would be profitable.

Key words: econometric models; hi-tech marketing; advertising; product line attractiveness; product development; nested logit models; Kalman filter
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1. Introduction

Managers in many technology product markets are faced with a variety of challenges. One challenge is to monitor changes in consumer's brand preferences over time. In practice, intrinsic brand preferences can be inferred from tangible performance measures such as sales after accounting for the effects of other factors that may have influenced these measures (e.g., Kamakura and Russell 1993). Given the rapid introduction and withdrawal of models in these markets, one needs to, while measuring the dynamics in brand preferences, partial out the effect of the changing portfolio of models on a brand's performance. For example, the introduction of the *Mavica* line of digital cameras by Sony helped it obtain market leadership and the effect of such changes in product line need to be accounted for. Besides monitoring these preference changes, managers are also interested in understanding the drivers of preferences over time. For example, extant research (e.g., Jedidi et al. 1999) recognizes the importance of advertising in influencing brand preferences. Hence, managers may be interested in understanding the role of advertising in driving the dynamics of brand preferences.

A second issue of interest to managers is to understand what drives the changes in a brand's performance over time. Given that the markets for technology products evolve rapidly, we usually observe some interesting dynamics in the performance of the key brands. For example, in the context of digital cameras, while Casio, the first brand to enter the market, moves from the position of market leader at the beginning of the data to being the lowest selling brand at the end of the data, Sony registers a steady increase in sales. As noted previously, one possibility is that changes in performance are tied to changes in intrinsic preferences. At the same time, they could also be because of (a) the changing portfolio of models in a brand's product line and/or (b) modifications in the attributes and prices of the models in the product line. This calls for an assessment of the relative influence of product line and intrinsic brand preferences on the performance of brands in a category. Such an assessment will guide managers on which aspect to emphasize to improve their brand's performance.

Third, notwithstanding the rapid introduction and withdrawal of models and changing consumer preferences, managers need to evaluate the effects of product attributes and marketing activities on the performance in the marketplace. A related issue is the need to assess the effects of attribute improvements, as well as the introduction of new models with enhanced product attributes on the performance of the brand. Given the high cost of new product development (Urban and Hauser 1993), managers in technology product markets would like to quantify the potential benefits from developmental efforts leading to attribute improvements so as to evaluate their feasibility.

In this paper, we develop a demand model for technology products that aims to address the above issues. We model consumer choice of digital cameras at the brand-model level (for example, Sony Mavica, Casio QV, etc.). A consumer's utility for a model of digital camera is a function of the attributes and the price of that model, with the consumer choosing the brand-model that maximizes utility or deciding not to purchase in the product category. We account for the potential correlation in preferences of models offered by a particular brand, using a nested logit model with the brand (e.g., Sony) at the upper level and its various models (e.g., Mavica, FD, DSC, etc.) at the lower level of the nest. At the aggregate level, we also allow for the potential correlation in utilities of digital camera models that share similar attributes by allowing for consumer heterogeneity in attribute preferences. In addition, we allow for heterogeneity in intrinsic brand preferences and in price sensitivities across consumers. We thus have a demand model that provides flexible substitution patterns while being parsimonious. The inclusive value across models in the nested logit reflects the attractiveness of the brand's product line. This attractiveness changes over time with entry and exit of models as well as because of changes in attribute and price levels. Hence, brand-level preferences are driven by the inclusive value across models as well as the intrinsic preferences for each of the brands.

To allow for time-varying intrinsic preferences at the brand level, we use a state-space model based on the Kalman filter. This Kalman filter component captures the dynamics of the intrinsic brand preferences as influenced by marketing actions such as advertising. In this way, we allow for changing brand preferences and can also understand the role that advertising plays in driving these preferences. While the brand level of the model captures the dynamics in the inclusive value and the brand preferences, the model choice part evaluates the tradeoffs consumers make between different attributes, and thus enables us to quantify the consumer valuation of these attributes. For completeness, our model specification also accounts for potential endogeneity in the pricing decisions of firms (Berry et al. 1995, Sudhir 2001). We carry out a simulation study to ensure that our proposed estimation procedure is able to recover the model parameters.

We estimate our model parameters on data for the U.S. digital camera market spanning 26 months from April 1997 through May 1999. Our results reveal that advertising influences brand preferences for three out of the four brands. All the brands appear to have gained from the changes in their product lines over time to varying degrees. We further investigate the extent to which each of the brands relied on price reduction versus product innovations to make their product lines attractive. We find that while a significant proportion of the gain because of product line changes may be attributed to decreasing prices in the case of Casio; the majority of the gain for Sony was because of the introduction of models with enhanced attributes. All brands except Casio also gain from increases in their intrinsic preferences. Overall, we find that the effect of the dynamics in the intrinsic brand preferences is higher than the corresponding effect of the dynamics in the product line for all the brands. Specifically, the trends in the sales of Casio and Sony are largely driven by the corresponding changes in brand preferences. Given these results, we also assess the profitability of increasing advertising expenditures and changing product attributes for various brand-models.

We provide an analysis of the robustness of our empirical results to alternative demand structures that also result in a flexible aggregate substitution pattern. In addition, we examine the sensitivity of our empirical results to various model assumptions.

The rest of this paper is organized as follows. We first review research related to this paper. We then present the demand model and discuss its estimation. Next, we describe the data. We then present our empirical results based on the digital cameras category and discuss their implications. Subsequently, we evaluate the appropriateness of alternative model specifications. Finally, we provide some concluding comments.

2. Related Research

Given our objectives of evaluating the effects of product attributes as well as capturing the dynamics in the brand preferences on consumer choice, our paper is related to three streams of research. The first stream pertains to studies that have modeled the effect of product attributes on consumer choice. In the context of consumer packaged goods, Fader and Hardie (1996) use household-level scanner data to model consumer choice amongst SKUs by projecting preferences on product attributes. In modeling consumers' choice of automobiles using aggregate data, Sudhir (2001) accounts for the effect of automobile characteristics to estimate consumers' preferences for these attributes. In this study, we use a model that captures the effects of the various attributes of a brand of digital camera using aggregate data to evaluate the impact of changes in these attributes on the brand's performance.

The second stream studies the effect of a firm or a brand's product line on its demand. Previous research has established the relationship between a firm's product line and the demand for its products, especially with respect to the length of the product line. Studies by Kekre and Srinivasan (1990), Bayus and Putsis (1999), and Draganska and Jain (2005) find a positive impact of a firm's product line length (included as a covariate) on its demand. By contrast, as in Draganska and Jain (2006), we explicitly account for the influence of the attributes and prices of individual models in a brand's product line (in addition to the effect of the product line length) on that brand's demand.

The third stream corresponds to those that model dynamic or time-varying parameters. Jedidi et al. (1999) account for the effects of advertising and promotions on dynamic brand preferences for packaged goods. Sudhir et al. (2005) model time-varying competition and investigate the effects of the dynamics in competitive intensity on prices. Xie et al. (1997) and Putsis (1998) use a state-space model based on the Kalman filter (Hamilton 1994, Harvey 1990) to estimate time-varying parameters in the context of new product sales.[1] Neelamegham and Chintagunta (2004) estimate a dynamic linear model to capture the time-varying impact of product attributes at the brand-model level—similar to our unit of analysis. The focus of that study is to obtain sales forecasts at the brand-model level. One limitation of that modeling approach that is overcome by our proposed approach is that the presence of a large number of brand-models requires aggregation of the data to the brand level for all models that are not the focus of the forecasting exercise. By contrast, our model structure requires the presence of a few brands that are stable over time but that could have several time-varying numbers of the model in their product lines. It is this feature that enables us to use a state-space approach based on the Kalman filter to account for dynamic brand preferences.

3. Model and Estimation

During each period t, consumer h is faced with the decision of purchasing a digital camera offered by one of the B brands that are in the market during that period or to not make a category purchase, in which case, the consumer is said to have chosen the outside or no-purchase alternative. Specifically, a consumer chooses to buy a model from the set of $M_{bt} = \{1, 2, \ldots, J_{bt}\}$ models offered by brand b, $b = 1, 2, \ldots, B$, where J_{bt} is the number of models offered by brand b at time t. We represent the consumer product choice behavior using the nested logit model. Under this approach, the consumer's decision is a function of the consumer's idiosyncratic needs, the preference for the brand, and the overall attractiveness of the models offered by the brand. The indirect utility that household h derives from model j offered by brand b at time t is given by

$$\begin{aligned} U_{hjbt} = {} & \alpha_t + \beta_{0hbt} + \theta H_{bt} + \beta_h X_{jbt} \\ & + \xi_{jbt} + (1-\sigma)e_{hjbt} + e_{hbt}, \end{aligned} \tag{1}$$

where β_{0hbt} is the household h's intrinsic preference for the brand name b at time t, H_{bt} is a vector of environmental factors (such as holiday season[2]) that affect the utility of brand b, X_{jbt} is the vector of attributes of model j offered by brand b at time t such as resolution, maximum number of images that can be stored, size of internal and external memory, type of storage media, size of the LCD and marketing variables such

[1] Other papers that have modeled dynamics using the Kalman filter include Naik et al. (1998), Akcura et al. (2004), and Naik et al. (2005).

[2] Although the presence of holidays may not be brand specific, we use the brand subscript for the environmental factors for the sake of generalizability.

as price, and β_h is the vector of consumer taste parameters corresponding to the product attributes. In addition, X_{jbt} may contain other factors such as the age of a model, which may have an effect on the consumer's perception of the model. To allow for the possibility that the age of a model may have a nonlinear effect on its utility, we include a quadratic term of this variable in the model in addition to the linear term. As in most technology products, with the diffusion of the innovation, we would expect some intrinsic category growth. The term α_t is a time-specific dummy, common to all brands and relative to the outside good, that captures the intrinsic category growth in a flexible manner without having to impose a specific functional form for such growth (e.g., via a linear and/or quadratic trend term or via a Bass-type specification).[3] The term ξ_{jbt} captures the effect of omitted attributes such as model color as well as other time-varying, brand-specific utility-influencing factors that are observed by the consumers but not by the researcher. It is assumed to have mean zero. The error term e_{hjbt} is an i.i.d. extreme value random error term that captures the idiosyncratic taste of household h for model j offered by brand b at time t. The error term e_{hbt} is the error component for all the models offered by brand b such that $(1-\sigma)e_{hjbt}+e_{hbt}$ is also an extreme value random variable. The parameter σ $(0<\sigma<1)$, which is the scale parameter in the nested logit specification, captures the extent to which the utilities of the models offered by a particular brand are correlated. Hence the model in Equation (1) takes the specification of the nested logit model with $B+1$ nests. For identification, we set the deterministic component of the utility of the outside alternative to zero. Under the assumptions of the nested logit model, we can express the probability of household h purchasing model j offered by brand b at time t, Pr_{hjbt} as

$$\mathrm{Pr}_{hjbt}=\frac{\exp\big((\delta_{jbt}+\mu_{hjbt})/(1-\sigma)\big)}{\big[1+\sum_{b'=1}^{B}D_{hb't}^{(1-\sigma)}\big][D_{hbt}^{\sigma}]}, \tag{2}$$

where

$$D_{hbt}=\sum_{j\in M_b}\exp\left(\frac{\delta_{jbt}+\mu_{hjbt}}{1-\sigma}\right). \tag{3}$$

D_{jbt} is the inclusive value; δ_{jbt} is the mean (across households) utility of model j offered by brand b at time t, and μ_{hjbt} is the deviation in the utility of household h from this mean. Specifically,

$$\delta_{jbt}=\alpha_\tau+\beta_{0bt}+\theta H_{bt}+\beta X_{jbt}+\xi_{jbt}, \tag{4a}$$

$$\mu_{hjbt}=\Delta\beta_{0hb}+\Delta\beta_h X_{jbt}. \tag{4b}$$

[3] For identification, we set $\alpha_t=0$ for the first period of the data.

The parameter β_{0bt} captures the incremental utility that the average household derives from brand name b at time t with respect to the outside alternative and is a measure of the intrinsic preference for the brand.[4] β is the vector of mean (across households) taste parameters corresponding to the effects of product attributes and other variables in the vector X_{jbt}. $\Delta\beta_{0hb}=(\Delta\beta_{0h1},\Delta\beta_{0h2},\ldots,\Delta\beta_{0hB})$ is the household-specific, time-invariant deviation in brand preferences from β_{0bt} and $\Delta\beta_h$ is the household-specific deviation from β of the effects of the variables in X_{jbt}.

3.1. Unobserved Heterogeneity and the Random Coefficients Nested Logit Model

When μ_{hjbt} in Equation (3) is zero, we obtain a standard nested logit model. This model implies that the pattern of substitution across models from different brands does not suffer from the IIA property. The extent of deviation from IIA depends upon the magnitude of the σ parameter. Nevertheless, the model does suffer from IIA across models within a brand even at the aggregate level. To overcome this limitation, we account for unobserved heterogeneity in the model by allowing μ_{hjbt} to be different from zero. In particular, we assume that the vector $\nu=(\Delta\beta_{0hb},\Delta\beta_h,\ b=1,2,\ldots,B)$ varies across households and follows a normal distribution, i.e., $\nu\sim\mathrm{N}(0,\Sigma)$. More importantly, even if each of the parameters follows an independent normal distribution, the IIA property is alleviated as different models within a brand share different attributes, and the presence of these attributes and their heterogeneous effects induces a correlation in the utilities of models within a brand. Hence, correlation in utilities has three sources in our model: (i) because of the assumption on the extreme value errors and the nested logit; (ii) because of heterogeneity in brand preferences, $\Delta\beta_{0hb}$; and (iii) because of heterogeneity in the effects of brand-model attributes, $\Delta\beta_h$.

Given the above distributional assumption on the vector, ν, the market share of model j offered by brand b at time t, s_{jbt} can be written as

$$s_{jbt}=\int_A\frac{\exp\big((\delta_{jbt}+\mu_{hjbt})/(1-\sigma)\big)}{\big[1+\sum_{b'=1}^{B}D_{hb't}^{(1-\sigma)}\big][D_{hbt}^{\sigma}]}\phi(\nu)\,\partial\nu. \tag{4c}$$

In the above expression, $\phi(\cdot)$ denotes the density of a multivariate normal distribution and the region of integration A is that which results in the choice of brand model jb. Hence our model described thus far is a random coefficient nested logit model.

[4] We use the terms intrinsic brand preference and brand preference interchangeably.

3.2. Modeling Dynamics in Brand Preferences

Note that in Equation (4a), we allow the parameter β_{0bt} that captures the mean intrinsic preference for brand b to vary over time. Consistent with the notion that advertising has an effect on the intrinsic preference for the brand name over time (see, for example, Jedidi et al. 1999), we model the dynamics of the mean (across consumers) brand preferences as

$$\beta_{0bt} = \bar{\beta}_b + \lambda\beta_{0bt-1} + \varpi_b Ad_{bt} + \varsigma_{bt}, \quad \text{where } \varsigma_{bt} \sim \mathrm{N}(0, \sigma^2_{\varsigma b}), \tag{5}$$

where β_{0bt} is the mean preference for brand b at time t, $\bar{\beta}_b$ is the time-invariant component of the mean preference for brand b, and Ad_{bt} is the level of advertising for brand b at time t. The parameters ϖ_b, $b = 1, 2, \ldots, B$ capture the contemporaneous effects of advertising on brand b's intrinsic preference. The parameter λ captures the extent to which the intrinsic brand preference carries over from period to period and can be interpreted as a measure of inertia in the preference for the brand. The error term ς_{bt} captures the change in the intrinsic preference for brand b at time t that is not explained by either the carry-over of brand preference from the previous period or the level of advertising. For example, the term ς_{bt} will account for the effect of the changes in the composition of consumers remaining in the market, which, in turn, will alter the brand preferences. One of the implications of Equation (5) is that the effect of advertising on brand preference carries over from period to period. Such a formulation is consistent with the finding that advertising has a long-term effect on brand preference (for example, Jedidi et al. 1999) and the extent of this carry-over will depend on the magnitude of the parameter λ, with higher values of λ, implying a higher level of carry-over, and hence a higher level of persistence.

3.3. Model Estimation

The objective of our estimation is to recover four sets of parameters in Equations (4a), (4b), (4c), and (5): (a) parameters $\Theta_1 = \{\alpha_t, \theta, \bar{\beta}_b, \lambda, \varpi\}$ in Equations (4a) and (5) that correspond to the mean preferences and other response parameters that influence the utility of all the models offered by a brand, (b) parameters $\Theta_2 = \{\beta\}$ in Equation (4a) that capture the effects of consumers' mean valuations of attributes (including price), (c) heterogeneity parameters, $\Theta_3 = \{\sigma_{\Delta h\beta}\}$ that correspond to the Cholesky decomposition of the matrix Σ, the covariance matrix corresponding to the heterogeneity distribution in Equation (4c), and (d) $\Theta_4 = \sigma$, the scale parameter of the nested logit model.

As in Berry et al. (1995), for a given set of the heterogeneity parameters Θ_3, and the scale parameter, σ, we can uniquely obtain the mean utilities $\delta_{jbt}/(1-\sigma)$ by inverting the brand-model share Equation (4c). Once we recover these mean utilities, we proceed with the estimation as follows: (i) estimate the parameters Θ_2 that affect the choice of a model offered by a brand conditional on that brand being chosen and (ii) estimate the brand-level parameters, Θ_1. To accomplish this, we need to decompose the components of the mean utility δ_{jbt}, into two components: (a) a component of utility that is common to all the models offered by a brand and (b) the deviations in the mean utilities of the individual models offered by the brand from this common brand-level mean utility. While we can identify the deterministic components of these mean utilities, the challenge is to decompose the unobserved (by econometrician) component of the mean utilities, ξ_{jbt} into these two components.

Recall that the term ξ_{jbt} in the expression for δ_{jbt} in Equation (4a) captures the effect of omitted attributes such as model color as well as other time-varying brand-specific factors that are observed by the consumers and may influence their utility of the models offered by the brand. We express ξ_{jbt} as

$$\xi_{jbt} = \xi_{bt} + \Delta\xi_{jbt}, \tag{6}$$

where ξ_{bt} captures the unobserved factors common to all the models offered by brand b at time t and $\Delta\xi_{jbt}$ is the corresponding model-specific deviation for model j. Since our objective is to isolate the dynamics in the intrinsic brand preferences, a key step in the estimation is to separate out these two components of the unobserved error term ξ_{jbt}. For purposes of identification, we need to set the model-specific deviation in the unobserved factors, $\Delta\xi_{jbt}$, to 0 for one of the models of each brand. We do this for a model that is available throughout the time series for each brand. We now discuss the estimation of the parameters in (i) and (ii) above.

3.3.1. Estimating the Parameters That Affect Model Choice (Θ_2).

Our identifying assumption that the model-specific deviation in the unobserved factors, $\Delta\xi_{jbt}$, is equal to 0 for one model by each brand implies that we can write the mean utility of the base model of brand b at time t as

$$\delta_{1bt} = \alpha_t + \beta_{0bt} + \theta H_{bt} + \beta X_{1bt} + \xi_{bt}, \tag{7}$$

where the subscript 1 refers to the base model. Subtracting Equation (7) from Equation (4a) for all the remaining models offered by brand b at time t, we have

$$\delta_{jbt} - \delta_{1bt} = \delta'_{jbt} = \beta\Delta X_{jbt} + \Delta\xi_{jbt}, \quad j = 2, \ldots, J_{bt}, \tag{8}$$

where $\Delta X_{jbt} = X_{jbt} - X_{1bt}$. Now in Equation (8), the left-hand side quantity is known since we have already computed δ_{jbt} by inverting the brand-model share

Equation (4c). So the β ($=\Theta_2$) parameters can be estimated via an instrumental variables regression that accounts for potential correlation between $\Delta\xi_{jbt}$ and the prices embedded in ΔX_{jbt}.

3.3.2. Estimating the Brand-Level Parameters (Θ_1). Recall that conditional on Θ_3, and the scale parameter, σ, we have thus far obtained the mean utilities $\delta_{jbt}/(1-\sigma)$ and estimated the parameters, β ($=\Theta_2$). Next, we need to estimate the parameters that influence choices at the brand level, Θ_1. For this, we first define the term R_{bt} as follows:

$$R_{bt} = (1-\sigma)\ln \sum_{j\in M_b} \exp\left(\frac{\delta_{jbt}}{1-\sigma}\right).$$

Substituting for δ_{jbt} from Equation (4a) and for ξ_{jbt} from Equation (6), we have

$$R_{bt}=(1-\sigma)\ln\sum_{j\in M_b}\exp\left(\frac{(\alpha_t+\beta_{0bt}+\theta H_{bt}+\beta X_{jbt}+\Delta\xi_{jbt}+\xi_{bt})}{1-\sigma}\right),$$

$$R_{bt}=\alpha_t+\beta_{0bt}+\theta H_{bt}+\xi_{bt}+(1-\sigma)$$
$$\cdot\ln\sum_{j\in M_b}\exp\left(\frac{(\beta X_{1bt}+\delta'_{jbt})}{1-\sigma}\right),$$

$$R_{bt}-(1-\sigma)\ln\sum_{j\in M_b}\exp\left(\frac{(\beta X_{1bt}+\delta'_{jbt})}{1-\sigma}\right)$$
$$=\alpha_t+\beta_{0bt}+\theta H_{bt}+\xi_{bt},$$

$$Q_{bt}=\alpha_t+\beta_{0bt}+\theta H_{bt}+\xi_{bt}, \quad \text{where}$$

$$Q_{bt}=R_{bt}-(1-\sigma)\ln\sum_{j\in M_b}\exp\left(\frac{(\beta X_{1bt}+\delta'_{jbt})}{1-\sigma}\right). \tag{9}$$

The term $(1-\sigma)\ln\sum_{j\in M_b}\exp(((\beta X_{1bt}+\delta'_{jbt})/(1-\sigma)))$ in the above expression is similar to the inclusive value of the nested logit model (Ben-Akiva and Lerman 1985), and can be treated as a measure of the effect of a brand's product line on its performance. Now, all the terms in Equation (9) are defined at the brand level. Further, the left-hand side of the equation (Q_{bt}) can be computed given Θ_3, σ, and β ($=\Theta_2$). So Equation (9) is once again a linear equation, where ξ_{bt} plays the role of the error term. Different from the situation faced when estimating the β ($=\Theta_2$) parameters, in this case, we do not have the price endogeneity issue to contend with as all the price information is embedded in Q_{bt}, the left-hand side of Equation (9). Hence, given Q_{bt}, the parameters in Equation (9) can be obtained via a linear regression. A key complicating factor, however, is that in Equation (9), we do not observe the values of brand preferences, β_{0bt}, at each time period t, but need to estimate them. For this, we use the Kalman filter algorithm, which is a recursive algorithm that is used to obtain efficient estimates of an unobserved state variable (brand preference in our case) at each period based on the information observed at that period. The Kalman filter is thus a two-equation system consisting of (i) an Observation Equation that relates the time-varying parameters to an observed dependent variable and (ii) a System Equation that characterizes the dynamics of the time-varying parameter. In our Kalman filter system, Equation (9) corresponds to the Observation Equation and Equation (5) corresponds to the System Equation. Consistent with the assumptions of the Kalman filter algorithm, we need to further assume that $\xi_{bt} \sim \mathrm{N}(0, \sigma^2_{\xi b})$. Details regarding the Kalman filter algorithm and its estimation can be found in Appendix A.

3.3.3. Overview of the Estimation Algorithm. The above two subsections discuss how we can estimate Θ_1 and Θ_2 given the heterogeneity parameters Θ_3, and the scale parameter $\Theta_4=\sigma$. That estimation yields the system of error terms $\binom{\Delta\xi_{jbt}}{\xi_{bt}}$. Now, the remainder of the estimation involves obtaining Θ_3 and Θ_4 by minimizing a quadratic form of these error terms. One way of doing this is by using a generalized method of moments (GMM) procedure to estimate the parameters. Specifically, $\{\Theta_1, \Theta_2\}$ are computed in an "inner" loop, whereas the algorithm searches for $\{\Theta_3, \Theta_4\}$ in an "outer" loop similar to the procedure suggested by Berry et al. (1995). A more detailed summary of the estimation algorithm can be found in Appendix B.

3.4. Simulation Study

To demonstrate the ability of the model and the estimation strategy to recover the true parameter values, we estimated the model using simulated data. As in the model, we allowed for consumer heterogeneity in the four brand preferences, resolution, and price. Further, we assumed that the covariance matrix corresponding to the heterogeneity distribution of these six parameters had variances equal to 2 and covariances equal to 1. The rest of the true parameter values were chosen to be the actual estimates reported in Table 3 (to be discussed later). Using these parameter values and the actual price, advertising, attributes, and holiday data from the digital camera category, we simulated the share data for each of the brand-model combinations for each of the 26 months as follows. As in the model (Equation (5)), we assumed that the brand preference was driven by advertising. To reflect the nested logit model specification, the household-specific idiosyncratic preferences were drawn from a generalized extreme value (GEV) distribution. The aggregate shares were generated from 10,000 household-level draws. We estimated the model parameters using 25 replications of simulated data. In Table 1, we present a summary of

Table 1 Elasticity Estimates from the Simulation Study

Brand-model	True value	Mean	Standard deviation
Price elasticities			
Casio QV70	−2.152	−2.120	0.064
Kodak DC210	−1.589	−1.620	0.078
Olympus D320L	−1.819	−1.847	0.049
Sony MVCFD5	−1.537	−1.591	0.041
Short-term advertising elasticities			
Casio	0.085	0.079	0.011
Olympus	0.080	0.071	0.011
Sony	0.096	0.090	0.016
Long-term advertising elasticities			
Casio	0.601	0.549	0.063
Olympus	0.794	0.679	0.131
Sony	1.193	1.055	0.201

the implied elasticity estimates across these 25 replications. Overall, the results reveal that for the range of parameter values considered, the model and the estimation procedure can recover the true elasticity values with a reasonable level of accuracy. Moreover, all the true elasticities are contained within the 95% confidence interval of the estimates.[5]

4. Data Description and Operationalization of Variables

4.1. Data

Our data consist of aggregate monthly observations on unit sales and prices of digital cameras collected via store audits for a period of 26 months from April 1997 through May 1999. In addition, the data consist of information on the features of each model marketed by the manufacturers in the category. The features include, for example, the maximum resolution in mega pixels, maximum number of images that can be stored, size of internal and external memory, type of storage media, and the presence or absence of self-timer capabilities. We supplemented these with data on monthly advertising expenditures by each of the brands during the corresponding period. The advertising data are obtained from *Competitive Media Reporting*. Hence, sales, price, and attribute data are at the model level (Sony DSCF1), whereas advertising data are at the brand level (i.e., for Sony across all its models).

We perform our empirical analysis on the four leading brands in this category: Casio, Kodak, Olympus, and Sony. Together these brands account for more than 93% of the sales in this category over the time period, and the four brands are present during all the 26 months of the data. We report the descriptive statistics for the four brands in Table 2. From Table 2, we can see Sony has the highest market share, which is almost twice that of the nearest competitor, Kodak. Olympus is a close third to Kodak in terms of market share and Casio has the lowest market share. Although Sony has the highest market share, it also commands the highest price. In contrast, Casio, which has the lowest market share, has the lowest average price. Sony's high market share despite its high price may potentially be attributed to the attractiveness of models in its product line and/or to a high intrinsic preference for the brand. It is of substantive interest to investigate which of these two plays a more dominant role in Sony's ability to command a higher price. The total advertising expenditure of the brands provides some evidence for the source of Sony's success. Among the four brands, Sony had the highest advertising expenditure while Casio had the lowest. In fact, Casio's advertising expenditure was just 7% of that spent by Sony during this period. Another reason for Sony's success could be its introduction of models with a floppy disk storage device. Its convenience revolutionized the digital camera market and was one of the reasons behind Sony's popularity despite bulkiness and higher price (*BusinessWeek* 2000).

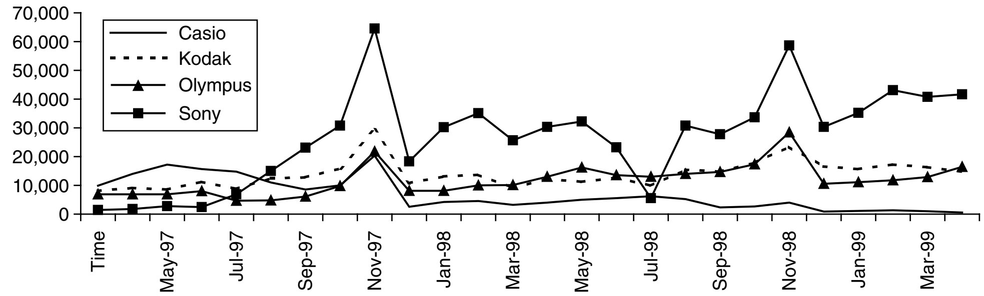
Table 2 Descriptive Statistics for the Digital Camera Brands

Brand	Average price (dollars)	Total unit sales	Market share (%)	Total advertising ('000 dollars)	Average age of models (months)	Average number of models
Casio	320	176,049	10.69	848.3	13.79	10.50
Kodak	485	360,778	21.90	9,223.4	14.18	8.00
Olympus	606	305,385	18.54	4,432	9.92	6.31
Sony	675	691,457	41.98	11,890.6	8.43	4.96

We report the time trend in monthly sales of these brands over the 26 months in Figure 1. Figure 1 reveals that although Casio was the largest selling brand at the beginning of the data, its unit sales steadily decreased over time and it ended up as the lowest selling brand. In contrast, although Sony has the lowest market share in the first few months, it soon overtook all the other brands to emerge as the largest selling brand. The other two brands, Kodak and Olympus, exhibit a gradual increase in unit sales over time. It will thus be interesting to investigate the reasons behind these contrasting trends in sales and relative market shares of the various brands. As in most technology product markets, the average price of the models sold by each of the brands declines over time. The decrease ranges from a high of 48% for Sony to about 22% in the case of Kodak. In addition, the number of models offered by each of the brands steadily increases during this period.

[5] For a more detailed discussion of the simulation study as well as for a summary of the parameter estimates, please refer to Appendix C posted on the journal's website at http://mktsci.pubs.informs@informs.org.

Figure 1 Unit Sales of Digital Camera Brands



4.2. Operationalization of Variables

4.2.1. Marketing Mix Variables. We estimate the consumer valuation of five features viz., resolution, number of images, presence or absence of floppy as a storage device, amount of external memory, and the presence or absence of self-timer.[6] We operationalized the price variable as the logarithm of the price of the model. We use the raw monthly brand advertising expenditure for the advertising variable. The age of a model is the number of months since the model was first introduced.

4.2.2. Market Size and Outside Alternative. To compute shares for the brand choice model, we need to define an outside or no-purchase alternative or the potential size of the market. Similar to Song and Chintagunta (2003), we assume that the total potential market size is 10 million—the number of households that used computers at home (U.S. Census Bureau 1997) because using digital cameras requires access to a computer. The respective shares are then computed from the sales of the brands and the market size as defined above.

4.2.3. Instrumental Variables for Price. As in Berry (1994), we use functions of observable product attributes (excluding price) offered by the model for the conditional model choice part of the estimation. In addition, we also use producer price index for computer peripheral equipment (SIC code 3577) obtained from the U.S. Bureau of Labor Statistics.

5. Results

As discussed in §3.4, we estimate four sets of parameters: Θ_1, Θ_2, Θ_3, and Θ_4. We report the results for these parameters in Table 3.[7] We first discuss the results pertaining to the model choice conditional on brand choice. We find that increasing a model's resolution has a significant positive effect on the probability of choosing that model. The provision of a floppy storage device and the presence of a self-timer have similar effects. The significant positive effect of floppy storage is consistent with the claim in the business press that Sony's introduction of models with floppy as the storage device was a key reason behind its success. As expected, we find that price has a negative effect on a model's share. While the coefficient of the linear age term is negative and significant, we find that the coefficient of the quadratic term is positive but insignificant. These results imply that as the age of a model increases, it is increasingly perceived as becoming obsolete.

Table 3 Model Results

Parameter	Estimate	T-values
Model choice conditional on brand choice		
Resolution	2.2582	4.6183
Number of images	−0.4594	−1.5406
Floppy	0.8312	2.5041
External memory	−0.1541	−0.9239
Self-timer	0.7867	5.056
Price	−2.1893	−5.0822
Age	−2.2186	−6.9305
Age squared	0.0137	0.1631
Brand choice		
Carry-over	0.927	13.3936
Constant (Casio)	−0.4273	−0.8688
Constant (Kodak)	−0.2457	−0.564
Constant (Olympus)	−0.3006	−0.6884
Constant (Sony)	−0.208	−0.5287
Advertising (Casio)	1.1517	2.3044
Advertising (Kodak)	0.0007	0.04
Advertising (Olympus)	0.1197	1.6979
Advertising (Sony)	0.2192	1.8358
Holiday	0.5386	5.0588
Sigma	0.9542	38.6984
Heterogeneity parameters		
Casio	0.0011	0.0001
Kodak	0.0064	0.00458
Olympus	0.057	0.03519
Sony	0.0337	0.01299
Resolution	0.4153	0.1892
Price	1.1029	2.3979

[6] Sony sells models with and without a floppy drive, which helps us identify the coefficient of the floppy variable.

[7] Not reported in Table 1 are the variances of the observation and system equation errors, which are 1.5 and 0.007, respectively.

We now discuss the brand choice results. Our estimates of the intrinsic growth parameters α_t, which proxy for category diffusion are statistically indistinguishable from zero. Hence we do not report those estimates here. Essentially, this finding implies that controlling for the changes in the product line and the intrinsic brand preferences effectively controls for growth in the category over the time range of our data. The parameter λ that captures the carry-over of brand preferences from period to period (CARRY-OVER) is 0.927. This is consistent with our expectation that the intrinsic brand preferences should be highly persistent, and should hence have a positive and high (close to 1) carry-over. The high carry-over of the intrinsic brand preferences is consistent with the notion that "brand equity" is an enduring construct (Keller 1998). The constant component of the intrinsic brand preferences that is invariant to marketing actions is highest for Sony and lowest for Casio. Advertising has a significant positive effect on the intrinsic brand preferences of Casio, Olympus, and Sony. Given that the carry-over coefficient is 0.927, the long-term effect of advertising is more than 13 times the short-term month-level effect. Hence, managers need to consider the total effect of advertising, particularly the long-term effect, while evaluating the effectiveness of their advertising campaigns. The estimate of σ (0.9542) implies that the correlation in the utilities of the models offered by the same brand is high.

As our approach explicitly accounts for all the models marketed by the competing brands, we can compute the 46×46 matrix of cross-price elasticities across all brand-models.[8] However, for illustrative purposes, we computed the model-specific price elasticities for four select models (one for each brand). The elasticities range from a high (in magnitude) of -2.02 (standard error of 0.358) for Casio QV70 to -1.47 (standard error of 0.274) in the case of Sony MVCFD5. Note that under the standard logit model, we would expect that high-priced models would also have higher (in magnitude) own price elasticities. The finding that the lowest priced Casio QV70 model has the highest magnitude of own price elasticity implies that our demand model is sufficiently flexible to overcome the logit model's restriction of elasticities being proportional to prices.

Given the carry-over in intrinsic brand preferences, the effect of advertising on the intrinsic brand preferences, and hence on sales also carries over from period to period (see Equation (6)). The short-term advertising elasticities for Casio, Olympus, and Sony are 0.0829 (standard error of 0.012), 0.0834 (standard error of 0.0211), and 0.097 (standard error of 0.0463), respectively. The corresponding long-term elasticities are 0.553 (standard error of 0.1086), 0.753 (standard error of 0.192), and 0.824 (standard error of 0.447), respectively. These values are in line with those in Lodish et al. (1995), Assmus et al. (1984), and Jedidi et al. (1999).

5.1. Intrinsic Brand Preferences and Inclusive Values Over Time

We present the intrinsic brand preferences and the inclusive values of the brands over time in Figures 2 and 3, respectively. The time trend in the intrinsic brand preferences reveals that the brand preference for Casio follows a declining trend. This may be attributed to limited advertising support as can be seen from the relatively small advertising budget compared to its competitors (Table 1). In addition, the advertising support for the brand declined steadily over time with more than 85% of the total advertising expenditure spent during the first 10 months. The preference for Sony, on the other hand, shows a significant increase over time with a steep increase in months 3, 4, and 5, the period when Sony launched the *Mavica* line of digital cameras with a floppy storage device. Note that the direct effect of the floppy disc attribute on shares *has already been controlled for via the inclusive value from the conditional model* part.

The inclusive value of Sony reveals an increasing pattern, especially during months 3–7, coinciding with the launch of several *Mavica* models. On the other hand, the inclusive value of Olympus increases initially and drops marginally toward the end of the data. The inclusive value of Casio decreases marginally during the period, with the value peaking during the 17th month of the data. The other brand, Kodak, sees a steady increase in its inclusive value throughout the data.

The above patterns in the intrinsic brand preferences and the inclusive values raise an interesting question: What is the effect of the dynamics in the intrinsic brand preferences on the sales of a brand relative to that of the dynamics in the inclusive values? To answer this question, we performed two sets of simulations for each brand. In the first simulation, we computed the market shares and the corresponding sales of the brand if the intrinsic preference of the brand had been the same for the entire period as in the first period. We then obtained the difference between the actual observed sales of the brand and the simulated sales. The difference is a measure of the extra sales that can be attributed to the dynamics in the intrinsic preference for the brand. A positive (negative) value of

[8] The total number of models offered by the four brands during this period was 46. However, because of the entry and exit of models, the number of models available in the market during any period was less than 46.

Figure 2 **Brand Preferences of Digital Camera Brands**

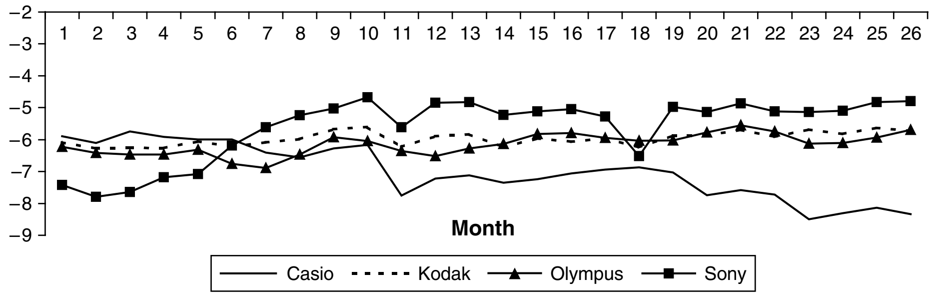
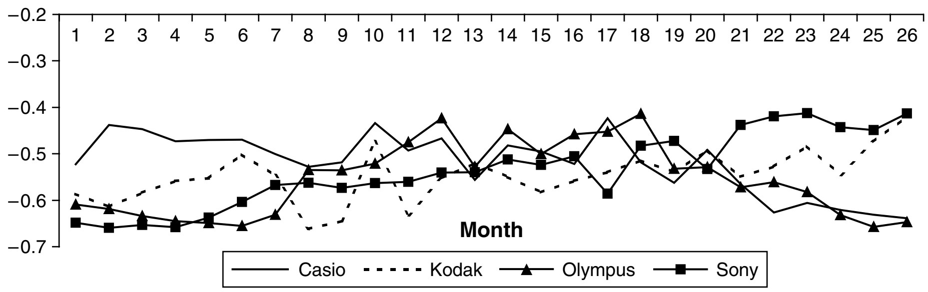


Figure 3 **Inclusive Values of Digital Camera Brands**



this measure at any period will imply a positive (negative) effect of the dynamics in brand preference during that period. We then performed the second simulation wherein the inclusive value of the brand was constrained to be the same as that in the first period. Once again, the difference between the true sales and the simulated sales can be attributed to the dynamics in the inclusive value.[9]

We present the total effect (both positive and negative) of these dynamics in terms of unit sales in Table 4. The net effect of the dynamics is the sum of the positive and the negative effects. All four brands seem to have benefited from the increase in inclusive values over time. From Table 4, we can see that Casio has gained the least at roughly 4,100 units over the 25 months.[10] Sony, which seems to have gained the most from the increase in its inclusive values, has gained roughly 15 times as much as Casio. The remaining two brands, Kodak and Olympus, seem to have gained approximately 8,400 and 12,400 units, respectively, in sales because of the dynamics in their inclusive values.

As discussed previously, the intrinsic preferences of all the brands except Casio exhibit an increasing trend over time, albeit to varying degrees. Correspondingly, these brands seem to have gained from the dynamics in their intrinsic brand preferences. However, these figures reveal that the effect of the dynamics in the intrinsic preference is higher than that of the dynamics in the inclusive values for all the brands. As seen in Table 4, the net positive effect of the dynamics in the intrinsic brand preference is roughly 2.5 times the net positive effect of the dynamics in inclusive value in the case of Kodak and Olympus. In the case of Sony and Casio, the effect of dynamics in brand preferences overwhelms the effect of dynamics in the inclusive values. For Casio, the effect of dynamics in brand preferences is about 30 times the corresponding product line effect. Hence it appears that the decline in the performance of Casio, as well as the ascent of Sony, seem to be driven by the corresponding changes in their intrinsic brand preferences rather than the changes in the attractiveness of their respective product lines.

5.1.1. Decomposing the Effects of the Drivers of Inclusive Value. In Equation (9), we can see that the inclusive value of a brand (the last term on the right-hand side of Equation (9)) is primarily driven by three factors: (a) the price of the models offered by the brand, (b) the number of models offered by the brand,

Table 4 **Total Effect of Dynamics on Unit Sales of Digital Camera Brands**

	Net effect of dynamics in inclusive value		Net effect of dynamics in brand preference	
Brand	Positive	Negative	Positive	Negative
Casio	4,505	−398	1,590	−128,919
Kodak	9,973	−1,541	33,818	−8,418
Olympus	14,421	−1,071	36,976	−12,788
Sony	60,182	−8	366,459	−780

[9] Note that because of the nonlinear nature in which the utilities enter the demand equation, the effects of the dynamics in the inclusive value and the intrinsic brand preference are not additive.

[10] Because the values are fixed at the first month levels, we compute the effects for the remaining 25 months of the data.

and (c) the attractiveness of the attributes (other than price) of the models in the brand's product line. Hence the inclusive value of the brand can be increased by lowering the price of its models, by increasing the attractiveness of model attributes, or just by offering more models without any enhanced benefits. As noted earlier, the prices of digital cameras declined steadily during the period of our analysis. Moreover, the number of models introduced by the brands increased steadily during this period. Hence it would be interesting to investigate (a) the contribution of the different drivers to the increase in sales and (b) the proportion of the total effect that is attributable to the increase in attractiveness of model attributes. To this end, we performed the following simulations.

(a) *Recovering the Effect of Price Decrease.* For each brand, we fixed the prices of all the models offered by the brand at the prices when the models were introduced. We then simulated the inclusive values and the corresponding sales levels. The difference between the actual sales and the simulated sales would be a metric of the increase in sales that is attributable to the decrease in prices. We present these results in the first column of Table 5. The results reveal that all the brands seem to have gained roughly the same amount in terms of unit sales because of price reduction. However, a comparison with the total increase in sales because of the increase in the inclusive value (which includes the price effect) presented in Table 4 implies that in the absence of price reduction, the net effect of the increase in inclusive value would have been lower by about 85% in the case of Casio. On the other extreme, in the case of Sony, the contribution of price reduction to the increase in inclusive value was only 8.2%. Hence the results reveal that during the period of our analysis, Casio (Sony) relied the most (least) of the four brands on price reduction as a driver of inclusive value.

(b) *Recovering the Effect of Increase in the Number of Models*. For each brand, we restricted the average utility of the models offered by the brand to be the same as the average utility of the models during the first period of analysis. We then computed the inclusive values and the corresponding sales for the brand with these restricted utilities, but with the actual number of models. This is tantamount to the brand just introducing new models without any modification in attribute benefits or price. For each brand, we also simulated the "base" sales with the inclusive value of the brand fixed at the same value as in the first period of analysis. The difference between these two simulated sales figures would be a measure of the contribution of increase in the number of models to increase in sales. We present these results in the second column of Table 5. For all the brands except Casio, the effect of increase in the number of models is higher than that of decrease in prices. Of the four brands, Olympus gained the most from adding more models to its portfolio while Casio gained the least. This is partly because of Casio and Kodak being in the market with several models before the entry of Olympus and Sony. The number of Casio models increased from 6 to 13 during the period of analysis, whereas Olympus had a slightly steeper increase in the number of models from 1 to 9. The change in the sales of the brands is approximately proportional to the natural logarithm of the ratio of the number of models in subsequent time periods to the number in the initial time period. Because this ratio is the smallest for Casio, we find that this brand benefits the least from increasing its number of models.

Table 5 Contribution of the Different Drivers of Inclusive Value to Increase in Sales

Brand	Increase in sales because of decrease in prices	Increase in sales because of increase in number of models	Increase in sales because of enhanced attributes	Percentage contribution of enhanced attributes (%)
Casio	3,851	2,131	5,155	46.3
Kodak	5,818	10,242	19,579	54.9
Olympus	4,968	19,163	26,115	52.0
Sony	4,950	10,416	109,059	87.7

(c) *Recovering the Effect of Enhanced Attributes*. For each brand, similar to the case above, we simulated the sales when the average utility of the models is the same as in the first period. However, in addition to allowing for variation in the number of models, we also allowed for the prices of the models as well as their ages to vary over time as in the data. The difference between these simulated and the actual sales of the brand provides a measure of the contribution of the enhanced attributes to the increase in sales. We present these results in the third column of Table 5. Of the four brands, Sony has gained the most from the introduction of enhanced attributes during the period of our analysis, while Casio gained the least. In fact, the sales gains for Sony because of the introduction of enhanced attributes are more than the corresponding gains of the remaining three brands put together. To assess the contribution of the enhanced attributes relative to that of the other drivers of inclusive value, we express it as a percentage of the total contribution of the three drivers in the last column of Table 5. Of the four brands, Sony was the most innovative with roughly 88% of the contribution of the three drivers coming from the introduction of enhanced attributes. The remaining three brands are clubbed together in terms of the contribution from the introduction of advanced benefits. However, in the case of Casio, less than half the total contribution may be attributed to its innovativeness. These results have face validity and are consonant with our study of the trade press.

Table 6 Effect of an Exogenous 1% Increase in Advertising Expense

Brand	Cumulative increase in advertising (dollars)	Cumulative increase in sales (units)	Cumulative increase in revenue (dollars)	Change in sales as a percentage of total brand sales (%)
Casio	8,843	718	245,250	0.41
Sony	118,906	6,381	4,090,119	0.92

5.2. Effect of Increasing Advertising Expenditures

Because advertising has a significant positive effect on the intrinsic brand preferences, managers can increase the intrinsic preference (and thus sales) for their brands by increasing their advertising expenditures. However, we need to evaluate if such an increase in advertising expenditure can be justified in terms of increased profitability. To this end, we performed the following simulation for the largest and the smallest brands viz., Casio and Sony, respectively. For each brand, we increased the advertising expenditure by 1% and simulated the corresponding intrinsic brand preferences, market shares, and sales.[11] The difference between the simulated and actual sales would give the incremental sales because of the change in advertising policy. We then multiplied the incremental sales by the brand's weighted (by market share) average prices to obtain the increase in revenue because of the increase in advertising. We present a summary of the cumulative increase in advertising, and the resulting cumulative increases in unit sales and revenue over the period of the data in Table 6. These results reveal that Sony gains more, both in terms of increase in unit sales, as well as in terms of percentage change in sales, from the increase in advertising expenditure compared to Casio. However, it should be noted that a 1% increase in the advertising expenditure in the case of Sony is about 13 times that of a corresponding increase in the case of Casio. In all cases, the increase in revenue that would accrue from the increased advertising expenditure exceeds the extra expense. While this may look attractive, we should note that only a fraction of the increased revenue would translate into extra profit for the firm. Assuming a 10% profit margin, we computed the increase in profits because of the change in advertising policy.[12] Under this assumption, the increase in advertising is still profitable for both Casio and Sony. Further analysis revealed that while Casio could have recovered the total extra advertising expense within the first two months of the data, Sony would have done so in eight months. Overall, our analysis implies that it would be worthwhile for Casio and Sony to increase their advertising expenditures. Specifically, the small advertising budget of Casio coupled with its declining sales and market share triggered by a decline in its intrinsic brand preference, provide sufficient grounds for increasing its advertising outlay.

[11] We performed this by simulation by increasing the advertising expenditure of one brand at a time.

[12] Bloomberg reports that the profit margin for digital cameras is around 10%–15%. The profit margins will be an even lower percentage of the retail prices to which we have access.

5.3. Effect of Exogenous Changes in Model Attributes

One of the characteristics of our model is that we can estimate the effect of modifying the level of a product attribute on brand sales. Specifically, we take the perspective of a Casio manager. Faced with declining sales, the manager needs to find ways of improving the brand's performance. Our analysis above revealed that the decline in Casio's sales may be attributed to the decline in brand preferences. Moreover, our results in the previous subsection reveal that Casio can increase its advertising expenditure and still be profitable. An alternative way of improving the brand's performance would be to introduce a new model with modified attributes. Such a modification will have a positive effect on the inclusive value of the brand, and thus increase its attractiveness to consumers.

To evaluate the effect of changes in product attributes on brand sales, we modified one feature of the Casio QV120 model at a time to mimic that of some of the best-selling models of Sony, Kodak, and Olympus. This is akin to Casio withdrawing the QV120 model and introducing a new model with the enhanced attributes. We then computed the revised sales levels for the Casio brand. Correspondingly, we obtained the extra sales and revenue that would accrue from the product attribute modification. We present the actual and the modified levels of each attribute and the corresponding effect of such a modification in terms of increase in sales and revenues for the Casio brand as a whole in Table 7. Of the two product attribute modifications, the increase in the maximum resolution from 0.307 mega pixels to 0.786 mega pixels has a greater impact in terms of extra sales generated. This product modification could potentially increase the Casio brand sales by about 2,369 units, an increase of 1.35%. Note that this is the increase in sales of Casio because

Table 7 Cumulative Effect of Exogenous Changes in Features of the Casio QV120 Model

Feature	Actual value	New value	Change in Casio brand sales	Change in Casio brand revenue (dollars)	Change in sales as a percentage of Casio sales (%)
Resolution (mega pixels)	0.307	0.786	2,369	869,346	1.35
Floppy	No	Yes	1,627	844,584	0.92

of consumers switching from other brands as well as from the outside alternative. This sales increase is thus the net gain to Casio. A comparison of this increase in sales with the total net effect of the increase in the inclusive value (in Table 4) reveals that Casio could have increased the net positive impact of the inclusive value by about 36% during this period had it modified the QV120 model to have these higher resolution values. Incorporating the floppy disk storage would have increased the sales of Casio by 1,627 units (0.92%).

To evaluate if such product developments would be profitable, we need to consider the extra revenues such a development would generate. A product modification that would enhance the maximum resolution from 0.307 mega pixels to 0.786 mega pixels would increase Casio's revenues over the 26-month period by approximately $870,000. Assuming a 10% profit margin, and a 26-month horizon to recover the cost of product development, this product modification would be profitable if the total cost of development were less than $87,000 (assuming no discounting). However, it is possible that the higher resolution may be introduced in more than one model with a marginal increase in development cost. Such a scenario would make the product modification profitable even if the development costs were higher. Moreover, it may be possible to modify the new product's pricing to obtain higher profits, which may permit a higher development cost. A similar analysis can be performed in the case of other product attributes. Hence, explicitly modeling the tradeoffs between product attributes would be helpful in evaluating the impact of product development on long-term profitability (see Ofek and Srinivasan 2002).

5.4. Managerial Implications

Our results provide several key insights to managers in the digital camera category. We find that intrinsic brand preferences as well as product line effects influence the sales of the four major brands in the market albeit at different levels (Table 4). For Sony, we find that the changes in product line (that contribute to dynamics in inclusive value) as well as changes in intrinsic brand preferences are the largest in the category, with the latter effect being about six times the former effect in relative terms. At the other extreme, for Casio, we find that although the launch of new models, lower prices, and enhanced attributes contribute positively to its sales, the decline in intrinsic brand preferences swamps any positive effect of the improvement in inclusive values. For these brands, managers need to devote sufficient resources to building their brand preferences, especially because these brands' preferences exhibit a significant response to advertising. The steep decline in the performance of Casio and the ascent of Sony to market leadership underscore the importance of advertising support. Indeed, our simulations reveal that Casio and Sony can further increase their profits by increasing their advertising budgets. For Kodak and Olympus, we find that the effects of the intrinsic brand preferences are marginally higher than the corresponding product line effects. We also find that Sony has gained significantly by introducing innovative new products (for example, floppy disk storage). Moreover, our simulations reveal that Casio could have performed better had it incorporated some of the attributes offered by its rivals into its products. Along similar lines, the model estimates reveal that as the age of the model increases, it is likely to be perceived as obsolete, and hence lead to a decrease in the preference of the model. Clearly, as the age of models in a brand's portfolio increases, one would expect the brand's product line to look less attractive from the consumers' perspective. Hence, augmenting the product line by introducing new models with enhanced product attributes can also strengthen the performance of a brand.

6. Alternative Model Specifications and Robustness Checks

In this section, we discuss alternative model specifications that result in flexible aggregate substitution patterns. In addition, we test the robustness of our results to two assumptions that we make in our estimation: (a) time-invariant attribute preferences and (b) exogenous advertising effects.

6.1. Alternative Ways of Allowing for Flexible Aggregate Substitution Patterns

As described in the model section, our demand model allows for a flexible substitution pattern at the aggregate level because of (a) the nested logit structure and (b) accounting for heterogeneity in attribute and brand preferences of consumers and in their price sensitivities. Here, we briefly explore other formulations that can also provide flexible aggregate substitution patterns.

One obvious alternative is a model that does not account for (a) but does account for (b). This would be a simple logit model that does account for heterogeneity, with the latter providing flexibility at the aggregate level. The statistically significant effect for the σ parameter in our nested logit model does seem to indicate that the nested logit may be preferred to the simple logit model. Nevertheless, we estimated a simple logit model with heterogeneity that allows for dynamics in brand preferences and compared the results with those from our model. The comparison revealed that our model fits the data better than the simple logit model with heterogeneity and has a lower sum of squared errors. Hence, based on model fit and the statistical significance of the σ parameter, we believe that our model is more appropriate for these data.

While our model assumes a brand primary nesting structure, it is likely that alternative models with an attribute at the upper level of the nest may be more appropriate. Some of the attributes such as resolution and price are continuous variables that need to be discretized to use them as primaries in our nesting structure. Because the levels of these attributes are not stable over time, it would make such a discretization very complicated and subjective. Other discrete attributes such as floppy disk storage are not available through the entire length of the data. Hence we estimated models wherein the following two attributes were at the upper level of the nest: (a) the presence or absence of a self-timer device and (b) the presence or absence of external memory. Overall, these two models yielded inferior fit compared to the model with brand primary nesting. Moreover, in both of these alternative models, the σ parameter was insignificant and close to zero, thereby implying that a simple logit model may be more appropriate than these alternatives.

Yet, another option would be to estimate a more flexible probit model that allows for the correlations between all the brand-models of digital cameras by estimating a full covariance matrix of the brand-model errors. Such a model would require the estimation of a large number of parameters for the covariance matrix. Even if we restricted the covariance matrix to a fewer number of parameters, there is a severe computational burden associated with estimating a probit model with so many alternatives. On the bases of model parsimony and ease of computation, our model would be preferable to a probit model. Finally, previous research has found that elasticities do not significantly differ between the aggregate logit and the aggregate probit models (Chintagunta 2001 provides a comparison in a three-alternative case).

6.2. Checking Robustness to Assumptions

6.2.1. Assumption of Time-Invariant Attribute Preferences. We have assumed that the effects of model attributes are time invariant, i.e., β in Equation (4a) is not subscripted by time. To evaluate if our assumption of time-invariant attribute preferences will affect the substantive findings, we estimated a model with a time trend in attribute preferences. Overall, the results remained largely unchanged upon inclusion of these time-varying attribute preferences. Moreover, the price elasticities (ranging from -2.572 (s.e. 0.382) for Casio QV70 to -1.843 (s.e. 0.301) for Sony MVCFD5) and short-term advertising elasticities (ranging from 0.064 (s.e. 0.012) for Casio to 0.0859 (s.e. 0.048) for Sony) did not differ significantly from those in the model with time-invariant attribute preferences. These results indicate that the assumption of time-invariant attribute preferences does not affect substantive implications obtained from the model once we have accounted for time-varying brand preferences, consumer heterogeneity, and price endogeneity.

6.2.2. Assumption of Exogenous Advertising Expenditures. We estimated the brand choice part of the model while correcting for the potential endogeneity of advertising. To accomplish this, we estimated the brand choice part of the model by using the control function approach (Petrin and Train 2005), which accounts for the endogeneity of the advertising variable. Specifically, in a first stage, the endogenous variable (advertising) is regressed on its instruments (in our case, product attributes and their combinations). The residual from this regression is then introduced as an additional regressor in the brand-level model estimation. The results from this analysis revealed that the estimates for the parameters at the brand-level did not change significantly upon accounting for the endogeneity of advertising. Moreover, the substantive results remained largely unchanged. For example, after accounting for the potential endogeneity of advertising, the short-term advertising elasticities for Casio, Olympus, and Sony were 0.0852 (s.e. 0.013), 0.0874 (s.e. 0.0232), and 0.1022 (s.e. 0.0471), respectively. These advertising elasticities are not significantly different from those obtained under the assumption of exogenous advertising. Hence we conclude that assuming the advertising variable to be exogenous will not affect our main conclusions.

7. Conclusions

Our research addresses the following managerial questions: (a) What are the relative importances of intrinsic brand preferences, prices, product attributes, and number of models in driving the performance of a brand? (b) Does advertising play an important role in driving preferences? (c) If so, would it pay for brands to increase advertising spending? (d) Under what circumstances would it be profitable for brands to engage in product development efforts that would lead to an improvement in the attributes of some of the existing models? Although set in the context of technology product markets, our model is flexible enough to be used with data from consumer packaged goods markets.

We find that intrinsic brand preferences have a much bigger effect on the performance of the brand than the inclusive value, which reflects model-level prices, product attributes, and the length of the brand's product line. Further, we find that some brands can increase their advertising expenditures and still increase their profitability. Casio, which has a relatively small advertising budget compared to the other leading players in the market, could have done better by increasing its advertising investments. Moreover, our analysis of the potential profit impact, that would accrue from Casio improving some of its product attributes, demonstrates the usefulness of our model in evaluating the feasibility and importance of such developmental efforts.

Our approach is subject to several caveats and limitations, addressing which may open up avenues for future research. Although we account for the effects of model obsolescence as the age of the model increases, our framework does not account for the dynamics in the consumer valuation of individual attributes in any general way. The varying number of models offered by a brand in different time periods complicates such an analysis. Although our framework can accommodate entry and exit of *models*, it cannot easily be adapted to situations where *brands* enter or exit the market. Adding flexibility to our model along these lines may be worthwhile. Additionally, while we model the effects of advertising on the intrinsic brand preferences, data limitations do not permit the decomposition of the role that advertising plays in informing consumers about new models from that of persuading consumers to buy the existing product line. Such research objectives may be more easily pursued if one had access to consumer-level data rather than the aggregate data at our disposal. Besides, the introduction of models with enhanced attributes may be accompanied by higher advertising expenditures. Correspondingly, we may not have been able to accurately decompose the effects of the dynamics in brand preferences and the changes in the brand's product line. One can obtain a more accurate decomposition if advertising data at the brand-model level were available. Moreover, our model assumes that the consumers notice all the changes in the portfolio of models offered by brand changes. However, because of limited cognitive capacity, it is likely that the consumers only consider the models that are close to their needs and may hence not be affected by the addition or withdrawal of other models. Moreover, it is likely that the retailers do not carry all the models offered by the brand at all times.[13]

We develop a demand model that captures the effects of changes in the portfolio of models offered by a brand, as well as the dynamics in its intrinsic preference on that brand's performance, and assess its validity through an extensive simulation study. Our model parsimoniously incorporates the information pertaining to all the models offered by a brand. Substantively, we provide insights into the relative importance of product line changes and dynamic brand preferences on the performance of a brand. We also assess the returns on changes in advertising budgets as well as product development efforts.

[13] We thank an anonymous reviewer for pointing this out.

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Appendix A. Steps in Kalman Filter Estimation

Step 1. We begin at time 0 by choosing $\beta_{00} = \{\beta_{010}, \beta_{020}, \ldots, \beta_{0B0}\}$ and Σ_0 to be our best guesses about the mean and the variance, respectively, of the vector of intrinsic brand preferences. In our empirical analysis, we lack genuine prior information, and hence specify a diffuse prior by defining Σ_0 to be a large number (Harvey 1990). Thus, at time 0, our knowledge of the unobserved state variable, the intrinsic brand preference, is given by the following probability distribution: $\beta_{00} \sim \mathrm{N}(\beta_{00}, \Sigma_0)$.

Step 2. Let $\beta_{0t\,|\,\tau}$ denote the minimum mean-square error estimate of the intrinsic brand preference vector at time t, given the model and all the observed data up through time τ. At any point in time $t-1$, we have observations of data from time 1 to $t-1$ and we can summarize our knowledge of $\beta_{0t-1\,|\,t-1}$ as follows:

$$\beta_{0t-1\,|\,t-1} \sim \mathrm{N}(\beta_{0t-1\,|\,t-1}, \Sigma_{t-1\,|\,t-1}).$$

$\beta_{0t-1\,|\,t-1}$ is thus the posterior distribution we obtain at $t-1$ after observing data $t-1$. Now, our best guess for β_{0t} at $t-1$, i.e., $\beta_{0t\,|\,t-1}$ and $\Sigma_{t\,|\,t-1}$ is given by

$$\beta_{0t\,|\,t-1} = \bar{\beta} + \Lambda\beta_{0t-1\,|\,t-1} + \omega Ad_t, \tag{A1}$$

$$\Sigma_{t\,|\,t-1} = \Lambda'\Sigma_{t-1}\Lambda + Q, \tag{A2}$$

where $\Lambda = \lambda \times I$, Q is a $J \times J$ (J = number of brands) diagonal matrix with σ^2_{sb} as the diagonal elements. This is our prior distribution for the unobserved brand preferences. For the sake of parsimony, we assume that σ^2_{sb} is the same for all brands.

Step 3. Prior to observing mean utilities at time t, our best guess for the vector Q_t in Equation (9) is given as

$$Q_{t\,|\,t-1} = \alpha_t + \beta_{0t\,|\,t-1} + \theta H_t + \xi_t.$$

Step 4. Once we recover the actual mean utility vector by "inverting" the market share in time t (i.e., δ_{jbt}), we can obtain the corresponding values of Q_t, and can hence calculate the prediction error in our forecast and the conditional variance of this prediction error. Note that for a given set of observed market shares, the contraction mapping algorithm in Berry et al. (1995) guarantees unique values of the mean utilities δ_{jbt}. Further, it can be easily verified that there is a unique value of Q_t for a given set of δ_{jbt}. Hence, for a given set of observed market shares, the values of Q_t are unique.

Given these values of Q_t, we can calculate the prediction error in our forecast and the conditional variance of this prediction error. These are used as inputs in the maximum likelihood estimation procedure.

$$\text{Prediction error} = \varepsilon_{t|t-1} = Q_t - Q_{t|t-1} = \delta_t - \{\alpha_t + \beta_{0t|t-1} + \theta H_t + \xi_t\}, \tag{A3}$$

$$\text{Variance of the prediction errors} = S_{t|t-1} = \Sigma_{t|t-1} + V, \tag{A4}$$

where V is a $B \times B$ (B = number of brands) diagonal matrix with σ_ξ^2 as the diagonal elements.

Step 5. Given our information on Q_t and Ad_t, we can update our estimate of the vector of state variables ($\beta_{0t|t}$) and the associated variance-covariance matrix ($\Sigma_{t|t}$). The exact expression for the posterior distribution of the vector of intrinsic brand preferences is obtained by specifying the joint normal distribution of β_{0t} and forecast error ε_t conditional on observed data (Meinhold and Singpurwalla 1983). The definition of conditional normal is used to obtain the optimal forecast of $\beta_{0t|t}$ conditional on observed forecast error $\varepsilon_{t|t-1}$. The exact expressions are given as follows:

$$\beta_{0t|t} = \beta_{0t|t-1} + \Sigma_{t|t-1}(S_{t|t-1})^{-1}\varepsilon_{t|t-1}, \tag{A5}$$

$$\Sigma_{t|t} = \Sigma_{t|t-1} - \Sigma_{t|t-1}(S_{t|t-1})^{-1}\Sigma_{t|t-1}. \tag{A6}$$

Step 6. We use $\beta_{0t|t}$ and $\Sigma_{t|t}$ as inputs in the next round for generating prediction equations $\beta_{0t+1|t}$ and $\Sigma_{t+1|t}$ in Step 2. We continue the recursions until $t = T$ at the end of the sample.

Appendix B. Steps in the Estimation Algorithm

The objective of our estimation is to recover four sets of parameters in Equations (4a)–(4c): (a) parameters $\Theta_1 = \{\alpha_t, \theta, \bar{\beta}_b, \lambda, \varpi\}$ in Equation (4a) that correspond to the mean preferences and other response parameters that influence the utility of all the models offered by a brand, (b) parameters $\Theta_2 = \{\beta\}$ in Equation (4a) that capture the effects of consumers' mean valuations of attributes (including price), (c) heterogeneity parameters $\Theta_3 = \{\sigma_{\Delta h\beta}\}$ that correspond to the Cholesky decomposition of the matrix Σ, the covariance matrix corresponding to the heterogeneity distribution in Equation (4c), and (d) $\Theta_4 = \sigma$, the scale parameter of the nested logit model. The estimation was done in the following steps with Steps 3–6 iterated until convergence.

Step 1. Identify one of the models offered by each brand as a base model.

Step 2. Start with a set of initial values for all the parameters.

Step 3. Given the observed market shares of each brand-model for each period, given these values of the heterogeneity parameters Θ_3 and the scale parameter σ, obtain the mean utilities δ_{jbt} using the contraction-mapping algorithm as in Berry et al. (1995).

Step 4. Subtract the mean utility of the base model for each period from the mean utilities of the other models for the same period. As in Equation (8), these differences in the mean utilities (δ'_{jbt}) can be related to the differences in the attributes of the corresponding brand-model and the base model. This equation can be used to estimate the parameters that affect model choice. In this estimation, we also account for price endogeneity.

Step 5. To estimate the brand choice parameters, we use Equation (9). The dependent variable for this estimation, Q_{bt} has two components. The first component, R_{bt}, can be computed directly as a function of the mean utilities δ_{jbt} recovered from the contraction mapping in Step 3 as $R_{bt} = (1-\sigma)\ln\sum_{j\in M_b}\exp(\delta_{jbt}/(1-\sigma))$. The second term, $(1-\sigma)\cdot\ln\sum_{j\in M_b}\exp((\beta X_{1bt} + \delta'_{jbt})/(1-\sigma))$, is a function of the differences in mean utilities (δ'_{jbt}) described in Step 3, the attributes of the base model, and the model choice parameters, (Θ_2), from the previous iteration. Hence, for a given set of heterogeneity parameters Θ_3, the scale parameter σ, and the model choice parameters, Θ_2, the dependent variable Q_{bt} can be uniquely obtained. With Equation (9) as the observation equation and Equation (5) as the system equation, we can estimate the brand choice parameters (Θ_1) using the Kalman filter algorithm described in Appendix A.

Step 6. As stated in §3.3.3, we use the system of equations described in Steps 4 and 5 and minimize the corresponding GMM objective function as in Berry et al. (1995) to recover the rest of the parameters, the heterogeneity parameters Θ_3 and the scale parameter σ. These values are used again in the next iteration in Step 3.

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