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The authors assess which brand asset metrics provide incremental information content to accounting performance measures in explaining stock return. The analysis focuses on the five "pillars" (i.e., central brand attributes) that form the basis for the newly updated Young & Rubicam Brand Asset Valuator model: differentiation, relevance, esteem, knowledge, and energy. Analysis shows that perceived brand relevance and energy provide incremental information to accounting measures in explaining stock returns. However, esteem and knowledge do not; that is, their effects are reflected in current-term accounting measures and in brand relevance and energy. The financial markets do not view brand differentiation as having incremental information content, but they should. Changes in differentiation are indicative of future-term accounting performance, which in turn affects stock return. These conclusions are invariant to the use of alternative accounting performance measures, risk adjustments, and the inclusion of additional brand attributes into the analysis.

Keywords: brand equity, brand dimensions, stock return, financial market performance, brand energy

The Financial Value Impact of Perceptual Brand Attributes

Marketing managers are under increasing pressure to justify marketing spending. The issue of quantifying the returns to marketing activities in financial terms is one of the greatest challenges facing marketing and brand managers today. For example, Rust and colleagues (2004, p. 76) note that marketers have not been held accountable for showing how marketing adds to shareholder value and that "this lack of accountability has undermined marketers' credibility, threatened the standing of the marketing function within the firm, and even threatened marketing's existence as a distinct capability within the firm."

Prior research has highlighted that accounting measures alone cannot adequately explain firm value. Oftentimes, firms have intangible assets or undertake strategies whose benefits are not accurately depicted in accounting valuation of firm assets or in the current-term accounting measures of financial performance (Srivastava, Shervani, and Fahey 1998). For example, marketing assets, such as brand attributes and brand-building strategies, have benefits that are not reflected fully in current-term performance outcomes. Some brand asset–building initiatives require significant investments and, at times, may come at the expense of current-term financial results. However, it is inappropriate to assume that all brand-building activities are warranted. Some may not justify their costs. Furthermore, different brand initiatives may generate different financial returns (Pauwels et al. 2004).

Brands are commonly assessed by customer mind-set measures (e.g., awareness, attitudes). However, it is widely acknowledged (e.g., Ailawadi, Lehmann, and Neslin 2003) that a primary limitation of customer mind-set measures is that they are unappealing for financial valuation purposes because they do not translate into dollar values. Mere assessment of brand attributes is insufficient. Rather, a link of these attributes to the financial bottom line needs to be established.

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Empirical assessment of the financial implications of customer mind-set measures of brand attributes is the focus of our study. In particular, we assess which brand attributes provide incremental information content to accounting measures in explaining stock return (i.e., which brand attributes add additional explanatory power to accounting variables in a stock return model). It is important to identify brand attributes that have incremental information content (separate from the effects that stem from their impact on current-term accounting outcomes) because they are particularly vulnerable to underinvestment. Because their effects are not fully reflected in current-term accounting measures, managers may have a tendency to underemphasize their importance, which would be detrimental to long-term business success.

Our analysis focuses on the five "pillars" (i.e., central brand attributes) that form the basis for the newly updated Young & Rubicam Brand Asset Valuator (Y&R BAV) model (Fudge 2005; Gerzema, Lebar, and Sussman 2005). A host of brand valuation models has been developed, but Y&R's is among the most visible. For example, Aaker (1996, p. 304) labels the undertaking as "the most ambitious effort to measure brand equity across products," and Keller (1998, p. 625) calls it "the most extensive research program on global branding to date." Using its extensive database, Y&R developed an empirically based theory of brand building, the BAV (Agres and Dubitsky 1996). The new Y&R BAV model adds brand "energy" (the degree to which a brand is perceived as innovative and dynamic) as an additional pillar to "differentiation," "relevance," "esteem," and "knowledge," which were the foundations of the previous model. We find that relevance and energy provide incremental information to accounting measures in explaining stock return. Esteem and knowledge do not provide incremental information content in that their effects are reflected in current-term accounting measures and in relevance and energy. The financial markets do not view differentiation as having incremental information content, but our results suggest that they should. In particular, changes in differentiation are indicative of future-term accounting performance, which in turn affects stock return. We assess this apparent marketplace anomaly and confirm that firms with increased (decreased) differentiation have positive (negative) abnormal stock returns in the subsequent period.

THE "UPDATED" Y&R BAV MODEL

What components constitute a firm's brand asset? Keller and Lehmann (2003, p. 28) comment that "customer mind-set includes everything that exists in the minds of customers with respect to a brand (e.g., thoughts, feelings, experiences, images, perceptions, beliefs, and attitudes)." Various conceptualizations emphasize different aspects of customer mind-set. However, similarities are present across most popular conceptualizations of brand assets. For our analysis, we focus on the five pillars that constitute the recently updated Y&R brand valuation framework (Fudge 2005; Gerzema, Lebar, and Sussman 2005).

The Y&R BAV model is based on the premise that brand is a multidimensional construct that can be assessed through customer perception measurements. The BAV perceptual metrics are not category specific; rather, they assess universal brand characteristics, such as perceived quality and distinctiveness. Although Y&R monitors more than 50 different aspects of brand perceptions, five brand pillars have emerged as the key dimensions for assessing brand health, and though each of the five pillars is posited to play a unique role in the brand life cycle, the joint assessment of the five-pillar pattern allows for a comprehensive diagnosis of a brand's health. Table 1 summarizes the BAV pillars, their meanings, and measurements.

Table 1

SUMMARY OF THE MODIFIED BAV FRAMEWORK: FIVE PILLARS OF THE BRAND ASSET

BAV Pillar	*Underlying Perceptual Metrics*	*Survey Scale*	*BAV Data*	*Meaning and Role of the Pillar*[a]
Differentiation	1. Unique 2. Distinctive	Yes/no Yes/no	% responding "yes" % responding "yes"	Perceived distinctiveness of the brand. Defines the brand and reflects its ability to stand out from competition. Is the "engine of the brand train;… if the engine stops, so will the train."
Relevance	1. Relevant to me	1–7 scale	Average score	Personal relevance and appropriateness and perceived importance of the brand. Drives market penetration and is a source of brand's staying power.
Esteem	1. Personal regard 2. Leader 3. High quality 4. Reliable	1–7 scale Yes/no Yes/no Yes/no	Average score % responding "yes" % responding "yes" % responding "yes"	Level of regard consumers hold for the brand and valence of consumer attitude. Reflects how well the brand fulfills its promises.
Knowledge	1. Familiarity with the brand	1–7 scale	Average score	Awareness and understanding of the brand identity. Captures consumer intimacy with the brand. Results from brand-related (marketing) communications and personal experiences with the brand.
Energy (new pillar)	1. Innovative 2. Dynamic	Yes/no Yes/no	% responding "yes" % responding "yes"	Brand's ability to meet consumers' needs in the future and to adapt and respond to changing tastes and needs. Indicates future orientation and capabilities of the brand.

[a]Based on Y&R documents. More information about BAV can be found at www.yrbav.com.

The initial framework, developed in the 1990s, was based on four pillars: differentiation, relevance, esteem, and knowledge (Agres and Dubitsky 1996). Implications from this model have helped shape thinking on various brand issues. For example, Aaker (1996, Chap. 10) uses the BAV model as one of the key inputs into formulating his "brand equity ten" and has continued to make use of the framework to highlight the crucial role of differentiation in brand building (Aaker 2004, p. 136; Aaker and Joachimsthaler 2000, p. 263). In collaboration with our study, Y&R recently modified its framework and introduced a fifth pillar called "brand energy."[1] The measure is based on the Y&R survey questions reflecting the degree to which the brand is viewed as (1) innovative and (2) dynamic.

The Pillars of the Initial Y&R BAV Model

Differentiation is the ability of the brand to stand apart from its competitors and is a central component in all conceptualizations of brand assets. The differentiation measure we use is based on the average of the responses to two questions. In the Y&R survey, respondents were asked to indicate whether they perceived the brand as "unique" and whether they perceived the brand as "distinctive." The differentiation measure is the average of the proportion of respondents who indicated that the brand was unique and the proportion of respondents who indicated that the brand was distinctive.

Differentiation is of little value unless it is relevant to the customer. As such, most conceptualizations of brand assets include a measure that assesses the personal appropriateness of the brand. Young & Rubicam asks respondents to rank a brand's relevance on a seven-point scale, ranging from "not at all relevant" (1) to "extremely relevant" (7), and we use the population average score as our measure of relevance.

Esteem reflects the level of respect, deference, and regard a consumer holds for a given brand. Although different operationalizations of esteem exist, four components constitute the most recent Y&R measure. These components are (1) the proportion of respondents who indicated that they believed the brand was of high quality, (2) the proportion of respondents who indicated that they believed the brand was a leader, (3) the proportion of respondents who indicated that they believed the brand was reliable, and (4) a rating (on a seven-point scale) that indicated the respondent's personal regard for the brand. A composite esteem measure is calculated by first computing z-scores for each of these four items across all brands and then averaging the four z-standardized measures.

For a brand to sustain a presence in the marketplace, people must be aware of it. As such, at its most basic level, knowledge encompasses brand awareness and the extent to which customers recall and recognize the brand. Young & Rubicam asks respondents to indicate on a seven-point scale their familiarity with a brand, which is explained to include the overall awareness of the brand and the understanding of what kind of product or service the brand represents.

The Fifth Y&R Brand Pillar: Energy

These four dimensions provided the foundation for the Y&R BAV framework. However, since the initial development of the BAV in the 1990s, marketplace changes and additional analysis have highlighted not only the strengths of the model but also aspects of it that could be improved. With marketplace changes happening so profoundly and swiftly, a dimension was needed to tap into the future-term capabilities of the brand. A brand has value to its current customers because of both its ability to fulfill customers' present needs and its future promises. Customers are likely to place a greater value on brands and to build stronger relationships with those they expect will be available in the future. Will the brand be able to meet the customer's needs in the future? Is the brand able to adapt and respond in a timely way to changing customer tastes and needs?

Thus, in consultation with Y&R, we advanced the idea that a brand energy measure (intended to capture the future-term capabilities of the brand more fully) be added to the Y&R model. Although this measure does not receive the emphasis of the other four brand dimensions, energy-related brand attributes have received some attention in academic research and industry analysis. For example, Keller and Aaker (1998) highlight that a company's reputation for product innovation enhances perceptions of brand extensions. Innovativeness is a component of *Fortune*'s Corporate Reputation measure. Techtel Corporation surveyed respondents on their perceptions of the "vitality and energy" of Internet firms, and Aaker and Jacobson (2001a) report that these perceptions are strongly associated with attitude toward the brand.

The Y&R energy measure is the average of two questions reflecting respondents' perceptions of a brand's innovativeness and dynamism. It is intended to reflect a brand's ability to adapt and respond in a timely way to changing customer tastes and needs. Gerzema, Lebar, and Sussman (2005) note that innovation changes how people feel and the way they behave. It translates good intentions into action, it breaks new ground, and it reframes categories. Perceptions of innovativeness result from new product introductions, line extensions, new inventions, and breakthroughs. Innovativeness captures both experiential and functional aspects of the brand. Brand dynamism is less specific to tangible product characteristics and more reflective of higher-order emotional benefits. It goes beyond product perceptions and helps shape a brand's persona.

Perception of innovativeness and brand dynamism are positively correlated. For example, Microsoft is rated high on both measures. However, differences also exist. Harley–Davidson is viewed as one of the most dynamic brands but only slightly above average in terms of innovativeness. Conversely, most pharmaceutical brands are viewed as innovative but below average in dynamism. Although industry effects may exist, differences among firms in the same industry are also present. For example, Toyota is viewed as more dynamic than Ford, and JetBlue is rated higher on both innovativeness and dynamism than Continental Airlines.

[1]Some previous work (e.g., Mizik and Jacobson 2005) made use of the term "brand vitality" to refer to the same construct. The measures are the same and differ only in labeling.

THE INFORMATION CONTENT OF BRAND ASSET DIMENSIONS

Although these brand attribute dimensions have conceptual merit, systematic analysis showing a link (or, perhaps, a lack thereof) between the brand pillars and financial performance is needed to substantiate their value. Young & Rubicam provided us access to its data for an assessment of the financial implications of the five BAV pillars. One aspect of this assessment involved stock return response modeling (Mizik and Jacobson 2004) to assess which, if any, of the Y&R pillars provided incremental information to accounting variables in explaining stock market performance.

Stock Return Response Modeling

Stock return response modeling assesses whether information contained in a measure is associated with stock return (i.e., changes in the market's expectations of future cash flows). The framework for establishing the information content of a measure stems from Ball and Brown's (1968) study, which stimulated an extensive research stream in accounting examining the relationship between financial information (e.g., earnings) and the capital markets. Recently, this framework has been extended to assessing the information content of nonfinancial measures. These studies assess the "incremental information content" or "value relevance" of nonfinancial measures (i.e., the degree to which a series provides added explanatory power to standard accounting information in explaining stock price movements). This development was motivated by observation that the stock market participants value firms on the basis not only of current-term accounting information (which does not reflect fully the state of intangible assets and new growth opportunities) but also of other information relevant to future performance.

Valuation Framework Underlying Stock Return Response Modeling

Consider the standard valuation model:

$$\text{(1)} \qquad \text{MktCap}_{it} = \sum_{T=t}^{\infty}\left(\frac{1}{1+r_{it}}\right)^{T-t} E(CF_{iT}),$$

where MktCap_{it} is the market capitalization of firm i at time t, $E(CF_{iT})$ is the expected cash flow in period T, and r_{it} is the discount rate. The stock market valuation of a firm depicts market expectations, typically assumed to be unbiased estimates, of the discounted value of the firm's future cash flows. Under the hypothesis of financial market efficiency, stock prices are also posited to reflect all available information and, as such, react only to unanticipated events (LeRoy 1989). Thus, we can express Equation 1 in terms of the previous period capitalization, expected rate of return given economywide conditions and the risk of the firm, and change in investor expectations of future cash flows:

$$\text{(2)} \qquad \text{MktCap}_{it} = (1+\text{Eret}_{it})\text{MktCap}_{it-1} + \sum_{T=t}^{\infty}\left(\frac{1}{1+r_{it}}\right)^{T-t} \Delta E(CF_{iT}),$$

where Eret_{it} is the expected rate of return for security i at time t and $\Delta E(CF_{iT})$ is the change in the expected cash flows at period T.

Dividing by previous market capitalization and rearranging terms gives us

$$\text{(3)} \qquad \text{StkRet}_{it} = \text{Eret}_{it} + \sum_{T=t}^{\infty}\left(\frac{1}{1+r_{it}}\right)^{T-t} \frac{\Delta E(CF_{iT})}{\text{MktCap}_{it-1}},$$

where StkRet_{it} is defined as the percentage change in market value; that is,

$$\frac{\text{MktCap}_{it} - \text{MktCap}_{it-1}}{\text{MktCap}_{it-1}}.$$

Equation 3 expresses stock return as a linear combination of expected return (Eret_{it}) and excess (or "abnormal") return. Expected return reflects the return on the stock that can be accounted for by economywide conditions (e.g., the risk-free rate of return) and the risk characteristics of the firm. Abnormal return is the difference between stock return and this expected return. It stems from the change in the expected discounted future size-adjusted cash flows brought about by unexpected events occurring between periods (t – 1) and t.

Work in accounting has established that unanticipated changes in accounting performance measures are associated with abnormal stock returns. Current-term accounting performance measures provide information about firm value both by depicting current-term results and by being indicative of future cash flows. That is, unanticipated changes in accounting performance measures change investor expectations of the firm's current and future cash flows and thus lead to a change in a firm's valuation.

However, stock market participants are forward looking. Not only do they react to current-term accounting information, but they also use other information in an attempt to anticipate future-term outcomes. Other factors (e.g., a firm's brand assets) can be hypothesized to affect future cash flows and, as such, investor expectations of them. Marketing assets have not only current-term effects but long-term effects as well (Srivastava, Tasadduq, and Fahey 1998). Because the effect of a change in a firm's brand assets on a firm's cash flows is unlikely to be completely captured in current-term accounting measures, changes in a firm's brand assets may have an effect on stock return incremental to that of accounting measures. That is, stock market participants appreciate the future-term cash flow implications of brand assets and will impound their effect into the price of the stock. As such, we can expect abnormal stock return to depend on both unanticipated changes in accounting measures and unanticipated changes in brand assets. That is,

$$\text{(4)} \qquad \text{StkRet}_{it} - \text{Eret}_{it} = \sum_{T=t}^{\infty}\left(\frac{1}{1+r_{it}}\right)^{T-t} \frac{\Delta E(CF_{iT})}{\text{MktCap}_{it-1}} = \sum_{j=1}^{J}\gamma_j U\Delta\text{AccP}_{jit} + \sum_{k=1}^{K}\beta_k U\Delta\text{BrandAsset}_{kit} + \varepsilon_{it},$$

where $U\Delta AccP_{it}$ is the unanticipated change in accounting performance measure j and $U\Delta BrandAsset_{kit}$ is the unanticipated change in brand asset k. Equation 4 provides the basic framework for assessing the information content of brand asset components: Which brand components do the financial markets believe contain information, separate from that reflected in contemporaneous accounting performance measures, that is indicative of the future performance of the firm?

The coefficients γ_j are the accounting performance response coefficients. They depict the effect of unanticipated changes in accounting measures (i.e., an earnings shock) on stock return. The link between unanticipated measures of accounting performance (in particular, earnings) and firm valuation has been extensively studied in accounting research (Kothari 2001).

Coefficients β_k depict the direct effect of unanticipated changes in the brand asset on stock returns. Significant values for β_k would imply that the brand asset measure provides incremental information to accounting performance in explaining financial market value. The null hypothesis is that $\beta_1 = \beta_2 = \ldots = \beta_k = 0$, which would imply that brand assets have no "incremental" information content to accounting measures. That is, the financial markets perceive the brand measures as providing no information about future earnings beyond that reflected in current-term earnings. The brand asset could still affect financial performance to the extent that it affects current-period earnings. In this case, the brand measure would have a significant bivariate association with stock return, but not a multivariate association.

Stock Return Response Modeling Versus Event Study Analysis

The methodology we use relies on much the same theoretical foundations as event study methods, but it differs on two important aspects. Both approaches build on the efficient markets hypothesis, and they both assess the stock return reaction to unanticipated events. The efficient markets hypothesis posits that a firm's valuation is an unbiased expectation of the sum of its discounted future cash flows, given the current information set available to investors. Without the efficient markets hypothesis, both research methodologies assess the effect of new information on investors' expectations of discounted future cash flows. Under the efficient markets hypothesis, this effect is also an unbiased estimate of actual discounted future cash flows.

The first fundamental distinction between event studies and our approach is that an event study assesses the stock market reaction to a specific, well-defined, discrete "unanticipated" event (or news release) occurring on a known date. Conversely, stock return response modeling assesses the stock market reaction to a nondiscreet continuous process over time (more precisely, to the "unanticipated" portion of this continuous process). Event studies typically consider only a short time frame around the event (e.g., days), whereas the stock return response modeling method allows for the study of processes that evolve over a longer time frame (i.e., months or years). For example, changes in brand perceptions may not be isolated to discrete events; rather, they may evolve over an extended period.

This distinction leads to a second fundamental difference—namely, a different interpretation of results. Event studies are designed as a natural experiment in which postevent behavior of the stock price is tested relative to the expected behavior (with expectations formed according to its preevent behavior). Thus, any significant findings are typically interpreted as being caused by the specific event studied. The interpretation in the stock return response modeling is not necessarily causal. Response modeling does not assess whether financial market participants use changes in a specific measure to update their expectations of future cash flows. Rather, the analysis assesses whether the financial markets react to information that is reflected in a particular measure.

RELATED PREVIOUS RESEARCH

Our study has commonalities with those of Aaker and Jacobson (1994, 2001b) and Barth and colleagues (1998). All three studies link a brand asset measure (or a component of the brand asset) to stock returns. Each study attempts to determine whether the measure provides incremental explanatory power to accounting performance measures in explaining stock returns.

Aaker and Jacobson (1994) used the EquiTrend database of Total Research Corporation (now part of Harris Interactive) to assess the information content of perceived quality and salience. These two dimensions formed the basis for the brand equity measure that EquiTrend proposed at the time. The analysis was based on data for 34 consumer product firms for the three-year period from 1990 to 1992 (i.e., 102 observations). Aaker and Jacobson found that perceived quality provided incremental explanatory power to earnings in explaining stock returns. Salience did not have a significant effect. Mizik and Jacobson (2004) extended the study to include additional firms and periods and found similar results.

Barth and colleagues (1998) assessed the information content of a brand equity measure generated by Financial World and a sample of 183 firms with data for some or all of the 1992–1996 period (404 pooled cross-sectional time-series observations). To form the brand asset measure, Financial World first assumes that earnings in excess of a 5% pretax return on capital are brand-induced earnings. Then, Financial World multiplies this figure by a "brand strength" factor to obtain brand value. Barth and colleagues found that the Financial World brand equity measure provides incremental information to that depicted in size-adjusted net income in explaining stock returns.

Aaker and Jacobson (2001b) investigated the information content of a brand attitude measure supplied by Techtel Corporation. They used quarterly data for 11 high-technology firms that had data available for all or some of the period 1988 (fourth quarter) through 1996 (fourth quarter) (206 observations). They found that changes in brand attitude were significantly related to stock returns. They explained this association by reporting that lagged brand attitude was significantly related to changes in return on equity. As such, the association between brand attitude and stock returns was interpreted as stemming from the stock market participants' anticipation and realization that brand equity leads return on equity.

Our study differs from this previous work most notably in that it is a more comprehensive analysis of brand asset components and their impact on financial performance. We assess the information content of a multitude of brand asset components. That is, whereas previous research has focused on aggregate measures of brand asset or one of the brand asset components, our study differs in terms of dimensionality of our brand asset measures and our ability to isolate the sources of potential effects. Aaker and Jacobson (1994, 2001b) find significant effects for one brand component—namely, perceived quality and attitude toward the brand, respectively. It is unclear which other dimensions have information content and whether their inclusion in analysis alters findings. Because brand asset components are likely to be correlated, bivariate analysis runs the risk of omitted variable bias. A limitation of analyses using the Financial World brand measure is that it is unclear which of its brand strength factors making up its earnings multiplier are inducing its association with stock return. The Financial World approach has also been criticized for the subjective manner in which the components making up the multiplier are calculated (Fernandez 2001). A particular concern is whether movements in stock price lead the analyst who is making these calculations to alter the brand strength factors. As such, it is unclear what underlies the information content of the Financial World measure. By assessing a host of brand attributes, we can assess which, if any, of these attributes provide incremental information content to accounting measures in explaining financial market performance.

DATA AND MEASURES

We combined data from four different sources to compile the data set used in our analysis. Table 2 summarizes the data sources and data items used. We obtained measures of brand perceptions and attitudes from the Y&B BAV database. The University of Chicago's Center for Research in Security Prices (CRSP) database provided stock returns information. Standard & Poor's COMPUSTAT database contained the information we used to construct accounting performance measures. Thomson Financial I/B/E/S database was the source of analysts' earnings-per-share (EPS) forecasts data we used in the sensitivity analysis. In our study, we use two measures of accounting performance—namely, return on assets (ROA) and sales. For the brand asset measures, we focus on the five pillars of the Y&R BAV model. However, we also undertake factor analysis on additional customer mind-set brand measures and assess whether these other dimensions have incremental information content or whether their inclusion in analysis alters conclusions about the five pillars of the BAV model.

Y&R Brand Metrics

Since 1993, Y&R's BAV initiative has undertaken large-scale surveys of consumers regarding perceptions of brands on a host of different brand metrics. The BAV survey and a monetary incentive are mailed to members of a large rotating consumer panel, which is balanced in terms of age, gender, and region. On average, 10,000 surveys are sent out in each U.S. data collection wave, and approximately 66% of them are completed and returned. Approximately 2400 unique brands are included in each data collection wave, and every respondent evaluates a subset (a cell) of approximately 120 brands. Large brands are included in multiple cells and, as such, have higher respondent bases than small brands. To date, Y&R has invested more than $100 million to support the BAV initiative.

The frequency of data collection has not been constant and has increased over time. We make use of surveys undertaken in 1993, 1997, 1999, 2000, 2001, 2002, 2003, and 2004 (i.e., eight waves). Table 3 presents the list of data collection waves with the corresponding calendar dates, which vary in time intervals from 4 to 14 quarters. As such, rather than having access to data at, for example, times t and t + 1, we have data for waves w and w + 1, with unequally spaced time between waves. Therefore, our models need to be expressed in terms of wave w rather than time t. For example, Equation 4 needs to be expressed as follows:

$$\text{StkRet}_{iw} = \text{Eret}_{iw} + \sum_{j=1}^{J} \gamma_j \text{U}\Delta\text{AccP}_{jiw} + \sum_{k=1}^{K} \beta_k \text{U}\Delta\text{BrandAsset}_{kiw} + \varepsilon_{iw}. \quad (5)$$

We restrict our analysis to "monobrand" publicly traded firms (i.e., firms in which a single brand represents the bulk

Table 2

DATA SOURCES AND DATA ITEMS

Data Source	*Measures*	*Frequency of Data Collection*
Y&R BAV database	BAV survey data: U.S. population brand perceptions	Waves (Table 3 provides specific calendar dates of BAV data collection)
CRSP database	Stock returns	Monthly holding period stock returns are accrued to line up with the BAV data collection waves
COMPUSTAT quarterly database	Operating income Total assets Sales	Quarterly accounting data Sales data are accrued to line up with the Y&R data collection waves Unanticipated ROA data are accrued to line up with the Y&R data collection waves
Thomson Financial I/B/E/S database	Analyst EPS Forecasts Actual EPS	Quarterly forecast and actual EPS data are accrued to line up with the Y&R data collection waves

Table 3
BRAND METRICS DATA TIME LINE

Data Collection Wave	*Period*	*Number of Observations*
1	3rd quarter 1993	117
2	1st quarter 1997	186
3	2nd quarter 1999	209
4	4th quarter 2000	209
5	4th quarter 2001	265
6	4th quarter 2002	270
7	4th quarter 2003	265
8	4th quarter 2004	257
Total		1778

Notes: This table presents the timeline of the Y&R BAV brand metrics data used in our study and the number of monobrand publicly traded firms we were able to identify in each wave.

of the firm's business). We identified 275 of these monobrands in the Y&R surveys. These firms include, for example, Starbucks, IBM, Wal-Mart, AOL, Yahoo, and Martha Stewart Living Omnimedia. Customer mind-set measures for these brands are available for all or some of the eight survey waves.

Because BAV metrics are collected on different scales (seven-point versus percentage of respondents), we z-standardize each of the measures to allow for comparability of coefficients. Figure 1 shows the behavior of the five brand asset pillars for a few of the brands in our analysis. It highlights both differences among brands and changes in brand attributes over time. For example, for Starbucks, there is an overall increase over time for each of the brand asset dimensions and a high level of differentiation. Conversely, IBM shows a decline for all attributes, with the most pronounced declines coming in terms of energy and differentiation. AOL shows a somewhat similar pattern to that of IBM, but the level of its brand components is lower than those of IBM. Yahoo also shows a drop in energy from its peak in 2000, but it differs from AOL and IBM in that it exhibits an increase in knowledge, relevance, and esteem over time. The behavior of the brand dimensions for Martha Stewart Living highlights how issues associated with Stewart's sales of ImClone stock in 2002 affected brand attributes. Declines in Wal-Mart attributes between 2002 and 2003 coincide with discrimination lawsuits and heightened publicity over its labor practices. These brand profiles and dynamics help illustrate that firms differ in their brand dimensions and exhibit changes in these dimensions for various reasons.

Accounting Performance

Next, we used the primary, full coverage, and research COMPUSTAT databases to obtain quarterly accounting data for 1988–2004. Our use of quarterly data enables us to line up the accounting measures to correspond with the Y&R data collection waves. We make use of data before the first survey to allow for more data points for estimation of the time-series model used to calculate our estimates of unexpected accounting performance. For our accounting performance measures, we use (operating income before depreciation/assets) and sales. Both measures (or, more precisely, the unanticipated components of these measures) have been shown in prior research to have information content (Kothari 2001).

Stock Return

Finally, we accessed the CRSP data files to obtain monthly stock returns data for our monobrand firms for the eight survey waves. The use of monthly returns data enables us to line up the measures of stock returns to correspond with the Y&R data collection waves. That is, we calculate continuously compounded stock return for firm and wave as $StkRet_{iw} = \log[\Pi^{l}_{m=k}(1 + ret_{im})]$, where $StkRet_{iw}$ is firm i's stock return between wave (w – 1) and wave w, ret_{im} is the holding period return for firm i in month m, k is the first month after wave (w – 1) date, and l is the last month in the quarter when the wave w survey takes place.

Stock return is influenced by economywide factors and by firm-specific (e.g., risk) characteristics. These effects need to be controlled for both to reduce potential omitted variable bias and to increase power in the analysis. To capture expected return, we include time-specific intercepts and firm characteristics: lagged size, as modeled by log(Market $Value_{iw-1}$), and lagged book-to-market equity, as modeled by the log(Book $Value_{iw-1}$/Market $Value_{iw-1}$), whose effects we allow to vary by time. As such, Equation 5 becomes

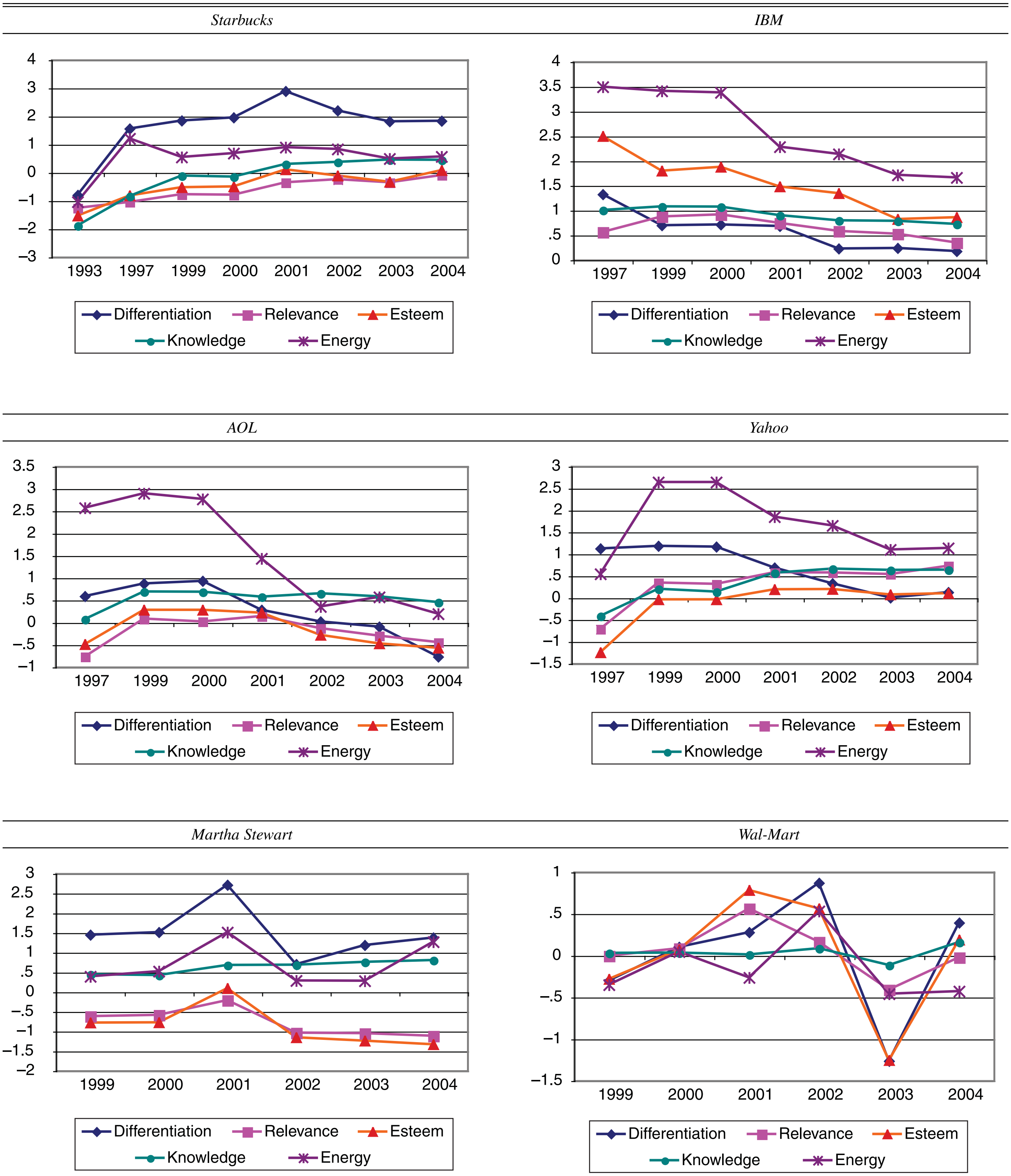
$$(6)\quad StkRet_{iw} = \sum_{j=1}^{J} \gamma_j U\Delta AccP_{jiw} + \sum_{k=1}^{K} \beta_k\ U\Delta BrandAsset_{kiw} + \sum_{w=1}^{W} \alpha_{1w} \times Wave_w + \sum_{w=1}^{W} (\alpha_{2t} \times \log\ MV_{iw-1} + \alpha_{3t} \times \log\ BMV_{iw-1}) \times Wave_w + \varepsilon_{iw}.$$

Different interpretations have been attached to Fama and French's (1993) empirical findings that the cross-sectional pattern of expected returns can be explained by two characteristics—namely, lagged size and book-to-market. Fama and French (1993, 1996) suggest that characteristics serve as a proxy for risk factors. They advocate a three-factor model that uses the market portfolio and mimicking portfolios for factors related to size and book-to-market to describe returns. An alternative interpretation (Daniel and Titman 1997) is that asset pricing is directly related to the size and book-to-market characteristics. We do not opine whether our characteristics reflect risk differences (consistent with Fama and French) or value characteristics (consistent with Daniel and Titman). However, we undertake a sensitivity analysis in which we use excess stock return based on the standard Fama–French three-factor model. None of our conclusions are affected; the estimated coefficients for the brand dimensions are in extremely close correspondence between the different approaches.

Unanticipated Measures

Because the stock market reacts only to unexpected information, explanatory factors in stock return response models should reflect only unanticipated changes in the measures.

Figure 1
EVOLUTION OF BRAND ASSET COMPONENTS OVER TIME FOR SELECTED BRANDS



Notes: Brand asset measures are z-standardized by component within our sample rather than raw scores. The starting year for the brand components differs across brands because the firms included in Y&R surveys have changed over time.

Typically, time-series forecasts are used as a proxy measure of market expectations, and the residuals from a time-series model serve as the estimates of the unanticipated components of the series. We test the dynamic properties of the brand asset components and find that brand asset dynamics are well represented by a random walk. As such, we use the difference in the brand asset measures between waves as the measure of the unanticipated components; that is, for each of the k brand asset components, we compute $U\Delta BrandAsset_{kiw} = BrandAsset_{kiw} - BrandAsset_{kiw-1}$. We also find that log of sales between waves is well approximated by a random walk. As such, our measure of unanticipated sales is $U\Delta Sales_{iw} = \log Sales_{iw} - \log Sales_{iw-1}$, which is simply a measure of sales growth over the wave.[2]

We find that quarterly accounting performance is best approximated by a fixed-effect, fourth-order autoregressive model adjusted for time-specific effects. That is, we use a model of the following form:

$$\begin{aligned}(7)\quad (ROA_{iq} - \overline{ROA}_q) = \alpha_i &+ \phi_1 \times (ROA_{iq-1} - \overline{ROA}_{q-1}) \\ &+ \phi_2 \times (ROA_{iq-2} - \overline{ROA}_{q-2}) \\ &+ \phi_3 \times (ROA_{iq-3} - \overline{ROA}_{q-3}) \\ &+ \phi_4 \times (ROA_{iq-4} - \overline{ROA}_{q-4}) + \varepsilon_{iq},\end{aligned}$$

where ROA_{iq} is the value of the accounting performance series for firm i in quarter q; ROA_{iq-1}, ROA_{iq-2}, ROA_{iq-3}, and ROA_{iq-4} are its lagged values; and $\overline{ROA}_q$ is the mean for ROA_{iq} series in quarter q. Equation 7 indicates that the deviation of a series from the economywide mean depends on a firm-specific amount and the extent to which the series deviated from the economywide mean during each of the previous four quarters. The coefficient α_i is the firm-specific constant, and ϕ_k is the kth-order autoregressive coefficient depicting the persistence of the series.

To obtain estimates of the parameters α_i and ϕ_1, ϕ_2, ϕ_3, and ϕ_4, we use the methodology that Anderson and Hsiao (1982) outline. That is, we take first differences of the data to remove the fixed effect and then obtain an instrumental variable estimate of $[(AccP_{iq-1} - \overline{AccP}_{q-1}) - (AccP_{iq-2} - \overline{AccP}_{q-2})]$ using $(AccP_{iq-2} - \overline{AccP}_{q-2})$ and $(AccP_{iq-3} - \overline{AccP}_{q-3})$ as instruments. After obtaining estimates of $\hat{\phi}_1$, $\hat{\phi}_2, \hat{\phi}_3$, and $\hat{\phi}_4$, we can calculate $\hat{\alpha}_i$ as the mean of $(AccP_{iq} - \overline{AccP}_q) - \Sigma_{k=1}^{4}\hat{\phi}_k \times (AccP_{iq-k} - \overline{AccP}_{q-k})$. This process provides us the coefficient estimates that enable us to calculate the unanticipated component ε_{iq}. Table 4 reports the estimation results. The dominant element in the model is the fourth-order coefficient of .575, which reflects the quarterly seasonality common across firms.

We use ε_{iq} as our measure of the unanticipated component of accounting performance for firm i in quarter q. For a given wave w, $U\Delta ROA_{iw} = \Sigma_{q=k}^{l}\varepsilon_{iq}$, where $U\Delta ROA_{iw}$ is the cumulative unanticipated change in the accounting performance between wave (w – 1) and wave w for firm i, k is the first quarter after wave (w – 1) date, and *l* is the quarter when the wave w survey takes place. That is, we use the sum of the quarterly residuals within a given wave as the estimate of the unanticipated component of ROA for that wave.

An alternative approach is to use analysts' forecasts instead of time-series forecasts and use the difference between the actual and the forecasted earnings as a measure of unanticipated earnings. As a sensitivity check, we obtained consensus earnings forecasts from the I/B/E/S database and replicated our analyses. As we subsequently report, our results are robust to alternative specifications of unanticipated earnings measures.

Table 4
AR(4) FIXED-EFFECTS MODEL

$$\begin{aligned}(ROA_{iq} - \overline{AccP}_q) = \alpha_i &+ \phi_1 \times (ROA_{iq-1} - \overline{AccP}_{q-1}) \\ &+ \phi_2 \times (ROA_{iq-2} - \overline{AccP}_{q-2}) \\ &+ \phi_3 \times (ROA_{iq-3} - \overline{AccP}_{q-3}) \\ &+ \phi_4 \times (ROA_{iq-4} - \overline{AccP}_{q-4}) + \varepsilon_{iq}\end{aligned}$$

		Parameter Estimate	*SE*	*t-Statistic*
	ϕ_1	.122	(.027)	[4.44]
	ϕ_2	.002	(.017)	[.10]
	ϕ_3	–.039	(.012)	[–3.23]
	ϕ_4	.583	(.008)	[77.26]
Number of observations	10,888			
F-statistic	2263.91			

Notes: Results of estimating the forecast model for accounting performance. To obtain estimate of the parameters ϕ, we use Anderson and Hsiao's (1982) procedure to estimate autoregressive coefficients in the presence of a fixed effect. That is, we take first differences of the data to remove the fixed effect and then form an instrumental variable estimate of $[(X_{iq-1} - \overline{X}_{q-1}) - (X_{iq-2} - \overline{X}_{q-2})]$ using $(X_{iq-2} - \overline{X}_{q-2})$ and $(X_{iq-3} - \overline{X}_{q-3})$ as instruments. This procedure generates consistent (i.e., asymptotically unbiased) estimates of the parameter ϕ_1.

The Merged Brand, Stock Return, and Accounting Data

Merging the three data sets yielded a pooled cross-sectional time-series panel of 890 observations. We do not have complete data available for all firms for all the years in our sample. To minimize any potential survivorship bias and to preserve the degrees of freedom, we did not impose the restriction of only including firms with a complete data set in the sample. As such, the sample size varies across waves.

Table 5 provides bivariate correlations for the variables. A majority of the bivariate correlations are significant. Changes in brand measures, accounting performance, and stock returns tend to move in the same direction, which is consistent with all the measures reflecting changes in the value of the firm. At issue is whether differential information is contained (1) for the brand asset components and accounting performance and (2) among the brand asset components. Are the potential effects of brand assets on stock return being fully reflected in accounting performance, or do they contain incremental information to accounting performance in explaining financial returns? Our empirical analysis addresses this issue.

[2]As a sensitivity test, we also assessed the stock market's beliefs about the dynamic properties of the brand asset dimensions and log sales by estimating a stock return response model that included both current and lagged values of the series. Consistent with the financial markets perceiving information reflected in these series as following a random walk, we could not reject the hypothesis that the coefficient for the lag of the series was of the same magnitude as but of the opposite sign from the coefficient for current value of the series.

Table 5

BRAND METRICS CORRELATIONS WITH FINANCIAL PERFORMANCE MEASURES

	Correlations							
	Stock Return	*UΔROA*	*Sales Growth*	*ΔDifferentiation*	*ΔRelevance*	*ΔEsteem*	*ΔKnowledge*	*ΔEnergy*
Stock return	1 1763							
UΔROA	.341 (.000) 1206	1 1212						
Sales growth	.234 (.000) 1581	.204 (.000) 1200	1 1603					
ΔDifferentiation	.033 (.222) 1361	.042 (.190) 956	.032 (.263) 1248	1 1496				
ΔRelevance	.078 (.004) 1361	.046 (.149) 956	.095 (.001) 1248	.187 (.000) 1496	1 1496			
ΔEsteem	.088 (.001) 1361	.111 (.001) 956	.107 (.000) 1248	.432 (.000) 1496	.502 (.000) 1496	1 1496		
ΔKnowledge	.136 (.000) 1361	.041 (.202) 956	.172 (.000) 1248	.081 (.002) 1496	.4057 (.000) 1496	.306 (.000) 1496	1 1496	
ΔEnergy	.171 (.000) 1361	.042 (.196) 956	.055 (.054) 1248	.393 (.000) 1496	.122 (.000) 1496	.415 (.000) 1496	.08 (.001) 1496	1 1496

Notes: This table presents the correlations of the changes in the Y&R BAV brand metrics data with stock returns, unanticipated ROA, and sales growth for the set of monobrand publicly traded firms we were able to identify. We present correlations as Pearson correlation coefficients, (significance), and number of observations.

The correlation among brand asset components stems from at least three possible sources. First, the intercomponent correlation might be due to a "halo" effect. When one component of a brand changes, this may affect perceptions of other components as well. Second, when management changes a brand, it might not focus on just one component. Rather, strategic changes may be undertaken across several components. Third, changes in one component might influence changes in other components as well; that is, the components of the brand asset may be causally interrelated. For these and other reasons, we expect and observe correlation among the brand asset components. This correlation still allows for unbiased estimates of the coefficients and their standard errors, but it may result in standard errors of a larger size that may make it difficult to isolate and separate out individual effects. The relatively large number of observations in our study help diminish this problem.

ESTIMATION METHODOLOGY: AN ERROR COMPONENTS MODEL WITH HETEROSKEDASTIC DISTURBANCES

Least squares estimation of Equation 6 will provide unbiased estimates of the coefficients. However, the estimates may not be asymptotically efficient. Thus, we relaxed some of the assumptions in the classical framework to allow for a more flexible error structure and more efficient estimation. Specifically, we made use of generalized least squares (GLS) estimation for the following two reasons: First, we have multiple observations by firm, which suggests the appropriateness of a random-effects error component model; second, the variance of the error might differ by period. This suggests that the error term in Equation 7 will take the following form:

$$\varepsilon_{iw} = \mu_i + \nu_{iw}, \text{ where } \mu_i \sim (0, \sigma^2_\mu) \text{ and } \nu_{iw} \sim (0, \sigma^2_w).$$

The variance term σ^2_μ reflects the multiple observations per firm, which we treat as homoskedastic. The main departure from the standard random-effects error component model is that rather than assuming homoskedasticity, we allow for a heteroskedastic disturbance based on differential variance across waves (i.e., σ^2_w varies by wave).

Several different estimation procedures have been advanced, which typically yield similar but not identical finite sample estimates. For example, following Baltagi and Griffin (1988), we make use of a two-step procedure to construct a feasible GLS (FGLS) estimator that is based on estimation of heteroskedasticity under repeated observations (Oberhofer and Kmenta 1974). The basic premise underlying the approach is that least squares estimation provides consistent estimates of the regression coefficients, which in turn generates residuals that have the same asymptotic properties as those computed from the true disturbances (Greene 2003). As such, we use the ordinary least squares residuals as the basis for forming an estimate of the variance–covariance matrix, which we then incorporate in the second phase, which is the conventional error components estimation. The FGLS estimator based on this estimated matrix has the same asymptotic properties as the GLS estimator.[3]

EMPIRICAL ANALYSIS

To assess the information content of the brand asset components measure, we regress stock returns on unanticipated ROA, unanticipated sales (i.e., sales growth), and the change in the brand asset components, controlling for expected return with annual dummy variables and firm-specific risk characteristics. Equation 6.1 in Table 6 reports the results of this estimation.

The significant estimated coefficient for unanticipated ROA (3.14) indicates that the financial markets react favorably to information contained in the measure. The information contained in $U\Delta ROA$ induces stock market participants to update their expectations about the firm's discounted future earnings and revise stock price accordingly. This effect is consistent with an extensive literature in accounting that has documented the information content of size-adjusted earnings measures. Indeed, the point estimate is in line with estimates reported in previous research. For example, Kormendi and Lipe (1987) report an estimate of 3.38. When a shock to ROA occurs, investors view it as containing information not only about changes in current-term results but also about future-term prospects. The longer the earnings shock is expected to persist into the future, the greater the weight the financial markets give to its implications on future performance.

However, the financial markets do not restrict their formulation of expected discounted future cash flows to ROA. Rather, other accounting measures may also provide signals as to both current- and future-term performance. We find that sales growth provides incremental explanatory power to unanticipated ROA in explaining stock return. The estimated coefficient of .405 is significant ($p < .01$). Here, too, the estimated response coefficient is in line with that reported in previous research. For example, Jacobson and Aaker (1993) report an estimated sales growth response coefficient of .38.

The central question of our analysis is which, if any, of the Y&R brand asset pillars provide incremental information content to accounting measures in explaining firm stock market performance. Equation 6.1 in Table 6 reports that two brand asset components, relevance and energy, have positive (.082 and .060, respectively) and statistically significant effects on stock return.[4] As such, the financial markets view information contained in changes in relevance and energy as providing a signal about the future-term prospects of the firm, which is incremental to that reflected in the accounting performance measures.

The three other Y&R brand asset dimensions—differentiation, esteem, and knowledge—have statistically insignificant effects. Not only are each of the individual coefficient estimates insignificant, but the joint hypothesis that the coefficients for these three dimensions are zero also cannot be rejected; that is, the F-statistic of 1.08 is well below the .05 critical value of 2.60. Furthermore, as Equation 6.2 in Table 6 shows, when the effects of these three brand dimensions are restricted to zero, the effects of the other variables in the model remain much the same.

In terms of relative explanatory power, the standardized regression coefficients are .32 for unanticipated ROA and .18 for sales growth. They are .07 for relevance and .08 for energy. As such, brand asset measures are not substitutes for accounting performance measures or reflective of the firm's future financial prospects, but they reflect incremental information that has a significant impact on stock returns. Furthermore, this impact is consistent over our sample period. For example, a Chow test on Equation 6.1 in Table 6 cannot reject the hypothesis that the effects are the same before 2000 and after 2000. In particular, the effect of energy is remarkably stable. The estimated coefficient is .062 for the pre-2000 waves and .060 for the post-2000 waves.

Analysis using alternative excess return measures generates results in close correspondence to those we report in Table 4. For example, the estimated brand effects for Equation 6.1 in Table 6, which makes use of excess returns from a three-factor Fama–French model, are as follows: differentiation (–.20, t-statistic = –1.11), relevance (.11, t-statistic = 2.94), esteem (.001, t-statistic = .04), knowledge (–.04, t-statistic = –.67), and energy (.05, t-statistic = 2.81).

The Role of Alternative Accounting Performance Measures and Analysts' Forecasts

Equation 6.1 in Table 6 indicates that market participants view information contained in relevance and energy as providing useful, nonoverlapping information to size-adjusted operating income and sales growth in explaining the financial prospects of the firm. It is possible that an alternative accounting measure better depicts both current- and future-term business performance and alters conclusions about the incremental information content of the brand assets.

The most commonly followed accounting performance measure is EPS, which is based on the net income metric. As such, the financial markets might place more weight on this measure than on the one based on operating income. Conversely, the financial market might place less weight on earnings because net income is more subject to earnings management and, as such, may be less indicative of actual firm performance. The main advantage of using an EPS-based measure is that it is systematically tracked and forecasted by analysts. As such, we can form unanticipated EPS measure based on the difference between analysts' forecasts (as opposed to a time-series forecast) and the actual value. We obtained analysts' EPS forecasts data from the Thomson Financial I/B/E/S database.

Equations 6.3 and 6.4 in Table 6 report the results of analyses, with the analysts-based estimates of EPS replacing the time-series-based estimate. The results of these analyses are in close correspondence to those in Equations

[3]Our model can also be viewed as a seemingly unrelated equations specification by wave with a constraint that the coefficients are constant across the waves. Empirically, for the analysis in this study, we find results based on ordinary least squares estimation to be in close correspondence to those based on FGLS estimation.

[4]Because the brand variables are sample means, the measure contains sampling error as an estimate of the population mean, which affects the standard errors in the stock return response model. The same is true for the unanticipated ROA variables used in the response modeling (it is a residual from an estimated regression model). However, if we take into account that the imputed regressors are measured with sampling error (Mizik and Jacobson 2007; Nijs, Srinivasan, and Pauwels 2006), the findings are in close correspondence to those reported in Table 6.

Table 6

THE INFORMATION CONTENT OF BRAND ASSET DIMENSIONS

	Equation 6.1	*Equation 6.2*	*Equation 6.3*	*Equation 6.4*	*Equation 6.5*	*Equation 6.6*
UΔROA (time-series residual)	3.14** [12.35]	3.13** [12.30]			3.11** [11.52]	
UΔEPS (analyst forecast residual)			3.71** [10.78]	3.71** [10.79]		3.75** [10.36]
Sales growth	.405** [6.27]	.415** [6.50]	.594** [8.55]	.595** [8.62]	.472** [6.61]	.592** [8.17]
ΔDifferentiation	–.026 [–1.40]		–.010 [–.61]		–.023 [–1.09]	–.013 [–.63]
ΔRelevance	.082* [2.02]	.094** [2.81]	.077* [2.11]	.079* [2.53]	.084* [1.98]	.081* [2.01]
ΔEsteem	–.013 [–.34]		.024 [.71]		–.030 [–.60]	–.007 [–.13]
ΔKnowledge	.082 [1.34]		–.025 [.46]		.100 [1.54]	–.014 [–.24]
ΔEnergy	.060** [3.05]	.052** [2.84]	.048** [2.57]	.047** [2.76]	.051* [2.24]	.054* [2.39]
Factor 1					.002 [.155]	.0076 [.48]
Factor 2					.018 [1.60]	.016 [1.37]
Factor 3					.00009 [.008]	.0025 [.21]
Factor 4					–.003 [–.30]	.0055 [.50]
Factor 5					.011 [1.01]	.0061 [.56]
Factor 6					–.019 [–1.66]	–.019 [–1.75]
Factor 7					.015 [1.41]	.013 [1.21]
Factor 8					.005 [.47]	–.003 [–.28]
Number of observations	890	890	988	988	801	940
Adjusted R^2	.31	.31	.28	.28	.28	.26

*Significant at $p < .05$.

**Significant at $p < .01$.

Notes: Dependent variable = stock return. Equations 6.1–6.6 also include (1) annual dummy variables to capture the effects of economywide factors and (2) annual effects for log(Market Value_{iw-1}) and log(Book Value/Market Value_{iw-1}) to capture firm-specific (e.g., risk) factors (i.e., these effects are allowed to vary by wave); t-statistics appear in brackets.

6.1 and 6.2. Some differences, albeit small, exist across the accounting performance response coefficients, which has some potential implications for other types of analyses.[5] These differences have no impact on our analysis with respect to the information content of brand asset dimen-

[5]Specifically, because COMPUSTAT has fewer firms reporting operating income than net income, the sample of observations we used in Equation 6.3 differs from that in Equation 6.1. As such, we had more cross-sectional observations for estimation of Equations 6.3 and 6.4 than Equations 6.1 and 6.2. Because of this difference, although we can conclude that the results are similar, we cannot directly compare the information content of unanticipated ROA with unanticipated EPS. However, we can do this by restricting the sample of observations to be the same. In doing so, we find that our unanticipated ROA has more information content (i.e., exhibits a greater association with stock return) than unanticipated EPS. The reason for this is not necessarily related to the predictive performance of time-series models compared with analysts' forecasts, which prior research has documented as comparable (e.g., Cheng, Hopwood, and McKeown 1992; Fried and Givoly 1982). Rather, the difference stems from the information content of operating income compared with net income. At least for the sample of firms used in our analysis, the financial markets view operating income as more informative than net income.

sions. In particular, relevance and energy have positive and statistically significant effects. Differentiation, esteem, and knowledge have nonsignificant effects. Further analysis based on other alternative earnings measures (e.g., net income, earnings before extraordinary items) also supports this finding. Our conclusions as to the information content of the Y&R brand pillars are invariant to the choice of alternative size-adjusted earnings measures.

The Role of Other Brand Attributes

As part of its survey, Y&R obtains information not only about brand perceptions related to the five pillars but also about other customer mind-set measures. Although Y&R surveys respondents on various different brand perceptions, since Wave 2, it has consistently tracked an additional 37 brand attributes (see Table 7), in addition to those that constitute the brand pillar measures.[6] Thus, another research question is whether any of these other brand attributes provide incremental information content to accounting measures and to brand relevance and energy. Furthermore, perhaps their inclusion in the model could alter conclusions regarding the role of differentiation, esteem, or knowledge.

To assess the role of these other brand perceptions, we undertook factor analysis of first differences in these 37 additional brand attributes. Working with first differences, as opposed to levels of the series, removes common brand-wide correlation across attributes and allows for a clearer interpretation of the factors. Making use of principal components analysis and a Varimax rotation, we find eight factors with eigenvalues greater than 1.00. Table 7 provides a list of these factors. Some of the factors we identify (e.g., sophisticated) are similar to the five brand personality factors that Aaker (1997) identifies. The other factors have a close correspondence with some of the "facets" that went into Aaker's factors.

We then included the factors uncovered from this analysis into our stock return response model. Equations 6.5 and 6.6 in Table 6 report the results of these expanded analyses. We find that none of the eight factors provide incremental information content. Each of the factors is individually statistically insignificant, and the hypothesis that they are jointly zero cannot be rejected. As a further sensitivity analysis, we allowed for a nine-factor solution and seven-factor solution. Again, we find no evidence of an additional brand dimension providing incremental information content.

Assessing Potential Marketplace Inefficiencies: Differentiation Anomaly

Next, we undertook several steps to assess potential marketplace anomalies. In contrast to the efficient markets hypothesis, there is a body of work that indicates that financial markets may be slow to incorporate the financial implications of strategic decisions (e.g., Eberhart, Maxwell, and Siddique 2004). Daniel and Titman (2003, p. 7) summarize this literature stream by concluding that "there is considerable evidence that investors under-react to information conveyed in management decisions." Rather than immediately impounding their implications into the price of the stock, this research suggests that in some instances, it may take time for the market to price some types of strategic decisions correctly.

Notably, although we observe little bivariate correlation between differentiation and stock return, unanticipated ROA, or sales growth, we find that unanticipated ROA is significantly correlated with the lagged change in differentiation. This lagged effect suggests that the effects of changes in differentiation are not fully reflected within the

[6]Other brand attributes (e.g., perceptions of corporate social responsibility) are also part of the BAV survey, but they have not been tracked for as long a period or as consistently across the waves. As such, we restrict analysis here only to brand attributes that Y&R surveyed continuously from the second wave. A considerable drop-off in the number of additional variables occurs if only variables surveyed continuously since the first wave are used in the analysis.

Table 7

FACTOR ANALYSIS OF ADDITIONAL BRAND ATTRIBUTES

A: Brand Measures Used in the Factor Analysis

Arrogant	Authentic	Best brand	Carefree	Cares about customers
Charming	Daring	Different	Down to earth	Energetic
Friendly	Fun	Gaining in popularity	Glamorous	Good value
Healthy	Helpful	High performance	Intelligent	Kind
Obliging	Original	Prestigious	Progressive	Restrained
Rugged	Simple	Straightforward	Stylish	Tough
Traditional	Trendy	Trustworthy	Unapproachable	Up-to-date
Upper class	Worth more			

B: Factor Analysis Solution

Factor	*Attributes with Highest Item-to-Total Correlations*
1. Virtuous	Trustworthy, cares about customers, high performance
2. Personable	Kind, charming, fun
3. Classic	Traditional, original, authentic
4. Basic value	Good value, simple, down to earth
5. Sophisticated	Stylish, upper class, glamorous
6. Hip	Different, trendy, gaining in popularity
7. Durable	Rugged, tough
8. Haughty	Arrogant, unapproachable

current period but rather take time to manifest themselves in financial performance.

The existence of this lagged relationship (in the absence of changes in differentiation having a contemporaneous association with stock return) suggests a potential marketplace anomaly and a trading rule. The financial markets are not accounting for the lagged effect of differentiation on size-adjusted earnings at the time the change in differentiation occurs (i.e., differentiation does not have a significant effect in the stock return model). Rather, the financial markets react only when the effects of increased (decreased) differentiation have been realized in terms of greater (lower) operating income. As such, the trading rule would be to buy stocks that increased in differentiation and sell short stocks that decreased in differentiation. Then, for the subsequent year, based on the observed positive correlation between lagged changes in differentiation and UΔROA and the positive contemporaneous correlation between UΔROA and stock return, presumably stocks that had previously increased in differentiation would outperform those that decreased in differentiation.

To assess this trading rule, we first divided our sample firms into two groups for each wave on the basis of whether they had an increase or a decrease in differentiation the previous wave. We then considered the risk-adjusted stock return for the two groupings.[7] The difference in average stock returns between the two groups is .107 (t-statistic = 4.56). This difference stems from the fact that whereas firms with increases in differentiation during the previous wave (516 observations) had a mean risk-adjusted abnormal return of .059 (t-statistic = 3.57), firms with decreases in differentiation during the previous wave (507 observations) had a risk-adjusted abnormal return of –.048 (t-statistic = –2.89). This differential is evident across periods. For each of the six available waves of data, the firm grouping that increased in differentiation in the previous wave had a positive mean risk-adjusted abnormal stock return in the subsequent period. Conversely, for each of the six available waves of data, the firm grouping that decreased in differentiation in the previous wave had a negative mean risk-adjusted abnormal stock return in the subsequent period. This finding has two potential explanations; either the financial markets do not appreciate the impact of differentiation on future earnings, or they do not recognize that the change in differentiation took place. We expect this anomaly to disappear (i.e., changes in differentiation will have a contemporaneous association with stock return rather than a lagged association) as market participants become aware of it, recognize that changes in differentiation lead profitability, and begin to pay more attention to brand differentiation.

The market's failure to incorporate information appears isolated to the brand differentiation component. Equation 8.1 in Table 8 is a regression of stock return on dummy variables indicating whether the series (stock return, ROA, sales growth, differentiation, relevance, esteem, knowledge, and energy) experienced an increase or decrease in the previous period, after we control for expected return. Consistent with efficient markets (and the absence of a trading rule), the effects of the dummy variables for previous wave stock return, ROA, sales growth, relevance, esteem, knowledge, and energy are statistically insignificant. The market has already incorporated the effects of these changes in the previous period. This is not the case for differentiation. Consistent with the previous analysis, we find that the firms that had an increase in differentiation during the previous wave had stock return .119 higher than firms that had a decrease in differentiation during the previous wave. This difference is significant at the 1% level. Equation 8.2 replicates the Equation 8.1 analysis but replaces the dummy variable indicating that lagged ROA increased with a dummy variable indicating that the lagged difference between EPS expected by analysts and actual EPS is positive. Again, we obtain the same implications as those stemming for Equation 8.1. Namely, the market has already incorporated information reflected in all the variables

[7]The number of observations available for this analysis is 1023. It is greater than the number of observations for the tests reported in Table 6 (which we discuss subsequently) because accounting data were not required for this test.

Table 8

THE ROLE OF PRIOR WAVE OUTCOMES ON STOCK RETURN

	Equation 8.1	*Equation 8.2*
$d_{Stkr\ (w-1)>0}$	.0009	.023
	[.03]	[.84]
$d_{U\Delta ROA\ (w-1)>0}$	.012	
	[.44]	
$d_{U\Delta EPS\ (w-1)>0}$		.017
		[.62]
$d_{Sales\ Growth\ (w-1)>0}$	.005	–.005
	[.17]	[–.19]
$d_{\Delta Differentiation\ (w-1)>0}$	.119*	.088*
	[4.15]	[3.19]
$d_{\Delta Relevance\ (w-1)>0}$	–.046	–.039
	[–1.43]	[–1.25]
$d_{\Delta Esteem\ (w-1)>0}$	.031	.011
	[.95]	[.35]
$d_{\Delta Knowledge\ (w-1)>0}$	.026	.035
	[.89]	[1.23]
$d_{\Delta Energy\ (w-1)>0}$	.016	.048
	[.46]	[1.42]
Number of observations	733	831

*Significant at $p < .01$.

Notes: Dependent variable = stock return. Each equation also includes (1) annual dummy variables to capture the effects of economywide factors and (2) annual effects for log(Market Value$_{iw-1}$) and log(Book Value/Market Value$_{iw-1}$) to capture firm-specific (e.g., risk) factors (i.e., these effects are allowed to vary by wave); t-statistics appear in brackets.

Legend:

$d_{\Delta Differentiation\ (w-1)>0}$: dummy variable taking the value of 1 if change in differentiation in previous wave was greater than 0 and 0 if otherwise.

$d_{\Delta Relevance\ (w-1)>0}$: dummy variable taking the value of 1 if change in relevance in previous wave was greater than 0 and 0 if otherwise.

$d_{\Delta Esteem\ (w-1)>0}$: dummy variable taking the value of 1 if change in esteem in previous wave was greater than 0 and 0 if otherwise.

$d_{\Delta Knowledge(w-1)>0}$: dummy variable taking the value of 1 if change in knowledge in previous wave was greater than 0 and 0 if otherwise.

$d_{\Delta Energy(w-1)>0}$: dummy variable taking the value of 1 if change in energy in previous wave was greater than 0 and 0 if otherwise.

$d_{U\Delta ROA\ (w-1)>0}$: dummy variable taking the value of 1 if unanticipated ROA in previous wave was greater than 0 and 0 if otherwise.

$d_{U\Delta EPS\ (w-1)>0}$: dummy variable taking the value of 1 if unanticipated EPS in previous wave was greater than 0 and 0 if otherwise.

$d_{Sales\ Growth\ (w-1)>0}$: dummy variable taking the value of 1 if sales growth in previous wave was greater than 0 and 0 if otherwise.

$d_{Stkr\ (w-1)>0}$: dummy variable taking the value of 1 if risk adjusted stock return in previous wave was greater than 0 and 0 if otherwise.

except differentiation. The estimated stock return differential between firms that had an increase versus a decrease in differentiation is .088.

Whether this is indeed a potential marketplace inefficiency that gives rise to a trading rule or a difference stemming from other sources (e.g., unmeasured risk; Fama 1998) remains a topic for further research. Many reported market anomalies tend to be explained away by risk considerations or by explanations consistent with efficient markets. For example, Fama and French (1996) show that the often-cited overreaction anomaly that DeBondt and Thaler (1985) report vanishes in a three-factor risk model. However, as a sensitivity test, we reassessed the "differentiation anomaly" on the basis of an abnormal stock return measure obtained from a Fama–French three-factor model and found results in close correspondence to those reported in Table 8. For example, the equivalent of Equation 8.1 using the Fama–French three-factor abnormal returns yields a .098 stock return differential (t-statistic = 3.83) for firms with increased versus decreased differentiation. Still, issues related to the calculation of expected return make it prudent for us to report this apparent mispricing as an empirical observation in need of further analysis.

DISCUSSION

Causation

Our analysis documents that information contained in the Y&R brand asset measures is associated with stock return. Note that our analysis does not imply causation between changes in the Y&R brand asset measures and stock return. The financial markets are not reacting per se to Y&R announcements about changes in brand attributes. Indeed, Y&R treats the data as proprietary and does not release the data or make them publicly available. Because Y&R does not announce (or even release at a later date) the results from its surveys, event study methods, which require a specific announcement date to allow for the specification of an event window, are not appropriate for assessing the information content of Y&R data. Thus, our analysis shows that the financial markets do not react to Y&R data per se but rather to the information that the Y&R brand measures reflect.

A possibility exists that the observed associations stem not from the effect of brand information on stock return but rather from the effect of stock return on brand perceptions. That is, changes in stock price induce respondents to alter their perceptions of the brand. This issue has cast doubt on the informativeness of, for example, *Fortune*'s Corporate Reputation measure. Studies (e.g., Fryxell and Wang 1994) have shown that rather than information reflected in the measure causing changes in firm performance, it is changes in firm performance that affect the evaluation of firm reputation.

Several considerations run counter to this reverse causation hypothesis in our analysis.[8] The results on differentiation, which we find to lead stock return, cannot be explained by reverse causation. Because the future cannot cause the past, changes in contemporaneous stock price cannot cause changes in lagged differentiation. Then, our model includes unanticipated earnings (ROA) and sales growth. Because we control for firm accounting performance, the reverse causation argument requires respondents not only to react to changing financial developments but also to react to developments incremental to those reflected in accounting measures. This is a stretch. For example, we do not believe that brand relevance increases because respondents (who are consumers responding to specific questions about a brand attribute and not financial analysts focused on measuring brand value) recognize that the price of the stock has gone up more than what is dictated by the firm's accounting results. It is more likely that brand relevance increases because respondents believe that the brand has increased in its appropriateness for them (i.e., is more likely to be in their consideration set). Furthermore, if the association stemmed from positive developments affecting respondents' perceptions, we would expect the halo to influence all BAV brand dimensions equally or, at least, something else in addition to relevance and energy. In particular, we would posit that esteem would be most likely affected by positive developments (e.g., firms doing well would be more highly regarded). However, only relevance and energy exhibit significant contemporaneous associations. The differential effects we find for brand dimensions are inconsistent with a reverse causation argument.

Differentiation

At first glance, our analysis would appear to suggest that the Y&R differentiation measure was not tapping information related to financial performance. We observed little bivariate correlation between changes in differentiation and stock return, unanticipated ROA, or sales growth. However, additional analysis suggested something different. We find that unanticipated ROA is significantly correlated with lagged changes in differentiation. That is, it takes time for the effects of differentiation to manifest themselves in financial performance. This lagged effect, in conjunction with the absence of an association between changes in differentiation and stock return, suggests a potential trading rule (buy/sell short stocks that increased/decreased in differentiation the previous wave). We find evidence consistent with the existence of this trading rule; that is, firms that increased in differentiation had a higher abnormal stock return the following period than firms that decreased in differentiation.

The lack of contemporaneous market response to changes in brand differentiation suggests that managers need to improve their information disclosure strategies (i.e., what and how they communicate to the financial community). If managers want the financial markets to immediately impound the effect of brand enhancements into current stock price, they need to articulate their brand strategy (and its intangible outcomes) to the financial community better. It is common for managers to labor under the belief

[8]Because of the properties of stock return, an instrumental variable approach for addressing reverse causation issues holds little promise. Valid instruments—in particular, predetermined (lagged) variables—will not exist in the context of efficient markets. At a minimum, the "weak instruments" problem will arise (Bound, Jaeger, and Baker 1995). Instead, the problem is best addressed by casting the problem in the omitted variable context. That is, both stock return and brand attributes may depend on a common influence (e.g., positive news about the firm). This motivates the inclusion of accounting variables in our models. As a sensitivity check, we also included unanticipated research and development and unanticipated advertising expenditures in the model. Our conclusions are not affected.

that their voluntary disclosures have no impact. However, theory and empirical evidence indicate that voluntary disclosures can have significant and long-lasting consequences. Information disclosures (ranging from new product announcements to "explaining" financial results) have been shown empirically to affect financial market outcomes (e.g., share price, trading volume, bid-ask spreads). Firms that send credible signals about their brand strategy and future prospects will be freer to undertake strategies that improve long-term performance (e.g., enhancing brand differentiation).

Relevance

Some recent work has attempted to highlight the important role of brand relevance. For example, Aaker (2004, p. 101) notes, "A brand seems very strong because tracking studies show that it retains a high level of trust, esteem, perceived quality, and perhaps even perceived innovativeness. However, its market share may be slipping…. Why?… The brand has become irrelevant to one or maybe more important segments." Our results suggest that the financial markets are appreciative of the role of brand relevance. We find that relevance has incremental (to UΔROA, sales growth, and energy) information content in explaining stock returns. The financial markets view brands gaining in relevance as having greater future profit potential. This finding can be explained by the idea that relevance leads financial performance (e.g., sales growth). The financial markets appreciate that relevance has delayed and carryover effects. When financial market participants see a firm gaining in relevance, they adjust the profit expectations in anticipation of the future-term effect and not just when the effect on accounting performance is actually realized.

Esteem

As evidenced by the correlation matrix in Table 5, esteem changes exhibit a highly significant bivariate association with stock return. However, our analysis (e.g., Equation 6.1 in Table 6) shows no direct effect of esteem on stock return. The reason for this lies in the relationship between esteem and UΔROA and sales growth. The effect of esteem appears to be fully captured in current-term accounting performance. That is, an indirect effect of esteem exists such that changes in esteem influence contemporaneous accounting shocks (both ROA and sales growth), which in turn influence stock return. However, the financial markets do not attach any incremental influence to esteem. That is, the financial markets do not place any additional value on perceived brand esteem that does not lead to changes in current-term performance. In other words, if an improvement in esteem has not been reflected in improved profits within a year, it is not going to increase profits in future years.

Knowledge

Although knowledge has a significant bivariate association with stock return, we do not find significant direct effects of knowledge on stock return in any of the Table 6 regressions. This lack of an effect can be tied both to the role of sales growth and to relevance. Knowledge affects firm value through its influence on sales growth. That is, we find that increases in knowledge are associated with increases in sales growth, which in turn influence investor expectations of current and future performance. However, knowledge has an additional indirect effect associated with relevance. In a model linking stock return to knowledge and unanticipated ROA, the effect of knowledge is positive and significant. However, this positive effect of knowledge diminishes when sales growth and relevance are included in the model. This result suggests that increases in knowledge that do not also induce increases in relevance are not incrementally valued by the financial markets. It is not just which brands consumers know but also what they think about these brands that matters.

Energy

Energy is a new Y&R brand asset pillar. It is a brand asset component not as heavily emphasized in existing brand equity conceptualizations, but we hypothesized it to be of importance. Energy taps the brand's future orientation and, as such, is a likely candidate to have value implications for the financial markets. Consistent with this view, we find that energy has a positive and statistically significant direct effect on stock return. Energy depicts information about performance not reflected in current-term earnings, sales growth, or other brand asset components.

The energy measure includes responses to questions about the brand being dynamic and innovative. We tested whether these measures had different effects on stock return. We find that both are significantly related to stock return and that the hypothesis that the effects are of the same magnitude could not be rejected, which supports the aggregation of the two measures into one construct.

We undertook additional analysis—more focused than the factor analysis—to understand both what the energy construct taps and how its effects might be similar or dissimilar to somewhat related measures. For example, we compared the effects of energy with a "buzz" measure—namely, the proportion of Y&R respondents that viewed the brand as gaining in popularity. This construct has commonalities with energy, but it differs from energy in that it is more current-term oriented. In a stock return response model that includes both constructs, we find that though the estimated effect of energy (.059) remains statistically significant at the 1% level, the estimated effects of gaining in popularity are small and statistically insignificant (i.e., .001, t-statistic = .27). As such, the financial markets view energy as a separate construct from buzz. Many of the activities used to create buzz will have effects that do not affect brand energy, which seems to differ primarily in terms of future-term orientation. Further theoretical and empirical research directed at understanding the value implications of brand energy is warranted.

CONCLUSIONS

Our study examined the information content of the brand dimensions in the recently updated Y&R BAV model. We find that stock return is associated not only with accounting performance measures but also with perceived brand relevance and energy. That is, information contained in these brand measures is associated with information that the financial market uses to update expectations of future cash flows. The information reflected in esteem and knowledge does not have incremental information content to accounting measures and relevance and energy in explaining stock return. Notably, we find evidence suggestive that the financial markets are not incorporating information about business prospects contained in differentiation. Rather than anticipating the future-term effects of differentiation, the markets react only when the effects of differentiation have been realized in accounting performance.

Several different approaches have been advanced for measuring a firm's brand equity. A common method is an "indirect" approach ("earnings split analysis") that involves decomposing a firm's earnings into those induced by brand variables rather than other factors. Our analysis suggests that this approach misses key aspects of a brand's value. A significant portion of a brand's impact on firm value is not reflected in current-term accounting performance measures. Our analysis shows that brand assets affect not only the current but also the future financial performance of a firm. Analysis based on a decomposition of current product-market outcomes will not capture this effect, which is a point that Srinivasan, Park, and Chang (2005) highlight. By using customer mind-set measures in conjunction with stock return response modeling, we are able to understand the long-term financial implications of brand asset components more fully.

We view our study as a first step in investigating the complexity of brand assets and their dynamic impact on firm performance. Many issues require further attention and research. For example, although we could not reject the hypothesis of homogeneity, industry-specific differences in brand asset effects may exist, and it would be worthwhile to explore the nature of these differences. As our data sample was dominated by large, well-established firms, the effects of brand assets on market valuation of small firms and for firms as they go through different growth stages are also areas that merit further study. Analysis of the dynamic relationship among brand attributes is also a useful direction for further research. Use of customer mind-set measures allows for the study of each of these areas and provides a platform for better understanding how brand assets affect firm financial performance.

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