

# Valuing Branded Businesses

The authors develop and validate a conditional multiplier approach for valuing branded businesses. The approach enhances traditional multiplier-based valuation by explicitly incorporating brand characteristics into the model. The authors present theoretical arguments why, develop a model to demonstrate how, and provide an empirical illustration to show that brand assets are not fully reflected in contemporaneous margins, and therefore valuation accuracy can be improved by incorporating information about the properties of the firm's brand asset directly into a valuation framework. The authors find that brand metrics have statistically significant associations with valuation multipliers and add incremental explanatory power to accounting variables in explaining valuation multipliers. Out-of-sample analysis shows a 16% improvement in the mean absolute error for predictions that take into account brand metrics compared with predictions based on accounting variables alone.

*Keywords:* enterprise valuation, relative valuation, brand, conditional sales multiplier

**W**ith efficient financial markets, the market value of a stock provides an unbiased estimate of the net present value of a firm's future cash flows. As such, stock market valuation typically provides a reliable measure of a firm's value and can be used as a starting point in, for example, merger and acquisition discussions. At times, however, an estimate of firm value is needed, but financial market data are unavailable. This occurs, for example, when a firm is not publicly traded or when a valuation is needed for a business unit rather than the entire corporate entity.

In 2006, Pfizer sold its consumer goods business units to Johnson & Johnson. Cadbury announced in 2007 that it would be divesting its North American beverage businesses. In 2008, the Swedish government sold V&S, which is best known for its Absolut Vodka brand, as part of a drive to privatize six state-owned companies. The Swedish government also explored the possibility of splitting V&S into separate brands and selling each one individually. Placing a value on these entities is complicated because they are branded businesses; that is, the brand asset represents a significant portion of the alienable value. Traditional financial valuation approaches have difficulty in valuing businesses with significant intangible assets (Barth, Beaver, and Landsman 1998; Lie and Lie 2002). Rarely do these traditional valuation approaches explicitly account for the incremental impact of intangibles, such as brand assets. Instead, the contribution of brand assets to firm value tends to be dealt with in an ad hoc or a subjective way.

In this study, we present a conditional multiplier-based valuation approach that explicitly incorporates brand characteristics into the business valuation model. Our objective is to advance business valuation methodology by assessing whether valuation accuracy can be improved by incorporating brand metrics into the valuation framework. As such, the study has a different objective from research that tries to isolate and place a value on the brand asset (e.g., Ailawadi, Lehmann, and Neslin 2003; Fischer 2007; Park and Srinivasan 1994; Shankar, Azar, and Fuller 2007; Simon and Sullivan 1993; Srinivasan, Park, and Chang 2005; Sriram, Balachander, and Kalwani 2007). Our focus is on using brand information to enhance predictive accuracy in the valuation of a branded business as an entire entity.

Analysis focused on prediction requires incorporating methodological considerations that are different from analysis focused on assessing causal effects (Shmueli 2009; Stock and Watson 2006). In particular, for prediction-based analyses, (1) measures of explanatory power, such as R-square and mean absolute error (MAE) are important; (2) omitted variable bias is not a problem and is actually desirable because it captures omitted information that enhances the information content of the variables included in the model; (3) the coefficients in forecasting models are not directly interpretable as structural parameters but rather are reduced-form estimates; and (4) external validity is paramount—that is, the model estimated using historical data must hold out-of-sample. We develop and test our conditional multiplier model following these considerations.

We apply our branded business valuation methodology to Young & Rubicam's Brand Asset Valuator (hereinafter, Y&R BAV) data. Our empirical analysis indicates that valuation can be significantly improved by incorporating information about the characteristics of the firm's brand asset into a valuation framework. We find that brand metrics have statistically significant associations with valuation multipliers and add incremental explanatory power to accounting variables in explaining valuation multipliers. Out-of-sample analysis shows a 16% improvement in predictive power (as measured by mean absolute prediction error) for predictions

---

Natalie Mizik is Gantcher Associate Professor of Business, Graduate School of Business, Columbia University (e-mail: nm2079@columbia.edu). Robert Jacobson is principle, Diogenes Consulting (e-mail: Bob.Jacobson@DiogenesConsulting.com). The authors thank Young & Rubicam for providing access to the brand data used in this study. They are grateful to Emina Hrustic, Ed Lebar, and Anne Rivers for sharing their insights. The views expressed in this article are strictly those of the authors and do not necessarily reflect those of Young & Rubicam.

---

that account for brand metrics compared with predictions based on accounting variables alone.

## Valuation Approaches

A host of different approaches to business valuation exists. Although these frameworks make different assumptions, they share some similarities and can be broadly classified into two general approaches (Damodaran 2002).<sup>1</sup> One framework is based on discounted cash flow (DCF) analysis. This approach is referred to as a direct valuation approach and attempts to estimate the intrinsic value of an asset on the basis of its fundamentals. It relies on the net present value rule, which means that the value of an asset is measured on the basis of discounted expected future cash flows.

Although DCF is theoretically appealing, such an analysis is not easy to implement because of the inherent uncertainty associated with the future. Undertaking a DCF valuation requires making projections of future cash flows and of a discount rate, which depends on the riskiness of the firm. Both estimations are difficult to make; a great deal of judgment and guesswork is typically involved in coming up with the necessary inputs.<sup>2</sup> This approach is particularly difficult to implement for initial public offerings, young firms, firms in dynamic industries, and firms with significant intangible assets (e.g., patents, valuable brands) (Kim and Ritter 1999).

Because of the difficulties in implementing DCF valuation, relative valuation methods are commonly used as an alternative or complementary approach. Relative valuation (also referred to as “comparable firm valuation” or “peer group valuation”) is based on the premise that similar assets should be priced similarly. As such, the value of an asset can be established according to how similar assets are priced in the market. Under relative valuation, the value of an asset is determined on the basis of the pricing of assets having comparable characteristics.

Unlike DCF valuation, relative valuation bypasses the requirement for making future-term performance projections. Instead, it relies on the market mechanism to reveal the asset’s price. The underlying assumption is that, on average, the market correctly prices assets, and therefore

the average valuation of assets having similar characteristics can be used to ascertain the value of another asset.<sup>3</sup>

## Multiplier Analysis

Relative business valuation approaches make use of “multiplier analysis.” A set of similar businesses is identified and their market value is linked to a common standardizing factor, or value driver. For example, firm value is often depicted as a multiple of an accounting measure, such as book value, earnings, or sales. For example, it is common (Berger and Ofek 1995; Damodaran 2002) for firm value to be expressed as a function of its sales:

$$(1) \quad \text{Firm Value}_{it} = \phi_{it} \times \text{Sales}_{it},$$

where  $\text{Firm Value}_{it}$  is a measure of the value of firm  $i$  at time  $t$ ,  $\text{Sales}_{it}$  is a measure of firm  $i$ ’s revenues at time  $t$ , and  $\phi_{it}$  is the sales multiplier for firm  $i$  at time  $t$ . The multiplier  $\phi_{it}$  transforms the accounting sales measure (i.e., the value driver) into firm value.

For valuation purposes, sales is taken as a known input, and the key consideration is deriving a multiplier ( $\phi$ ) that can be applied to the sales figure to come up with a predicted value of the enterprise. For example, in the simplest version of the process, the valuation of a business could be determined by multiplying the sales of the business by the value-to-sales ratio of comparable publicly traded firms in the same industry. Berger and Ofek (1995) use sales multipliers to impute the implied value for each of the diversified firms’ business lines as if they were independent entities, and they examine the difference between a firm’s total value and the sum of imputed values for its business lines to examine the effects of business diversification.

As Liu, Nissim, and Thomas (2007) note, valuation based on multiples boils down a complex function of discount rates and future cash flows into a simple proportional relationship: Predicted firm value equals the level of the value driver for the firm times the corresponding multiplier. Because the multiple is an average or typical ratio of firm value to the value driver for a set of firms having similar characteristics, the key consideration in relative valuation methods is determining which characteristics make assets similar or comparable.

Bhojraj and Lee (2002) argue that the choice of the peer group should be a function of the variables that drive cross-sectional variation in a given valuation multiple. They suggest (p. 434) that “any normative approach to selecting comparable firms should reflect the fundamental concepts that underpin equity valuation” and that an industry-based approach with firm-specific adjustments is a sensible way to capture these factors. They show that predictive performance of multipliers can be significantly enhanced with more thorough and systematic peer group selection.

---

<sup>1</sup>An additional approach, contingent-claim valuation, has also been recently developed. It uses option-pricing models to measure the value of assets that share option characteristics. This approach is typically used for valuing traded financial assets and has not received much attention for valuing businesses (for an exception, see Chen and Zhang 2003).

<sup>2</sup>Studies show that DCF valuation is affected by the interests and incentives of the party undertaking the valuation. For example, Gilson, Hotchkiss, and Ruback (2000) report “strategic distortions” in DCF valuations of bankrupt firms. They find significant relationships between DCF valuation errors and conflicting financial interests of stakeholders in the bankruptcy negotiations. Specifically, they find that DCF valuation errors are systematically related to (1) relative bargaining strength of claimholders (junior versus senior), (2) existence of outside bids, (3) management’s equity stake, and (4) management turnover.

---

<sup>3</sup>A limitation of relative valuation methods is that because they rely on market valuation of similar firms, they are vulnerable to temporal out-of-sample inaccuracy if an entire sector is consistently under- or overvalued at a given period.

## **Interindustry Effects**

As a starting point, relative valuation analysis is typically undertaken at an industry or a business sector level to control for business environment effects and for general future growth prospects. Alford (1992) examines the impact of rules for selecting comparables (e.g., based on industry, size, and earnings growth) on the accuracy of valuation using multiples. He reports that valuation errors go down when the peer group is based on industry affiliation. Because industrial sectors are defined more narrowly—that is, when moving to the three-digit Standard Industrial Classification (SIC) code level from the one- or two-digit level—valuation accuracy improves, but no error reduction occurs when going from the three- to the four-digit SIC level. Alford also finds that controlling for size and growth in addition to industry membership does not improve valuation accuracy. He concludes that industry membership is an effective criterion for selecting comparable firms.

## **Intraindustry Effects**

Although value multipliers have some stability across firms in the same industry, significant intraindustry differences can and do exist (Kim and Ritter 1999). That is, even among firms within the same industry, firms may differ in attributes that affect valuation and thus yield differing value-to-sales ratios. For example, Johnson & Johnson paid \$16.6 billion in 2006 for the consumer unit of Pfizer, which had annual sales of \$3.9 billion at the time. This is a value-to-sales multiple of 4.3. Procter & Gamble's 2005 purchase of Gillette for \$57 billion represented a value-to-sales ratio of approximately 5.7. Prior research points to differences in profitability as the key factor explaining within-industry differences in multipliers.

*Profit margin.* A sales multiple measures the value of a business relative to the revenue it generates. Although it offers some advantages over other multiples (e.g., a sales figure is easily available and is less subject to accounting distortions and transitory fluctuations than other accounting metrics), the sales multiple does not reflect differences in profitability across firms. Indeed, a firm can be generating sales but losing money. A firm must be able to generate cash flows over the long run for the business to have value. Differences in business value are related to differences in profit margins. Damodaran (2002) provides a model that shows how the sales multiplier is an increasing function of profit margin. That is, all else being equal, firms with higher margins should have higher value-to-sales multiples. He finds empirically for specialty chemical firms that a 1-unit increase in net margin is associated with a 5.71-unit increase in the sales multiplier.

Indeed, several studies document the role of incorporating earnings and margins in enhancing the accuracy of relative valuation methods. For example, Boatsman and Baskin (1981) report that valuation accuracy increases when comparable firms are selected within the same industry on the basis of similarity of earnings growth. Barth, Beaver, and Landsman (1998) and Barth, Elliott, and Finn (1999) also find systematic relationships between multiples and financial performance and report that multiples tend to decrease

as firm financial health decreases. Bajaj, Denis, and Sarin (2004) provide further evidence that firm profitability has an economically important impact on industry-adjusted multiplier ratios.

*Intangible assets.* Prior research is much less clear on how intangible assets, such as brand, should be incorporated into multiplier-based valuation analysis. Most valuation approaches tend to view intangibles as affecting accounting fundamentals and, as such, as already being incorporated into multiplier analysis through their impact on contemporaneous accounting metrics. For example, Damodaran (2002) argues that the impact of intangibles is already reflected in higher profit margins and therefore should not be treated separately, because that would amount to double counting.

Barth, Beaver, and Landsman (1998) follow a similar logic in their study. They begin with a firm valuation model that defines firm value as an additive function of recognized net assets (book value of equity) and unrecognized net assets (i.e., intangibles). Because unrecognized net assets are not directly observable, they argue that net income provides information about the unrecognized intangible assets. Consistent with their arguments, they find that net income is more informative in explaining firm value in industries with high levels of unrecognized intangibles than in industries with low levels of intangibles. Their findings suggest that intangible assets (or at least a portion of intangible assets) are reflected in the contemporaneous financial performance of the firm.

However, current-term accounting measures may not fully reflect factors that affect differences in future-term profitability and valuation. Nonfinancial measures can provide useful incremental information to accounting metrics in determining valuation. For example, firms may have different brand attributes that have long-term profit implications. Although the effects of some of these brand attribute differences are reflected in the current-term accounting metrics, some of the effects may be long-term or may occur only in the future. In such cases, the effects will not be reflected in contemporaneous performance metrics (Mizik and Jacobson 2008).

Kohlbeck and Warfield (2007) address the role of intangibles in valuing firms in the banking industry. They propose that intangibles have two effects on the future cash flow stream. As do Barth, Beaver, and Landsman (1998), Kohlbeck and Warfield argue that intangibles lead to greater earnings in the current period. However, they also argue for an additional influence of intangibles that pertains to the dynamic properties of earnings. They provide evidence that suggests that firms with greater intangibles have more persistent earnings. This higher persistence results in a greater net present value of cash flows and a consequently higher earnings multiplier.

## **Incorporating the Impact of Brand Assets into Business Valuation**

Marketing theory and the empirical evidence has been consistent in highlighting the importance of brands in affecting financial performance (e.g., Dekimpe and Hanssens 1999;

Pauwels et al. 2004; Srivastava, Shervani, and Fahey 1998; Van Heerde, Helsen, and Dekimpe 2007). Brands increase the perceived value of products, thereby attracting customers and influencing customers' preferences and choices (e.g., Swait and Erdem 2007). This immediate brand impact can be reflected in a higher price premium, volume premium, and revenue premium for the branded product (Ailawadi, Lehmann, and Neslin 2003; Keller and Lehmann 2003, 2006). As such, some of the effect of brands is reflected in current-term sales and profit margins.

However, brands build customer loyalty and attachment and thus can affect future consumption patterns and firm risk (Johnson, Herrmann, and Huber 2006; Keller 1993; McAlister, Srinivasan, and Kim 2007). In turn, this can affect a firm's future financial performance that is incremental to current-term effects. Several marketing studies report a link between perceptual brand attributes (e.g., Aaker and Jacobson 1994, 2001; Mitra and Golder 2006; Mizik and Jacobson 2008) or product market-based brand measures (Barth et al. 1998) and a firm's future-term financial performance. Therefore, we hypothesize that brand assets have a direct impact on valuation multipliers, incremental to their effect on current accounting performance.

To explicitly allow for the effects of brand assets on firm valuation, we can decompose the value multiple  $\phi_{it}$  in Equation 1 into three components: (1) the baseline amount (e.g., the industry average), (2) the amount derived from the firm's current profitability being above or below the base level, and (3) the amount derived from the presence of brand assets that are above or below the base level (e.g., industry average). This decomposition leads to the following:

$$(2) \quad \text{Firm Value}_{it} = [\phi(\text{Baseline})_{it} + \phi(\text{Current Profitability})_{it} + \phi(\text{Brand})_{it}] \times \text{Sales}_{it} + \varepsilon_{it},$$

where  $\phi(\text{Baseline})_{it}$  is the sales multiplier when firm profitability and the brand assets are at the industry average,  $\phi(\text{Current Profitability})_{it}$  is the incremental sales multiplier due to firm profitability deviating from the industry average level, and  $\phi(\text{Brand})_{it}$  is the incremental sales multiplier due to the brand assets of a firm deviating from the industry average and is not reflected in current profitability.

The key element of Equation 2 is that it allows the differences in brand assets across firms within a sector to be reflected not just in different sales levels or through an indirect effect (i.e., running through the brand impact on current profitability) on the multiplier but also through a direct effect of brand on the multiplier.

## Empirical Methodology

To undertake a valuation analysis of a business, two inputs are required: a measure of a firm's "value driver" and an appropriate multiplier. The measure of the value driver (e.g., sales) is available from accounting reports or profit/loss statements; it is taken as a given input. However, to better understand the interplay of brand effects in determining business valuation, we also undertook analyses assessing the effect of brand dimensions on the sales value driver. We

report this analysis in Appendix A. The determination of the appropriate multiplier is the focus of valuation analysis.

### Assessing the Impact of Brand Assets on the Sales Multiplier

Consider a valuation multiplier model of the following form:

$$(3) \quad \text{Value-to-Sales}_{it} = \phi_{it} = \alpha_i + \beta \times X_{it} + \sum_{t=1}^T \sum_{k=1}^K \gamma(k, t) \times S(k, t) + \varepsilon_{it},$$

where  $\text{Value-to-Sales}_{it}$  is the value-to-sales ratio ( $\phi_{it}$ ) for firm  $i$  in period  $t$ ,  $X_{it}$  is a vector of observed explanatory factors (which may include accounting metrics, such as profit margin, and nonfinancial measures, such as brand metrics),  $\alpha_i$  is a firm-specific constant,  $S(k, t)$  is an indicator function that takes the value of 1 if the firm is in sector  $k$  for period  $t$  and 0 if otherwise, and  $\varepsilon_{it}$  is a white-noise error. Equation 3 depicts the value-to-sales ratio of a firm as a function of a yearly industry mean, a set of observed firm factors  $X_{it}$ , and a firm-specific constant.

Although Equation 3 can be estimated for publicly traded firms, it cannot be used to predict the value-to-sales ratio for other firms that are not publicly traded or for business units of publicly traded firms. Other measures of the value-to-sales ratio, which are needed to estimate the firm-specific mean  $\alpha_i$ , are not available for entities that are not publicly traded.

Given the information available, what is the best way to use this limited information to generate value-to-sales predictions? One approach would be to estimate Equation 3 for publicly traded firms using fixed-effects estimation, obtain an estimate of  $\hat{\beta}$ , and then use this estimate to compute the value-to-sales multiplier of firm  $j$  as follows:

$$(4) \quad \hat{\phi}_{jt} = \hat{\beta} \times X_{jt} + \hat{\gamma}(k, t) \times S(k, t).$$

Unlike Equation 3, the Equation 4 prediction model sets the firm-specific effect  $\alpha_i$  equal to zero because  $\alpha_i$  is unobserved and cannot be estimated for private businesses. However, this constraint may well be inappropriate. Indeed,  $\alpha_i$  might be a major component determining the value-to-sales multiplier.

An alternative approach would be to use an estimation model that does not make this unwarranted assumption and does not require information that is unavailable for prediction purposes. Rather, the model specification can be modified to use only information that is available for prediction purposes. The resulting valuation multiplier model has the following form:

$$(5) \quad \phi_{it} = \delta \times X_{it} + \sum_{t=1}^T \sum_{k=1}^K \gamma(k, t) \times S(k, t) + \eta_{it}.$$

The estimated coefficients from Equation 5 could then be used to generate the value-to-sales multiplier for firm  $j$ :

$$(6) \quad \hat{\phi}_{jt} = \hat{\delta} \times X_{jt} + \hat{\gamma}(k, t) \times S(k, t).$$

Equation 5 explicitly omits the firm-specific effects  $\alpha_i$  at the estimation stage. To the extent that the firm-specific effects  $\alpha_i$  are correlated with explanatory factors in  $X_{it}$ , the estimated effects of  $\hat{\delta}$  will pick up some of their influence. That is, least squares estimation of Equation 5 will generate  $\hat{\delta}$  estimates that compound the effects of  $X_{it}$  and  $\alpha_i$ . In other words, the model parameters estimated in Equation 5 are biased (i.e.,  $E[\hat{\delta}] \neq \beta$ ). The bias reflects some of the impact of the unobserved firm-specific information in  $\alpha_i$ . The magnitude of the bias and the extent to which the unobserved information will be accounted for in the model depend on the classic omitted-variable bias conditions—that is, the  $\text{corr}(\alpha_i, X_{it})$ , the magnitude of  $\alpha_i$ , and the variation of  $\alpha_i$  compared with the variation of  $X_{it}$ .

When the analysis is focused on the causal effect of an explanatory factor, it is more appropriate to use Equation 3 and the fixed-effects estimator  $\hat{\beta}$  because it is unbiased and reflects only the impact of  $X_{it}$  on  $\phi_{it}$ .<sup>4</sup> In the forecasting context, however, the issue does not revolve around obtaining an unbiased estimate of the structural parameters  $\beta$  (Stock and Watson 2006). Rather, the goal is to extract as much information content from the series  $X_{it}$  as possible. The estimated parameter  $\hat{\delta}$  will be a biased estimate of  $\beta$ , with the estimate reflecting not just the effect of  $X_{it}$  but also some of the impact of firm-specific effect  $\alpha_i$ . In a forecasting context, this is desirable in that it improves predictive performance of the model. Instead of seeking to minimize the effect of omitted factors, forecasting is enhanced by incorporating this additional information (“bias”) into the estimated effect.<sup>5</sup> As such, the biased estimate  $\hat{\delta}$  is more advantageous for use in a forecasting context. For this reason, we choose Equation 5 for our empirical analysis.

### ***Hypothesis Testing in the Presence of Correlated Errors***

A difficulty in undertaking analysis based on Equation 5 is related to evaluating the statistical significance of the coefficient estimate  $\hat{\delta}$ . The problem is that because not all the impact of  $\alpha_i$  is captured by  $X_{it}$ , the error in Equation 5 has a

<sup>4</sup>In the presence of measurement error, Equation 5 can yield more accurate estimates than Equation 3. Taking first differences to remove the fixed effects may exacerbate the effects of measurement error (Griliches and Hausman 1986). That is, the “signal-to-noise” ratio tends to be lower for differenced data than for levels data. In this case, the researcher is faced with the unenviable task of choosing between omitted variable bias and measurement error bias. Because our focus is on prediction rather than interpretation of the structural parameters, we face no such dilemma.

<sup>5</sup>It is not uncommon for the magnitude of the bias to be large. For example, the biased estimate  $\hat{\beta}$  might have the opposite sign from the structural parameter estimate  $\beta$ . Because of this bias, no causal interpretation can be attached to the coefficient estimate of  $\hat{\delta}$ . However, in the context of prediction, this bias is desirable. It means that the variable is reflecting not only its own impact but also the impact of other factors omitted from the model. By reflecting some of the effects of these omitted factors, model pre-

dictive performance will be enhanced. In dramatic contrast to structural parameter modeling, all else being equal, coefficients for variables correlated with omitted factors are informative in the context of prediction.

firm-specific component. Ignoring this intrafirm correlation generates biased estimates of the standard errors and renders standard statistical significance tests inappropriate. Ordinary least squares estimation assumes that the error terms are independent and identically distributed. The independence assumption is violated in panel data analysis when a firm-specific effect remains in the error term. When both the error term and the independent variable are positively autocorrelated, least squares estimates of the standard errors are biased and understate the true standard errors.

This is the spurious-regression phenomenon highlighted by, for example, Granger and Newbold (1974) in the time-series context. The conventional t-statistic does not have a standard normal limiting distribution, which invalidates the use of, for example, the t-distribution to test the hypothesis that a coefficient is statistically significant. In the presence of autocorrelated series, the number of occasions when  $|t|$  is greater than 1.96 is much greater than 5%. The higher the autocorrelation in the series, the greater is the probability of observing a t-statistic above  $|1.96|$  (i.e., the greater is the extent to which ordinary least squares standard errors understate the true standard errors). Although spurious regression is most widely discussed in a pure time-series context, it also comes into play in analysis of panel data. For example, Kao (1999) shows that though it is unrelated to the number of cross-sectional observations, the spurious regression problem increases with the number of time-series observations.<sup>6</sup>

To circumvent this problem, we use cluster-robust standard errors estimation (Arellano 1987; White 1984), which relaxes the assumption of error independence and allows for correlation within a “cluster” (i.e., observations coming for the same firm but in different years). Cluster-robust standard errors are a generalization of heteroskedastic robust standard errors (White 1980). By assigning each observation to a cluster, the approach allows for consistent estimates of standard errors in the presence of correlation of an unknown form within the cluster.

Rather than assuming that the error correlation is zero as in least squares analysis, cluster-robust standard errors are based on estimates of the covariance between residuals within a cluster. Under the assumption that the covariance structure is the same across clusters, cluster-robust standard

errors estimation (Arellano 1987; White 1984), which relaxes the assumption of error independence and allows for correlation within a “cluster” (i.e., observations coming for the same firm but in different years). Cluster-robust standard errors are a generalization of heteroskedastic robust standard errors (White 1980). By assigning each observation to a cluster, the approach allows for consistent estimates of standard errors in the presence of correlation of an unknown form within the cluster.

<sup>6</sup>Petersen (2009) offers the insight that as the number of periods of data used in the analysis doubles, ordinary least squares analysis assumes a doubling in the amount of information. However, if the explanatory factors and the error exhibit autocorrelation, the amount of unique information increases by a factor less than two. Consider the extreme case when both the independent variable and the error follow unit root processes. In this case, each additional observation provides no additional information and has no effect on the true standard error. However, the standard error estimated from ordinary least squares assumes that each additional observation provides additional unique information, and the estimated standard error shrinks accordingly and unduly.

errors provide consistent estimates of the standard errors of the coefficients as the number of clusters grows. The use of robust standard errors does not change the coefficient estimates but affects the standard errors and, therefore, the t-statistic.<sup>7</sup>

## Models

The previously described estimation framework enables us to undertake empirical analysis to assess whether, which, and to what extent brand metrics provide incremental explanatory power to return on sales in explaining the value-to-sales ratio. We undertake this assessment using two models. The first model (Equation 7) uses aggregate analysis and links the log of the enterprise value-to-sales ratio to return on sales, five brand metrics (differentiation, relevance, esteem, knowledge, and energy), and a set of sector-specific annual dummy variables that reflect different industry groupings in our sample:<sup>8</sup>

$$(7) \quad \log(\phi_{it}) = \delta_2 \times \text{ROS}_{it} + \sum_{b=1}^5 \beta_b \times \text{Brand Asset}_{bit} + \sum_{t=1}^T \sum_{k=1}^K \gamma(k, t) \times S(k, t) + \eta_{it}$$

The second model is similar in format to Equation 7, but it allows for sector-specific differences in the slope coefficient. That is, we estimate Equation 8 for each of our sectors separately:

$$(8) \quad \log(\phi_{it}) = \delta(k)_2 \times \text{ROS}_{it} + \sum_{b=1}^5 \beta(k)_b \times \text{Brand Asset}_{bit} + \sum_{t=1}^T \gamma(k, t) \times Y(t) + \eta_{it}$$

where  $Y(t)$  is an indicator function that takes the value of 1 if the period is  $t$  and 0 if otherwise, and all other variables are defined as described previously.

By comparing the results from Equations 7 and 8 with the results from models that exclude the brand metrics, we can assess the extent to which brand metrics provide incremental predictive power to sectorwide effects and return on sales in explaining the enterprise value-to-sales ratio.

## Related Research

To the best of our knowledge, no study has directly examined the extent to which brand assets have an incremental impact on sector effects and current accounting performance in enhancing the prediction of valuation multipliers. However, some studies share some commonalities with our investigation.

Kerin and Sethuraman (1998) assess the association between the market-to-book equity ratio and the *Financial World* estimate of brand value. As we do, they link a brand metric to a stock market multiplier. A central difference in the approaches is related to the use of accounting information reflecting profitability. We include a measure of profitability (i.e., return on sales) in our model, whereas they do not. As such, in contrast to Kerin and Sethuraman, we assess whether the brand asset has incremental predictive power to earnings information. Kerin and Sethuraman note that their study confirms that the *Financial World* brand value estimate and the market-to-book ratio are jointly correlated with cash flows. Our analysis goes beyond an assessment of joint correlation and investigates the incremental predictive power of brand metrics.

Barth and colleagues (1998) report a market value equation that includes earnings and the *Financial World* brand value metric as explanatory factors. As such, although this was not the authors' intent, this equation can potentially be viewed as a valuation model. However, several issues limit conclusions that can be drawn from this analysis about the ability of brand metrics to enhance the accuracy of firm valuation. For example, their model does not include any sector-specific effects (e.g., they do not include either an intercept or a slope adjustment in their model to control for potential differences across industries). After taking comparables into account, the *Financial World* metric may not be significant. Their estimates of statistical significance are also subject to concerns about the failure to address autocorrelation issues inherent in their market value metric. Barth and colleagues recognize the autocorrelation in their Equation 1 and try to supplement their use of biased least squares standard errors with a statistic known as "Z2." However, subsequent research has shown that the Z2 measure does not achieve this goal. For example, Gow, Ormazabal, and Taylor (2008, p. 7) state that Z2 produces "Type I error rates ... rejecting a true null hypothesis more than

<sup>7</sup>As a sensitivity check, we also estimated a model that allowed for autocorrelated (i.e., dissipating) firm-specific residuals. That is, rather than assuming the same correlational structure for all the firm's observations, as depicted by the firm-specific effects model and incorporated in the cluster-robust standard-errors model, the autocorrelated-errors model allows for a decay in the association for years further apart. We obtained results similar to those we report. We also undertook a simulation study to test the hypothesis that the coefficient estimate  $\hat{\delta}$  is statistically significant in the presence of autocorrelated residuals. We generated a bootstrap distribution that mirrored the procedures of Granger, Hyung, and Jeon (2001) and Kao (1999). This enabled us to find the 5% critical value for the ratio of the coefficient estimate to the least squares standard errors. We need to create a bootstrap distribution because, in the presence of autocorrelation, the conventional t-statistic does not have a standard normal limiting distribution. By comparing the ratio of the coefficient to the least squares standard errors, we can assess the statistical significance of the estimates. All our conclusions are unaffected by this alternative specification, which is consistent with highly autocorrelated residuals having properties similar to firm-specific effects.

<sup>8</sup>We also examined the role of other accounting measures. For example, we considered an expanded model that also included earnings growth. Far and away, the dominant accounting determinant of the multiplier is profit margin. Although other accounting variables affect the multiplier in some segments, their effects are modest, and their correlation with the brand metrics is small. Because the inclusion of additional accounting variables does not alter our conclusions, we present the more parsimonious modeling results.

30% of the time at the 1% level in the setting where it is most commonly used.”

There are also several concerns that are inherent to all studies using the *Financial World* estimate as a brand metric. For example, the metric attributes all earnings in excess of a 5% return to brand effects. To the extent that the firm has other factors leading to a return greater than 5% (e.g., monopoly power, unique technological capabilities), the *Financial World* estimate may be inappropriately attributing excess returns to brand. Furthermore, the *Financial World* measure is subjectively estimated, which creates the concern that the analyst estimating the brand value observes that the brand is trading at a higher multiple and then allocates this difference to brand value (i.e., a higher multiple causes the brand estimate rather than the brand estimate causing the higher multiple).

In summary, although prior research provides several key insights, to date studies have not adequately addressed the extent to which brand metrics enhance the valuation of branded businesses. This is the intent of our study.

## Data and Measures

We pulled data from three different sources to create the data set for our analyses. We obtained brand asset measures from the Y&R BAV database. The stock market data (prices and number of shares) came from the University of Chicago’s Center for Research in Security Prices database. We used Standard & Poor’s COMPUSTAT database to obtain the necessary accounting measures to combine with the stock market data to compute enterprise value and accounting performance measures. Table 1 provides a list of the financial variables we use in the analyses, their definitions, and respective COMPUSTAT data numbers for COMPUSTAT-based metrics.

### Brand Asset Metrics

Our branding data come from the Y&R BAV initiative, which has undertaken large-scale annual surveys of consumer brand perceptions since 2000. We use BAV data that were collected during the fourth quarter of each year for the period 2000–2006. In addition, Y&R undertook brand surveys on a sporadic basis before 2000, and we use data obtained in the two prior data collection waves (undertaken

in the first quarter of 1997 and the second quarter of 1999) for our out-of-sample analysis. More than 2000 brands are included in each survey wave. Among the surveyed brands, we identified a set of 250 publicly traded monobrand firms (i.e., firms that use a branded house strategy such that the vast majority of their business is aligned with a single brand name) for which complete accounting and stock market data are available for at least some of the 2000–2006 period.

We focus on the five pillars of the Y&R BAV model: perceived brand differentiation, relevance, esteem, knowledge, and energy. Differentiation captures perceived distinctiveness of the brand. Relevance measures consumers’ perceptions of personal relevance, appropriateness, and the importance of the brand. Esteem assesses the level of regard consumers have for the brand and the valence of consumer attitude. Knowledge is a measure of familiarity and understanding of the brand identity. Energy measures consumers’ perceptions of brand innovativeness and dynamism. It reflects a brand’s ability to meet consumers’ future needs and respond to changing conditions.<sup>9</sup>

Raw BAV perceptual brand metrics are collected on different scales, some on a seven-point scale and others as a percentage of respondents viewing the brand as possessing a given attribute. To allow for comparability of the coefficients and relative impact of individual brand attributes, we z-standardize each of the measures.

### The Valuation Multiplier

We use enterprise value/sales as our valuation multiplier. We use enterprise value as our measure of firm value (i.e.,

<sup>9</sup>See, for example, Mizik and Jacobson (2008) for a detailed discussion of the individual metrics and an overview of the five-pillar BAV model, which adds energy to the previous four-pillar BAV model (Agres and Dubitsky 1996). Although the BAV model and results have been widely discussed (e.g., Aaker 1996; Keller 1998), because BAV data are Y&R’s proprietary material, BAV data have had only limited use in academic research. Nonetheless, Y&R grants access to its data, and the data have been used in prior academic research (e.g., Bronnenberg, Dhar, and Dubé 2005; Mizik and Jacobson 2008; Romaniuk, Sharp, and Ehrenberg 2007).

**TABLE 1**  
**Variable Definitions for Firm i, Year t**

| Variable                                | Formula  | COMPUSTAT Data Items   |
|---|--|--|
| Market Capitalization <sub>it</sub>     | $price_{it} \times shares_{it}$  |  |
| Enterprise Value <sub>it</sub>          | $Market\ Cap_{it} + Debt_{it} + Minority\ Interest_{it} + Preferred\ Stock_{it} - Cash_{it}$ | $price \times shares + (data51 + data45) + (data53 + data55 - data36)$ |
| Operating Income <sub>it</sub>          | $\sum_{q=1}^4 Operating\ Income\ before\ Depreciation_{iq}$                                  | $\sum_{q=1}^4 data21_{iq}$ , where q is quarter in year t              |
| Sales <sub>it</sub>                     | $\sum_{q=1}^4 Sales_{iq}$  | $\sum_{q=1}^4 data2_{iq}$ , where q is quarter in year t               |
| Enterprise Value-to-Sales <sub>it</sub> | $Enterprise\ Value_{it}/Sales_{it}$  |  |
| Return on Sales <sub>it</sub>           | $Operating\ Income_{it}/Sales_{it}$  |  |

the numerator) because our focus is on valuing a business as a whole. We compute enterprise value of firm *i* in period *t* as market capitalization of the firm plus its debt, plus minority interest and preferred shares, less total cash and cash equivalents:

$$\text{Enterprise Value}_{it} = \text{Market Cap}_{it} + \text{Debt}_{it} + \text{Minority Interest}_{it} \\ + \text{Preferred Stock}_{it} - \text{Cash}_{it}.$$

Enterprise value better reflects the cost of buying a company than market value in that, for example, it takes into account debt (which increases the purchase cost) and cash (which offsets some of the cost). Enterprise value summarizes the claims of all the security holders—debt holders, preferred shareholders, and minority shareholders, in addition to the claims of common equity holders. The enterprise value measure is neutral with regard to capital structure, and as such, it is more appropriate when analyzing companies that have different capital structures (Bhojraj and Lee 2002).

We chose to use sales as the standardizing variable (i.e., denominator) rather than, for example, a measure based on earnings or book value for several reasons. First, sales data are more readily tracked and available for the individual brands or business units of a firm than other performance metrics. As such, if earnings data are unavailable, our model can still be estimated and used with only a slight modification of the estimating equation—namely, return on sales would be omitted as an explanatory factor. Second, earnings and cash flows can be negative and will make valuation impossible or may introduce significant sample selection biases (Liu, Nissim, and Thomas 2002). Third, sales are less affected by accounting manipulation. Because investors are now more cautious about relying on accounting earnings data, it is advantageous to use measures that are less affected by discretionary accounting choices (Damodaran 2002). Finally, marketing managers are more comfortable thinking in terms of sales multiples. However, because our model includes return on sales as a factor explaining the value-to-sales ratio, our analysis incorporates considerations addressed in analysis attempting to control for factors that affect the value-to-earnings multiplier.

### Accounting Data

We used the COMPUSTAT database to obtain quarterly accounting information, which we converted into annual measures. Because some firms in our data sample have fiscal years that end in months other than December, we use the quarterly rather than the annual COMPUSTAT database. For balance sheet items, which we use in computing enterprise value, we use the measure at the end of the calendar year. For income statement items, we annualize the measure by taking the sum of the four quarterly values for the calendar year. In addition to sales, operating income before depreciation is the other central income statement item in our analysis. We measure the profit margin (i.e., return on sales) metric as operating income before depreciation divided by sales.

### Classifying Sectors

Sales multiples differ across firms because of industrywide or sector-specific effects (e.g., growth prospects, risk). Therefore, firms must be grouped together by sector. Several different approaches, each with advantages and disadvantages, have been used in prior research. Deciding on the number of sectors typically involves a trade-off between homogeneity and having a sufficient sample size to provide an accurate estimate of the sector mean. While we undertook sensitivity assessments, for our primary analyses we focused on and allowed for seven different sectors: (1) industrial, (2) finance, (3) retail and apparel, (4) high technology, (5) consumer nondurables, (6) consumer durables, and (7) travel and transport. In our analysis, we allow for sector-specific annual effects (i.e., the intercepts differ by sector for a given year) and for differential effects by sector (i.e., the slope coefficients differ by sector).

### Summary Statistics

Merging the three data sources resulted in 1244 pooled cross-sectional time-series observations with a complete set of data available for the firm. Table 2 provides summary mean statistics for the measures used in our analysis for the entire sample and by sector. We observe a variety of notable, and expected, differences in the brand metric

**TABLE 2**  
**Sample Characteristics (Period: 2000–2006)**

|                          | Full Sample | Industrial Firms | Financial Firms | Retail and Apparel Firms | High-Tech Firms | Nondurable Goods Firms | Durable Goods Firms | Travel and Transport Firms |
|--------------------------|-------------|------------------|-----------------|--------------------------|-----------------|------------------------|---------------------|----------------------------|
| (Enterprise value/sales) | 1.92        | 1.45             | 3.37            | 1.13                     | 2.98            | 2.00                   | 1.17                | 1.56                       |
| Return on sales          | .171        | .152             | .325            | .121                     | .201            | .187                   | .137                | .143                       |
| Differentiation          | .034        | -.324            | -.638           | .501                     | -.184           | .103                   | .238                | -.386                      |
| Relevance                | .106        | -.295            | -.821           | .216                     | -.268           | 1.138                  | .394                | .028                       |
| Esteem                   | .043        | .051             | -.738           | .016                     | -.352           | .832                   | .928                | .039                       |
| Knowledge                | -.015       | -.450            | -.342           | .122                     | -.609           | .763                   | .396                | .439                       |
| Energy                   | .027        | .432             | -.685           | -.244                    | .652            | -.401                  | .554                | -.261                      |
| Number of observations   | 1244        | 128              | 80              | 395                      | 304             | 181                    | 57                  | 99                         |

Notes: The table reports mean values of each data item. All brand variables are z-standardized.



scores across sectors. For example, the high-tech sector has the highest rating on energy, while the consumer non-durable sector has the highest ranking on relevance. The mean of the enterprise value-to-sales ratio is 1.92 for the entire sample. Substantial differences in the ratio exist across sectors. The mean value-to-sales ratio is the highest for the financial sector (3.37) and lowest for the retail and apparel sector (1.13). These differences are associated with differences in margins. That is, sectors with higher (lower) mean return on sales tend to have higher (lower) value-to-sales ratios. However, as the histograms for the multiplier show in Figure 1, substantial differences in the enterprise value-to-sales ratio are observed between firms within a given sector.

## Empirical Analysis

### Aggregate Analysis

We begin our multiplier analysis by estimating a model to be used as a standard for comparison. It involves regressing the log (value-to-sales ratio) on return on sales and annual dummy variables for all firms in our data set.<sup>10</sup> Equation 3.1 in Table 3 reports the results, which highlight the positive association between return on sales and value to sales. The estimated coefficient is 5.41 and is statistically significant at the 1% level.<sup>11</sup> As we discussed previously, this finding is expected because firms with higher profit per dollar of sales create more value per dollar of sales than those with lower profit margins. Both Equation 3.1 and Equation 3.2 also include sector-specific annual dummy variables, though we do not report this in Table 3. The most notable, but also expected, feature of these dummies is that the coefficients for the high-tech sector dummies are higher than those in any other sector. This finding is consistent with the greater growth opportunities high-tech sector firms experienced during the study period. The R-square statistic indicates that the model is able to explain approximately 61% of the variation in the data, with return on sales accounting for approximately 60% of that explanatory power and the annual sector dummies accounting for the remaining 40%.

We expand Equation 3.1 to include the five BAV pillars (differentiation, relevance, esteem, knowledge, and energy). Equation 3.2 in Table 3 reports the results of estimating this model (i.e., Equation 7). We observe some evidence of brand effects. Differentiation, relevance, and energy have positive effects (.098, .069, and .070, respectively), but only

differentiation is significant at the 5% level, with energy significant at the 10% level. Knowledge has a negative estimated effect (-.093), and it too is significant at the 10% but not at the 5% level.<sup>12</sup> The estimated coefficient for esteem (-.016) is not significantly different from zero.

Although Equation 3.1 shows some statistically significant brand effects, the incremental explanatory power gained by adding brand variables to the model is modest. The R-square statistic in Equation 3.2 (.6335) is only 3.6% greater than the R-square statistic in Equation 3.1 (.6115). Another indication of limited incremental increase in explanatory power gained by adding brand metrics to the model comes from an assessment of MAE (i.e., the average of the absolute value of the error terms). The MAE from Equation 3.1 is .391; it is .382 in Equation 3.2. This is an improvement of only 2.4%. The brand variables in Equation 3.2 provide only a minor increase in predictive power over Equation 3.1, which does not take brand measures explicitly into account.

There are several possible reasons the brand variables provide only a limited increase in explanatory power. One is that brand effects are already reflected in current-term accounting metrics. That is, the financial market's anticipation of brand effects reflected in the enterprise value may be captured in current-period sales and in current-term return on sales. In other words, brand variables affect current-period sales and current-period return on sales, but the brand effects showing up in Equation 3.2 reflect only the effects incremental to those running through current-term accounting measures.

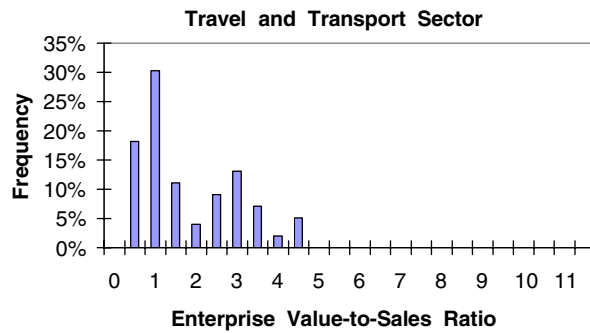
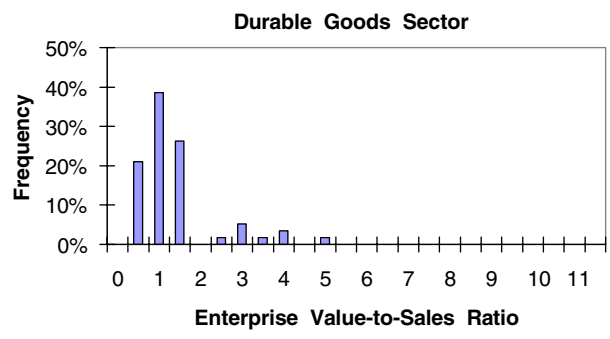
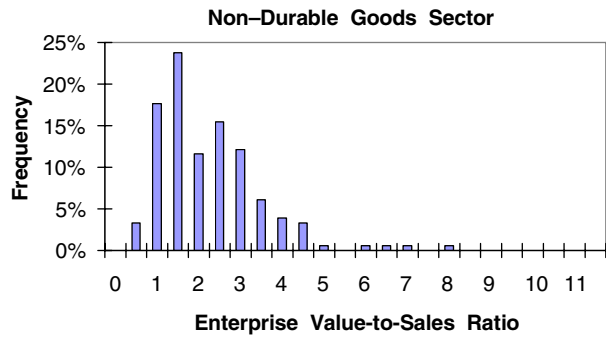
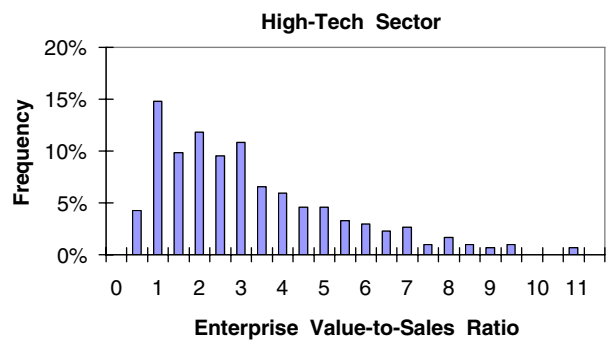
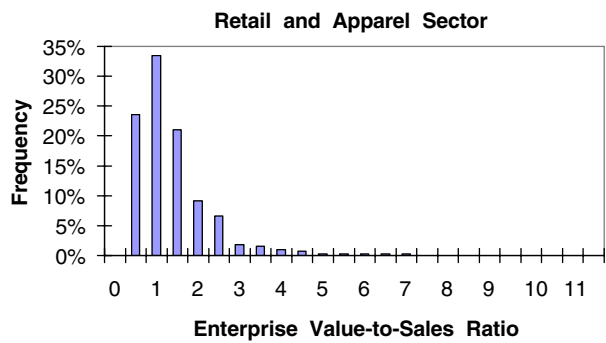
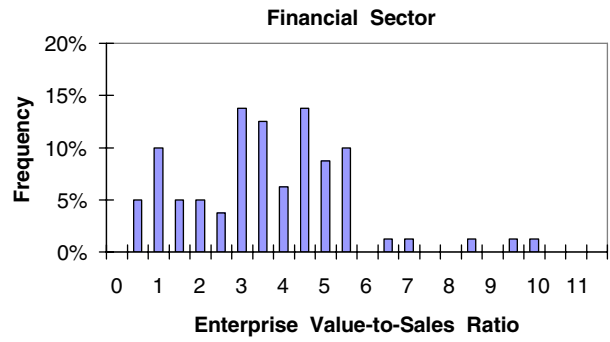
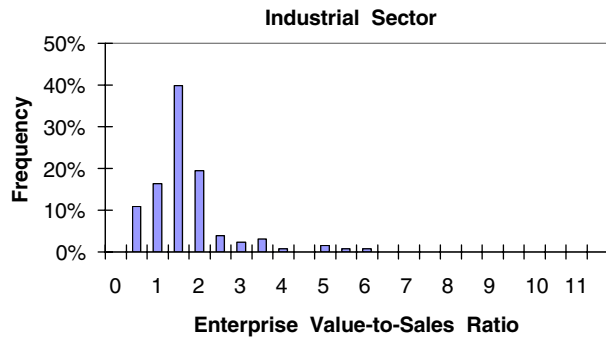
Another possibility is that brand effects differ across sectors. Although the models in Table 3 include sector-specific annual dummy variables, which allow differential sector effects to influence the intercept, the specification does not allow the effect of profitability and brand (i.e., the slope coefficients) to differ by sector. To assess the possibility of differential brand effects by sector, we estimate sepa-

<sup>10</sup>We work with logarithms of the value-to-sales ratio to minimize the role of outliers. Other approaches (e.g., Winsorizing the data) generate similar findings to those we report.

<sup>11</sup>Although the difference in cluster-robust standard errors relative to ordinary least squares standard errors differs by model, the difference is most notable for the estimated standard error for the return-on-sales coefficient. The cluster-robust standard errors are approximately twice the size of the standard errors for ordinary least squares. However, the extent of association is large enough so that conclusions as to statistical significance are not affected. The increase in the standard errors of the coefficients for the brand metrics is not as dramatic, but because the strength of the association is not that strong, conclusions regarding statistical significance are affected.

<sup>12</sup>The negative coefficient for knowledge should not be interpreted as brand familiarity causing a decrease in firm value. First, as we discussed previously, the coefficient estimates cannot be treated as structural parameters. The intent of the analysis is for the coefficient estimates to be as reflective as possible of the information contained in the metric, which is central in a forecasting context, rather than in isolating the causal effect of the variable. However, we can conclude that the knowledge metric, after controlling for other brand dimensions, is reflective of information that is negatively correlated with the value-to-sales ratio. For example, the knowledge metric may have a positive correlation with the maturity of the firm. The maturity of the firm is likely to be negatively correlated with future growth prospects and, thus, the value-to-sales ratio. Therefore, the negative coefficient for knowledge may be reflecting some of this effect. Second, as we report in Appendix A, knowledge has a significant, positive effect on sales. Because the sales metric is in the denominator in the value-to-sales multiplier, this result indicates that the bulk of the performance effect of knowledge is associated with contemporaneous sales (the denominator) rather than with the forward-looking value measure, which is in the numerator of the multiplier metric. Conversely, the positive coefficient for differentiation indicates that it has a greater association with the future-term effects reflected in the value numerator rather than the sales denominator.

**FIGURE 1**  
**Within-Sector Distribution of Enterprise Value-to-Sales Ratios**



rate models by sector. If the effects of return on sales and brand assets differ by sector, aggregation across sectors could mask the role of brand in influencing the value-to-sales ratio. Alternatively, because the effect of return on sales is also allowed to differ by sector, these sector-specific models could show that brand metrics have an even smaller effect than those reported in Table 3.

### Sector-Specific Analysis

Table 4 reports the results of the sector-specific analysis. Equations 4.11–4.17 in Table 4, Panel A, report the estimated coefficients from the basic (i.e., our standard for comparison) sector-specific model that links the value-to-sales ratio to return on sales and sector-specific annual dummy variables. Return on sales has a statistically significant effect for each of the sectors, but the magnitude of the response coefficient differs across sectors. It is largest for retail and apparel firms (8.97) and smallest for high-technology firms (3.74).

Table 4, Panel B, reports the results of linking the value-to-sales ratio to return on sales, the five brand metrics, and sector-specific annual dummy variables (i.e., estimating Equation 8). Equations 4.21–4.27 in Table 4, Panel B, report the results. Again, we observe significant differences in the estimated effects.

**TABLE 3**  
**Valuation of Branded Businesses: Aggregate Analysis**  
**Dependent Variable: Log(Enterprise Value/Sales) (N = 1244)**

$$\text{Model 3.1: } \phi_{it} = \delta_1 \times \text{ROS}_{it} + \sum_{t=1}^T \sum_{k=1}^K \gamma(k, t) \times S(k, t) + \eta_{it}$$

$$\text{Model 3.2: } \phi_{it} = \delta_2 \times \text{ROS}_{it} + \sum_{b=1}^5 \beta_b \times \text{Brand Asset}_{bit} + \sum_{t=1}^T \sum_{k=1}^K \gamma(k, t) \times S(k, t) + \eta_{it}$$

|                 | Equation 3.1 |             | Equation 3.2 |             |
|-----------------|--------------|-------------|--------------|-------------|
|                 | Estimate     | t-Statistic | Estimate     | t-Statistic |
| Return on sales | 5.41**       | 14.16       | 5.33**       | 14.98       |
| Differentiation |              |             | .098*        | 2.44        |
| Relevance       |              |             | .069         | 1.17        |
| Esteem          |              |             | -.016        | -27         |
| Knowledge       |              |             | -.093        | -1.77       |
| Energy          |              |             | .070         | 1.91        |
| R <sup>2</sup>  | .6115        |             | .6335        |             |
| MAE             | .391         |             | .382         |             |

\* $p < .05$ .

\*\* $p < .01$ .

Notes: Each equation includes annual sector-specific dummy variables (not reported). t-statistics are the ratios of the estimated coefficient to the cluster-robust standard error. MAE is the mean of absolute value of the forecast error; that is,  $|\text{Enterprise Value}_{it} - \text{Enterprise Value}_{it}|$ .

*Industrial firms.* For industrial firms, there is evidence of a statistically significant association for energy, with an estimated coefficient of .148. The coefficients for differentiation, relevance, and esteem are both substantially smaller and insignificant. Knowledge has an estimated effect that is similar to that of energy (.155), but it is not statistically significant. In terms of MAE, Equation 4.21 represents a 17.4% improvement in predictive power over Equation 4.11.

*Financial firms, durable goods firms, and travel and transport firms.* Three sectors—financial, durable goods, and travel and transport—have similar estimated models. The estimated coefficients for return on sales in these sectors are similar at 4.81, 4.67, and 4.95, respectively. Furthermore, for each of these sectors, the only brand metric with a statistically significant effect is differentiation. Here, too, the estimated effects are similar (.472, .304, and .382, respectively). In terms of MAE, brand metrics provide the greatest improvement in predictive power for durable goods firms (30%), with a 16% improvement for travel and transport firms and a 7.6% improvement for financial firms.

*Retail and apparel firms.* For retail and apparel firms, return on sales has a large estimated effect (8.83). None of the brand effects are significant individually, and the joint hypothesis that all five of the brand coefficients are zero cannot be rejected. Consistent with the lack of effect, Equation 4.23 provides only a 2% decrease in MAE compared with Equation 4.13. To verify this finding further, we conducted additional analyses, separating this sector into apparel firms and retail firms. We find results consistent with the aggregate analysis. Firms in both these subsectors share the common feature that their value-to-sales multiplier is not affected by the brand attributes and is highly responsive to return on sales. Indeed, the coefficient on return on sales for these firms is the highest among the sectors we examined.

*High-technology firms.* Consistent with accounting literature that notes that valuation models perform worst in dynamic industries, we observe the lowest R-square statistic and the highest MAE in the high-technology sector. The impact of return on sales is also the smallest (3.98) for high-technology firms. Current profitability is less informative about future performance than in other sectors. We find statistically significant effects for three brand variables: differentiation, relevance, and knowledge. Although differentiation and relevance have positive effects (.185 and .416, respectively), the estimated effect of knowledge is negative (-.287). Equation 4.24 provides a 7% decrease in MAE compared with Equation 4.14.

*Consumer nondurables.* For consumer nondurables, the return-on-sales effect is of a relatively large magnitude (7.44). Knowledge is the only brand asset that has a statistically significant effect (.191). The other brand metrics are statistically insignificant, and the joint hypothesis that these four brand metrics as a group are equal to zero cannot be rejected. Equation 4.25 shows an improvement in MAE of 9% over Equation 4.15.

**TABLE 4**

**Valuation of Branded Businesses: Analysis by Sector: Dependent Variable: Log(Enterprise Value/Sales)**

$$\text{A: Model 4.1: } \log(\phi_{it}) = \delta_1 \times \text{ROS}_{it} + \sum_{t=1}^T \sum_{k=1}^K \gamma(k, t) \times S(kt) + \eta_{it}$$

|                        | Equation 4.11: Industrial Firms | Equation 4.12: Financial Firms | Equation 4.13: Retail and Apparel Firms | Equation 4.14: High-Tech Firms | Equation 4.15: Nondurable Goods Firms | Equation 4.16: Durable Goods Firms | Equation 4.17: Travel and Transport Firms |
|------------------------|---------------------------------|--------------------------------|---|--------------------------------|---------------------------------------|------------------------------------|---|
| Return on sales        | 6.52**<br>(5.42)                | 5.14**<br>(5.83)               | 8.97**<br>(15.85)                       | 3.74**<br>(6.65)               | 7.69**<br>(9.64)                      | 7.82**<br>(5.52)                   | 6.69**<br>(13.29)                         |
| Number of observations | 128                             | 80                             | 395                                     | 304                            | 181                                   | 57                                 | 99  |
| R <sup>2</sup>         | .6308                           | .6648                          | .5544                                   | .3747                          | .7503                                 | .6369                              | .7027                                     |
| MAE                    | .283                            | .340                           | .347                                    | .520                           | .224                                  | .289                               | .362                                      |

$$\text{B: Model 4.2: } \log(\phi_{it}) = \delta(k)_2 \times \text{ROS}_{it} + \sum_{b=1}^5 \beta(k)_b \times \text{Brand Asset}_{bit} + \sum_{t=1}^T \gamma(k, t) \times Y(t) + \eta_{it}$$

|                        | Equation 4.21: Industrial Firms | Equation 4.22: Financial Firms | Equation 4.23: Retail and Apparel Firms | Equation 4.24: High-Tech Firms | Equation 4.25: Nondurable Goods Firms | Equation 4.26: Durable Goods Firms | Equation 4.27: Travel and Transport Firms |
|------------------------|---------------------------------|--------------------------------|---|--------------------------------|---------------------------------------|------------------------------------|---|
| Return on sales        | 6.22**<br>(7.35)                | 4.81**<br>(7.33)               | 8.83**<br>(13.66)                       | 3.98**<br>(7.90)               | 7.44**<br>(1.88)                      | 4.67**<br>(5.95)                   | 4.95**<br>(8.71)                          |
| Differentiation        | .008<br>(.10)                   | .472*<br>(2.09)                | .041<br>(.63)                           | .185*<br>(1.96)                | -.086<br>(-1.84)                      | .304*<br>(2.51)                    | .383**<br>(3.00)                          |
| Relevance              | .015<br>(.16)                   | .291<br>(.99)                  | .084<br>(.83)                           | .416*<br>(2.27)                | -.044<br>(-.62)                       | .251<br>(1.48)                     | -.289<br>(-1.87)                          |
| Esteem                 | -.037<br>(-.36)                 | -.029<br>(-.14)                | .055<br>(.60)                           | -.207<br>(-1.23)               | -.025<br>(-.42)                       | -.175<br>(-1.69)                   | .032<br>(.17)                             |
| Knowledge              | .155<br>(1.07)                  | -.053<br>(-.26)                | -.061<br>(-.69)                         | -.287**<br>(-2.69)             | .191**<br>(2.92)                      | -.226<br>(-1.93)                   | .081<br>(.35)                             |
| Energy                 | .148**<br>(3.32)                | .110<br>(.61)                  | -.026<br>(-.39)                         | .098<br>(1.43)                 | .131<br>(1.75)                        | .093<br>(.71)                      | .066<br>(.52)                             |
| Number of observations | 128                             | 80                             | 395                                     | 304                            | 181                                   | 57                                 | 99  |
| R <sup>2</sup>         | .7215                           | .7391                          | .5645                                   | .4711                          | .7772                                 | .8021                              | .7769                                     |
| MAE                    | .241                            | .316                           | .339                                    | .486                           | .205                                  | .222                               | .313                                      |

\*p < .05.

\*\*p < .01.

Notes: Each equation (Models 4.1 and 4.2) also includes annual dummy variables. t-statistics, which are the ratio of the estimated coefficient to the cluster-robust standard error, are in parentheses. MAE is the mean of absolute value of the forecast error; that is, |Enterprise Value<sub>it</sub> - Enterprise Value<sub>it</sub>|.

**Case Study Illustration**

To illustrate our conditional valuation multiplier approach and its relationship to other approaches, we compare forecasts that can be generated for the enterprise value-to-sales ratio for Hewlett-Packard (HP) for 2005. Appendix B details the computations underlying this illustration. In the four quarters of 2005, HP had total sales of \$86,696 million, and its enterprise value was \$76,298 million. As such, its enterprise value-to-sales ratio was .88.

If this ratio was not available but rather needed to be predicted (i.e., enterprise value was not known), one commonly used estimate would be the mean value of the multi-

plier for high-technology firms in 2005. This estimate is 2.82. Another commonly used estimation approach would incorporate HP's profitability into the analysis (i.e., use the parameter estimate in Equation 4.14 along with HP's return on sales) to generate a predicted value for HP's multiplier. This approach, which reflects not just the sector average but also the difference in HP's return on sales from the sector average, generates an estimated multiplier of 1.317. Using the approach we advance takes into account not just the industry mean and a firm's current-term profit margin but also the degree to which the firm's brand assets differ from the sector mean. Using the Equation 4.24 parameters, along

with measures of return on sales and brand assets, generates an estimated multiplier of .9658.

This case illustration shows that the yearly sector mean (2.83) substantially overstates the actual HP enterprise value-to-sales multiplier (.88). Using HP-specific information allows for enhanced forecasts. Substantial improvement is achieved by accounting for the extent to which HP profitability differs from the sector mean (i.e., the estimated multiplier is 1.317). Further improvement is gained by also incorporating the degree to which HP's brand assets differ from the sector average (i.e., the estimated multiplier is .9658).

Note that the enterprise value-to-sales ratio for HP in 2004 (.68) was below the 2005 figure (.88), though the predicted value for 2004 (1.07) was above the 2005 prediction (i.e., the prediction error is a larger negative number in 2004 than in 2005). Although this could merely be estimation error, it is consistent with other events taking place at HP. In particular, Carly Fiorina was dismissed as chairman of the board and chief executive officer early in 2005. This management change can be hypothesized to be associated with an increase in the multiplier. It remains a direction for further research to determine whether further improvements in predictive accuracy can be achieved by extending our conditional multiplier methodology to incorporate additional tangible and intangible asset considerations (e.g., management quality) into our modeling framework.

### **Summary**

Analysis of sector-specific models provides different insights from those implied by the aggregate model. While the aggregate analysis shows that statistically significant brand effects offer little improvement in predictive power (i.e., only a 2.4% improvement in MAE), the sector-specific models suggest that the brand metrics provide substantially more predictive power. Only for the retail and apparel sector are brand variables as limited in their impact as they are in the aggregate analysis. For the other six sectors, we observe gains in predictive power ranging from 7% to 30%, with the average across these six sectors being 10%.

## **Sensitivity Analysis**

To assess the stability and validity of our results, we undertook several additional analyses. In particular, we examined the performance of our valuation model out-of-sample to determine whether the conclusions drawn from Table 4 extend to other periods. We also undertook a factor analysis to assess whether a more parsimonious grouping of brand attributes would be more appropriate for valuation purposes. Finally, we assessed the valuation framework by examining predictive performance of the model in the absence of profit margin data.

### **Out-of-Sample Predictive Accuracy**

Although assessments of statistical significance and improvement of within-sample predictive accuracy have merit, it is also useful to test how well the model parameters can be used out-of-sample to predict the value-to-sales

ratio. For example, because model parameters may not be estimated with sufficient accuracy or model parameters may change over time, differences may exist between in-sample performance and out-of-sample performance. Indeed, a comprehensive model that offers superior explanatory power in-sample may yield inferior predictions to a more parsimonious model out-of-sample. As such, we attempt to assess the ability of Equation 4.2 and the model parameters reported in Table 4 to predict value-to-sales ratios for periods other than 2000–2006, the period for which the model parameters were estimated.

Young & Rubicam also engaged in brand surveys in 1997 and 1999. We did not include these waves of data in our analysis because the sampling was at unequal intervals from the other survey waves we used in our analysis, which would have had an impact on some of our analyses—in particular, our sensitivity analysis based on an autoregressive error structure. Excluding these years of data from the model estimation has the benefit of providing a means to conduct an out-of-sample assessment of predictive accuracy. Using the parameter estimates from Table 4, we assess how much predictive accuracy is gained by incorporating brand metrics into a value-to-sales multiplier model.

Table 5 reports the MAE across the six sectors in Table 4 that show evidence of brand effects. That is, we excluded retail and apparel firms from this analysis because Equation 4.4 showed no role for brand effects in-sample (i.e., the estimated brand coefficients were both small and statistically insignificant), and therefore we had no reason to believe that they would provide any improvement in predictive power out-of-sample. Indeed, we confirmed this empirically. Table 5 shows estimates from four predictive models. Model 5.1 uses the annual sector mean of the value-to-sales ratio as the prediction. Model 5.2 uses the annual sector mean and the return on sales for the firm multiplied by the estimated coefficients in Table 4, Panel A, to predict the value-to-sales multiplier. Model 5.3 extends Model 5.2 by including brand metrics and the estimated coefficients from Table 4, Panel B. Model 5.4 excludes return on sales and bases predictions on the annual sector mean and the brand metrics.

Model 5.1 has an MAE of .57. Accounting for return on sales reduces the MAE to .3483 (i.e., a 64% improvement). Including brand metrics in the analysis further enhances predictive power, as the MAE falls to .2993—a 16% reduction in prediction error. As such, the out-of-sample improvement in predictive power is actually greater than the in-sample results suggest (i.e., only a 10% reduction in MAE). Notable, predictions made both for firms for 1997 and for 1999 show a similar improvement of 16%.

### **Lack of Available Earnings Data**

In some instances, earnings data are not available for use in a valuation analysis. This can occur, for example, because of the proprietary nature of earnings information. Although sales typically can be obtained from outside sources, obtaining earnings data for a firm typically requires the cooperation of the firm's managers. This cooperation may not be forthcoming. In such practical applications, valuation

**TABLE 5**  
**Out-of-Sample Predictions for Years 1997 and 1999**

| Mean Absolute Forecast Error (N = 161) |  |       |                                     |
|--|--|-------|-------------------------------------|
| <b>Forecasting Models:</b>             |  |       |                                     |
| 5.1:                                   | $\text{Enterprise Value}_{it} = \text{Sales}_{it} \times [\hat{\gamma}(k, t)]$   |       |                                     |
| 5.2:                                   | $\text{Enterprise Value}_{it} = \text{Sales}_{it} \times [\hat{\gamma}(k, t) + \hat{\delta}(k)_1 \times \text{ROS}_{it}]$  |       |                                     |
| 5.3:                                   | $\text{Enterprise Value}_{it} = \text{Sales}_{it} \times [\hat{\gamma}(k, t) + \hat{\delta}(k)_2 \times \text{ROS}_{it} + \sum_{b=1}^5 \hat{\beta}(k)_b \times \text{Brand Asset}_{bt}]$ |       |                                     |
| 5.4:                                   | $\text{Enterprise Value}_{it} = \text{Sales}_{it} \times [\hat{\gamma}(k, t) + \sum_{b=1}^5 \hat{\beta}(k)'_b \times \text{Brand Asset}_{bt}]$   |       |                                     |
| Model                                  | Explanatory Variables  | MAE   | Improvement                         |
| 5.1                                    | Sector yearly mean   | .5719 |                                     |
| 5.2                                    | Sector yearly mean, return on sales  | .3483 | 5.2 improvement over 5.1 = 64%      |
| 5.3                                    | Sector yearly mean, return on sales, BAV brand metrics   | .2993 | 5.3 improvement over 5.2 = 16%      |
| 5.4                                    | Sector yearly mean, BAV brand metrics  | .4366 | 5.4 improvement over 5.1 = 31%      |
|  |  |       | 5.4 reduction compared to 5.2 = 25% |

Notes: We excluded firms in the retail and apparel sector from the analysis because of the lack of observed brand impact in-sample. MAE is the mean of absolute value of the prediction error; that is,  $|\text{Enterprise Value}_{it} - \text{Enterprise Value}_{it}|$ .

can proceed in the absence of earnings information with a simple modification of Model 4.2; specifically, return on sales as an explanatory factor can be dropped from the estimating equation. This modified model links the value-to-sales ratio to annual sector dummies and brand metrics. To the extent that brand metrics are correlated with current-period return on sales, their estimated coefficients will reflect some of the effect of return on sales when it is excluded from the model.

We assessed the out-of-sample predictive power of this modified model. As we report in Model 5.4 of Table 5, the model generated an out-of-sample MAE of .4366. This represents a 31% improvement in predictive accuracy over a model based just on annual sector means. However, it is a 26% reduction in accuracy from predictions based on the sector mean and return on sales. This reduction was expected given that not all the variation in firms' return on sales can be explained by brand attributes. However, the improvement in predictive accuracy over the sector mean further supports the use of brand metrics for valuation purposes.

### Factor Analysis Assessment

We also undertook a factor analysis to examine the effects of collinearity in our branding data and to ascertain the benefits of a more parsimonious specification. Because the brand metrics are correlated with each other, collinearity may induce inaccuracies in the coefficient estimates. Although collinearity still allows for unbiased coefficient estimates, they may not be estimated with sufficient precision (as evidenced by larger standard errors). Even in the absence of collinearity (e.g., because of estimation error), a parsimonious model can yield more accurate predictions than a more expansive model. An approach for dealing with both potential issues is to conduct a factor analysis on the

brand metrics to reduce their dimensionality and then to relate the resulting factors to the value-to-sales ratio.

We undertook this analysis and obtained a two-factor solution. One factor was relevant stature (a factor of an approximately equal weighting of relevance, knowledge, and esteem), and the other was differentiated energy (a factor primarily based on differentiation and energy). We then replaced the five brand metrics in Equation 4.2 with these two factors. Although we found statistically significant brand effects using these two brand factors, the explanatory power exhibited by the brand factors was noticeably diminished compared with the models that allow for separate brand effects. Relevance and knowledge both load positively on one factor, but they tend to exhibit different associations with the value-to-sales ratio. This observation is most prominent for the high-tech sector (i.e., Equation 4.24), for which relevance has a positive effect and knowledge has a negative effect. Although factor analysis essentially makes use of the average of relevance and knowledge, the results of Equation 4.24 suggest that the difference between relevance and knowledge would be a more appropriate measure.

Aggregation will always result in a loss of explanatory power within sample, but out-of-sample analysis sometimes may yield different conclusions. However, this is not the case here. We found that the two-factor brand model had an out-of-sample MAE of .337. This represents only a 3% decrease in MAE from the analysis based only on sector effects and return-on-sales data and is a 13% increase in MAE compared with analysis that allows for separate effects for each of the five brand metrics. As such, the out-of-sample analysis fully supports the in-sample analysis, indicating that an approach based on factor analysis is inferior to allowing for separate brand effects.

## Conclusion

We propose a conditional multiplier framework that incorporates brand assets into a relative business valuation. We demonstrate its use and performance using Y&R BAV brand metrics. Not only do brand assets influence contemporaneous accounting drivers of business valuation, but our analyses also show that brand assets influence firm valuation through direct effects on sales multipliers.

We find that brand metrics provide significant incremental explanatory power to profitability measures in explaining the value-to-sales ratio. Incorporating brand-related information into the valuation model enhances out-of-sample predictive power by 16%. However, the importance and the impact of brand dimensions are different across sectors. For the seven sectors we examine, brand metrics reduce in-sample MAEs from 2.4% in retail and apparel to 30% in consumer durable goods.

Our goal was to assess whether brand metrics enhance predictions of the value-to-sales ratio. In this forecasting context, rather than trying to obtain unbiased coefficient estimates of the causal effect, the goal was to extract as much information from the brand metrics as possible. As such, the estimated parameters for the brand metrics reflect not just their causal impact on the value-to-sales ratio but also their ability to depict the effect of other factors omitted from the model. In contrast to least squares standard errors, which tend to understate confidence intervals, we used cluster-robust standard errors that allow for the assessment of statistical significance in the presence of omitted firm-specific variables. However, the coefficient estimates cannot be interpreted as structural parameters. This makes it problematic to attach causal interpretations to the estimated model coefficients.

However, we can report that brand metrics have different associations with the value-to-sales ratio across different industrial sectors. For example, we find that differentiation is the brand metric most reflective of information influencing sales multiples in several sectors. A possible explanation for this finding is that as product markets and services become more commoditized and the offerings are similarly priced, brand differentiation is a key factor in attracting consumers. Differentiation is needed to stand out in the crowded space of similar offerings.

Notably, we find no association between the brand metrics and value-to-sales ratio in our retail and apparel sector. In this sector, profit margin is the only significant predictor of the value-to-sales multiplier. Perhaps consumers' tastes and preferences for apparel change too fast with the seasonal fashion, so current brand attitudes and perceptions in this sector have little predictive value incremental to profit margin about future financial performance. That is, if brand dimensions are not associated with information affecting current-term performance (sales or profit margin), they are not viewed by the financial markets as being likely to affect future-term performance.

There are several promising avenues for further research in this area. First, we focus on the five key metrics that con-

stitute the BAV model. Other brand asset components might also add incremental explanatory power and improve valuation predictive performance in some or all sectors. As part of additional sensitivity analyses, we find that the Y&R brand metric "gaining in popularity" is related to the value-to-sales ratio for firms in the retail and apparel sector. However, although it is statistically significant, the metric provides only modest improvements in explanatory power both in-sample and out-of-sample. Still, the notion that other brand metrics might provide additional explanatory power should be explored further.

Second, other intangible assets, such as management quality, customer satisfaction, a firm's innovation strategy, measures of technological capabilities (e.g., patents, patent citations), and product pipeline, may also play a role in influencing firm valuation and therefore may provide improvement in forecasting business valuation. If consistent measures of other intangible assets are available, they can be easily incorporated into our valuation framework. We view this direction as a particularly valuable avenue for further research.

## Appendix A Assessing the Impact of Brand Assets on Sales

Although sales is a given input into the valuation modeling, it is still useful to appreciate the extent to which brand assets affect not just the multiplier but also the value driver. Consider the following sales model:

$$(A1) \quad \log(\text{Sales}_{it}) = \lambda_i + \sum_{b=1}^5 \theta_b \times \text{Brand Asset}_{bit} + \sum_{t=1}^T \sum_{k=1}^K \zeta(k, t) \times S(kt) + \varepsilon_{it},$$

where  $\text{Sales}_{it}$  is total revenue of firm  $i$  in year  $t$ ,  $\lambda_i$  is a firm-specific effect,  $\text{Brand Asset}_{bit}$  is a set of brand metrics, and  $S(kt)$  is an indicator function that is equal to 1 if the firm is in sector  $k$  for period  $t$  and 0 if otherwise. Prior research has documented that sales series typically have a unit root (and we confirm this with formal tests in our data), which is reflected in the error term in Equation A1. This error term takes the form  $\varepsilon_{it} = \varepsilon_{it-1} + \eta_{it}$ , where  $\eta_{it}$  is a white-noise error. To address this error structure, we take first differences of the data, which removes the fixed effect and unit root structure of the error and yields the following:

$$(A2) \quad \Delta \log(\text{Sales}_{it}) = \sum_{b=1}^5 \theta_b \times \Delta \text{Brand Asset}_{bit} + \sum_{t=1}^T \sum_{k=1}^K \zeta(k, t) \times \Delta S(kt) + \eta_{it}.$$

While Equation A2 links sales growth to the change in brand assets, the coefficient  $\theta_b$  can be interpreted as depicting the effect of brand asset  $b$  on sales in Equation A1 (i.e.,

the structural interpretation of the model parameters does not change under a first-difference transformation).

The results of estimating Equation A2 appear in Table A1. We find that two brand asset components, knowledge and esteem, have a significant impact on contemporaneous sales. Among the five brand asset metrics, knowledge shows the greatest positive impact on sales (.073). This effect is significant at the 1% level. Esteem also has a positive impact on sales (.031) and is significant at the 5% level. Differentiation, relevance, and energy do not show statistically significant impacts on contemporaneous sales.

We assess the possibility that brand effects differ across sectors. We reestimated Equation A2, allowing the effects of brand assets to vary by sector. We did not find statistically significant intersector differences. The F-statistic of assessing the restriction that the brand effects are the same across the sectors was equal to .97 and below the 5% critical value of 1.47.

**TABLE A1**  
**Brand Impact on Contemporaneous Sales**  
**(Dependent Variable = Sales Growth; N = 943)**

$$\text{Model: } \Delta \log(\text{Sales}_{it}) = \sum_{b=1}^5 \theta_b \times \Delta \text{Brand Asset}_{bit} + \sum_{t=1}^T \sum_{k=1}^K \zeta(k, t) \times \Delta S(kt) + \eta_{it}$$

|                 | Estimate | t-Statistic |
|-----------------|----------|-------------|
| Differentiation | -.00433  | -.61        |
| Relevance       | .00619   | .39         |
| Esteem          | .03123*  | 2.20        |
| Knowledge       | .07259** | 3.11        |
| Energy          | -.00760  | -1.02       |

\*p < .05.  
\*\*p < .01.  
Notes: Each equation also includes annual sector-specific dummy variables (not reported).

**Appendix B**  
**Estimating the HP Enterprise Value-to-Sales Ratio for 2005**

|                     | Data Inputs <sup>a</sup>       |                    | Model Parameters   |   | Forecasts                       |  |   |
|---------------------|--------------------------------|--------------------|--|---|---------------------------------|--|---|
|                     |                                |                    | Estimated Adjustment Coefficient for Return on Sales (Equation 4.14) | Estimated Adjustment Coefficients for Return on Sales and Brand Effects (Equation 4.24) | Forecasted Multiplier           |  |   |
|                     | 2005 High-Tech Sector Averages | 2005 HP Input Data |  |   | Based on Sector Peer Group Only | Based on Sector Peer Group and Return on Sales | Based on Sector Peer Group, Return on Sales, and Brand Attributes |
| Value-to-sales      | 2.823                          |                    |  |   | 2.823                           | 1.317  | .966  |
| log(value-to-sales) | .762                           |                    |  |   |                                 |  |   |
| Return on sales     | .214                           | .084               | 3.74   | 3.98  |                                 |  |   |
| Differentiation     | .315                           | .760               |  | .185  |                                 |  |   |
| Relevance           | .293                           | 1.072              |  | .416  |                                 |  |   |
| Esteem              | .466                           | 1.437              |  | .207  |                                 |  |   |
| Knowledge           | .635                           | .799               |  | .287  |                                 |  |   |
| Energy              | .318                           | .732               |  | .098  |                                 |  |   |

<sup>a</sup>All brand variables are z-standardized.

Notes: In the four calendar quarters of 2005, HP had sales of \$86,696 million, and its enterprise value was \$76,298 million. We try to predict the enterprise value-to-sales multiplier for HP in 2005, which we assume is unknown, though it is .88.

- Using the 2005 high-tech sector mean multiplier value provides an estimate of 2.82.
- If both the sector mean multiplier and the difference in profitability between HP and the sector are considered, this generates an estimated multiplier of 1.317. This is computed from the exponentiation of the logarithm of the high-tech sector average multiplier of .762 plus the estimated coefficient for return on sales in Equation 4.14 times the difference in HP return on sales from the sector average; that is,  $1.317 = \exp\{.762 + (3.74) \times [(.084) - (.214)]\}$ .
- If the sector mean multiplier, the difference in HP profitability from the sector, and the differences in HP brand perceptions from the sector mean are considered, this generates an estimated multiplier of .9658. This is computed from the exponentiation of the logarithm of the high-tech sector average multiplier of .762 plus the estimated coefficient for return on sales in Equation 4.24 times the difference in HP return on sales and from the sector average and the estimated coefficients for the brand assets times the differences in HP brand assets from the sector average; that is,  $.9658 = \exp\{.762 + (3.98) \times [(.084) - (.214)] + (.185) \times [(-.760) - (-.315)] + (.416) \times [(1.072) - (-.293)] + (-.207) \times [(1.437) - (-.466)] + (-.287) \times [(.799) - (-.635)] + (.098) \times [(.732) - (.318)]\}$ .

**REFERENCES**

Aaker, David A. (1996), *Building Strong Brands*. New York: The Free Press.

——— and Robert Jacobson (1994), "The Financial Information Content of Perceived Quality," *Journal of Marketing Research*, 31 (May), 191–201.

——— and ——— (2001), "The Value Relevance of Brand Attitude in High-Technology Markets," *Journal of Marketing Research*, 38 (November), 485–93.

Agres, Stuart J. and Tony M. Dubitsky (1996), "Changing Needs for Brands," *Journal of Advertising Research*, 36 (1), 21–30.



- Ailawadi, Kusum L., Donald R. Lehmann, and Scott A. Neslin (2003), "Revenue Premium as an Outcome Measure of Brand Equity," *Journal of Marketing*, 67 (October), 1–17.
- Alford, Andrew W. (1992), "The Effect of the Set of Comparable Firms on the Accuracy of the Price-Earnings Valuation Method," *Journal of Accounting Research*, 30 (1), 94–108.
- Arellano, Manuel (1987), "Computing Robust Standard Errors for Within-Groups Estimators," *Oxford Bulletin of Economics and Statistics*, 49 (4), 431–33.
- Bajaj, Mukesh, David J. Denis, and Atulya Sarin (2004), "Mean Reversion in Earnings and the Use of E/P Multiples in Corporate Valuation," *Journal of Applied Finance*, 14 (1), 4–10.
- Barth, Mary E., William H. Beaver, and Wayne R. Landsman (1998), "Relative Valuation Roles of Equity Book Value and Net Income as a Function of Financial Health," *Journal of Accounting and Economics*, 25 (1), 1–33.
- , Michael Clement, George Foster, and Ron Kasznik (1998), "Brand Values and Capital Market Valuation," *Review of Accounting Studies*, 3 (1–2), 41–68.
- , John A. Elliott, and Mark W. Finn (1999), "Market Rewards Associated with Patterns of Increasing Earnings," *Journal of Accounting Research*, 37 (2), 387–413.
- Berger, Philip G. and Eli Ofek (1995), "Diversification's Effect on Firm Value," *Journal of Financial Economics*, 37 (1), 39–65.
- Bhojraj, Sanjeev and Charles M.C. Lee (2002), "Who Is My Peer? A Valuation-Based Approach to the Selection of Comparable Firms," *Journal of Accounting Research*, 40 (2), 407–439.
- Boatsman, James R. and Elba F. Baskin (1981), "Asset Valuation with Incomplete Markets," *Accounting Review*, 56 (1), 38–53.
- Bronnenberg, Bart J., Sanjay K. Dhar, and Jean-Pierre Dubé (2005), "Market Structure and the Geographic Distribution of Brand Shares in Consumer Packaged Goods Industries," working paper, Booth School of Business, University of Chicago.
- Chen, Peter F. and Guochang Zhang (2003), "Heterogeneous Investment Opportunities in Multiple-Segment Firms and the Incremental Value Relevance of Segment Accounting Data," *Accounting Review*, 78 (2), 397–428.
- Damodaran, Aswath (2002), *Investment Valuation: Tools and Techniques for Determining the Value of Any Asset*, 2d ed. New York: John Wiley & Sons.
- Dekimpe, Marnik G. and Dominique M. Hanssens (1999), "Sustained Spending and Persistent Response: A New Look at Long-Term Marketing Profitability," *Journal of Marketing Research*, 36 (November), 397–412.
- Fischer, Marc (2007), "Valuing Brand Assets: A Cost-Effective and Easy-to-Implement Measurement Approach," MSI Working Paper Series, Report 07-107.
- Gilson, Stuart C., Edith S. Hotchkiss, and Richard S. Ruback (2000), "Valuation of Bankrupt Firms," *Review of Financial Studies*, 13 (1), 43–74.
- Gow, Ian D., Gaizka Ormazabal, and Daniel J. Taylor (2007), "Correcting for Cross-Sectional and Time-Series Dependence in Accounting Research," working paper, Graduate School of Business, Stanford University.
- Granger, Clive W.J., Namwon Hyung, and Yongil Jeon (2001), "Spurious Regressions with Stationary Series," *Applied Economics*, 33 (7), 899–904.
- and Paul Newbold (1974), "Spurious Regressions in Econometrics," *Journal of Econometrics*, 2 (2), 111–20.
- Griliches, Zvi and Jerry A. Hausman (1986), "Errors in Variables in Panel Data," *Journal of Econometrics*, 31 (1), 93–118.
- Johnson, Michael D., Andreas Herrmann, and Frank Huber (2006), "The Evolution of Loyalty Intentions," *Journal of Marketing*, 70 (April), 122–32.
- Kao, Chihwa (1999), "Spurious Regression and Residual-Based Tests for Cointegration in Panel Data," *Journal of Econometrics*, 90 (1), 1–44.
- Keller, Kevin Lane (1993), "Conceptualizing, Measuring, and Managing Customer-Based Brand Equity," *Journal of Marketing*, 57 (January), 1–22.
- (1998), *Strategic Brand Management*. Englewood Cliffs, NJ: Prentice Hall.
- and Donald R. Lehmann (2003), "How Do Brands Create Value?" *Marketing Management*, 12 (3), 26–31.
- and ——— (2006), "Brands and Branding: Research Findings and Future Priorities," *Marketing Science*, 25 (6), 740–60.
- Kerin, Roger A. and Raj Sethuraman (1998), "Exploring the Brand Value-Shareholder Value Nexus for Consumer Goods Companies," *Journal of the Academy of Marketing Science*, 26 (4), 260–73.
- Kim, Moonchul and Jay R. Ritter (1999), "Valuing IPOs," *Journal of Financial Economics*, 53 (3), 409–436.
- Kohlbeck, Mark and Terry D. Warfield (2007), "Unrecorded Intangible Assets: Abnormal Earnings and Valuation," *Accounting Horizons*, 21 (1), 23–31.
- Lie, Erik and Heidi J. Lie (2002), "Multiples Used to Estimate Corporate Value," *Financial Analysts Journal*, 58 (2), 44–54.
- Liu, Jing, Doron Nissim, and Jacob Thomas (2002), "Equity Valuation Using Multiples," *Journal of Accounting Research*, 40 (1), 135–62.
- , ———, and ——— (2007), "Is Cash Flow King in Valuations?" *Financial Analysts Journal*, 63 (2), 1–13.
- McAlister, Leigh, Raji Srinivasan, and MinChung Kim (2007), "Advertising, Research and Development, and Systematic Risk of the Firm," *Journal of Marketing*, 71 (January), 35–48.
- Mitra, Debanjan, and Peter N. Golder (2006), "How Does Objective Quality Affect Perceived Quality? Short-Term Effects, Long-Term Effects, and Asymmetries," *Marketing Science*, 25 (3), 230–48.
- Mizik, Natalie and Robert Jacobson (2008), "The Financial Value Impact of Perceptual Brand Attributes," *Journal of Marketing Research*, 45 (February), 15–32.
- Park, C.S. and V. Srinivasan (1994), "A Survey-Based Method for Measuring and Understanding Brand Equity and Its Extendability," *Journal of Marketing Research*, 31 (May), 271–88.
- Pauwels, Koen, Jorge Silva-Risso, Shuba Srinivasan, and Dominique M. Hanssens (2004), "New Products, Sales Promotions, and Firm Value: The Case of the Automobile Industry," *Journal of Marketing*, 68 (October), 142–56.
- Petersen, Mitchell A. (2009), "Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches," *Review of Financial Studies*, 22 (1), 435–80.
- Romaniuk, Jenni, Byron Sharp, and Andrew Ehrenberg (2007), "Evidence Concerning the Importance of Perceived Brand Differentiation," *Australasian Marketing Journal*, 15 (2), 42–54.
- Shankar, Venkatesh, Pablo Azar, and Matthew Fuller (2007), "BRAN\*EQT: A Model and Simulator for Estimating, Tracking, and Managing Multicategory Brand Equity," MSI Working Paper Series, Report 07-108.
- Shmueli, Galit (2009), "To Explain or to Predict?" working paper, Department of Decision, Operations and Information Technologies, University of Maryland.
- Simon, Carol J. and Mary W. Sullivan (1993), "The Measurement and Determinants of Brand Equity: A Financial Approach," *Marketing Science*, 12 (1), 28–52.
- Srinivasan, V., Chan Su Park, and Dae Ryun Chang (2005), "An Approach to the Measurement, Analysis, and Prediction of Brand Equity and Its Sources," *Management Science*, 51 (9), 1433–48.
- Sriram, S., Subramanian Balachander, and Manohar U. Kalwani (2007), "Monitoring the Dynamics of Brand Equity Using Store-Level Data," *Journal of Marketing*, 71 (April), 61–78.
- Srivastava, Rajendra K., Tasadduq A. Shervani, and Liam Fahey (1998), "Market-Based Assets and Shareholder Value: A Framework for Analysis," *Journal of Marketing*, 62 (January), 2–18.
- Stock, James H. and Mark W. Watson (2006), *Introduction to Econometrics*, 2d ed. Boston: Addison-Wesley.
- Swait, Joffre and Tülin Erdem (2007), "Brand Effects on Choice and Choice Set Formation Under Uncertainty," *Marketing Science*, 26 (5), 679–98.
- Van Heerde, Harald, Kristiaan Helsen, and Marnik G. Dekimpe (2007), "The Impact of a Product-Harm Crisis on Marketing Effectiveness," *Marketing Science*, 26 (2), 230–48.
- White, Halbert L. (1980), "A Heteroskedastic-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity," *Econometrica*, 48 (4), 817–38.
- (1984), *Asymptotic Theory for Econometricians*. New York: Academic Press.

Copyright of *Journal of Marketing* is the property of American Marketing Association and its content may not be copied or emailed to multiple sites or posted to a listserv without the copyright holder's express written permission. However, users may print, download, or email articles for individual use.