Brand Equity as a Revenue Multiplier

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Abstract

This paper develops and illustrates a revenue multiplier methodology to estimate brand equity that addresses two major drawbacks in extant brand equity measurement methods: (i) Our methodology requires data only from easily available secondary sources; and (ii) Marketing mix impacts are explicitly modeled so as to allow a more accurate estimate of brand equity. For each specific brand, brand equity is measured as a multiplier that quantifies the difference in market response between that of the branded product and that estimated for an equivalent unbranded product with exactly the same market mix actions. This meshes extremely well with the notion that brand equity is the incremental effect of brand name on product value. In particular, we utilize frontier estimation tools to estimate the revenue of each brand's "unbranded equivalent", with each brand's brand equity revenue multiplier reflecting the degree to which the brand's observed revenues exceed this amount. The methodology is illustrated using data for the top 25 US beer brands and the results agree with intuition, theory and financial data-based brand equity valuations.

"If this business were split up, I would give you the land and bricks and mortar, and I would take the brands and trademarks, and I would fare better than you."

\- John Stuart, former CEO of Quaker Oats

Introduction

Brands are now widely recognized to be one of, if not *the*, most valuable assets that a firm owns. It is not surprising then that the valuation of brand assets has taken on an increasingly important role in recent years. The term that encompasses this notion of valuing such brand assets is *Brand Equity*. While there are numerous definitions of the brand equity construct, most researchers and practitioners today agree that brand equity is essentially the difference in the values that accrue to a product with and without its brand identity.

Measuring brand equity is no trivial task. Consider the following scenario: Our task is to evaluate the brand equity component of a branded automobile, say the Honda Accord. To answer this, we need to know what the value of the Honda Accord would be if it were shorn of its brand name. Clearly, no such generic entity readily exists, so constructing a simple comparative valuation method is out of the question. We could compare the Honda Accord to another (observed) automobile, but that wouldn't quite work since we would be comparing two different products (with different attribute sets) which have two different marketing effort allocations (promotion and distribution levels, etc.). Such a comparison would ultimately give us a biased picture of the Honda Accord's brand equity. In addition to this conceptual difficulty in measuring brand equity, there also are noteworthy effort and financial costs related to collecting and processing the required data. Thus, ideally a good measure of brand equity would only use data that are readily available to analysts and allow the construction of an unbranded mirror for any branded product.

This paper develops a methodology to estimate brand equity (hereafter, BE) that requires data from only easily available secondary sources and explicitly models product attribute and other marketing mix impacts so as to allow a more accurate estimate of brand equity. In particular, BE is estimated as the brand-specific component of revenue shorn of the impact of both observed and unobserved product attributes as well as other marketing mix and category factors. That is, in adherence to the BE definition, the proposed methodology creates, for each particular brand, a unique reference baseline that has identical marketing mix investments including product features but no brand name and then compares the estimated product-market outcome for this "unbranded equivalent" with that of the branded entity. The ratio of these values is what we term the *brand equity multiplier*.

The paper proceeds as follows. The next section provides a brief literature review that serves to position this study. We next develop the conceptual framework to estimate our revenue multiplier measure of BE. Then the framework is empirically illustrated using beer data and the results discussed. Finally, we conclude with a summary which forwards managerial implications and directions for future research.

Brand Equity Measurement

The brand equity measurement literature is classified based on the level at which the brand equity outcome is measured. In particular, the consumer-based perspective (Keller 1993) proposes individual consumer level measures while the product-market perspective (Leuthesser 1988; Keller and Lehmann 2003; 2006) expounds market level measures.

The consumer-based perspective looks at consumer perception constructs such as attitude, awareness and liking for a brand and translates these perceptual measures into brand equity measures such as brand affect (Bousch et al. 1987) and brand-specific associations (Bhat and Reddy 2001). These studies require individual level data collected through surveys or experiments and, as such, this information is costly and time-consuming to collect. Generally, these studies also are subject to the above described confounding of marketing mix and brand impacts on the measured outcome.[1] Further, these measures are based on the stated preferences of respondents and consequently may not reflect real world (revealed preference) outcomes.

The product-market perspective derives brand equity estimates from more accessible market level outcome data routinely collected by the firm or syndicated data providers. One stream of this literature uses firm level financial data to generate BE estimates based on measures such as acquisition prices (Mahajan, Rao and Srivastava 1994) and residual market values (Simon and Sullivan 1993). These BE estimates, however, are typically "firm equity" measures since the financial measures used are at the firm level and most firms are multi-brand firms (Aaker and Jacobson 1994). That is, for a particular brand not only are its marketing mix and brand effects confounded with each other, they are also confounded with those of the firm's other brands.

A second stream of the product-market BE literature, which is most in line with the approach forwarded in this paper, utilizes readily available brand level market results such as sales, profits and prices or syndicated individual level scanner choice data. In particular, measures such as the additional willingness-to-pay for a branded product compared to an unbranded one (Aaker 1991, 1996; Sethuraman 2003), market-share and relative prices (Chaudhari and Holbrook 2001), segment-wise brand preferences (Kamakura and Russell 1993), revenue premiums (Ailawadi, Lehmann and Neslin 2003), and profit differentials (Dubin 1998; Goldfarb, Lu and Moorthy 2007) are used to estimate BE.

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[1] Conjoint studies have explicitly estimated brand name impact on stated preference or choice while controlling for product attribute differences (Srinivasan 1979; Park and Srinivasan 1994), but do not account for the impact of other marketing mix variables. These studies also require significant primary data collection.

While these product-market BE measures are brand specific, they still suffer from the confounding of brand and marketing mix (product attributes, promotion, price and distribution) effects. Four issues lie behind this: (i) The impact that marketing mix actions have on the measured market outcome of a brand is typically not modeled. Thus, their impact on the outcome may be improperly attributed to brand equity. (ii) A store brand, private label or low share brand typically is taken as the "baseline brand" and it's BE (along with any unmeasured marketing mix effects) is assumed to be an a priori fixed value, typically zero. The difference in the chosen outcome measure for this baseline brand and that for a particular "non-baseline" brand provides the measure of that particular brand's BE. Since the "true" BE of the baseline brand is almost certainly positive, all of the BE estimates are biased downwards. (iii) Further, the baseline brand's marketing mix decisions and their impact are not the same as those of any particular non-baseline brand. Consequently, the estimated BE of each non-baseline brand implicitly includes these marketing mix impact differences in its BE estimate. This bias may be positive for some brands and negative for others. (iv) Finally, the BE and marketing mix confound is exacerbated by the fact that multiple items (SKUs or stock keeping units which identify distinct variants, flavors, sizes, etc.) typically share a brand name, and the SKUs that make up the baseline brand are very likely to differ in not only number but in their marketing mix from those of each particular non-baseline brand. In addition to these issues, general market characteristics such as market size and input costs also influence the observed market outcomes of all products. As a result, a fifth BE measurement bias could manifest itself if these are not modeled.

Our proposed methodology, discussed below, utilizes readily available secondary data but unlike earlier efforts it directly addresses the issues outlined above by explicitly modeling the impact of product attribute, promotion and distribution actions as well as brand effects and does so without the use of an ad hoc baseline brand relative to which all other brand outcomes are evaluated. The BE-category size confound also is addressed by explicitly modeling the impact of category characteristics.

Brand Equity as a Revenue Multiplier

Product-market outcomes such as revenue for any product level in the category, be it a brand or SKU, are tied to category-wide factors as well as the product's marketing mix actions and brand equity. Thus,

$$\text{Market Response} = f\left(\begin{matrix}\text{Category} \\ \text{Charateristics}\end{matrix}, \begin{matrix}\text{Marketing Mix} \\ \text{Actions}\end{matrix}, \begin{matrix}\text{Brand} \\ \text{Equity}\end{matrix}\right). \tag{1}$$

Our aim is to identify the impacts that category characteristics and a product's marketing mix actions have on the market outcome of interest and, in effect, remove them from the observed market outcome measure, thereby, leaving us with a more accurate estimate of brand equity (the effect of brand name on the outcome). The combined impact of the first two factors described in (1) provides an estimate of the outcome that would result for an unbranded product that has identical components to those of the branded product. Once the estimated outcome for this "unbranded equivalent" (UE) is removed from the branded product's observed outcome, what is left is the impact of the brand name itself – our measure of brand equity.

We choose revenue as our metric of market response for a variety of reasons. (i) Revenue is recorded in scanner data at every level of product aggregation. (ii) Revenue has previously been used as a BE metric (e.g., Ailawadi, Lehmann and Neslin 2003). (iii) The economic rationale behind the parametric restrictions in our model applies readily to revenue. We also utilize a general multiplicative formulation that accommodates various response shapes and rates including both diminishing and increasing returns (Lilien, Kotler and Moorthy 1992).

$$\begin{matrix}\text{Product}\\ \text{Revenue}\end{matrix} = \left[\begin{matrix}\text{Revenue of the}\\ \text{Unbranded Equivalent}\end{matrix}\right] \left[\begin{matrix}\text{Brand Equity}\\ \text{Multiplier}\end{matrix}\right]. \tag{2}$$

This multiplier formulation implies that the Brand Equity Multiplier (BEM) for a particular branded product is simply a multiple of the market outcome that would arise to its unbranded equivalent UE (i.e., an unbranded product with exactly the same product attributes, promotion, price and distribution). This formulation implies that BE scales up or down the value of (or demand for) non-brand product characteristics. Equation (2) implies that the accuracy of our brand equity measure BEM depends on how well we estimate the revenue that would accrue to the UE. For each branded product analyzed, this requires a reasonably complete description of its marketing mix (as well as general category conditions) so that their impacts on revenue can be accurately estimated and used to derive the revenue particular to each branded product's unique UE. To spell this notion out further we identify the revenue of the UE of each brand as a multiplicative function of the marketing mix decisions[2] of the brand, general category level sales drivers, and a random error term (non-systematic revenue shocks that can be interpreted as measurement error). This results in a more detailed expression for product revenue.

$$\text{Revenue} = \underbrace{\left[\begin{matrix}\text{Category}\\ \text{Drivers}\\ \text{Impact}\end{matrix}\right]\left[\begin{matrix}\text{Product}\\ \text{Impact}\end{matrix}\right]\left[\begin{matrix}\text{Promotion}\\ \text{Impact}\end{matrix}\right]\left[\begin{matrix}\text{Distribution}\\ \text{Impact}\end{matrix}\right]\left[\begin{matrix}\text{Random}\\ \text{Shocks}\end{matrix}\right]}_{\text{Revenue due to Unbranded Equivalent}}\left[\begin{matrix}\text{Brand Equity}\\ \text{Multiplier BEM}\end{matrix}\right]. \tag{3}$$

In equation (3), we decompose revenue into broad determinants of product demand which we label "revenue components" and use observable measures (detailed in the data section) to capture the effect of each revenue component. In addition, since a brand typically encompasses numerous SKUs, each with slightly different marketing mix characteristics, an

[2] Since our dependent variable revenue is constructed from price and quantity data, including any function of price as an explanatory variable is not appropriate.

analysis of SKU rather than brand level revenues allows for more accurate estimation. Each SKU associated with each particular brand, thus, has its own unique UE. These considerations give rise to a more explicitly defined revenue expression

$$\begin{aligned}\text{Revenue}_{jt} = e^{\beta_0} \prod_{a=1}^{A} \begin{pmatrix}\text{Category} \\ \text{Drivers}_{a,t}\end{pmatrix}^{\beta_a} \prod_{c=1}^{C} \left(\text{Product}_{c,j}\right)^{\beta_c} \prod_{d=1}^{D} \left(\text{Promotion}_{d,jt}\right)^{\beta_d} \\ \prod_{m=1}^{M} \left(\text{Distribution}_{m,jt}\right)^{\beta_m} e^{\eta_{jt}} \text{ BEM}_{b(j)}\end{aligned}, \qquad (4)$$

where *j* refers to a particular SKU, *b* to a particular brand, *b(j)* to the brand *b* that contains SKU *j*, and *t* to each time period. The various measures outlined below for the UE revenue components are referred to generically. η_{jt} is the random error. Any systematic brand level revenue impact unexplained by the analysis variables is captured by the brand equity multiplier term BEM.

Data

Beer data collected from a variety of readily available sources are used to illustrate our methodology. The US beer market is a well defined and mature product category with characteristically little change in the total quantity of beer sold during our sample period 2002 - 2005. As with sales, distribution, promotion and price levels differ widely across brands and SKUs. Distribution is a major determinant of sales, and promotions – especially advertising ($1.175 billion in 2005) and retail merchandising (features, displays, and temporary price reductions) are utilized heavily. However, while the category is dominated by a handful of big brands and manufacturers with extensive distribution and large promotional programs (Anheuser-Busch, SAB Miller, Molson-Coors and Pabst account for over 81% of US sales), smaller, more regionally distributed brands compete quite effectively. Indeed, the collective share of the top 25 beer brands we analyze is slowly falling. Note also that even these major brands have numerous SKUs that receive limited distribution and promotion.

In order to achieve a reasonably accurate partitioning of SKU level revenues into those related to brand equity and those that would accrue to the SKU's unbranded equivalent, it is necessary to identify and use a variety of measures to reflect the impact of the UE revenue components outlined in equation (4). These data and their readily available sources are outlined in Table 1 and detailed forthwith. Table 2 briefly profiles the 25 top selling beer brands.

Revenue

For our revenue measure, **Revenue**, we use monthly AC Nielsen national revenue data pertaining to the various SKUs that constitute the top 25 beer brands sold in food stores for the years 2002 to 2005.[3] We define "brand" as the identifier for any group of products which share a nominal label, "variant" as a subset of the brand that differs from other variants of the same brand by some identifier or descriptor in the label, and "SKU" as any packaging or size of the product that differs from other products of the same variant. For example, Budweiser is a brand, Bud Light and Bud Ice are two variants of Budweiser, and a six pack of 12 ounce Bud Light longneck bottles is a different SKU from a six pack of Bud Light 12 ounce cans.

Note that a SKU level analysis allows each branded SKU to be compared to its own unique unbranded equivalent. Any higher level product (i.e., variant or brand) analysis will necessarily utilize a less comparable UE (i.e., the marketing mix description of a variant is less accurate since it must be represented as averages or sums over the SKUs that share the variant name). For example, outside of a few high sales "star" SKUs, most SKUs do not sell nearly as well and are not distributed as widely. Furthermore, each SKU has at least one product attribute difference from its other similarly branded SKUs. If the data were aggregated to the brand level,

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[3] Each 4-week period is referred to as a month. The beer category is defined as lagers and light beers since they constitute the vast majority of all malt beverages sold (i.e., malt liquors, stouts, ales and flavored malt beverages are not included in the analysis).

then these large SKU level marketing mix differences that do exist and strongly influence revenues would be ignored and their impact likely attributed either positively or negatively to brand equity. Furthermore, SKU level analysis has merit since most consumer, retailer and manufacturer decisions are made at the SKU level (Fader and Hardie 1996).

In order to keep the number of SKUs analyzed to a reasonable level, we removed SKUs that were not sold over at least half the sample time span, had sales totaling less than $10 million over the four year period, or had a distributional reach of less than 10%ACV (i.e., 10% of food stores, weighted by store revenue, sold at least one unit of the product). Consequently, our dataset contains 13,777 observations pertaining to 278 SKUs which constitute 25 brands. These SKUs account for over 90% of category revenue in US food stores. In turn, food stores account for about 88% of total beer sales at all food, drug and mass merchant outlets.

Product

The multi-attribute model literature (Lancaster 1966; Horsky and Nelson 1992) highlights the importance of product attributes in the consumer choice decision. These product attributes can be tangible and objective (such as weight in ounces) or intangible and subjective (such as expert or consumer ratings of taste) but must be relevant to consumers (Keller 1998), not be unique to a brand[4], and show enough variation across the SKUs to allow identification of their impact on choice. Beverage Industry trade publications (e.g., Adams Beer Handbook) and the AC Nielsen scanner data SKU descriptions provide easily observed objective attributes that differentiate SKUs by beer type, beer color, packaging and country of origin. In particular, five types of beer are identified (Regular, Dry, Lite (low calorie), Ice and Craft). Correspondingly, four binary dummy variables are used to represent whether or not a particular SKU is a **Dry**,

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[4] Both figuratively and econometrically, attributes unique to a brand cannot be identified as separate from the brand and, thus, form part of BE.

Lite, **Ice** or **Craft** beer rather than Regular. Similarly, three dummy variables identify whether a SKU's color is **Amber**, **Light**, or **Golden** rather than Dark. A number of packaging related dummy variables also are utilized. In such, a dummy variable **Can** represents whether the container is a can as opposed to a bottle. Four dummy variables correspond to packages other than a Small Pack (packs of whatever number with a total of less than 72 ounces). These are **6Pk-12Oz** (for a 6 pack of 12 ounce containers), **6Pk-Non12Oz** (for a 6 pack of non-12 ounce containers), **12Pk** (for a 12 pack of containers), and **Case** (for 18, 20, 24 and 30 pack sizes). Lastly, dummy variables for **Europe** and **Mexico** are used for beers originating in these regions against the reference North America.[5]

These objective SKU level attributes are coarse and not likely to fully capture SKU level objective attribute differences. In addition, subjective attributes that are not easily observable to the researcher such as "taste" or "attractiveness of packaging" may differ between two objectively identical SKUs. To specifically account for subjective taste differences across products, for each variant (and, thus, for each of its SKUs) we use an overall beer rating on a 0-5 scale provided by a panel of experts and beer aficionados at two online data sources (www.beerpal.com and www.ratebeer.com). Since it is likely that these beer ratings partially depend on the measured objective product attributes, we regressed the beer ratings on the objective attributes (R^2=0.64) and use the residuals, which we term **Subjective Taste,** as a measure of taste that is not explained by the objective attributes. To further avoid any confounding of unobserved SKU level product attribute impacts with BE due to omitted objective and subjective product attributes (like attractiveness of packaging), we also include a latent SKU level random effect ζ_j specific to each SKU *j*. To illustrate, consider that the

[5] Fosters is Australian but brewed under license in Canada. It is denoted as a North American brand. Since it is the lone Australian brand, denoting it as such would cause identification problems between the brand equity of Fosters and the country of origin Australia.

Modelo Especial 12 pack of 12 ounce cans SKU outsells the 24 pack of 12 ounce cans SKU of the same brand and variant by over a hundred to one on average. If the former SKU sells better because of, say, more attractive packaging or more convenient transport and storage, then the observed product elements would not entirely capture this. Furthermore, this effect is unrelated to BE (it is intra-brand and intra-variant) and might collect in the BE term if unaccounted for.

Promotion

The key promotional drivers behind grocery product sales are typically advertising and retail merchandising (displays, features and temporary price reductions). Consequently, from the Leading National Advertisers database we acquired the annual advertising expenditure (**AdSpend**) of each variant in each year studied. Each SKU within a variant is assigned its variant's ad spend and this annual amount is used as a proxy for the monthly ad spends. Standard scanner data provides numerous measures of retail merchandising. We utilize **%ACVMerch** which denotes the percentage of food stores, weighted by store revenue, in which the SKU underwent some form of retail merchandising during each month. Please note that the levels of these promotion investments as well as those for distribution are likely to be correlated with brand equity. In such, a potential endogeneity problem arises which we discuss and deal with in the forthcoming estimation section.

Distribution

How much distribution (consumer access) a SKU has is obviously a huge determinant of its sales. To this end, a standard scanner data measure – the monthly percentage of stores, weighted by store revenue, which carried each particular SKU (**%ACVDistbn**) is utilized. Shelf presence also is a key determinant of sales (Little 1979; Guadagni and Little 1983; Hoch et al. 1995). While data concerning the number of facings a SKU receives or its location on the shelf are not easily found, standard scanner data does provide a variable, **SKUNum** which denotes on a monthly basis the average number of different SKUs for each variant carried by a store that sold that particular variant. The more SKUs of a particular variant on the shelf, typically the more shelf space and, thus, shelf presence it has. Correspondingly, the more likely each of its particular SKUs is to be noticed.

Category Drivers

Various economic and demographic factors are likely to impact industry-wide revenues (and hence, the sales of the particular SKUs). The monthly number people in the US over age 21 (**USAdults**), obtained from the U.S. Census Bureau, provides a nice proxy for changes in total market size. Input prices are likely to impact retail prices and, hence, revenues. So, from the Bureau of Labor Statistics database, the producer price index for long haul trucking in the US (**FreightPPI**) serves as an input cost measure. Since imported beer prices are affected by foreign exchange rates (**ExchgRate**), a monthly averaged index of the Canadian Dollar, Mexican Peso and Euro exchange rates per US dollar (obtained from the Federal Reserve website) act as an additional cost measure for the imported brands. Seasonality also is prevalent in this industry, so three simple quarterly dummies (**Fall**, **Winter** and **Spring**) are utilized. To proxy for additional unobserved factors that that may influence market level demand, three yearly time dummies (**Year2002**, **Year2003** and **Year2004**) are also instituted.

Estimation

To facilitate econometric analysis, we follow standard procedure and linearize equation (4) by taking the log of both sides. Our model is thus[6]:

[6] For dummy variables, the formulation x^{β} is replaced by $e^{\beta x}$, which when logged becomes βx rather than $\beta \log x$.

$$
\begin{aligned}
\text{Ln}\left(\text{Revenue}_{jt}\right) = &\left[\beta_0 + \sum_{a=1}^{A}\beta_{1a}\text{Ln}\left(\text{Category Drivers}_{\text{a,t}}\right)\right] + \left[\sum_{c=1}^{C}\beta_{2c}\text{Ln}\left(\text{Product}_{c,j}\right) + \zeta_j\right] \\
&+ \sum_{d=1}^{D}\beta_{3d}\text{Ln}\left(\text{Promotion}_{d,jt}\right) + \sum_{m=1}^{M}\beta_{3m}\text{Ln}\left(\text{Distribution}_{m,jt}\right) + \eta_{jt} + \text{Ln}\left(\text{BEM}_{b(j)}\right); \\
&\eta_{jt} \sim \text{IID } N\left(0, \sigma_\eta{}^2\right); \\
&\zeta_j \sim \text{IID } N\left(0, \sigma_\nu{}^2\right); \\
&\text{Ln}\left(\text{BEM}_{b(j)}\right) \sim f_{EXP}\left(\lambda\right).
\end{aligned} \tag{5}
$$

The random error pertaining to each SKU-month is denoted as η_{jt}. As previously discussed, to account for systematic, SKU-specific factors unobserved by the researcher or omitted in the data, we also model revenue heterogeneity among SKUs using a mean-zero random effects ζ_j specific to each SKU *j* (Allenby, Arora and Ginter 1998).

Our revenue multiplier measure of brand equity - BEM - which represents any systematic brand level revenue impact unexplained by the analysis variables is estimated through the use of a third random variable $\text{Ln}\left(\text{BEM}_{b(j)}\right)$ defined at the brand level. We argue that a brand must provide added value or its producer would not utilize the brand name and would rather sell it as its unbranded equivalent. That is, given our multiplier formulation, BEM must be greater than or equal to one (i.e., $\text{Ln}\left(\text{BEM}_{b(j)}\right) \geq 0$**)**. If a particular brand's BEM were less than one, then its unbranded equivalent would earn more revenue than it does. Since the only difference is the brand name, it must be that the brand name actively destroys product value. Correspondingly, the firm would be better off withdrawing the brand name from the product.[7] In sum, our BEM

[7] With new brands it is possible that not yet enough market data are available to weed out underperforming brands (with BEM<1). However, this is unlikely to be the case with long-standing brands in a mature category such as beer. Furthermore, grocery brand withdrawals are numerous (Haig, 2005), which suggests that firms withdraw failed brands and products fairly quickly.

measure for each brand is modeled as an asymmetric random effect constrained to lie on $[1,\infty)$ due to the firm's rational, profit maximizing behavior.

This "positive" support for the parametric distribution of $\mathrm{Ln}\left(\mathrm{BEM}_{b(j)}\right)$, the implicit assumption that every brand's BEM comes from this parametric distribution, and the fact that the three "error" terms $\left(\eta_{jt}, \zeta_j \text{ and } \mathrm{Ln}\left(\mathrm{BEM}_{b(j)}\right)\right)$ are distributed independently of one another and defined at different levels of aggregation (SKU-month, SKU and brand, respectively) allow the parameters to by identified. The independence assumption enables us to write the density of the non-normal error term (at any suitable level of aggregation) as the product of the densities of the error components. The symmetrically distributed error components are distinguished from each other because they are defined at different levels of data aggregation. Both the skew and level of aggregation in the BE error term distinguish it from the two symmetric error components. The identification of the BEM (and implicitly the relaxation of the "base brand" problem) comes directly from the assumption of a parametric functional form for the one-sided distribution of $\mathrm{Ln}\left(\mathrm{BEM}_{b(j)}\right)$. Clearly, a flexible or nonparametric density would not be empirically separable from the normal error components. The question thus becomes one of selecting an appropriate distribution in the positive domain that captures the behavior of $\mathrm{Ln}\left(\mathrm{BEM}_{b(j)}\right)$ well. Following Van Den Broek et al. (1994), we define $\mathrm{Ln}\left(\mathrm{BEM}_{b(j)}\right)$ as distributed exponential with parameter λ, where λ is distributed gamma with hyper-parameters α and γ. That is, $\mathrm{Ln}\left(\mathrm{BEM}_{b(j)}\right) \sim f_{Exp}(\lambda)$ with $\lambda \sim f_{Gamma}(\alpha,\gamma)$.[8] This can be alternatively interpreted as an

[8] Other positive distributions for $\mathrm{Ln}\left(\mathrm{BEM}_{b(j)}\right)$ provide very similar fit and parameter estimates.

assumption that the BEM density has a modal value of one and assigns small probability to very large values of BEM.

We apply Bayesian (Markov Chain Monte Carlo) methods to obtain estimates of the parameter values in our proposed framework. The MCMC sampling scheme used is fairly standard and details are available from the authors upon request. The results from the MCMC routine give us samples from the joint posterior distribution of the parameters of interest. Once we have these posterior samples of the parameters, brand specific BEM estimates are obtained by straightforward computation. Similarly, estimates of any other metrics based on the parameters and data can be easily constructed.

Endogeneity Issues

A key concern in the estimation of BE models is endogeneity. Marketing decisions such as distribution and promotion are likely to depend on the state of BE while also investing in the maintenance of brand assets. At the very least, these decisions are correlated with brand equity and may cause an endogeneity problem. A correction (instrumentation) approach to this problem is out of the question for two reasons. First, there is very little variation in the levels of these marketing investments over time, making the instrumental variables approach difficult since only the variation across brands matters. Secondly, and perhaps more importantly, not many variables exist that are correlated with these marketing decisions but are independent of brand equity. In other words, good instruments are not readily available to the researcher. Given that endogeneity cannot be "corrected" for, we address the issue by taking a different approach. We discuss this below.

We start with the assumption that each brand's marketing investments are at a stationary baseline level. Since the endogeneity problem is only on account of the brand level correlations between these variables and brand equity, we decompose each variable into a brand level capturing its stationary baseline and deviations from this baseline.[9] We use this decomposition to construct two different implementations of our proposed framework. These two specifications effectively provide upper and lower bounds to the BEM measure. The first specification, which we label the *Expansive* BEM, uses *only* the deviations from the stationary baseline as covariates. As a consequence, we completely avoid distribution and promotion endogeneity since the deviations are independent across brands. We term this the “Expansive” BEM approach because everything brand related in distribution and promotion is captured by the BEM term. On the other hand, if there are components of the baseline levels of distribution, merchandising or advertising that are unrelated to BE, then they too are captured by the BEM term. In that sense, the Expansive BEM may overstate the “true” BEM and offers an approximate upper bound to the measure.

The other specification we estimate is labeled the *Intrinsic* BEM approach. It uses *both* the stationary baseline level “means” and the “deviations” from these means as covariates. Since the “Intrinsic” BEM specification retains the stationary baseline levels of distribution and promotion as covariates, only those parts of BE independent of distribution, promotion and the other covariates are collected in the BEM term. As such, the Intrinsic label refers to the notion of residual brand equity. However, since any BE contained in distribution or promotion is left out, the Intrinsic BEM may understate the “true” BEM and, consequently, can be thought of as an approximate lower bound of the true BEM.[10]

[9] For example, at any point in time, the average advertising level of *all* Miller SKU’s will constitute the baseline and departures from this will be labeled “deviations”.

[10] As mentioned previously, in the likely event that true residual BEM is positively or negatively correlated with distribution and promotion for any brand, the intrinsic BEM would be overstated or understated, respectively.

As discussed above, distribution and promotion are potentially correlated with BE and we can mitigate endogeneity effects by splitting these measures into stationary baseline levels and deviations from these baseline levels. We now elaborate on what reasonable stationary baseline levels of distribution and promotion could be.

Variant level advertising data from the *Leading National Advertisers* show that firms tend to advertise one or two beer variants heavily while spending little or nothing on the other variants. Firms likely expect the impact of advertising one or two variants of the brand (e.g., Budweiser advertises Bud Light and Budweiser) to spillover onto their other variants (such Budweiser Select or Bud Ice) since the other variants also carry the same brand name. Hence, taking a simple average of the advertising level across all the variants of a brand would understate the advertising done by mainstream brands (such as Budweiser and Miller which span many variants), while relatively inflating that of more focused brands (e.g., Heineken and Corona have at most two variants). Hence, we take the average advertising spend across only the top quartile of the highest revenue variants for each brand as the stationary baseline advertising level (**Mean LnAdSpend**) for that brand. Since the number of variants for brands in the sample ranges from one and five, we take the top quartile to be the top selling variant for those brands with fewer than five variants and the top two variants for those brands with five variants. Deviations from this mean level of advertising (**Delta LnAdSpend**) are computed for each variant and carry over to each SKU of that variant.

Similarly, for retail merchandising a simple average of the Ln%ACVMerch levels across all of the SKUs of a brand could be taken as that brand’s baseline merchandising level. But, once again such an approach would weight all SKUs equally and mainstream brands with a large number of SKUs would have their mean retail merchandising level understated because the larger selling SKUs are more likely to be promoted heavily. Hence, for each brand, we use the average Ln%ACVMerch level of its top quartile of highest revenue SKUs as the baseline retail merchandising level (**Mean Ln%ACVMerch**). Deviations from this stationary baseline level differ for each brand by SKU and by time period (**Delta Ln%ACVMerch**).

Reasoning similar to that for merchandising also applies to distribution. For each brand, we take the average distribution level of the brand's top quartile of highest revenue SKUs as a proxy for the brand's baseline distribution level (**Mean Ln%ACVDistbn**). Deviations from this stationary baseline level differ for each brand by SKU and by time period (**Delta Ln%ACVDistbn**). We assume that for each brand, these time varying deviations from the stationary baseline are uncorrelated with the stationary, time invariant BE level of that brand which, *prima facie*, is a reasonable assumption.

Thus, the promotion and distribution terms for the Intrinsic BEM specification of equation (5) are detailed as shown in the two equations below:

$$\begin{aligned}\sum_{d=1}^{D=4}\beta_{3d}\mathrm{Ln}\left(\mathrm{Promotion}_{jt}\right) &= \beta_{31}\mathrm{Mean\ Ln\ \%ACVMerch}_{b(j)} + \beta_{32}\mathrm{Mean\ Ln\ AdSpend}_{b(j)} \\ &+ \beta_{33}\mathrm{Delta\ Ln\ \%ACVMerch}_{jt} + \beta_{34}\ \mathrm{Delta\ Ln\ AdSpend}_{v(j)t}\end{aligned}, \qquad (6)$$

$$\begin{aligned}\sum_{m=1}^{M=3}\beta_{4m}\mathrm{Ln}\left(\mathrm{Distribution}_{jt}\right) &= \beta_{41}\mathrm{Mean\ Ln\ \%ACVDistbn}_{b(j)} + \beta_{42}\mathrm{SKUNum}_{v(j)t} \\ &+ \beta_{43}\mathrm{Delta\ Ln\ \%ACVDistbn}_{jt}\end{aligned}. \qquad (7)$$

The Expansive BEM specification is the same as the Intrinsic one except with $\beta_{31} = 0, \beta_{32} = 0$ and $\beta_{41} = 0$. Thus, endogeneity in distribution and promotion is avoided because their steady state brand level influences (subscripted *b(j)*) are collected into brand equity. In sum, the Expansive BEM measure includes the brand's leverage in distribution, merchandising and advertising. For example, high BE brands would likely find it easier to gain distribution in retail outlets than would low BE brands. The Intrinsic BEM measure does not include these influences.

This has implications for brand valuation derived from estimated BE. Brand valuation is heavily contextual and the value of a brand will differ by buyer, seller and application. For instance, a firm looking to buy or sell a brand might be more likely to look at the Expansive BEM to value the brand because it values the intangible brand assets built through distribution and promotion. Alternatively, a firm looking internally to modify, extend or pare a brand line might be more interested in an Intrinsic brand value because the firm already owns the supplier and retailer relationships and is only looking for the change in residual BE due to a change in its brand lines.

Results and Discussion

Since the beer industry analysis is meant as an illustration of our proposed methodology, we focus on reality checks and result validation. In particular, we check whether the revenue component parameter and BEM estimates agree with theory and intuition, and compare previous brand equity valuations for particular brands with those derived using our proposed revenue multiplier measure.

Revenue Component Parameter Estimates

Tables 3a and 3b show the MCMC estimates and related statistics for the Intrinsic and the Expansive BE specifications, respectively. Overall, the parameter estimates are intuitive.

The parameters of the product attributes which make up the Product Revenue Component are reasonable and many are significantly different from zero. American tastes are well supported in that, all else being equal, Craft and Lite beers are preferred to other beer types. Similarly, preferences run toward Cans and Light colored beers. Case and 12 Pack SKUs generate higher revenues than smaller package sizes. Interestingly, Subjective Taste has a negative impact on revenues indicating that beers that are rated high on taste tend to have lower revenues. This is intuitive since highly rated beers typically are specialty brews or super premium[11] beers which have smaller target markets. Note also that the unobserved SKU attribute differences term ζ_j captures a significant amount of SKU level revenue variation. Indeed, the variance of the SKU specific random effect $\left(\sigma_\eta^2\right)$ is roughly ten times the size of the unexplained error variance in each observation $\left(\sigma_\zeta^2\right)$, which suggests (i) the clear presence of latent SKU level attributes, (i.e., not all relevant SKU level attributes are modeled) and (ii) that the bulk of the unexplained variation in revenues is attributable to this systematic latent SKU level factor.

The revenue impacts of the variables in the Promotion Revenue Component bear the expected signs. In the Intrinsic BEM specification, higher brand levels of merchandising imply higher revenues. Higher brand levels of advertising spending, however, fail to show a significant positive effect. A reason for this latter result is that newer variants, which generally earn less revenue than more established variants, are advertised more heavily by many brands in the sample (e.g., Corona, Heineken, Molson, and Labatt). As we would expect, under both specifications, the deviations from stationary brand mean levels significantly and positively relate to revenue. That is, revenues clearly drop with decreases in merchandising and advertising from their mean brand levels.

For distribution, the Intrinsic specification results show that the revenue elasticity (i.e., parameter value) of distribution with respect to the stationary mean distribution level is approximately one. This suggests that increases in distribution raise revenues in almost the same

[11] Beers are commonly classified into Super Premium, Premium and Popular classes based on their positioning and price (Adams Beer Handbook).

proportion. In addition, under both specifications the parameter for the deviation from the brand mean distribution level indicates decreasing returns to scale for incremental distribution changes. Also, as expected, the more shelf presence (i.e., the greater the number of SKUs) a variant has, the larger are the sales of its various SKUs.

The Category Driver variables also show strong significance and intuitive appeal. The time dummies decrease from year to year, reflecting the slight downward trend in the revenue total of the top 25 beer brands. As for the seasonal dummies, beer consumption unsurprisingly rises along with outdoor temperatures. The size of the US adult population also positively impacts sales revenue. The exchange rate parameter is also positive indicating that the cheaper imports become in US dollars, the higher is their sales revenue. This is consistent with a price elasticity of greater than one in absolute terms for these beers.[12] Similarly consistent with beer price elasticities exceeding one, increases in the cost of long haul freight raise prices and lower revenue.

Discussion of BEM Revenue Multiplier Estimates

Columns 2 and 4 of Table 4 display the estimated Intrinsic and Expansive BEM for each of the 25 brands in the sample.

Intrinsic BEM Estimates

The Intrinsic BEM revenue multiplier for any particular brand represents an approximate lower bound for brand equity - the impact that brand specific unobserved influences have on its revenue. While his measure subsumes any impact (on account of its multiplicative nature) that the brand has on the *effectiveness* of distribution, merchandising and advertising it ignores the role of brand on the *levels* of the same constructs. Correspondingly, brands that have worked

[12] A regression of the log of beer volume sold against our observed marketing mix variables and price per unit volume over the sample data results in a price elasticity estimate of approximately -3.

hard at defining a distinct image score highly. In particular, niche brands in the super premium class such as Pacifico Clara, George Killian's and Amstel rate in the top ten as do more mainstream super premium brands such as Samuel Adams (ranked 1), Heineken (ranked 4) and Corona (ranked 5). Budweiser ranks second suggesting that Budweiser, unsurprisingly, has strong residual brand equity in addition to its distribution and promotion strengths.

The mean Intrinsic BEM of 1.15 implies that the brand represents about 13%[13] of the average beer brand's revenues. This percentage ranges from 26% for Samuel Adams to 3% for Coors (which has the lowest Intrinsic BEM of 1.04) High revenue but low Intrinsic BEM brands such as Miller, Michelob and, especially, Coors rely on their high levels of distribution, appealing observable product attributes (their SKUs are largely Light colored and Lite type beers that are the most popular) and heavy advertising and retail merchandising to earn revenue (see Table 2 for details on these market mix factors). Miller and Michelob also are the only brands that have variants with significant differences in their product and price characteristics. Michelob spans the super premium (Michelob Amber Bock and Michelob Ultra Light) and premium (Michelob and Michelob Light) classes, while Miller spans the popular (Miller High Life) and premium (Miller Lite, Miller Genuine Draft) classes. This implies that brands must be wary when extending their brand lines. When new variants and their SKUs differ strongly from the original brand line, brand equity is diluted.[14]

Expansive BEM

The Expansive BEM revenue multiplier includes as part of brand equity the impact that the brand's distribution, advertising and merchandising investments have on revenues. Since some, but not all, of the level of these investments is likely due to the brand name, this brand

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[13] The percent contribution of BE to revenue is computed as [(BEM-1)/BEM].

[14] It is likely that the variant names assume the driver's role and not the parent or family brand name (Aaker 1996).

equity measure presents an approximate upper bound for brand equity. With respect to this Expansive BEM, the top 5 brands are Corona, Budweiser, George Killian's, Samuel Adams and Heineken, respectively. The level of brand investments clearly plays a role in these results in that these brands have among the highest levels of distribution, retail merchandising and advertising. Alternatively, brand also clearly impacts the effectiveness of these brand investments since Samuel Adams rates above Heineken despite lower levels on all three investments. These differences in marketing mix factors and correspondingly disparate Expansive BEMs also explain why two brands with very similar Intrinsic BEMs (say, Budweiser and Samuel Adams) can have quite different revenues. Budweiser greatly outsells Samuel Adams at least partly because its distribution level and advertising spend far exceed those of Samuel Adams. In addition, Budweiser's highly available and advertised SKUs generally have more favorable product attributes (Light colored, Lite type, 12 Packs or Cases).

The average Expansive BEM of 2.33 implies that the beer brands in the US market attribute 57% of their revenues on the average to brand name. Indeed, even the smallest Expansive BEM estimate of 1.14 for Molson significantly exceeds one. These upper bound estimates of brand equity appear reasonable in that intangible assets in general represent about half the assets (52%) of non-financial non-farm firms (Federal Reserve Board, Q4 2004) and brand equity is the principal intangible asset of beer companies.

Figure 1 plots both the Expansive and Intrinsic BEM estimates for our 25 brands. The brands roughly cluster into four quadrants. This brand mapping reveals insights into how well the various brands have exploited their distribution and promotion opportunities to complement brand building efforts. The top-right quadrant contains brands that have both high Expansive BEM and high Intrinsic BEM. Hence, these brands have successfully exploited distribution and promotion opportunities to build a high Intrinsic BEM while both investing in significant levels of distribution and promotion and borrowing from their high Intrinsic BE to enhance these levels and their effectiveness. We label this quadrant the “developed brands” quadrant. Correspondingly, note that four of the five “developed brands”– Budweiser, Corona, Heineken and Natural – are the leaders in the premium, the super premium and the popular beer classes. The fifth brand, Samuel Adams, is the leading national Craft beer. The majority of brands fall into the bottom-left quadrant which encompasses the brands that have both relatively low Expansive and Intrinsic BEMs. These brands have failed to build a strong Intrinsic BEM (i.e., they lack the additional unobserved “something”) and simultaneously have not invested heavily in distribution or promotion or been unable to leverage their modest Intrinsic BEMs to strongly augment their distribution and promotion opportunities. We label this the “weakly developed brands” quadrant.

The remaining two quadrants are sparse. The bottom-right “supply developed” quadrant has two brands – Busch from the Anheuser-Busch stable and George Killian’s from the Molson-Coors stable. These two brands have relatively high Expansive BEMs but low Intrinsic BEMs. As such, their parent breweries have leveraged their overall relationships with channel partners to attain fairly high distribution and promotion levels and effectiveness for these brands. The top-left “demand developed” quadrant has relatively high Intrinsic BEM and low Expansive BEM. This suggests that while consumers demand the “something extra” that the brand has, the distribution and promotion for the brand are relatively weak. Correspondingly, there exists an opportunity to raise revenue by expanding distribution and promotion. The sole brand in this quadrant – Pacifico Clara – is a small niche brand aimed at Hispanic consumers.

External Validity and Comparisons with Previous Brand Equity Valuations

We now perform some reality checks and examine the external validity of the BEM methodology. To highlight the importance of accounting for the impact of marketing mix and brand name separately, we compare our BEM estimates to those provided by the revenue premium methodology proposed by Ailawadi, Lehmann and Neslin (2003; henceforth, ALN). Since their brand equity measure is a dollar metric, we introduce a dollar metric measure derived from our BEM measure – the *Revenue Dollar Premium*. We utilize this value because BEM does not measure the absolute monetary size difference between the revenues of a brand and its particular unbranded equivalent. Rather, a brand's BEM is a percentage mark-up of its unbranded equivalent's revenues. Thus, two brands can have the same BEM but quite disparate revenues if their observed marketing mix (including product attributes) differs greatly.

The Revenue Dollar Premium is the dollar difference between the observed revenue earned by the brand and the estimated revenue of its unbranded equivalent. Conceptually,

$$\text{Revenue Dollar Premium}_b = \sum_{j \in b} \sum_{t=1}^{T} \left\{ \begin{bmatrix} \text{Revenue from} \\ \text{Branded SKU } j \end{bmatrix} - \begin{bmatrix} \text{Revenue from Unbranded} \\ \text{Equivalent of SKU } j \end{bmatrix} \right\} \quad . \tag{8}$$

Since the focus of this study is equity at the brand level, we aggregate revenue dollar premiums to this level in equation (8) by summing across all time periods and all SKUs that share a brand name. Columns 3 and 5 in Table 4 present our Revenue Dollar Premium estimates. Column 6 presents actual total revenue figures, while Column 7 provides revenue premium estimates using ALN's technique. Since the latter method computes the revenue premium of a brand as the difference in revenue earned by all the SKUs under that brand name with the revenue sum of all the SKUs under the predefined baseline brand name, it confounds the marketing mix and BE effects of each brand. Furthermore, additional bias is added since the market mix of the baseline brand (Molson, a low sales brand) is not the same as that of the other brands and the brand equity of Molson is unlikely to be zero as it is assumed. These BE measurement biases show clearly in that the high revenue brands (which also typically have much greater promotion and distribution levels) are estimated to have ALN premiums that generally account for well over half of their total revenues. Similarly, the lesser distributed and promoted brands typically have much smaller absolute and relative ALN premiums. Our Revenue Dollar Premium measure, on the other hand, takes these market mix influences into account and provides brand equity estimates that are generally much smaller and more realistic. The average revenue dollar premium ranges from $29.5 million per annum for Intrinsic BEM to $134.8 million per annum for Expansive BEM - much lower than the ALN average of $192.8 million.

Next, we investigate whether our BEM estimates are stable over time. To test temporal stability, we estimated the model separately for three two year time span subsets (2002-03, 2003-04 and 2004-05) and compared these BEM estimates with those of our four year estimation. The correlation with the full sample BEM estimates in all three cases exceeds 0.8. Furthermore, for all three time sub-intervals, the BEM estimates for all 25 brands are within the 95% Highest Probability Density (HPD) interval of their full sample BEM. Thus, we infer that the BEM estimates are stable across time.

Three compelling examples of the external validity for our BEM methodology come from comparisons with brand valuations based on financial data. First, our results are quite consistent with the late 1980’s financial firm level brand equity valuations derived by Simon and Sullivan (1993). They found that food product firms on average and Anheuser-Busch, in particular had a BE contribution equal to 35% of the firm’s replacement value. The average Intrinsic and Expansive BEMs of 1.15 and 2.33 correspond to, as previously stated, percent revenue markups of 13% to 57% which bound their 35% figure extremely well. In addition, the estimated percent contribution of brand name on a revenue-weighted basis over all the Anheuser-Busch brands ranges from 20.7% for Intrinsic BEM to 76.6% for Expansive BEM. These values also bound the Simon and Sullivan estimate neatly. Despite the different time periods for the two analyses, a reasonable degree of agreement occurs which lends validity to our BEM measure.

The other two comparisons we make are with previous dollar metric financial brand equity valuations. These valuations utilize discounted cash flows to compute the net present value of a firm's or brand's equity. Such values represent the dollar returns to brand assets and are used, for example, by analysts to value firms and brands in mergers and acquisitions. Hence, we utilize the dollar-metric Revenue Dollar Premium measure derived from our BEM discussed earlier as the basis for comparison. Using the Revenue Dollar Premium estimates for the Miller and Budweiser brands, we calculate simple, rough-cut net present value brand equity valuations and compare these with previous financial brand equity values generated for the Budweiser brand and combined Miller brands.

South African Breweries (SAB) merged with the Miller Brewing Company in 2001 to create the world's second largest brewing company (behind Anheuser-Busch). At that time, SAB Miller listed the goodwill of its Miller assets at $4.25 billion. This goodwill principally represents the net present value of the various Miller brands' brand equities. In Table 5, we use the sum of the annual Intrinsic BEM Revenue Dollar Premiums for the Miller Brewing Company's brands (Miller, Milwaukee's Best and Icehouse) which total $92.3 million per year from Table 4 as the yearly value of the brand at retail grocery outlets and then adjust this figure to account for retail mark-ups, retail sales through non-grocery channels, on-premise (bar) sales and non-US sales. We utilize the Intrinsic BEM because this measure aligns more naturally with the estimated residual brand earnings that financial analysts use to value brands. The resulting annual brand equity figure of $283.4 million when discounted in perpetuity using a discount rate of 7.3% (the rate used by SAB Miller in their calculations) provides a net present value estimate for the brand equity of the Miller brand portfolio of $3.88 billion, which is quite close to the reported value of $4.25 billion.

The brand consultancy InterBrand estimated the brand value of Budweiser at $11.93 billion in 2005. We again (see Table 5) use the Intrinsic BEM annual Revenue Dollar Premium for the Budweiser brand ($338.5 million from Table 4) as the yearly value of the brand at retail grocery outlets and then adjust this figure as we did that for Miller. Assuming a discount factor of 10.7%[15], we arrive at a global brand value for Budweiser of $11.06 billion. Once again, despite using rough cut calculations, broad assumptions and entirely different methods and data sources, this computed brand value is quite similar to that estimated by InterBrand. We believe this is a powerful vote of confidence for the proposed methodology and BEM measure.

In sum, the proposed revenue multiplier brand equity measurement methodology reasonably captures the influence of marketing mix (promotion, distribution and both observed and unobserved product attributes) and category factors that previous methodologies have typically included as part of their brand equity estimates. Correspondingly, a more accurate measure of brand equity is identified which, in fact, agrees rather well with equity measures derived from alternative financial data sources. Further, the proposed BEM measure is also intuitive and credible, objective, grounded in theory, based on readily available data, a single-number measure (which facilitates easier tracking and communication), robust and stable, reasonably complete (in that it captures facets of BE not captured by summary measures), and able to assess the potential of future brand line extensions. In such, it meets nine of the ten ideal

[15] We arrive at a discount rate of 10.7% for Anheuser-Busch by using (i) a risk-free rate of 5% (close to the historical average), (ii) Anheuser-Busch's stock beta of 0.62 (Yahoo company profiles) as a proxy for risk, and (iii) a long term market risk premium of 9.2% (Bowman 2001).

criteria for a BE measure as enumerated by the Marketing Science Institute (1999). As for the tenth criterion, akin to other product-market measures, our measure is diagnostic only to the extent that it can identify changes in BE over time or differences across brands.

Managerial Implications, Extensions and Conclusion

Managers have long felt the need for a reliable brand equity measurement system (Keller 1998) and our proposed methodology represents a step forward in constructing a BE measurement system that overcomes two key problems in extant measurement schemes. (i) Data that is readily available from firm and syndicated data sources (scanner data, product attribute information, etc.) are required rather than costly and time consuming survey data. (ii) The impact of category characteristics and, especially, marketing mix actions (product, price, promotion and distribution decisions) on sales is explicitly accounted for. Thus, the potential bias of our brand equity measure is reduced. This methodology was demonstrated for the 25 largest US beer brands and the results exhibit face validity and agree with brand values computed from alternative financial data sources.

Several implications for both marketing practitioners and academics emerge. First, a comparison of our brand equity revenue multiplier measure BEM across brands provides a direct measure of how impactful a brand name itself is to consumer choice relative to the impacts of its competitors' brand names. A comparison of our secondary brand equity measure, Revenue Dollar Premium, across brands allows the relative financial impact of the brand to be assessed since this premium depends not only on the BEM but also on the inherent appeal of the product, price, promotion and distribution associated with the brand (i.e., the brand's unbranded equivalent). Further, tracking a brand's revenue multiplier BEM or Revenue Dollar Premium over time provides a simple running diagnostic of a brand's "health" and the success of its branding program (Sriram, Balachander, and Kalwani 2007). Also, note that the availability of both the Expansive and Intrinsic BEM measures gives managers some insight into the role of marketing mix investments in creating and maintaining brand equity.

Second, more robust and accurate BE measurement allows product demand to be more accurately specified and the influences of its non-brand determinants (marketing mix and category factors) to be more accurately measured. For instance, the expected return on marketing mix investments (Rust, Lemon and Zeithaml 2004) such as product design changes and distribution expansion will be more accurately forecasted if the influences of these factors are better understood.

Third, the dollar-metric Revenue Dollar Premium measure derived from our BEM measure yields reasonable brand valuations. Correspondingly, these easily estimated premiums have a direct application to situations that require financial valuations of equity at the brand level. This is propitious since standard financial, stock market and accounting data are typically at the firm level and, thus, not fully appropriate. Hence, the methodology is appropriate for brand valuations central to mergers and acquisitions and, more broadly, to organizational arrangements such as franchising contracts and brand alliances that require a limited transfer of rights to a brand name for a period of time or in particular geographic area.

Fourth, the revenue multiplier methodology is applicable to brand structures more general than the Brand-SKU hierarchy assessed in this paper. For example, questions can be addressed concerning ingredient branding (e.g., how much does “Intel Inside” contribute to the premium earned by a Dell computer?), co-branding (e.g., what are the contributions of Citibank and Southwest to a co-branded credit card?), and endorsement valuation (e.g., how much does Marriott contribute to the equity of “Holiday Inn by Marriott”?). Similarly, one could investigate the contributions of different levels in a brand hierarchy (i.e., corporate, family, brand, variant; Aaker 1996). Such a hierarchical study also may lead to a better understanding of umbrella branding (Erdem 1998). A related methodological opportunity is the use of more general parametric forms that would allow correlations between the BEMs in a set of brands and result in brand maps along the lines of Chintagunta (1994).

Fifth, the framework naturally lends itself to assessing whether particular private label or store brands have brand equity. This is possible since our BEM measure does not require a particular real world product (typically a store brand or low share national brand) to be assumed to have a predefined equity level (usually zero) that all other brand equities are estimated relative to. Both manufacturers and retailers would have interest in assessing whether private labels have brand equity and how this equity has evolved over time.

In sum, the proposed BEM methodology to assess brand equity is an intuitive, useful and precise tool appropriate for both managers and researchers. Our brand equity revenue multiplier holds well against the Marketing Science Institute’s ideal characteristics for a BE measure, but, more importantly, is (i) easy to implement and (ii) provides a more accurate measure of brand equity because non-brand influences such as the marketing mix factors that typically confound equity measures are explicitly accounted for. Further, this measure and methodology are extendable to assess brand equity issues in a variety of organizational arrangements (e.g., franchising, brand alliances and store brands) and branding structures (e.g., corporate, variant, ingredient and umbrella branding).

Table 1

US Beer Market Summary of Variables

Revenue Component	Variable	Description	Mean	Source
PRODUCT				
Type	$Craft_j$	Craft type = 1, otherwise = 0	0.04	Aggregate Scanner Data (AC Nielsen)
	Dry_j	Dry type = 1, otherwise = 0	0.01	
	Ice_j	Ice type = 1, otherwise = 0	0.12	
	$Lite_j$	Lite type = 1, otherwise = 0	0.40	
	$Regular_j$	Regular type = 1, otherwise = 0	0.43	
	Subjective $Taste_j$	Regression residual of beer ratings (0-5 scale) on all objective product attributes	-0.02	Internet and Regression Residual
Beer Color	$Amber_j$	Amber color = 1, otherwise = 0	0.05	Aggregate Scanner Data
	$Light_j$	Light color = 1, otherwise = 0	0.74	
	$Golden_j$	Golden color = 1, otherwise = 0	0.19	
	$Dark_j$	Dark color = 1, otherwise = 0	0.01	
Packaging	6Pk-12Oz $_j$	6 Pack of 12 oz. Containers = 1, else 0	0.24	Aggregate Scanner Data
	6Pk-Non12Oz $_j$	6 Pack, Non -12 oz. Containers = 1, else 0	0.07	
	12Pk $_j$	12 Pack = 1, otherwise = 0	0.30	
	$Case_j$	Pack of 18 or more containers = 1, else 0	0.26	
	$SmallPack_j$	Pack with total volume < 72 oz.=1, else 0	0.13	
	Can_j	Can = 1, otherwise = 0	0.47	
	$Bottle_j$	Bottle = 1, otherwise = 0	0.53	
Origin	$Europe_j$	European brewer = 1, otherwise = 0	0.06	Trade Publications (Adam's Beer Handbook)
	$Mexico_j$	Mexican brewer = 1, otherwise = 0	0.09	
	North $America_j$	North American brewer = 1, otherwise = 0	0.85	
PROMOTION	$AdSpend_{jt}$	Annual ad spend in $ millions	30.61	Leading National Advertisers
	$\%ACVMerch_t$	%ACV that promoted SKU	13.48	Aggregate Scanner Data
DISTRIBUTION	$\%ACVDistbn_{jt}$	%ACV that carried SKU	31.53	Aggregate Scanner Data
	$SKUNum_{jt}$	For a SKU, the average number of SKUs its variant has in a store that carries it	7.87	
CATAGORY DRIVERS	$USAdults_t$	US population over 21 years old in millions	206.72	Bureau of Labor Statistics
	$FreightPPI_t$	Long haul freight PPI	115.43	
	$ExchgRate_t$	Foreign currency exchange rate per US dollar	1.37	US Federal Reserve
	$Fall_t$	Fall = 1, otherwise = 0	0.24	Aggregate Scanner Data
	$Winter_t$	Winter = 1, otherwise = 0	0.24	
	$Spring_t$	Spring = 1, otherwise = 0	0.23	
	$Summer_t$	Summer = 1, otherwise = 0	0.29	
	Year 2002_t	Year 2002 = 1, otherwise = 0	0.26	
	Year 2003_t	Year 2003 = 1, otherwise = 0	0.25	
	Year 2004_t	Year 2004 = 1, otherwise = 0	0.23	
	Year 2005_t	Year 2005 = 1, otherwise = 0	0.27	

Subscripts *j* and *t* denote SKU and period, respectively.

Table 2
US Beer Market Summary Statistics by Brand

Brand[a]	Origin	Revenue Share		[b]	[b]	[c]	
						0.00	2.76
Modelo Especial	Mexico	0.50%	0.09	23.08	5.66	1.65	2.05
Pacifico Clara	Mexico	0.50%	0.09	27.50	8.96	1.68	2.16
Mean		4.00%	0.068	40.9	14.5	35.56	1.89
Std Dev		6.40%	0.065	16.70	8.70	5.29	0.53
George Killian's	USA	0.50%	0.08	37.28	11.62	4.69	2.40
Dos Equis	Mexico	0.50%	0.09	55.76	20.96	3.56	2.16
		0.70%	0.06	18.30	4.43		

[a] Sorted in descending order by revenue share.
[b] Revenue weighted average over all the brand's SKUs over the entire sample period.
[c] Average yearly advertising spend.

Table 3a
Estimates for the Intrinsic BEM Model

Revenue Component	Variable	Mean	2.5% HPD	97.5% HPD
	Intercept	-11.90	-18.25	-5.55
PRODUCT	**Craft**	0.36	-0.37	1.02
Type	Dry	-0.15	-1.15	0.76
	Ice	0.15	-0.11	0.42
	Lite	0.34	0.23	0.46
	Regular		Reference Attribute	
Color	Amber	0.30	-0.43	1.05
	Light	0.77	0.23	1.38
	Golden	0.58	-0.01	1.19
	Dark		Reference Attribute	
Packaging	6Pk-12Oz	0.02	-0.15	0.16
	6Pk-Non12Oz	0.20	-0.05	0.42
	12Pk	0.60	0.42	0.78
	Case	1.09	0.88	1.31
	SmallPack		Reference Attribute	
	Can	0.19	0.07	0.30
	Bottle		Reference Attribute	
Origin	Europe	0.24	-0.11	0.56
	Mexico	0.45	0.12	0.80
	N. America		Reference Attribute	
	Subjective Taste	-0.33	-0.59	-0.13
PROMOTION	**Mean Ln%ACVMerch**	0.22	0.01	0.44
	Delta Ln%ACVMerch	0.17	0.16	0.18
	Mean LnAdSpend	0.00	-0.04	0.03
	Delta LnAdSpend	0.02	0.02	0.03
DISTRIBUTION	**Mean Ln%ACVDistbn**	1.16	0.85	1.52
	Delta Ln%ACVDistbn	0.96	0.94	0.97
	SKUNum	0.02	0.02	0.03
CATAGORY DRIVERS	**USAdults**	3.77	2.37	5.17
	FreightPPI	-0.27	-0.64	0.10
	ExchgRate	0.07	0.01	0.12
	Fall	-0.16	-0.17	-0.15
	Winter	-0.18	-0.18	-0.17
	Spring	-0.13	-0.14	-0.12
	Summer		Reference Season	
	Year 2002	0.22	0.18	0.25
	Year 2003	0.12	0.10	0.15
	Year 2004	0.07	0.05	0.08
	Year 2005		Reference Year	
Variance Components and Fit	**Variance η**	0.02	0.02	0.02
	Variance latent SKU ς	0.22	0.19	0.27
	Log Marginal Density		-9900.62	
	λ	0.14	0.002	0.32

The bold font indicates that the 95% Highest Probability Density (HPD) intervals do not include zero and are hence significant in a Bayesian sense.

Table 3b
Estimates for the Expansive BEM Model

Revenue Component	Variable	Mean	2.5% HPD	97.5% HPD
	Intercept	-7.39	-13.74	-1.07
PRODUCT	**Craft**	0.41	-0.22	1.17
Type	Dry	-0.12	-1.19	0.98
	Ice	0.08	-0.22	0.37
	Lite	0.31	0.18	0.44
	Regular		Reference Attribute	
Color	Amber	0.25	-0.78	1.12
	Light	0.84	0.19	1.55
	Golden	0.52	-0.15	1.24
	Dark		Reference Attribute	
Packaging	6Pk-12Oz	0.03	-0.14	0.21
	6Pk-Non12Oz	0.17	-0.04	0.41
	12Pk	0.57	0.41	0.74
	Case	1.07	0.91	1.32
	SmallPack		Reference Attribute	
	Can	0.16	0.05	0.30
	Bottle		Reference Attribute	
Origin	Europe	0.69	0.35	1.24
	Mexico	0.27	-0.22	0.66
	N. America		Reference Attribute	
	Subjective Taste	-0.31	-0.58	-0.08
PROMOTION	**Delta Ln%ACVMerch**	0.17	0.16	0.18
	Delta LnAdSpend	0.02	0.02	0.03
DISTRIBUTION	**Delta Ln%ACVDistbn**	0.96	0.94	0.97
	SKUNum	0.02	0.02	0.03
CATAGORY	**USAdults**	3.78	2.39	5.22
DRIVERS	FreightPPI	-0.27	-0.65	0.10
	ExchgRate	0.06	0.01	0.12
	Fall	-0.16	-0.17	-0.15
	Winter	-0.18	-0.18	-0.17
	Spring	-0.13	-0.14	-0.12
	Summer		Reference Season	
	Year 2002	0.22	0.18	0.25
	Year 2003	0.12	0.10	0.15
	Year 2004	0.07	0.05	0.09
	Year 2005		Reference Year	
Variance	**Variance η**	0.02	0.02	0.02
Components and Fit	**Variance latent SKU ς**	0.23	0.19	0.28
	Log Marginal Density		-10590.12	
	λ	0.72	0.41	1.15

The bold font indicates that the 95% Highest Probability Density (HPD) intervals do not include zero and are hence significant in a Bayesian sense.

Table 4

BEM and Revenue Dollar Premium Estimates under both Specifications

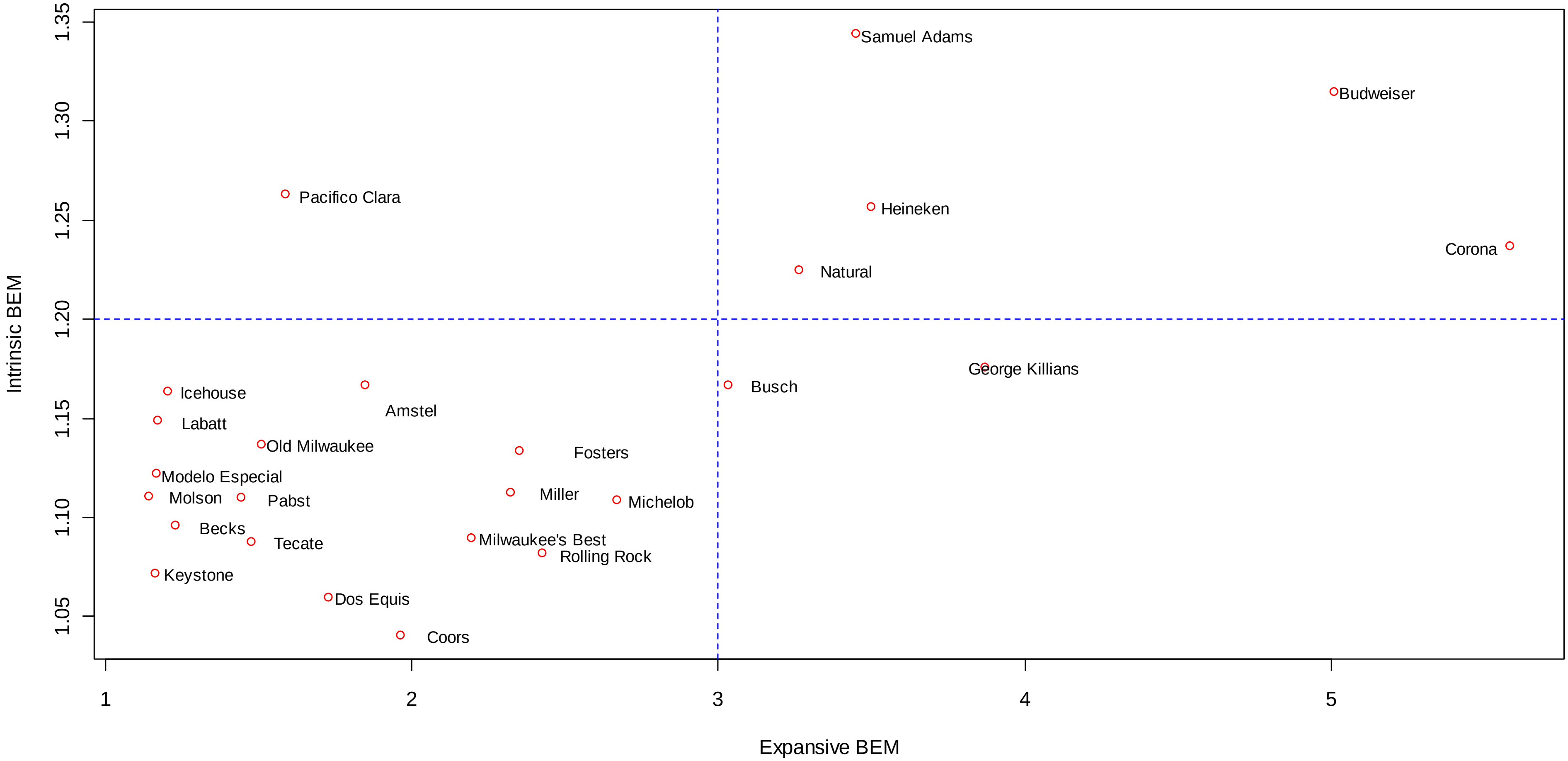
	Intrinsic Model		Expansive Model			
Brand[a]	**BEM**	**Revenue Dollar Premium[b] ($Mn/Yr)**	**BEM**	**Revenue Dollar Premium[b] ($Mn/Yr)**	**Total Revenue ($Mn/Yr)**	**ALN[c] Revenue Premium[d] ($Mn/Yr)**
Budweiser	1.32	338.50	5.01	1277.00	1638.74	1609.91
Miller	1.11	72.10	2.32	440.75	814.73	785.89
Coors	1.04	18.34	1.96	233.43	503.83	474.99
Corona	1.24	74.70	5.58	375.25	476.63	447.79
Michelob	1.11	27.95	2.67	192.78	339.08	310.25
Busch	1.17	36.83	3.03	192.40	299.07	270.23
Natural	1.23	42.88	3.26	181.85	268.55	239.72
Heineken	1.26	38.18	3.50	155.68	229.75	200.92
Milwaukee's Best	1.09	13.47	2.19	93.45	186.12	157.29
Keystone	1.07	4.97	1.16	9.53	85.86	57.02
Samuel Adams	1.34	14.76	3.45	48.65	74.01	45.18
Tecate	1.09	4.99	1.48	20.21	69.53	40.69
Labatt	1.15	6.07	1.17	7.06	63.32	34.48
Icehouse	1.16	6.71	1.20	8.67	61.06	32.22
Old Milwaukee	1.14	4.69	1.51	13.97	56.58	27.74
Becks	1.10	3.90	1.23	8.42	52.97	24.13
Rolling Rock	1.08	2.96	2.42	22.48	44.36	15.53
Amstel	1.17	4.53	1.85	14.31	41.81	12.98
Pabst	1.11	3.08	1.44	9.46	41.23	12.39
Molson	1.11	2.27	1.14	2.77	38.94	10.10
Fosters	1.13	3.57	2.35	17.69	36.47	7.63
George Killian's	1.18	3.61	3.87	20.01	30.12	1.28
Dos Equis	1.06	1.54	1.73	11.18	29.96	1.12
Modelo Especial	1.12	2.95	1.16	3.51	29.10	0.27
Pacifico Clara	1.26	4.52	1.59	8.87	28.83	0.00
Mean	1.15	29.52	2.33	134.77	221.62	192.79
Std Dev	0.08	67.70	1.22	267.04	354.11	354.11

[a] Brands sorted in descending order by revenue.
[b] Calculated using equation (8).
[c] Ailawadi, Lehman and Neslin (2003).
[d] Sum of revenues for focus brand's SKUs minus the sum of revenues for the sale brand Pacifico Clara's SKUs.

Table 5
Brand Valuation Calculations using Intrinsic Revenue Premium Estimates

	Miller Brewing Co.	Budweiser	Source
Brand value ($ Bn)	**4.25**	**11.93**	SEC filings, Interbrand
Annual Revenue Premium ($Mn)	92.3	338.5	Table 4
Remove 20% retailer margin ($Mn)	73.8	270.8	Cost data from one supermarket chain
Add 12% sales from other channels ($Mn)	83.9	307.7	AC Nielsen
Add 60% on premise ($Mn)	209.7	769.3	Adams Beer Handbook
Add 26% & 35% from non US markets ($Mn)	283.4	1183.6	Adams Beer Handbook
Discount rate used to Discount Future Cash Flows	7.30%	10.70%	SEC filings for Miller; For Budweiser, 5% risk free rate, Anheuser-Busch stock beta of 0.62 and long term US market premium of 9.2%
Estimated Brand Value ($Bn)	**3.88**	**11.06**	Present value of discounted cash flows

Figure 1
Mapping of BEMs into Brand Development Quadrants



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