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A Conjoint Approach for Consumer- and Firm-Level Brand Valuation

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ABSTRACT

This paper develops and tests a reduced-form, conjoint methodology for measuring brand equity. The proposed approach (i) provides objective dollarmetric values for brand equity without requiring one to collect perceptual or brand association data, (ii) captures the effects of awareness and availability in the marketplace as sources of brand equity, (iii) accounts for competitive reaction, (iv) allows the mix of branded and unbranded firms to affect industry size, and (v) uses consideration set theory to project market-share estimates from the conjoint experiment to the marketplace. Managers can use the approach for developing customized strategies for targeting customers, monitoring brand 'health', allocating resources, and determining the values of brands in a merger or acquisition.

The empirical results suggest that the proposed metric for measuring consumer-level brand equity has convergent validity; in addition the magnitudes *and* strengths of brand equity vary considerably across consumers and brands. At the firm level, the results show that previous methods are likely to overstate brand equity, especially for products with low market shares. Finally, the results show that the external validity for the proposed brand equity measures is high.

Keywords: Brand equity; brand valuation; choice models; conjoint analysis, competition, Nash equilibrium.

INTRODUCTION

There is a vast and burgeoning literature on how to measure consumer- and firm-level brand equity (see Keller and Lehmann 2006 for a detailed literature review). Some researchers (e.g., Ailawadi et al. 2003) propose that firm-level brand equity be measured directly using market-level data. Others (e.g., Srinivasan et al. 2005) suggest that one should first collect primary data to measure consumer-level brand equity and then use this information, combined with market-level data, to estimate firm-level brand equity. Our proposed method is in the spirit of the latter approach since we measure both consumer- and firm-level brand equities.

Keller and Lehmann (2006) identify four components of brand value: (i) Biased perceptions, (ii) Image associations, (iii) Incremental value, a component that that is not related to product attributes or benefits, and (iv) Inertia value. This paper develops a utility model that captures all these components of brand equity. The proposed model allows for different information-processing strategies and provides objective estimates of brand equity without directly measuring consumer perceptions and brand image associations.

Two critical design features of the methodology are that: (i) The experiment must include unbranded products for determining the values for products with no brand equity, and (ii) All choice sets in the conjoint experiment must include the no-purchase option. This feature is key for obtaining unambiguous dollarmetric estimates of brand equity. In addition, it allows the market size to vary depending on the players in the market. At the firm level, the two key features of the model are that it (a) Explicitly allows brand equity to depend on objective measures of awareness and availability, and (b) The marketing policies (e.g., market prices *and* advertising levels) of all products in the industry are endogenously determined. Hence, the model provides objective estimates for brand equity after simultaneously allowing for competitive reaction, demand and supply adjustments, and consumer heterogeneity.

The methodology was tested using data from a choice-based conjoint experiment. The results show that the proposed metric for measuring consumer brand equity has convergent validity and is externally valid. Furthermore, the brand equity estimates vary considerably across methods. After briefly reviewing the literature, we describe the brand equity measurement model. Next, we report the results from a commercial application. We conclude by discussing the main findings and proposing directions for future research.

LITERATURE REVIEW

Extant methods for measuring brand equity differ in terms of whether they measure brand equity at the consumer or firm level, the marketing outcomes measured (utility or monetary value), and the benchmark definition of what would happen when a product turns unbranded.

Consumer-Level Brand Equity

Srinivasan (1979) and Kamakura and Russell (1993) define consumer-level brand equity as the component of utility that is intrinsic to the brand and cannot be explained by the product attributes. This measure captures the incremental and inertia values of a brand but only provides relative values of brand equity. Park and Srinivasan (1994) measure brand equity by the difference between a consumer's overall utility from a brand and her utility based only on objective product attributes. This definition accounts for biased perception and uses a benchmark product that is defined in terms of objective attributes. Swait et al. (1993) define consumer brand equity by the equalization price, the price that equates the utility of a brand to the utility the same product would obtain in a marketplace with no brand differentiation. Since the authors define the equalization price "with respect to any utility of interest" (Swait et al., p. 29), this measure does not provide dollarmetric values of brand equity. In this paper, we define brand equity as the difference in the consumer's willingness-to-pay (WTP) for a branded product with a particular set of features and an *identical* unbranded product.

Firm-Level Brand Equity

Ailawadi et al. (2003) define brand equity as the revenue premium a brand generates compared with a private label product. Srinivasan et al. (2005) define firm-level brand equity as the incremental profit contribution obtained by the brand in comparison to an identical unbranded product, assuming that the prices of both products are the same. To obtain this measure, the authors adjust the results of their demand experiment using subjective estimates of push-based awareness and push-based availability data from a panel of industry experts. Dubin (1998, pp. 77–127) defines brand equity as the incremental profitability that the firm would earn operating with the brand name compared to operating without it. The key distinction among these three methods is that the first two specify the unbranded scenario exogenously; the third (Dubin's method) derives the unbranded scenario endogenously using a competitive equilibrium approach. In this paper, we adopt Dubin's definition to measure firm-level brand equity. For comparison, we specify the unbranded scenarios both endogenously and exogenously.

THE CONSUMER MODEL

In this section, we first present a utility model that captures all four components of brand value on choice (Keller and Lehmann 2006, p. 751). We then show how a reduced-form version of this model, which obviates the need to measure consumer perceptions and brand image association, can be used to develop an objective measure of brand equity.

Model Structure

Consider a choice set consisting of J-1 branded products (or services), one unbranded product, and the no-purchase option. By definition, the unbranded product is a product with no brand equity. Examples include a private label or a generic product. Our study operationalizes the unbranded product as a hypothetical new product. This conjoint design is a critical part of our methodology for measuring *both* consumer- and firm-level brand equity.

Let J index the unbranded product, $\tilde{x}_{ijm}$ be consumer i's perceived value of attribute m for product j, $\tilde{\mathbf{x}}_{ij} = (\tilde{x}_{ij1}, \cdots, \tilde{x}_{ijM})'$, and p_j be the price of product j. Let z_{ijk} denote consumer i's image association of product j on image dimension k (k=1. …, K). Suppose consumer i (i=1, …, I) considers buying one unit of product j from the available set of products (j=1, …, J). Assume that the consumer's preferences can be modeled as a quasilinear utility function in which the status quo is represented by an individual-specific composite good with unit price p_i^w. Let q_i denote the number of units of the composite good purchased by consumer i. Then the utility function for this consumer depends on the quantity q_i of the composite good and on whether or not the consumer makes a choice from the set of available products (j=1, …, J).

Let $U_i(n_{ij}, q_i)$ denote consumer i's utility function, where n_{ij} = 1 if consumer i chooses product j and 0 otherwise. Let w_i be consumer i's budget. For all i, assume that consumers maximize $U_i(n_{ij}, q_i)$, subject to the budget constraints $n_{ij}p_j + q_i p_i^w \le w_i$.

Suppose initially that the consumer's preferences are directly based on the attribute dimensions (including prices and brands). We say that the consumer's preferences are based on 'attribute space.' Later, we shall examine the case where the consumer first transforms the attribute information into perceived benefits ('benefit space') and then forms preferences based on these benefit dimensions.

Since a utility-maximizing consumer will always exhaust her budget, the indirect utility function for consumer i if she purchases product j (i.e., $n_{ij} = 1$ and $q_i = \frac{w_i - p_j}{p_i^w}$) is

$$(1) \qquad U_i(n_{ij}, q_i) = b_{ij0} + \sum_{k=1}^{K} b_{ik}^{z} z_{ijk} + \sum_{m=1}^{M} b_{im}^{x} \tilde{x}_{ijm} + b_i^p \frac{w_i - p_j}{p_i^w} + \nu_{ij}, \text{ for all } i = 1,\dots,I,\ j = 1,\dots,J,$$

where for each consumer i, $\tilde{x}_{ijm}$ (z_{ijk}) is that consumer's perceived level of attribute m (image association k) for product j, b_{ij0} is an intercept specific to product j that captures both the incremental and inertia values of brand j, b_{im}^{x} (b_{ik}^{z}) is the importance of perceived attribute m (image association k), b_i^p is the marginal effect of income or price sensitivity, and ν_{ij} is an error term. If consumer i chooses the no-purchase option, her indirect utility function is

$$(2) \qquad U_i(0, q_i) = b_i^p \frac{w_i}{p_i^w} + \nu_{i0}, \text{ for all } i = 1,\dots,I.$$

One approach for measuring brand equity is to work directly with Equation (1). This approach allows one to estimate the effects of different sources of brand equity. However, it entails collecting data on market prices, perceived and objective attribute values for each brand (Srinivasan and Park 1994), and brand image associations (Swait et al. 1993). An alternative approach (described below) is to work with objective attribute values and infer the impact of attribute perception bias and image associations on brand values from the model. This approach is simple to use, does not require subjective perceptions and image association data, and avoids all problems associated with measurement error and multicollinearity.

Following Kamakura and Russell (1993), let x_{jm}be the objective level of attribute m for product j. For any consumer i, let θ_{ijm} be an individual-specific perceptual bias parameter for attribute m and product j and θ_{ijm0} be a measurement intercept parameter. Let δ_{ijm} be a consumer specific parameter that captures the effect of the price signal on the perception of attribute m for product j. Then for consumer i, the perceived level of attribute m for product j is

(3) $\tilde{x}_{ijm} = \theta_{ijm0} + \theta_{ijm} x_{jm} + \delta_{ijm} p_j + e_{ijm}$, for all $i = 1,\ldots,I;\ j = 1,\ldots,J;\ m = 1,\cdots,M$,

where e_{ijm} is a stochastic term that captures perceptual errors.

In contrast to Kamakura and Russell, Equation (3) allows for price to serve as a signal for the quality of an attribute. Thus, suppose a high price for product j signals a higher level for attribute m (i.e., higher quality) in that product to consumer i. Then, $\delta_{ijm} > 0$. In the special case where $\delta_{ijm} = 0$, the price of product j has no signal value to consumer i for the attribute in question. In general, price signals can vary across both brands and attributes.

Equation (3) allows for different perceptual biases across attributes. For example, suppose consumer i is fully informed about attribute m in product j or can verify the level of this attribute prior to purchase (i.e., attribute m is a 'search' attribute). Then, $\theta_{ijm} = 1$ and $\theta_{ijm0} = \delta_{ijm} = 0$. Alternatively, suppose consumer i misperceives that the level of attribute m for product j (e.g., a branded product) is higher than its true value. Then, in general, $\theta_{ijm} \neq 1$ (i.e., the attribute is an 'experience' or 'credence' attribute).

Following Jedidi and Zhang (2002), set p_i^w to 1. Substituting Equation (3) for the perceived attributes $\tilde{x}_{ijm}$ into Equation (1) and collecting terms leads to:

(4) $$U_i(n_{ij}, q_i) = b_{ij0} + \sum_{m=1}^{M} b_{im}^x \theta_{ijm0} + \sum_{k=1}^{K} b_{ik}^z z_{ijk} + \sum_{m=1}^{M} b_{im}^x \theta_{ijm} x_{jm} - (b_i^p - \sum_{m=1}^{M} b_{im}^x \delta_{ijm}) p_j + b_i^p w_i + \sum_{m=1}^{M} b_{im}^x e_{ijm} + \nu_{ij}.$$

Clearly, the parameters $b_{im}^x, \theta_{ijm0}, \theta_{ijm}$, and δ_{ijm} cannot be identified unless we impose some restrictions on the model. However, for measuring brand equity, it is not necessary to impose any restrictions. Specifically, one can estimate the joint effects of all the parameters using a reduced-form approach. Thus, Equation (4) can be compactly written as:

(5) $$U_i(n_{ij}, q_i) = \beta_{ij0} + \sum_{m=1}^{M} \beta_{ijm} x_{jm} - \beta_{ij}^p p_j + \varepsilon_{ij}, \text{ for all } i = 1,\ldots,I,\ j = 1,\ldots,J,$$

where $\beta_{ijm} = b_{im}^x \theta_{ijm}$ is a regression coefficient that captures the reduced-form, brand-specific effect of objective attribute m, $\beta^{p}_{ij} = b^{p}_{i} - \sum_{m=1}^{M} b^{x}_{im}\delta_{ijm}$ captures the reduced-form effect of price on the utility of Brand j, $\beta_{ij0} = b_{ij0} + \sum_{m=1}^{M} b^{x}_{im}\theta_{ijm0} + \sum_{k=1}^{K} b^{z}_{ik} z_{ijk}$ is a brand-specific coefficient that captures the incremental effects of a brand such as inertia and brand associations, and $\varepsilon_{ij} = \sum_{m=1}^{M} b^{x}_{im} e_{ijm} + \nu_{ij}$ is a composite, heteroskedastic error term. The distributional assumptions for ε_{ij} (j=1, …, J) are discussed below in the Model Estimation subsection.

As Equation (5) shows, a utility model in which both attribute and price effects vary across brands and individuals can capture all the four sources of brand value and also control for price signalling. From a control point of view, the effects of the z_{ijk}'s can be measured if data on brand image associations are available. However, from an estimation viewpoint, this is not necessary since these image effects are automatically absorbed in the brand-specific intercept β_{ij0}Note that although Equation (5) captures multiple sources of brand equity, it does not reveal which specific perceptions or image association(s) brand equity arises from. Thus if the management objective is to understand brand equity at the perception or image association levels, it is necessary to supplement the method by collecting perceptual data.

The general model in Equation (5) requires one to estimate separate utility functions for each brand. Consequently, estimation problems can arise if the number of brands and/or attributes is large. One way to address this is to assume that all perceptual parameters are invariant across attributes (i.e., $\theta_{ijm} = \theta_{ij}\ \forall m$). Then, Equation (4) simplifies to:

(6) $$U_i(n_{ij}, q_i) = \beta_{ij0} + \theta_{ij} \sum_{m=1}^{M} b^{x}_{im} x_{jm} - \beta^{p}_{ij} p_j + \varepsilon_{ij}.$$

In Equation (6) only the intercept, price coefficient, and the 'proportional halo' parameter θ_{ij} vary by brand. Furthermore, Equation (6) implies that halo effects are proportional across attributes. Note that this condition may not hold. For example, Crest toothpaste may have a much higher halo effect for ‘cavity prevention’ than for ‘whitening.’

Suppose the consumer evaluates products in terms of their perceived benefits (‘benefit space’) and not in terms of ‘attribute space.’ Furthermore, suppose the relationships among the objective stimuli (i.e., the physical attributes, prices, and brands) and perceived benefits are stochastic and vary across individuals. Then, the consumer’s preferences can be modeled using a reduced-form utility function that is analogous to Equation (5). See Appendix A.

In summary, Equation (5) allows for general information–processing strategies (i.e., attribute vs. benefit processing) by consumers and captures various sources of brand equity. Importantly, for measuring brand equity, there is no need to obtain subjective data on brand attribute perceptions or brand image associations.

Model Estimation

A utility-maximizing consumer will select product j if and only if two conditions are simultaneously satisfied: (i) Her utility for product j is greater than the utility from the no-purchase option, and (ii) The utility from product j has the maximum value in a given choice set. Let s index a choice occasion or observation (s=1,…,S) in a conjoint experiment. Let $U_{ijs} = U_{is}(n_{ij}, q_i) = V_{ijs} + \varepsilon_{ijs}$ and $U_{i0s} = U_{is}(0, q_i) = \varepsilon_{i0s}$ denote the utility from the purchase of product j and the no-purchase option on choice occasion s, respectively.[1] Then, consumer i will choose product j on choice occasion s if

(7) $$U_{ijs} = \max_{1 \le l \le J} U_{ils} \ge U_{i0s},$$

and will not choose any product if

(8) $$U_{ijs} < U_{i0s},\ j = 1, \ldots, J,\ s = 1, \cdots, S.$$

Assume that each of the ε_{ijs}’s (j=0, …, J) follows an independent and identical extreme value distribution. Both distributional assumptions are reasonable given the choice-based conjoint design. Thus, brand alternatives are randomized both within and across choice sets. Hence the independence assumption holds. At first glance, the homoskedasticity assumption may seem anomalous since ε_{ijs} is a composite error term. However, this is not an issue because scale and taste parameters are inherently confounded in multinomial logit models and the model parameters are both brand- and individual-specific. Finally, although the ε_{ijs}'s (j=0, …, J) are independent, the Bayesian estimation approach allows the brand-specific parameters to co-vary in the population. (See the Web Appendix.) Then consumer i's choice probability for product j (P_{ijs}) and her non-purchase probability (P_{i0s}) on occasion s are:

$$(9) \qquad P_{ijs} = \frac{\exp(V_{ijs})}{1+\sum_{l=1}^{J}\exp(V_{ils})}, \qquad\qquad P_{i0s} = \frac{1}{1+\sum_{l=1}^{J}\exp(V_{ils})}.$$

To capture consumer heterogeneity, assume that $\boldsymbol{\beta}_i = \{\beta_{ijm}, \beta_{ij}^{p}, j=1, \ldots, J; m=1, \ldots, M\}$, the joint vector of regression (part-worth) parameters, follows a multivariate normal $N(\bar{\boldsymbol{\beta}}, \boldsymbol{\Omega})$. The covariance matrix $\boldsymbol{\Omega}$ is non-diagonal and captures the covariation of the model parameters (including the brand intercepts) in the population.

Because the model includes the no-choice option, all main effects and interactions are identified. In addition, the model allows the probability of the no-purchase option (and thus the total share of the J brands) to vary as a result of changes in competitive prices or branding status (i.e., a brand loses its name).

The model parameters are estimated using a Bayesian estimation procedure (see the Web Appendix). This procedure allows one to compute dollarmetric consumer-level brand equity (see Equation (12) below) as part of the iteration process and provides confidence intervals for brand equity values at different levels of aggregation. Hence managers can choose customized marketing strategies after performing an appropriate risk-return analysis.

THE MEASUREMENT OF BRAND EQUITY

Consumer-Level Brand Equity

We now discuss how Equation (5) can be used to measure brand equity at the individual level. Following Jedidi and Zhang (2002, p. 1352), define a consumer's WTP as "the price at which a consumer is *indifferent* between buying and not buying the product." Using this definition, consumer i's WTP for product j, R_{ij}, is given by:

$$(10) \qquad R_{ij} = \frac{\beta_{ij0} + \sum_{m=1}^{M} \beta_{ijm} x_{jm}}{\beta_{ij}^{p}}, \text{ for all } i = 1,\ldots,I,\ j = 1,\ldots,J,$$

where $\beta_{ij}^{p} > 0$. Recall that brand equity BE_{ij} was defined as the difference in WTP between a branded and an *identical* unbranded product. For any product j this difference is given by:

$$(11) \qquad BE_{ij} = \frac{\beta_{ij0} + \sum_{m=1}^{M} \beta_{ijm} x_{jm}}{\beta_{ij}^{p}} - \frac{\beta_{iJ0} + \sum_{m=1}^{M} \beta_{iJm} x_{jm}}{\beta_{iJ}^{p}}, \text{ for all } i = 1,\ldots,I,\ j = 1,\ldots,J.$$

Equation (11) has an intuitive interpretation. Brand equity is the sum of three effects: (i) The incremental WTP due to the main effect of brand $\left(\frac{\beta_{ij0}}{\beta_{ij}^{p}} - \frac{\beta_{iJ0}}{\beta_{iJ}^{p}}\right)$, (ii) The incremental WTP due to enhanced attribute perception of the brand $\left(\frac{\sum \beta_{ijm} x_{jm}}{\beta_{ij}^{p}} - \frac{\sum \beta_{iJm} x_{jm}}{\beta_{iJ}^{p}}\right)$, and (iii) Differences in price sensitivity for a branded and an unbranded product $(\beta_{ij}^{p} \text{ vs. } \beta_{iJ}^{p})$. Equation (11) allows one to measure how prices and enhanced attribute perceptions affect brand equity overall. However, this model does not allow one to measure how a specific image association affects brand equity since these effects are absorbed in the main effect of brand (see (i) above).

Our definition for consumer-level brand equity is effectively the price premium that a consumer is willing to pay for that brand over the price that this consumer is willing to pay for an identical unbranded product. (Notice the use of the same x_{jm} values but different part-worth values β_{ijm} in computing BE_{ij} in Equation (11).) This definition is different from those used in previous studies. In terms of our notation, Kamakura and Russell (1993, p. 12) define brand equity as β_{ij0}, scaled so that the mean value across *all* brands in the market is zero. Consequently, their measure of brand equity is non-monetary; in addition, it does not separate out the effect of biased perceptions. Swait et al. (1993) define brand equity by the equalization price, which corresponds to R_{ij} in Equation (10). This correspondence occurs because Swait et al. (1993, p. 28) set the utility of the unbranded product to zero ($V^R \equiv 0$). Note that it is critical for the experimental design to include both the unbranded product J and the no-choice option. Without including these options, it is not possible to estimate β_{iJ0} and β_{iJm} (m=1, …, M); hence, one cannot obtain dollarmetric measures of brand equity (BE_{ij}).

Firm-Level Brand Equity

At the firm level, brand equity is defined as the incremental profit that the firm would earn by operating with the brand name compared to operating without it. Let $\mathbf{p}=(p_1, \ldots, p_J)'$ be the price vector for products j=1, …, J. Let $\mathbf{Z}=\{Z_{j1}, \ldots, Z_{jL}; j=1, \ldots, J\}$ be a vector of L marketing activities such as advertising. Let $M_j(\mathbf{p}, \mathbf{Z})$ be product j's expected market share given the competitive marketing decisions $\mathbf{p}$ and $\mathbf{Z}$. Let p_j and c_j respectively, be the unit price and variable cost per unit of product j. Let $F_j(\mathbf{Z}_j)$ be the sum of the fixed costs for product j and other costs associated with nonprice marketing activities (e.g., advertising). Let Q_j denote the expected quantity of product j that is sold and T the total product category purchase quantity per year for the entire market. Then the expected annual profit earned by product j is given by

$$\text{Profit}_j = Q_j \times (p_j - c_j) - F_j(\mathbf{Z}_j),\ j = 1, \cdots, J, \tag{12}$$

where $Q_j = T \times M_j(\mathbf{p}, \mathbf{Z})$. Similarly, the expected profit that product j would have earned if it were unbranded is

$$\text{Profit}_j' = Q_j'(p_j' - c_j) - F_j(\mathbf{Z}_j'), \tag{13}$$

where $Q_j^{'} = T \times M_j^{'}(\mathbf{p}', \mathbf{Z}')$ is the expected quantity that product j would have sold if it were unbranded and priced at $p_j^{'}$, and $\mathbf{p}'$ and $\mathbf{Z}'$ are the new industry equilibrium values for prices and marketing activities. We assume that the category volume T is unaffected when a branded product becomes unbranded. However, note that because of the no-choice option, the model allows the choice probability of the composite good to change as a result of a product becoming unbranded. Thus, the total sales volume of the J products *can* change when any product turns unbranded (i.e., $\sum_j Q_j^{'} \neq \sum_j Q_j$). Therefore, the brand equity of product j is:

(14) $$BE_j = \text{Profit}_j - \text{Profit}_j^{'}, \; j = 1, \cdots, J.$$

We now discuss how to measure $M_j, M_j^{'}, Q_j$ and $Q_j^{'}$.

Determining M_j :If <u>all</u> products enjoy full awareness and full distribution, M_j is simply the average choice probability in the sample (see Equation (9)). However, this assumption is unrealistic.

To adjust for lack of full awareness and distribution, consider for now a market with three products j=1, 2 and 3. Let c= (d_1 , d_2, d_3) be a subset of products where d_j is a dummy (coded 1= yes and 0 = no) that indicates whether product j belongs to the subset. Let π_j^A denote the proportion of consumers in the population who are aware of product j and π_j^D the proportion of distribution outlets where product j is available (e.g., % ACV). In general, both these proportions are endogenous and depend on the marketing policies chosen by different firms in the industry. Follow the standard approach and assume that these proportions are locally independent (Silk and Urban 1978).[2] Then $\pi_j = \pi_j^A \pi_j^D$ is the proportion of consumers who are aware of product j and are able to purchase it from a distribution outlet. This implies that the awareness- and availability-adjusted market share for product j=1 (say) is given by

(15) $$M_1 = \pi_1(1-\pi_2)(1-\pi_3)P_1^{(1,0,0)} + \pi_1\pi_2(1-\pi_3)P_1^{(1,1,0)} + \pi_1(1-\pi_2)\pi_3 P_1^{(1,0,1)} + \pi_1\pi_2\pi_3 P_1^{(1,1,1)},$$

where, for example, $\pi_1(1-\pi_2)(1-\pi_3)$ is the probability that product 1 is the only product that a consumer is aware of and that is available for purchase and $P_1^{(1,0,0)}$ is the choice probability of product 1 in the set c=(1,0,0) computed using Equation (9). In contrast to conventional models, Equation (15) does not constrain the sum of market shares to equal one. This model property is critical because it allows marketing policies (e.g., the advertising budgets chosen by branded and unbranded products) to affect the market shares and volumes for different products and hence the dollar values of brand equity for different firms.

More generally, let $c_k \in C$ be a subset of brands (including the no-purchase option) sold in the marketplace and ϕ_k be the associated probability for that choice subset. Let $P_j^{c_k}$ be the probability of choosing product j from choice set c_k. Then, the awareness- and distribution-adjusted market share for product j is:[3]

(16) $$M_j = \sum_{c_k \in C} \phi_k P_j^{c_k}.$$

Determining $Q_j^{'}$: To estimate this quantity, it is necessary to determine the price levels $p_j^{'}$ and marketing policies $\mathbf{Z}_j^{'}$ that the firm would choose for product j if it were unbranded. In addition, one needs to determine the combined effect of these policies on the levels of awareness and distribution ($\pi_j^{A'}$ and $\pi_j^{D'}$) and on $M_j^{'}$.

Several methods can be used to determine these values. One approach is to follow Srinivasan et al. (2005) and use ratings by experts to estimate the levels of "push-based" awareness and "push-based" availability. This method is easy to implement. However, it is subjective and does not provide guidance on how to determine the "push-based" prices for different brands. An alternative approach is to assume that the branded product would have price, awareness, and distribution levels equal to the corresponding values of a private label or a weak national brand (e.g., Ailawadi et al. 2003). This method provides objective values for price, awareness, and distribution. However, like the previous method, it does not allow these values to depend on the joint effects of the marketing policies chosen by different firms in the industry *including both branded and other products* (e.g., generics and private labels).

To address these issues, we use a third approach that is similar in spirit to Choi et al. (1990) and Goldfarb et al. (2008). As discussed earlier, the joint effect of awareness and availability for product j is given by $\pi_j = \pi_j^A \pi_j^D$. However, in general, the relationship between awareness and availability is nonrecursive. For example, more retailers will stock a product whose awareness is high. But, if more retailers stock a product, consumer awareness will also increase (e.g., as a result of in-store displays for that product). To simultaneously allow for these feedback effects between awareness and availability and the effects of the marketing policies $Z_{j1}, \ldots, Z_{jL}$ (e.g., advertising spending and trade promotions), let

(17a)
$$\pi_j^D = \gamma_0^D (\pi_j^A)^{\gamma_A^D} \prod_{l=1}^{L} (Z_{jl})^{\gamma_l^D},$$

(17b)
$$\pi_j^A = \gamma_0^A (\pi_j^D)^{\gamma_D^A} \prod_{l=1}^{L} (Z_{jl})^{\gamma_l^A}, j = 1, \cdots, J,$$

where γ_0^A and γ_0^D are constants and $\gamma_D^A, \gamma_A^D, \gamma_l^A$ and γ_l^D $(l = 1, \cdots, L)$ are elasticity parameters. Combining Equations (17a) and (17b) leads to the following reduced-form equation:

(18)
$$\pi_j = \gamma_0 \prod_{l=1}^{L} Z_{jl}^{\gamma_l}, j = 1, \cdots, J,$$

where the γ's are elasticity parameters that measure the joint effects of marketing activities on π_j. As discussed in the empirical example, these parameters can be estimated using objective data on awareness, availability, and marketing activities for existing brands in the marketplace. These specifications assume a current effects model; in general, however, awareness and distribution can depend on the lagged effects of marketing variables. To capture such effects it will be necessary to use a dynamic specification for the awareness and distribution modules and to embed this in a multiperiod game-theoretic model.

The Market Equilibrium. Suppose each firm produces a single product, firms do not cooperate, and all firms choose their marketing policies simultaneously. Then, each firm chooses p_j and $\mathbf{Z}_j$ (and the implied awareness and distribution levels) to maximize:

(19) $$(p_j - c_j)Q_j(p, Z) - F(Z_j), \quad j = 1, \cdots, J,$$

where $Q_j = T \times M_j(\mathbf{p}, \mathbf{Z})$. Then the first-order conditions for the Nash equilibrium are:

(20) $$Q_j + (p_j - c_j)\frac{\partial Q_j}{\partial p_j} = 0; \qquad (p_j - c_j)\frac{\partial Q_j}{\partial Z_j} - \frac{\partial F_j}{\partial Z_j} = 0, j = 1, \cdots, J.$$

Given the estimates for the model parameters, one can numerically solve the system of equations in (20) to calculate the set of equilibrium prices p_j and marketing decisions $\mathbf{Z}_j$ (j=1, …, J) that would be chosen when product j becomes unbranded. These equilibrium quantities can be used to calculate $\text{Profit}_j^{'}$. Note that for this method the levels of price, awareness, and availability for any given product (branded or unbranded) are endogenously determined.

In the empirical study, we shall use all three approaches (Industry Expert, Private Label, and Nash) to calculate $\text{Profit}_j^{'}$ and to compute the dollar values of firm-level brand equity.

AN EMPIRICAL APPLICATION: DESIGN AND MODEL SPECIFICATION

We illustrate the methodology using data from a choice-based conjoint study on yogurt we conducted in a Mediterranean country. The sample consists of 425 representative consumers. The yogurt category was chosen for several reasons. Yogurt is a product category that most consumers are familiar with in the country where the study was conducted. In addition, the competitive set includes both national and multinational brands.

The attributes in the conjoint design were chosen by asking 21 subjects in a pilot study to state the attributes that were most important to them when choosing among yogurt brands. The most frequently mentioned attributes were brand name (95%), flavor (71%), yogurt quality (52%), quality of packaging (47%), and price (42%). Each subject was also asked to state his or her willingness to pay for a 125 gram (4.4 oz.) container of yogurt. Based on the results, we concluded that prices ranging from $0.15 to $0.30 per 125-gram container were credible. At the time of the study, the market prices varied between $0.18 and $0.24 per container.

Design of Conjoint Experiment

Based on the results of the pilot study, conjoint profiles were created based on the three most important attributes: (1) Brand name, (2) Price, and (3) Flavor. Fat content and package size were not included as attributes because the products contain undifferentiated ingredients; furthermore, all brands are sold in the same package sizes (125-gram containers). In addition, as the pilot study showed, most consumers associate quality, taste, and texture with the brand name rather than with the product attributes.

The brand attribute has six levels: A hypothetical new product with the name Semsem and five of the leading brand names in the market (STIL, Yoplait, Chambourcy, Mamie Nova, and Delice Danone). According to the sponsoring company's internal documents, these five leading brands jointly account for 88% market share. The hypothetical new product was introduced to respondents using the following neutral concept test format:[4]

"Semsem is a new flavored yogurt about to be introduced in the market. Semsem offers the same package size and flavor assortments as the brands currently available in the market. Semsem is the product of a new dairy company."

Note that the attribute-level details of Semsem (e.g., price) were not included in the concept description; however, they were included as treatment variables in the experiment.

The experimental design used six price levels for a 125-gram yogurt container ($0.15,

$0.18, $0.21, $0.24, $0.27, and $0.30) and the three most popular flavors (vanilla, banana, and strawberry). These three flavors combined account for 95% of consumer purchases.

We used a cyclic design approach for constructing choice sets (see Huber and Zwerina 1996). We generated six choice designs of 18 choice sets each for the conjoint experiment. We first divided the full factorial of 108 (=6×6×3) profiles into six mutually exclusive and collectively exhaustive orthogonal designs of 18 profiles each. For each orthogonal plan, we used the cyclic design procedure to generate a choice design of 18 choice sets each. Each choice set included three yogurt profiles. Note that using the full factorial design allows us to estimate brand-specific attribute effects (i.e., brand interaction effects). As previously noted, this feature of the experimental design is necessary to capture all sources of brand equity.

Each participant in the study was randomly assigned to one of the six choice designs. After the conjoint task was explained, each participant was presented a sequence of 18 choice sets of yogurt in show-card format. The participant's task was to choose at most one of the three alternatives (including the no-purchase alternative in all scenarios) from each choice set shown. We controlled for order and position effects by counterbalancing the position of the brand and randomizing the order of profiles across subjects. For validation purposes, we asked each respondent to perform the same choice task on five holdout choice sets. The holdout choice sets were designed so that no yogurt profile dominated any other profile on all attributes. We used different holdout choice sets across the six choice designs.

To assess the validity of our brand equity measurement, we asked respondents to evaluate each of the five brands on alternative dimensions of brand equity that have been proposed in the literature (e.g., Aaker 1991 and Agarwal and Rao 1996). In addition, we asked them brand-specific questions regarding awareness, satisfaction, intention, and brand loyalty.

Model Specifications

We used the data from the conjoint experiment to estimate a family of six nested models. In addition, we compared our model results to those obtained by using the Swait et al. (1993) methodology. The six nested models were selected to test for all possible sources of brand equity. Let $BRAND_{kj}$ denote a 0/1 dummy variable that indicates whether yogurt profile j is made by Brand k. The following brand indexes were used: The hypothetical new product Semsem (k=1), STIL (k=2), Yoplait (k=3), Chambourcy (k=4), Mamie Nova (k=5), and Delice Danone (k=6). Using vanilla as the base level, let $FLAV_{1j}$ and $FLAV_{2j,}$ respectively, be the dummy variable indicators of the strawberry and banana flavors. Let $PRICE_j$ be the price level of yogurt profile j. We specified the following general utility function:

$$(21) \quad V_{ij} = \sum_{k=1}^{6} \beta_{ik}^{b} BRAND_{kj} + \sum_{k=1}^{6}\sum_{l=1}^{2} \beta_{ilk}^{f} BRAND_{kj} \times FLAV_{lj} + \sum_{k=1}^{6} \beta_{k}^{p} BRAND_{kj} \times PRICE_{j}, \ \ j = 1, 2, 3,$$

where the β_{ik}^{b} parameters measure the main effect of brand and the β_{ilk}^{f} and β_{k}^{p} parameters measure the brand-specific effects of flavor and price respectively.

Each nonprice parameter in Equation (21) is specified at the individual-level; however, the price parameters are not. Although this specification is not general, allowing the price coefficients to be heterogeneous can be problematic. One potential difficulty can arise if the price coefficient is extremely small (close to zero) or has the wrong sign for some consumers. In this case, the consumer's WTPs for different brands (see Equation (10)) can be large and can even be negative or approach infinity. For example, in a conjoint study on midsize sedans, Sonnier et al. (2008) found that the heterogeneous price coefficient model yielded negative WTP estimates for between 13% and 23% of the subjects. In addition, they report implausible WTP estimates (in the hundreds of thousands of dollars) for some subjects. One way to address these difficulties is to constrain the price coefficient so that lower prices always have higher utilities. Another common approach is to constrain the price coefficient to be equal across respondents (e.g., Jedidi et al. 2003). A third approach is to constrain the price coefficients to one. In a choice model, this means that consumers maximize surplus instead of utility. The latter two methods are equivalent if the utility function is quasilinear (Jedidi and Zhang 2002). In most practical applications, all three approaches lead to price coefficients that are non-zero and have the proper signs. We follow Jedidi et al. (2003) and constrain the price coefficients to be common across respondents.

We estimated the general model in Equation (21) and five special cases. To assess the effect of brands, we estimate a nested model in which the intercept, the effect of flavor, and price sensitivity are all common across brands. This model, which we refer to as the "No Brand-Effect Model" is specified as:

$$V_{ij} = \beta_i^b + \sum_{l=1}^{2} \beta_{il}^f FLAV_{lj} + \beta^p PRICE_j, \;\; j = 1, 2, 3. \tag{22}$$

The second model captures the brand effect only through the intercepts as in Kamakura and Russell (1993). This "Brand Main-Effect Model" is:

$$V_{ij} = \sum_{k=1}^{6} \beta_{ik}^b BRAND_{kj} + \sum_{l=1}^{2} \beta_{il}^f FLAV_{lj} + \beta^p PRICE_j, \;\; j = 1, 2, 3. \tag{23}$$

The third model captures the incremental utility due to enhanced attribute perception from the brand. It allows brands to affect consumer utility through both the intercept and the attributes. This "Brand-Attribute Interaction Model" is:

$$V_{ij} = \sum_{k=1}^{6} \beta_{ik}^b BRAND_{kj} + \sum_{k=1}^{6} \sum_{l=1}^{2} \beta_{ilk}^f BRAND_{kj} \times FLAV_{lj} + \beta^p PRICE_j, \;\; j = 1, 2, 3. \tag{24}$$

The fourth model, which we refer to as the "Brand-Price Interaction Model" allows price sensitivity to vary across brands as follows:

$$V_{ij} = \sum_{k=1}^{6} \beta_{ik}^b BRAND_{kj} + \sum_{l=1}^{2} \beta_{il}^f FLAV_{lj} + \sum_{k=1}^{6} \beta_k^p BRAND_{kj} \times PRICE_j, \;\; j = 1, 2, 3, \tag{25}$$

Finally, the fifth model constrains all the parameters in the general model (Equation (21)) to be fixed across respondents. We refer to this model as the "No Heterogeneity Model."

We used Markov Chain Monte Carlo (MCMC) methods to estimate each of the five models described above. (See the Web Appendix.) For each model, we ran sampling chains for 100,000 iterations. Convergence was assessed by monitoring the time-series of the draws and by assessing the Gelman-Rubin (1992) statistics. In all cases, the Gelman-Rubin statistics were less than 1.1, suggesting that convergence was satisfactory. We report the results based on 40,000 draws retained after discarding the initial 60,000 draws as burn-in iterations.

Goodness of fit. We used the Bayes Factor (BF) to compare the models. This measure accounts for model fit and automatically penalizes model complexity. Table 1 reports the log-marginal likelihoods (LML) for all the models. Kass and Raftery (1995, p. 777) suggest that a value of log BF= $(\mathrm{LML}_{M_1} - \mathrm{LML}_{M_2})$ greater than 5.0 provides strong evidence for the superiority of model M_1 over model M_2. Hence the LML results in Table 1 provide strong evidence for the empirical superiority of the Brand-Attribute Interaction Model relative to all other models.

[Insert Table 1 about here]

The "No Heterogeneity" model performed very poorly. This shows that a model that fails to allow for differences among consumers is unsatisfactory. The "No Brand Effect" model also provides a poor fit. Although this model captures some differences across consumers, it fails to capture the effect of brands on consumer preferences. All other models performed much better than the "No Heterogeneity" and "No Brand Effect" models. As Table 1 shows, the main effects of brand contributed most to the improvement in LML, followed by the brand-attribute interaction effects. Allowing brands to have different price sensitivities did not contribute significantly to overall model fit. Hence brands have a significant effect on attribute perceptions but do not appear to affect price sensitivity.

Predictive validity. The estimated parameters for each model were used to test that model's predictive validity for both the calibration and holdout samples. As discussed, the calibration data for each consumer included 18 choice sets and the holdout sample included five choice sets. Except for the "No Heterogeneity" model, all models have hit rates that are significantly higher than the 25% hit rate implied by the chance criterion. Consistent with the earlier model comparison results, the "No Brand Effect" model has relatively poor predictive validity. All other models have hit rates that are statistically indistinguishable.

Parameter Values. We now discuss the parameter estimates for the selected "brand-attribute interaction" model. Table 2 summarizes the posterior distributions of the parameters by reporting their posterior means and 95% posterior confidence intervals.

Brand Main Effects. There is considerable variability in the brand-specific intercepts. Delice Danone (the market leader) has the highest mean intercept value of 5.71. The unbranded product (Semsem) has the lowest mean intercept value of 3.36. This provides face validity for the use of a hypothetical product to operationalize an unbranded product. The mean intercept value for STIL is not significantly different from that of the unbranded product. This is not surprising since STIL is a weak national brand that has historically spent very little on brand-building activity. The brand-specific intercepts for Yoplait, Chambourcy, and Mamie Nova all have overlapping 95% posterior confidence intervals.

[Insert Table 2 about here]

Brand Interaction Effects. Since vanilla was the base yogurt flavor, all parameter estimates should be interpreted relative to vanilla. Overall, consumers prefer the vanilla to the banana flavor. Except for the unbranded product (Semsem), consumers are indifferent between the vanilla and strawberry flavors for any given brand. However, these results vary across brands. For example, consumers have a significantly higher utility for a strawberry-flavored yogurt from Delice Danone than from one made by the unbranded product.

Price Effects. The main effects of price have the expected sign and are significant. To provide more insight regarding consumer price sensitivities across products, Table 2 reports the average price elasticity of each product across respondents when price is \$0.24 (approximately the average market price across brands) for a 125-gram yogurt container. Note that, since the price coefficients are the same for all brands, the price elasticity differences across brands in Table 2 are due to the differences in brand choice probabilities.

Consumer heterogeneity. Consumers appear to be heterogeneous in their yogurt preferences. This is evident from the large value of LML for the no-heterogeneity model and the relatively large heterogeneity variances for the estimated parameters (see Tables 1 and 2).

EMPIRICAL RESULTS: CONSUMER-LEVEL BRAND EQUITY

We now use the results to compute the individual-level brand equities and their associated confidence intervals. In addition, we assess the convergent validity of our measures of brand equity and compare our results to those obtained by using Swait et al.'s (1993) methodology.

We used the MCMC draws of the parameters to estimate brand equity (BE_{ij}) for each individual and for each brand's yogurt flavor (see Equation (11)). For example, consider a strawberry-flavored yogurt made by Yoplait. Then, we can use the estimates of the posterior means in Table 2 to illustrate how to compute brand equity for this combination as follows:

$$\mathrm{BE_Y} = \frac{3.97 - 0.03}{0.16} - \frac{3.36 - 0.63}{0.16} = 24.6 - 17.1 = 7.6 \text{ cents} = \$0.076.$$

The first (second) term in this equation measures the WTP for a branded (unbranded) strawberry-flavored yogurt. Thus, on average, a consumer is willing to pay an extra $0.08 for the strawberry-flavored yogurt made by Yoplait.

Table 3 reports the posterior means and 95% confidence intervals of these consumer-level brand equities for different brands and flavors. Figure 1 depicts how the distributions of these brand equity values vary across consumers for different brands. Since these consumer-level brand equities vary across *both* brands and flavors, we also measured the overall brand equity for any given brand as the weighted average across the three yogurt flavors. For weights, we used each consumer's self-stated percentage of the occasions on which he or she purchases each of the three yogurt flavors.[5] The distributions of these overall brand equities for different brands are shown in the rightmost panels in Figure 1.

[Insert Table 3 and Figure 1 about here]

Table 3 shows that, regardless of flavor, STIL has no brand equity. This is not surprising since STIL has not invested signficantly in brand-building activities. The market leader, Delice Danone, enjoys the highest brand equity. On average, consumers are willing to pay a premium of up to $0.16 per 125-gram container for Delice Danone over the price they are willing to pay for an identical 125-gram container of an unbranded yogurt. There are no significant differences between the brand equities of vanilla- and banana-flavored yogurts. Consumers attach higher brand equity to a strawberry-flavored yogurt compared to a vanilla-flavored one. This is true for Delice Danone. For Mamie Nova, Chambourcy, and Yoplait, however, the results are less significant (p = 0.1 level). As Figure 1 shows, there is considerable consumer-level heterogeneity in brand equity for all brands.

Convergent Validity

Following Agarwal and Rao (1996), we examined the convergent validity of our brand equity measure with each of the following seven proxies suggested in the marketing literature for measuring consumer-level brand equity (Aaker 1991): Awareness, Perceived Quality, Brand Associations, Preference, Price Premium, Loyalty, and Satisfaction.

[Insert Table 4 about here]

Table 4 reports the mean scores for each brand on each of these seven measures and their respective correlations with our proposed brand equity measure. (Detailed results are available from the authors.) As in Agarwal and Rao (1996), both individual- and aggregate-level correlation coefficients were computed. The individual correlations (Ind.Cor) are based on the individual-level brand equity measures computed across flavors. The aggregate correlations were computed analogously using the aggregate measures of brand equity.

The results show high congruency at the aggregate level between our brand equity measures and all other measures. The lower individual-level correlations are similar to those reported by Agarwal and Rao (1996). The unbranded product, Semsem, received the lowest mean preference score (1.22) and the lowest dollarmetric preference value (-0.06) among all brands. (Neither value is shown in Table 4.) This is consistent with the finding that Semsem has the lowest mean intercept across all brands (Table 2) and provides face validity for using a hypothetical new product as a benchmark for a product with no brand equity.

Comparison to the Swait et al. model

The data were used to estimate the Swait et al. model (1993). To capture observed consumer heterogeneity, we followed Swait's et al.'s approach and used gender, household size, and household income as sociodemographic covariates. The log-likelihood for the general model where all parameters vary by brand is -9670.84. All the price-brand interaction coefficients are insignificant ($0.3 < p < 0.8$). (This result is consistent with our finding that price effects do not vary across brands. See Table 2.) The model was therefore rerun constraining the price parameters to be common across brands. This model has a log-likelihood of -9676.24, which is significantly better than that of the "No Heterogeneity" and "No Brand Effect" models but much worse than those of the other models. See Table 1.

The hit rates for the calibration and holdout samples are, respectively, 42% and 41%. Both values are higher than the 25% hit rate using the chance criterion. However, both hit rates are considerably lower than the corresponding hit rates for the ME+brand interaction model in Table 1 (77.1% and 62.8%).

[Insert Table 5 about here]

Table 5 reports the results for the Swait et al. model. The absolute values of the price and brand main effect estimates are lower than the corresponding estimates using the proposed model (see Table 2). For example, the price coefficient in the Swait et al. model is -0.1 whereas the corresponding estimate using our model is -0.16. This difference in parameter estimates stems mainly from the fact that the Swait et al. MNL model does not capture unobserved heterogeneity.[6]

The mean equalization prices range from $ 0.18 for Semsem to $0.34 for Delice Danone, the market leader (Table 5). Interestingly, compared to our brand equity estimates, the equalization prices in the Swait et al. model do not display much variability across subjects.

To test for method congruency, we computed the correlation between the consumer-level equalization prices and our measures of brand equity. This correlation is low (0.38). This is not surprising since both metrics are based on different theoretical conceptualizations. Recall that for our method, the average brand equity for Delice Danone is $0.16 (see Table 3). This is the same as the difference between the average equalization price for Delice Danone ($0.34) and the average equalization price for Semsem ($0.18) using the Swait et al. model.

However, this result is not surprising. For any given brand, Swait et al.'s definition of the equalization price and the constraint that the unbranded product has zero utility ($V^R = 0$; see Equation (3) in their paper) implies that the equalization price for any consumer is equivalent to the willingness to pay for that consumer.

Summary. These results show that the proposed metric for measuring consumer brand equity is valid. In addition, our method provides detailed information to managers regarding the magnitudes of brand equity across individuals, brands, and product forms. This individual-level and market-level information can be used by managers to develop customized marketing strategies and to allocate resources across products. In addition, by conducting such studies over time, managers can track the 'health' of their brands.

EMPIRICAL RESULTS: PROFITABILITY AND FIRM-LEVEL BRAND EQUITY

We first discuss how to estimate the profitabilities of different brands. We then compare different methods for determining the dollar values of firm-level brand equity. We conclude by performing external validation tests.

Profitability

Table 6 presents the predicted profits for each brand in the market. The calculations are based on the following information for 125-gram yogurt containers provided by the sponsoring company: common variable costs across brands of \$0.1307, fixed 7% wholesale margins, and fixed \$0.04 retail margins. The predicted market share for each brand was obtained by computing the choice probability of each brand/flavor conditional on its retail price for each MCMC draw of the parameters and conditional on the current brand awareness and availability for that brand (see Equation (16)). The individual-level brand awareness data were collected directly from respondents by asking them at the beginning of the survey to list all brands of yogurts they were aware of. The correlation between our survey awareness measures and those from internal company records is 0.97. We obtained the brand annual advertising spending, availability, and market price data from the sponsor company's internal records. Table 6 reports these statistics. Note that, although the annual advertising budgets appear to be low by U.S. standards, they were high in real terms.[7]

Table 6 also reports the weighted market shares for each brand and their associated 95% posterior confidence intervals. Profitability varies considerably across the five brands. STIL is barely profitable, primarily because of its low price and low availability. Delice Danone, the market leader, makes the most profit because of its attractiveness, high awareness, and high availability, all of which translate into high market share.

[Insert Table 6 about here]

<u>Firm-Level Brand Equity</u>

Firm-level brand equity is defined as the incremental profitability that the firm would earn operating with the brand name compared to operating without it. These values can be converted into net present values if we know the appropriate marginal cost of capital for each firm and the projected growth rate for the industry (see Jagpal 2008, pp. 425-29). To predict the profit of a product if it were unbranded, we used each of the three methods discussed earlier: competitive Nash equilibrium, industry expert, and private label.

Competitive (Nash) Equilibrium Approach. To implement this approach, it is necessary to determine how the marketing policies of different firms affect awareness and availability. Using the data in Table 6, we obtained the following estimates for Equation (18):

$$\pi_j = 0.57\mathrm{Adv}_\mathrm{j}^{0.23}$$

where Adv_j is the annual advertising spending (in $ million) for brand j. Both parameter estimates are significant at $p < 0.01$ and Adj. R-square=0.52. Thus a 1% increase in advertising is expected to lead to a 0.23% increase in the joint probability of awareness and availability for any product j. In fact, the advertising elasticities based on market share are: Yoplait (0.09), Chambourcy (0.05), Mamie Nova (0.12), and Delice Danone (0.12).[8]

Next, we used MATLAB to derive the equilibrium marketing strategies (prices and advertising budgets) for each product when it turns unbranded. To check for stability of the Nash solutions, we varied the starting values and tested for negative definiteness of the Hessian. In predicting the market share for an unbranded product, we used the estimated parameter values for the hypothetical new product (Semsem). Table 7 reports the equilibrium prices, advertising budgets, market shares, and profits for each product when it becomes unbranded. For example, without its brand equity, Delice Danone would have achieved only 5.6% of market share and an annual profit of $2.33 million. This implies that Delice Danone's brand-building efforts contributed an incremental 53.4% (= 59%-5.6%) share points and an incremental annual profit of about $24 million (= $26.31-$2.33 million).

[Insert Table 7 about here]

The Industry Expert Approach. To determine the would-be levels of availability and awareness when a product becomes unbranded, we followed Srinivasan et al. (2005) and asked three industry experts: "In your best judgement, what would have been the levels of the brand's availability and its awareness had the brand not conducted any brand-building activities and relied entirely on the current level of push through the channel?" Srinivasan et al. (2005) refer to these estimates as "push-based" awareness and "push-based" availability. The average inter-judge correlation is 0.69 for push-based awareness and 0.61 for push-based availability, suggesting that the ratings are fairly reliable.

Table 8 reports the average estimates of push-based awareness and push-based availability across experts in the panel. To implement the Srinivasan et al. method in a competitive context, it was necessary to choose a value for the "push-based" price. The Nash methodology was used to compute these values. Table 8 reports these equilibrium prices and the resulting market shares and profits when each product turns unbranded.

[Insert Table 8 about here]

Interestingly, although the industry expert approach led to prices that are similar to those obtained using the proposed method, it led to market share and profit estimates that are considerably lower. The primary reason for this discrepancy is that the experts' estimates of push-based awareness and push-based availability appear to be significantly biased downwards. For example, the experts' estimate of the joint probability of push-based awareness and availability for STIL is $\pi=0.05$ (=0.25×0.20), which is approximately one-tenth the corresponding value of 0.46 obtained using the Nash approach (see Table 7). Besides the effect of errors in human judgment, the downward bias of the industry expert approach stems from the fact that the experts' estimates of awareness and availability focus exclusively on push-based factors. For example, the expert approach implicitly assumes that unbranded products do not engage in any pull-based marketing activities (e.g., advertising for building awareness). The Nash method allows *both* push-based and pull-based factors to affect availability and awareness. Consequently, the experts' estimates of awareness and availability are considerably lower than the corresponding values using the Nash method.

The Private Label Approach. This approach assumes that a branded product would attain the same levels of awareness, availability, and price as the corresponding values for a private label if it becomes unbranded. Since there is no private label in the industry, STIL was used as a proxy for a private label. Table 9 reports the market shares and profits for each product if it were unbranded. Overall, the private label approach gave much lower profit values for the unbranded product than the Nash method. This is not surprising since STIL is a heavily subsidized government-owned product; hence, STIL's price and advertising levels are sub-optimal. Specifically, STIL's price of \$0.185 is lower than the optimal Nash price of \$0.248

(see Table 7). Similarly, STIL's annual advertising budget of $0.001M is very small compared to the corresponding optimal Nash advertising budget of $0.389M (see Table 7). Thus STIL, a government-owned brand, may not serve as a good private label benchmark.

[Insert Table 9 about here]

Table 10 presents each brand's equity computed as the difference between that brand's current profit and the profit the product would have earned if it were unbranded (see Tables 6-9). As Table 10 shows, brand equity varies considerably across the five brands. It might appear paradoxical that STIL should make *higher* profits when it is unbranded. However, there is a historical reason for this. STIL, a government-owned firm with monopoly power till the mid 1980s, has been mismanaged and has made continuous losses in spite of being heavily subsidized by the government. Consequently, STIL has negative brand equity. Not surprisingly, our model predicts that STIL will be more profitable if it becomes unbranded.

Table 10 also reports the proportion of profit for each product that is due to the brand name. Except for Delice Danone, these proportions vary considerably across methods for any given product. Interestingly, both the expert and private-label methods attribute a very high proportion of profits to the brand name for brands with low market shares. For example, according to the Nash method, only 7% of Chambourcy's profits can be attributed to brand name. In contrast, the expert and private label methods attribute almost all of Chambourcy's profit (92% and 94%, respectively) to the Chambourcy brand name. As discussed previously, these discrepancies occur because previous methods do not adjust for competitive responses, lead to lower estimates for "push-based" awareness and availability, and do not use a benchmark product with identical attributes levels.

[Insert Table 10 about here]

Comparison With Other Measures. We now compare our firm-level brand equity measures to those obtained from the revenue premium, adjusted revenue premium, and Dubin (1998) methods using STIL as the private label.

The revenue premium measure is defined as the difference in revenue between a branded yogurt and STIL. The adjusted revenue premium measure adjusts the revenue premium measure to allow for the effect of variable costs per unit, VC_j. (See Ailawadi et al. 2003). Dubin's measure (1998, p. 117) is defined as follows:

$$\text{Dubin's Equity}_j = \text{Volume}_j(\text{Price}_j - VC_j)\left[1 - \left(\frac{s_j(1-s_j)(\varepsilon_j - 1)}{(1-\text{share}_j)(\varepsilon_{STIL} - s_j)}\right)\right], j = 2, \cdots, 5,$$

where s_j is the volume of Brand j divided by the sum of the volumes of Brand j and the private label STIL, and ε_j and ε_{STIL} are the price elasticities of Brand j and the private label product, respectively.[9] Note that the entire term in brackets represents the proportion of the brand's margin that is due to the brand name.

Table 11 reports the results. The unadjusted revenue premium measure leads to the highest brand equity values across methods. This is not surprising since the revenue-based metric for measuring brand equity does not adjust for variable costs or advertising spending. For every brand, the adjusted revenue premium measure produces a higher brand equity value than that obtained by using Dubin's approach. However, these discrepancies vary by brand, and are the lowest (in proportional terms) for the market leader, Delice Danone. These results are not surprising because Dubin's metric for measuring brand equity adjusts for the effects of competitive responses when a product becomes unbranded.

For every brand, the proposed method gives lower firm-level brand equity values than Dubin's method; in addition, the former attributes a lower proportion of firm-level brand equity to brand name. The discrepancies across both methods vary by brand and are the lowest (in proportional terms) for the two major brands in the market, Delice Danone and Mamie Nova.

[Insert Table 11 about here]

There are several reasons for these discrepancies. First, in contrast to our method, Dubin (1998) assumes that the total quantity sold by the industry is unaffected when a branded product becomes unbranded (see Dubin 1998, Equation (14), p. 90). As shown in Table 6, the total industry volume at present is 826,875 (125-gram) yogurt containers and the combined volume-based market share of the five brands analyzed is 86%. Hence, the total quantity currently sold by the five brands is 711,112 (=0.86*826,875) yogurt containers. According to the Dubin method, this quantity should remain the same regardless of whether a branded product becomes unbranded. According to our Nash-based method, however, the total quantity sold by the five brands will fall to 554,006 (=0.67*826,875) containers when Delice Danone turns unbranded—a reduction of 22.1%.[10] Second, Dubin's metric for measuring firm-level brand equity is based solely on gross margins (see Equation (4) in Dubin's paper); our metric is based on net margins, after adjusting for advertising costs. Finally, Dubin's method implicitly assumes that all products have the same levels of awareness and availability; our method explicitly allows both awareness and availability to be endogenously determined based on demand-pull and demand-push factors. Consequently, Dubin's brand equity estimates are lower than the corresponding values using our Nash-based method.

Validity of Firm-Level Brand Equity Measures

To validate the proposed measures of firm-level brand equity, the market share estimates for the model were compared with two other sets of market share estimates (see Table 12). The first is based on the average self-stated market shares in the sample for different brands. The second set of market shares was obtained in a separate study of 600 subjects conducted by an independent consulting firm.[11] The Mean Absolute Deviation (MAD) between our estimates and those obtained by the consulting firm is 0.025. The corresponding MAD between our estimates and the self-stated market shares in our sample is 0.021. These results show excellent congruence among the three sets of market share estimates. Since the computation of brand profits depends crucially on the market share estimates, this result provides strong support for the external validity of our firm-level brand equity measures.

[Insert Table 12 about here]

CONCLUSIONS AND FUTURE RESEARCH DIRECTIONS

This paper proposes a methodology for estimating brand equity. Key features of the model are that it provides an objective dollarmetric value for measuring *both* consumer- and firm-level brand equity, shows how to use consideration set theory to translate market-share estimates from the conjoint experiment to the marketplace, does not require one to collect perceptual data, and allows for competitive reactions by all firms. Hence managers can use the model to measure brand equity at different levels of aggregation, develop customized strategies for targeting customers, monitor brand health, and revise brand marketing policies over time. In addition, since the model provides a dollarmetric value for firm-level brand equity, managers can use our method for resource allocation and for determining the financial values of brands that they seek to buy or sell in a merger or acquisition.

The empirical results show that the effect of brand on consumers' willingness to pay varies across both individuals *and* product forms; in addition, the proposed metric for consumer brand equity has convergent validity. The results also show that our firm-level brand equity estimates have high internal and external validities. Managerially, the key finding is that the estimates of brand equity for a given brand vary considerably across methods; in particular, the results suggest that previous methods are likely to overstate firm-level brand equity, especially for products with low market shares.

Future research is necessary to address a number of issues. These include developing a more general approach for estimating the model when the number of brands and attributes is large; generalizing the awareness and availability modules to relax the independence assumption and to allow for dynamic marketing mix effects in a game-theoretic setting; and developing new approaches for estimating willingness to pay based on heterogeneous price coefficients in the utility function. Although this study illustrated our conjoint-based methodology for measuring brand equity using a simple product category (yogurt), the method can be used to measure brand equity for more complex products and services such as mutual funds (e.g., Wilcox 2003), telecommunications (e.g., Iyengar et al. 2008), durable goods (e.g., Srinivasan et al. 2005), and products in different phases of the product life cycle. Finally, since we used only one method for defining an unbranded product, future research should test alternative ways of operationalizing an unbranded product.

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FOOTNOTES

1. Since the utility function in Equation (6) is quasilinear, the income effect $b_i^p w_i / p_i^w$ is irrelevant in a choice model. This leads to $U_{i0s} = \nu_{i0s} = \varepsilon_{i0s}$.
2. This assumption is not general. For example, a consumer's store purchase decisions could depend on her awareness levels for different brands.
3. An alternative approach is to compute the average weighted choice probability. That is, $M_j = \frac{1}{I}\sum_i \pi_j \exp(V_{ij}) \Big/ (1 + \sum_l \pi_l \exp(V_{il}))$. However, this approach is not theoretically correct.
4. Although we used a neutral concept to operationalize an unbranded product, it is possible that consumers could draw inferences about attributes/benefits based on the information provided for the unbranded product, including the name itself (Semsem in our study). To address this potential design issue, one could include more than one name to define the unbranded product and use name as an additional treatment in the conjoint experiment (e.g., generic brands). Our empirical results, however, show that our use of a hypothetical product to operationalize an unbranded product does have face validity.
5. The aggregate responses to a question asking respondents to specify the percent of times they buy each flavor were as follows: vanilla (39%), strawberry (37%), and banana (24%).
6. Because taste parameters and error variances are inherently confounded in MNL models (see Swait and Bernardino 2000, p.4), MNL parameters tend to be smaller in absolute value in models with high error variances. Since our model accounts for unobserved heterogeneity, its error variances are lower than the corresponding error variances in the Swait et al. model. Consequently, the parameter estimates using our

model tend to have higher absolute values than the corresponding estimates in the Swait et al. model.

7. Around the time of the study, the average advertising rate for a 30-second TV spot in the Mediterranean country was only $2904; in addition, the national TV channel (the main TV channel) had an average daily viewership of 48.3%. See http://www.marocinfocom.com/detail.php?id=1617. We used this information to approximate the real advertising spending by Delice Danone (the market leader). Suppose Delice Danone had spent its entire annual advertising budget ($1.1 million) on TV. Then Delice Danone would have obtained 18,295 GRPs (=48.3*1.1m/2,904) per annum. Note that this level of real advertising is almost double the corresponding average level of real advertising by packaged-goods firms in the U.S. (about 10,000 GRPs per annum).
8. The advertising share elasticity for Brand j is given by $(0.23*M_j)/Adv_j$. We could not compute STIL's advertising elasticity because of STIL's very low (almost nil) advertising budget.
9. These price elasticities are market level elasticities computed after accounting for the effects of brand awareness and availability (see Equation (16)). In contrast, the elasticities in Table 2 are average elasticities for the sample computed assuming full awareness and full availability (see Equation (9)).
10. The combined market share of the five brands when Delice Danone turns unbranded is 0.67. This information is not included in Table 7.
11. It was not possible to perform an additional validation analysis using scanner data. Such data were not collected at the time of the study in the Mediterranean country where the study was conducted.

TABLES

TABLE 1: MODEL PERFORMANCE COMPARISON[1]

Model	LML	Hit rate	Holdout Hit
Brand Main Effect (ME)	6144.9	0.768	0.623
ME+Brand-Attribute Interaction	**6049.9**	0.771	0.628
ME+Brand-Price Interaction	6159.9	0.770	0.632
General-All Effects	6054.9	0.771	0.629
No Brand Effect	9019.2	0.495	0.408
No Heterogeneity	9789.7	0.413	0.245

1. LML denotes Log-Marginal Likelihood.

TABLE 2: PARAMETER ESTIMATES FOR SELECTED MODEL: POSTERIOR MEANS AND 95 % CONFIDENCE INTERVALS

	Main Effects	Interaction Effects with			Average Price
Brand	(Intercepts)	Strawberry	Banana	Price (in Cents)	Elasticity
	3.36[*]	**-0.63**	**-0.89**	**-0.16**	**-3.64**
Semsem	(3.05, 3.69)[**]	(-1.30, -0.22)	(-1.29, -0.41)	(-0.167, -0.150)	(-3.84, -3.44)
	0.57[***]	0.39	0.52		
	3.47	-0.43	**-1.1**	**-0.16**	**-3.55**
STIL	(3.11, 3.81)	(-0.94, 0.02)	(-1.49, -0.69)	(-0.167, -0.150)	(-3.75, -3.36)
	0.90	0.45	0.45		
	3.97	-0.03	**-0.72**	**-0.16**	**-3.60**
Yoplait	(3.64, 4.26)	(-0.31, 0.27)	(-1.11, -0.37)	(-0.167, -0.150)	(-3.80, -3.40)
	0.56	0.19	0.31		
	4.16	-0.16	**-1.01**	**-0.16**	**-3.42**
Chambourcy	(3.81, 4.48)	(-0.44, 0.11)	(-1.40, -0.65)	(-0.167, -0.150)	(-3.61, -3.23)
	0.77	0.27	0.64		
	4.63	-0.13	**-0.49**	**-0.16**	**-3.29**
Mamie Nova	(4.29, 4.98)	(-0.41, 0.14)	(-0.84, -0.16)	(-0.167, -0.150)	(-3.47, -3.09)
	0.77	0.38	0.74		
	5.71	0.06	**-0.69**	**-0.16**	**-2.42**
Delice Danone	(5.38, 6.02)	(-0.17, 0.30)	(-1.00, -0.40)	(-0.167, -0.150)	(-2.56, -2.28)
	0.78	0.35	0.58		

[*] Posterior mean for parameter. All "significant" coefficients are highlighted in boldface.

[**] 95% posterior confidence interval for parameter.

[***] Heterogeneity variance.

TABLE 3: CONSUMER-LEVEL BRAND EQUITY MEASURES (in $): POSTERIOR MEANS AND 95 % CONFIDENCE INTERVALS

	Brand				
Flavor	STIL	Yoplait	Chambourcy	Mamie Nova	Delice Danone
Vanilla	0.01* (-0.01, 0.02)	0.04 (0.02, 0.06)	0.05 (0.03, 0.06)	0.08 (0.06, 0.09)	0.14 (0.13, 0.16)
Strawberry	0.02 (-0.01, 0.05)	0.07 (0.05, 0.09)	0.08 (0.05, 0.09)	0.11 (0.08, 0.13)	0.19 (0.17, 0.21)
Banana	-0.01 (-0.04, 0.02)	0.04 (0.01, 0.07)	0.04 (0.02, 0.07)	0.10 (0.08, 0.13)	0.15 (0.13, 0.18)
Overall	0.01 (-0.01, 0.02)	0.05 (0.04, 0.06)	0.06 (0.04, 0.07)	0.10 (0.08, 0.11)	0.16 (0.15, 0.18)

*To be read: On average a consumer is willing to pay a maximum of 1¢ extra to obtain a vanilla-flavored yogurt from STIL rather than from Semsem.

TABLE 4: COMPARISON WITH ALTERNATIVE CONSUMER-LEVEL BRAND EQUITY MEASURES

Brand Equity Measure	STIL	Yoplait	Chamb.	M. Nova	D. Danone	Ind. Cor.	Agg. Cor.
Awareness	0.56	0.62	0.61	0.88	0.98	0.21*	0.96**
Perceived Quality***	5.64	6.36	6.36	6.84	7.62	0.41	0.99
Brand Associations***	5.03	5.81	5.91	6.68	7.95	0.43	1.00
Preference (Paired Comparison)	1.66	2.22	2.49	3.21	4.20	0.52	1.00
Price Premium (Dollar Metric)	-0.02	-0.02	-0.01	0.03	0.11	0.43	0.96
Loyalty	0.05	0.06	0.08	0.18	0.59	0.39	0.93
Satisfaction****	2.70	3.35	3.50	3.70	4.44	0.46	0.98

* Across-brand correlation between individual-level Awareness and our individual-level brand equity measure.
** Across-brand correlation between aggregate Awareness and our aggregate brand equity measure.
*** An average quality (brand association) score across eight items measured on a seven-point scale.
****An average satisfaction score across three satisfaction items measured on a five-point scale.

Table 5: Swait et al. (1993) Model Comparisons:
Multinomial Logit Estimation Results and Equalization Price Estimates

Brand	Main Effect (Intercept)	Interaction-Effects with Strawberry	Banana	Price	Income	# of Kids	Male	Equalization Price in $
Semsem	**2.16**[*]	0.02	-0.09	**-0.10**	-0.02	**0.08**	**-0.30**	0.18
	0.14[**]	0.10	0.10	0.004	0.02	0.03	0.10	(0.176-0.185)***
STIL	**2.33**	**-0.43**	**-0.48**	**-0.10**	0.04	**0.15**	-0.13	0.20
	0.17	0.14	0.15	0.004	0.03	0.03	0.09	(.182-.227)
Yoplait	**2.25**	0.07	-0.10	**-0.10**	**0.09**	-0.03	-0.12	0.21
	0.17	0.14	0.15	0.004	0.03	0.03	0.09	(.201-.215)
Chambourcy	**2.43**	-0.15	**-0.31**	**-0.10**	**0.11**	0.03	-0.03	0.23
	0.16	0.14	0.15	0.004	0.03	0.03	0.09	(.212-.242)
Mamie Nova	**3.06**	0.06	0.06	**-0.10**	*-0.05*	0.01	0.03	0.29
	0.16	0.13	0.14	0.004	0.03	0.03	0.08	(.290-.296)
Delice Danone	**3.62**	*-0.24*	**-0.36**	**-0.10**	**0.07**	**-0.08**	*0.15*	0.34
	0.16	0.13	0.13	0.004	0.03	0.03	0.08	(.324-.358)

[*] Parameter estimates in boldface are significant at $p < 0.05$. Parameter in italics are significant at $p < 0.1$.

[**] Asymptotic standard error for parameter.

[***] 95% heterogeneity interval. That is 95% of the subjects's Equalization Prices fall between $0.176 and $0.185.

TABLE 6: BRAND PROFITS*

Brand	Awareness	Availability	Retail Price ($)	Mfr. Price ($)	Margin ($)	Adv. ($M)**	Pred. Share (95% C.I.)	Profit ($M)
STIL	0.56	0.25	0.185	0.136	0.005	0.001	0.025 (0.019, 0.031)	0.10
Yoplait	0.62	0.40	0.235	0.182	0.052	0.120	0.047 (0.040, 0.055)	1.88
Chambourcy	0.62	0.32	0.240	0.187	0.056	0.169	0.036 (0.030, 0.044)	1.50
Mamie Nova	0.88	0.70	0.240	0.187	0.056	0.306	0.160 (0.140, 0.180)	7.11
Délice Danone	0.98	0.90	0.240	0.187	0.056	1.099	0.590 (0.553, 0.630)	26.31

*Variable cost per unit is $0.1307. Retailers make $0.04 per yogurt container of 125 grams. Wholesalers make 7% of the manufacturer price. Total market size is 826,875 yogurt containers of 125 grams.
**Annual Advertising budget in millions of dollars.

TABLE 7: PROFITS WHEN PRODUCTS TURN UNBRANDED: THE NASH APPROACH

Brand	Awareness ⑨ Availability	Retail Price ($)	Mfr. Price ($)	Margin ($)	Adv. ($M)	Pred. Share (95% C.I.)	Profit ($M)
STIL	0.46	0.248	0.194	0.063	0.389	0.032	1.285
						(0.025,0.040)	
Yoplait	0.48	0.248	0.194	0.064	0.415	0.034	1.368
						(0.027,0.043)	
Chambourcy	0.48	0.248	0.194	0.064	0.420	0.034	1.389
						(0.027,0.043)	
Mamie Nova	0.49	0.248	0.195	0.064	0.471	0.038	1.558
						(0.030,0.048)	
Délice Danone*	0.55	0.251	0.197	0.066	0.711	0.056	2.330
						(0.045,0.068)	

* Reads as follows: If Delice Danone turns unbranded, its Nash price would be $0.251 and its Nash advertising spending $0.711 million. The outcome of these decisions is a joint probability of awareness and availability of 0.55 and a market share of 0.056.

TABLE 8: PROFITS WHEN PRODUCTS TURN UNBRANDED: THE INDUSTRY EXPERT APPROACH

Brand	Push-Based Awareness	Push-Based Availability	Retail Price ($)	Mfr. Price ($)	Margin ($)	Adv. ($M)*	Pred. Share (95% C.I.)	Profit ($M)
STIL	0.25	0.20	0.249	0.196	0.065	0.000	0.0043	0.230
							(0.0034,0.0054)	
Yoplait	0.16	0.20	0.250	0.196	0.065	0.000	0.0029	0.155
							(0.0023,0.0036)	
Chambourcy	0.13	0.20	0.250	0.196	0.065	0.000	0.0024	0.127
							(0.0019,0.0030)	
Mamie Nova	0.47	0.37	0.251	0.198	0.067	0.000	0.0186	1.026
							(0.015,0.023)	
Délice Danone	0.62	0.52	0.255	0.201	0.070	0.000	0.0455	2.635
							(0.037,0.055)	

* Since advertising is a brand-building activity, this approach implicitly assumes that advertising spending is zero if a product turns unbranded.

TABLE 9: PROFITS WHEN PRODUCTS TURN UNBRANDED: THE PRIVATE LABEL APPROACH

Brand	Private Label Awareness	Private Label Availability	Retail Price ($)	Mfr. Price ($)	Margin ($)	Adv. ($M)	Pred. Share (95% C.I.)	Profit ($M)
STIL	0.56	0.25	0.185	0.136	0.005	0.001	0.023 (0.018, 0.028)	0.088
Yoplait	0.56	0.25	0.185	0.136	0.005	0.001	0.023 (0.018, 0.028)	0.090
Chambourcy	0.56	0.25	0.185	0.136	0.005	0.001	0.023 (0.018, 0.028)	0.089
Mamie Nova	0.56	0.25	0.185	0.136	0.005	0.001	0.026 (0.021, 0.032)	0.103
Délice Danone	0.56	0.25	0.185	0.136	0.005	0.001	0.049 (0.041, 0.057)	0.191

TABLE 10: FIRM-LEVEL BRAND EQUITY ESTIMATES ($Million)

Brand	Nash	Indust. Expert	Private Label	% Profit due to Brand Equity Nash	% Profit due to Brand Equity Expert	% Profit due to Brand Equity P. Label
STIL	-1.19	-0.13	0.01	*	*	0.11
Yoplait	0.51	1.73	1.79	27%	92%	95%
Chambourcy	0.11	1.37	1.41	7%	92%	94%
Mamie Nova	5.55	6.08	7.00	78%	86%	99%
Délice Danone	23.98	23.67	26.12	91%	90%	99%

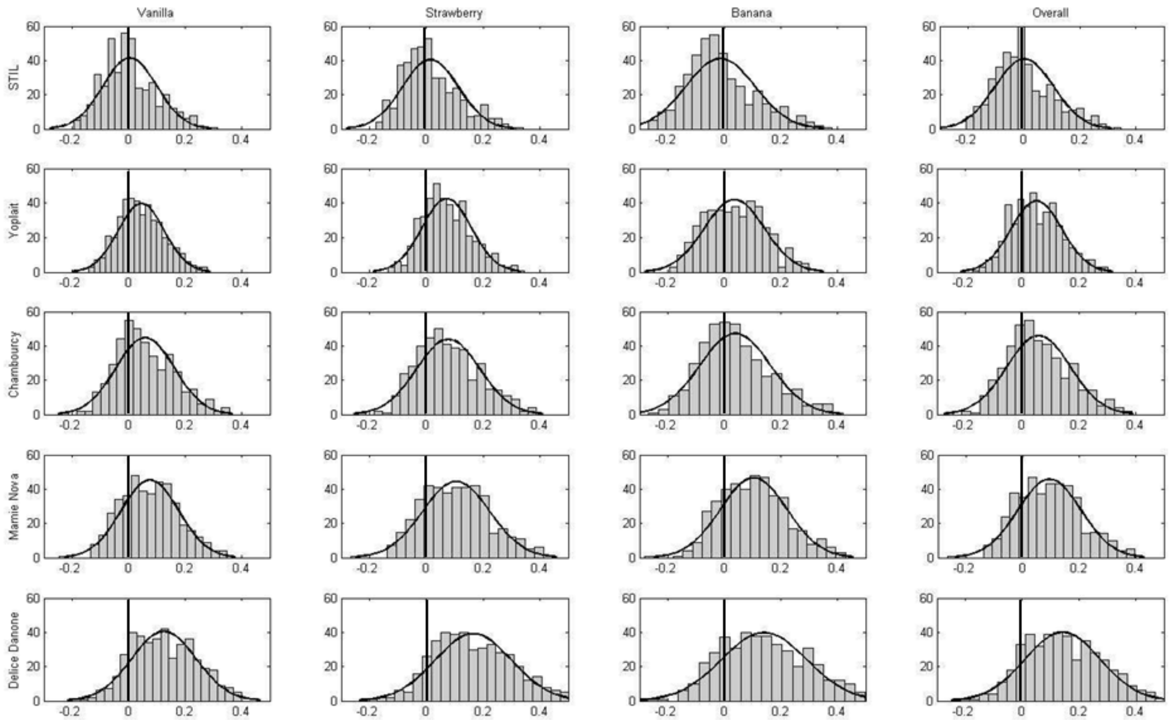
* % profit due to brand equity cannot be computed because brand equity is negative.

TABLE 11: ALTERNATIVE MEASURES OF BRAND EQUITY ($M)*

Brand	Revenue Premium Unadjust.	Revenue Premium Adj.	Dubin's Approach Elasticity	Dubin's Approach % Profit	Dubin's Approach Equity
STIL			-2.89		
Yoplait	4.25	1.90	-3.58	0.74	1.48
Chambourcy	2.73	1.57	-3.70	0.71	1.19
Mamie Nova	21.84	7.31	-3.23	0.87	6.42
Délice Danone	88.36	27.31	-1.57	0.95	25.90

* The revenue premium and Dubin's measures of brand equity are computed relative to STIL.

FIGURE 1:THE DISTRIBUTION OF CONSUMER-LEVEL BRAND EQUITY FOR EACH BRAND/FLAVOR AND OVERALL (IN $)*



* To facilitate comparisons across brands and flavors, the heavy vertical lines in the figures mark the points in the distributions where the consumer-level brand equities are zero.

APPENDIX A: THE CONSUMER MODEL IN BENEFIT SPACE

In Equation (3), we assumed that consumers' preferences are based on 'attribute space.' That is, there is a one-to-one mapping from objective to perceptual attributes. Here, we extend the model to the case where the consumer first transforms the objective attributes into perceived benefits ('benefit space') and then forms preferences based on these benefit dimensions.

Let R be the number of benefits and $\tilde{y}_{ijr}$ be consumer i's uncertain level of perceived benefit r (r=1, …, R). Let b^y_{ir} be the impact of perceived benefit r on utility. Suppose consumers form preferences based on benefit space. Then, Equation (1) becomes:

$$\text{(A1)} \qquad U_i(n_{ij}, q_i) = b_{ij0} + \sum_{k=1}^{K} b^z_{ik} z_{ijk} + \sum_{r=1}^{R} b^y_{ir} \tilde{y}_{ijr} + b^p_i \frac{w_i - p_j}{p^w_i} + \nu_{ij}, \text{ for all } i = 1, \ldots, I,\ j = 1, \ldots, J.$$

To model the links among the perceived benefits and objective attribute levels, let λ_{ijmr} be the loading of objective attribute m on benefit r for consumer i and product j, λ_{ijr0} be a measurement intercept parameter, and δ_{ijr} be an individual-specific parameter that captures the effect of the price signal on perceived benefit r for product j. Then, for consumer i, the perceived level of benefit r for product j is

$$\text{(A2)} \qquad \tilde{y}_{ijr} = \lambda_{ijr0} + \sum_{m=1}^{M} \lambda_{ijmr} x_{jm} + \delta_{ijr} p_j + \mu_{ijr}, \text{ for all } i = 1, \ldots, I,\ j = 1, \ldots, J,\ r = 1, \cdots, R,$$

where μ_{ijr} is a stochastic term that captures perceptual errors.

Substituting Equation (A2) for the perceived attributes $\tilde{y}_{ijk}$ into Equation (A1) and collecting terms, we obtain

$$\text{(A3)}\ U_i(n_{ij}, q_i) = b_{ij0} + \sum_{r=1}^{R} b^y_{ir} \lambda_{ijr0} + \sum_{k=1}^{K} b^z_{ik} z_{ijk} + \sum_{m=1}^{M} \Big(\sum_{r=1}^{R} b^y_{ir} \lambda_{ijmr}\Big) x_{jm} - \Big(b^p_i - \sum_{r=1}^{R} b^y_{ir} \delta_{ijr}\Big) p_j + b^p_i w_i + \sum_{r=1}^{R} b^y_{ir} \mu_{ijr} + \nu_{ij}.$$

As in the 'attribute space' model, the parameters $b^y_{ir}, \lambda_{ijr0}, \lambda_{ijmr}$, and δ_{ijr} cannot be separately identified; however, their joint effects can. Thus, Equation (A3) can be written as:

(A4) $$U_i(n_{ij}, q_i) = \beta_{ij0} + \sum_{m=1}^{M} \beta_{ijm} x_{jm} - \beta_{ij}^{p} p_j + \varepsilon_{ij}, \text{ for all } i = 1,\ldots,I,\ j = 1,\ldots,J,$$

where $\beta_{ijm} = \sum_{r=1}^{R} b_{ir}^{y} \lambda_{ijmr}$ is a regression coefficient that captures the reduced-form, brand-specific effect of objective attribute m, $\beta_{ij}^{p} = b_i^{p} - \sum_{r=1}^{R} b_{ir}^{y} \delta_{ijr}$ captures the reduced-form effect of price on the utility of brand j, $\beta_{ij0} = b_{ij0} + \sum_{r=1}^{R} b_{ir}^{y} \lambda_{ijr0} + \sum_{k=1}^{K} b_{ik}^{z} z_{ijk}$ is a brand-specific coefficient that captures the incremental effects of a brand such as inertia and brand associations, and $\varepsilon_{ij} = \sum_{r=1}^{R} b_{ir}^{y} \mu_{ijr} + \nu_{ij}$ is a composite error term.

Note that the reduced-form 'benefit-space' model in Equation (A4) has the same algebraic form as the reduced-form 'attribute space' model in Equation (5). Similarly, we can show that a reduced-form model can capture more general consumer decision processes where consumers' preferences are based on both attribute and benefit space. (Combine Equation (3) and Equation (A4).)

A Conjoint Approach for Consumer- and Firm-Level Brand Valuation

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WEB APPENDIX: MODEL ESTIMATION

We estimate the utility model in Equation (5) using a hierarchical Bayesian, multinomial logit approach. Consider a sample of I consumers, each choosing at most one product from a set of J products. Let s indicate a choice occasion. If consumer i contributes S_i such observations, then the total number of observations in the data is given by $S = \sum_{i=1}^{I} S_i$. Let $y_{ijs} = 1$ if product j is chosen on choice occasion s; otherwise, $y_{ijs} = 0$. Let j = 0 denote the index for the no-choice alternative. Thus, $y_{i0s} = 1$ if the consumer chooses none of the products. Let $\boldsymbol{\beta}_i$ = $\{\beta_{ijm}, \beta^{p}_{ij}$, j=1, …, J; m=1, …, M$\}$ denote the joint vector of regression parameters. Then the conditional likelihood, $L_i|\boldsymbol{\beta}_i$, of observing the choices consumer i makes across the S_i choice occasions is given by

(W1) $$L_i \mid (\boldsymbol{\beta}_i) = \prod_{s=1}^{S_i} \prod_{j=0}^{J} P_{ijs}^{y_{ijs}},$$

where the P_{ijs} are the choice probabilities defined in Equation (9).

To capture consumer heterogeneity, we assume that the individual-level regression parameters, $\boldsymbol{\beta}_i$, are distributed multivariate normal with mean vector $\overline{\boldsymbol{\beta}}$ and covariance matrix $\boldsymbol{\Omega}$. Then, the unconditional likelihood, L, for a random sample of I consumers is given by

(W2) $$L = \prod_{i=1}^{I} \int L_i \mid \boldsymbol{\beta}_i f(\boldsymbol{\beta}_i \mid \overline{\boldsymbol{\beta}}, \boldsymbol{\Omega}) d\boldsymbol{\beta},$$

where $f(\boldsymbol{\beta}_i \mid \overline{\boldsymbol{\beta}}, \boldsymbol{\Omega})$ is the multivariate normal $N(\overline{\boldsymbol{\beta}}, \boldsymbol{\Omega})$ density function.

The likelihood function in Equation (W2) is complicated because it involves multidimensional integrals, making classical inference using maximum likelihood methods difficult. We circumvent this complexity by adopting a Bayesian framework to make inferences about the parameters and using MCMC methods, which avoid the need for numerical integration. The MCMC methods yield random draws from the joint posterior distribution and inference is based on the distribution of the drawn samples.

For the Bayesian estimation, we use the following set of proper but noninformative priors for all the population-level parameters. Suppose $\bar{\boldsymbol{\beta}}$ is a p × 1 vector and $\boldsymbol{\Omega}^{-1}$ is a p × p matrix. Then the prior for $\bar{\boldsymbol{\beta}}$ is a multivariate normal with mean $\boldsymbol{\eta}_\beta = 0$ and covariance $\mathbf{C}_\beta =$ diag(100). The prior for $\boldsymbol{\Omega}^{-1}$ is a Wishart distribution, W($\mathbf{R}$, ρ) where ρ = p+1 and $\mathbf{R}$ is a p × p identity matrix.