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This study examines brand dispersion—variance in brand ratings across consumers—and its role in the translation of brand assets into firm value. Dispersion captures the covert heterogeneity in brand evaluations among consumers who like or dislike the brands, which would affect an investor's decision to buy or sell a stock. The higher the dispersion, the more inconsistent and polarized the brands' cross-consumer ratings. Multiple analyses on 730,818 brand–day observations provide robust evidence that brand dispersion fluctuations affect stock prices. Brand dispersion has Januslike effects: it harms returns but reduces firm risk. Furthermore, downside dispersion has a stronger impact on abnormal returns than upside dispersion, indicating an asymmetry in brand dispersion's effects. Moreover, dispersion tempers the risk-reduction benefits of higher brand rating in both the short run and long run. Without modeling dispersion, brand rating's impact on firm value can be over- or underestimated. Managers should consider dispersion a vital brand-management metric and add it to the brand-performance dashboard.

Keywords: brand, brand performance, rating, dispersion, firm performance

The Impact of Brand Rating Dispersion on Firm Value

> "Love me or hate me, both are in my favor…. If you love me, I'll always be in your heart…. If you hate me, I'll always be in your mind."
>
> —Unknown

Enhancements in consumer-level brand evaluations endow stock market benefits for firms with increased returns (Lane and Jacobson 1995) and reduced risk (Rego, Billett, and Morgan 2009). Although previous research has noted that there is a (seemingly clear) effect of mean-level consumer product evaluations, no one has examined whether brand *dispersion*—that is, heterogeneity or variance in such evaluations across consumers—affects stock performance.[1]

This is a worthwhile question to pursue because there is potentially added information in variance that could inform short- to medium-term brand performance beyond the mean. Specifically, if the source of the variance is brand discordance, dispersion would be a bad signal to investors, whereas if the source is stable heterogeneity in evaluations, dispersion could be a good thing (e.g., a sign of a popular niche of brand lovers), a bad thing (e.g., there is a core of dissatisfied users and brand haters), or a neutral signal.

Our research reports a descriptive analysis of how one measure of variance correlates with firm value, using a unique BrandIndex data set. This data set is at the daily level with more than three million panel users for more than 2,600 brands from multiple countries (the United States, the United Kingdom, and Germany). Findings from this data set suggest that (1) changes in brand dispersion have a direct effect on stock returns and idiosyncratic risk, (2) this effect

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[1]Our focus on the new metric of brand dispersion and the embodied heterogeneity in brand ratings across consumers is also motivated by recent literature on the variance in consumer word of mouth (WOM) (Godes and Mayzlin 2004; Liu 2006; Sun 2012).

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is asymmetrical for downside versus upside dispersion, and (3) there are indirect effects (interplay) between dispersion and brand rating. Specifically, there are Januslike direct effects: dispersion is associated with lower abnormal returns on the one hand and a reduction in firm idiosyncratic risk on the other hand. Furthermore, downside dispersion is more associated with returns than is upside dispersion. Dispersion also limits the rewards the firm may earn from brand rating improvements.

BRAND DISPERSION AND FIRM VALUE

Conceptually, brand dispersion provides information about heterogeneity in brand quality ratings, which may reflect inconsistency and polarization into brand lovers and haters in ways that would affect the level, timing, and volatility of prospective cash flows of the firm. This information may affect investors' decisions to buy or sell a stock, likely leading to changes in firm abnormal return and idiosyncratic risk (Luo 2009; Srinivasan and Hanssens 2009).

Researchers suggest that investors scan the market environment constantly for information on brands and their performance prospects (see, e.g., McAlister, Sonnier, and Shively 2012). There is increasing support for the notion that investors are sensitive to such brand changes and these expectations quickly affect stock prices (see, e.g., Mizik and Jacobson 2008) given such information's value relevance for firm cash flow prospects. Tirunillai and Tellis (2012) document that investors respond to the day-to-day online chatter of product quality, which likely indicates their responsiveness to changes in the BrandIndex information.

We acknowledge that it is unlikely that investors continually monitor BrandIndex data daily for signs of changes in variance and then make buy/sell decisions on the basis of those data. The notion that all investors are either interested in tracking variance or homogeneous in their responses is also counterintuitive. Thus, the finding of strong associations between the variance information embodied in the BrandIndex data and firm value is far from obvious. Nevertheless, it is possible that the BrandIndex measures can be interpreted as a surrogate for other data sources that are more widely observable to investors. We offer some speculations for these interpretations in the "Implications" section.[2]

Direct Effects of Brand Dispersion on Firm Value

Dispersion–abnormal returns. We expect that increases in brand dispersion have a negative impact on firm returns. Investors may be sensitive to brand dispersion because it may indicate brand inconsistency. (Brand consistency is thought to be a core element of brand equity.) Keller (2008, p. 641) holds that "a consistent thread of meaning—which consumers can recognize—should reflect the key sources of equity for a brand and its core brand associations." Brands that are inconsistent manifest the presence of less harmonized brand meaning and weaker relationships with consumers. Higher dispersion may also connote more consumer polarization with less congruent symbolic value of the brand (e.g., Batra, Ahuvia, and Bagozzi 2012; Smith and Park 1992). Thus, increases in dispersion negatively affect the level and timing of prospective cash flows and brand value, leading to a negative relationship between dispersion and abnormal returns.

H_{1a}: Increases in brand dispersion have a negative impact on abnormal returns.

Dispersion–idiosyncratic risk. There are competing arguments for the dispersion–risk link. On the one hand, dispersion could be associated with greater idiosyncratic risk because inconsistent brands would be subject to more consumer defections to rival offers. Furthermore, such brands would enjoy less of a buffer from environmental or competitive shocks. Thus, increases in dispersion would lead to more vulnerable cash flows (Luo, Homburg, and Wieseke 2010; Tuli and Bharadwaj 2009) with higher idiosyncratic risk.

On the other hand, arguments based on consumer polarization into brand lovers and haters would suggest that increases in dispersion are associated with lower risk. Specifically, as increasing dispersion reflects more consumers toward the extremes (more brand lovers and more brand haters), the predictability of both extreme camps' future purchase behaviors improves. Brand lovers, characterized by strong attitudinal loyalty and lowered price sensitivity, are less vulnerable to competition (Mela, Gupta, and Lehmann 1997), producing more secure and predictable future cash flows. Paradoxically, more brand haters may also enhance the predictability of the firm's cash flows. The more the marginal consumers who are prone to switch become brand haters and exit the firms' customer base (i.e., "lost for good"), the more predictable the future cash flows with lower fluctuations (Bolton 1998).[3] Thus:

H_{1b}: Increases in brand dispersion have a positive impact on idiosyncratic risks.

$H_{1b(alt)}$: Increases in brand dispersion have a negative impact on idiosyncratic risks.

Asymmetric Effects of Brand Dispersion on Firm Value

Investors' reactions to upside versus downside dispersion may be asymmetrical.[4] We define downside (upside) dispersion as the observed variability in cross-consumer brand ratings when the brand ratings are lower (higher) than the neutral point. Prior studies have also used this semivariance approach (Rego, Billet, and Morgan 2009; Tuli and Bharadwaj 2009). Increases in upside dispersion reflect a shift to more brand lovers, whereas increases in downside dispersion reflect a shift to more brand haters. Investors may be more sensitive to the shift to the downside because downside, negative information is more diagnostic and influential and, thus, more likely to catch attention and affect investor decisions. For example, Tirunalli and Tellis (2012) find stronger effects of downside, negative (vs. upside, positive) information in user-generated content on stock returns

[2]Appendix A reveals some anecdotal evidence (reports from, e.g., *The Wall Street Journal*, *Bloomberg*, *Forbes*, *Washington Post*, *Financial Times*, *Fortune*) that investors are aware of and respond to the BrandIndex data. Other sources of brand dispersion information could include brand communications, social media postings, Google searches, and daily online chatter (Luo, Zhang, and Duan 2012; Tirunalli and Tellis 2012).

[3]For example, Apple devotees love the brand and can reliably be counted on to purchase the latest products, whereas others who do not like Apple will never buy their products. Both aspects of this bifurcation thus increase the predictability of prospective cash flows, that is, lowered firm idiosyncratic risk.

[4]We thank an anonymous reviewer for this insight.

and idiosyncratic risk. Erdem, Mayhew, and Sun (2001) also report a similar asymmetrical effect for downside versus upside price discrepancies. Thus:

H_2: Increases in downside brand dispersion are more likely to be related to (a) abnormal returns and (b) idiosyncratic risks than those in upside dispersion.

Indirect Effects of Brand Dispersion on Firm Value: Interaction with Brand Rating

We expect that brand dispersion may also mitigate the stock market performance benefits of mean-level brand ratings.[5] Dispersion's indirect role is related to its ability to affect investors' confidence in—and thus response to—brand rating information. Essentially, high dispersion can indicate to investors that brand rating improvements may not be that credible, certain, or reliable (Tversky and Kahneman 1983). Dispersion indicates a lack of consensus and limits the "social proof" of brand ratings (Cialdini 1993). Increasing dispersion thus weakens the conviction of future cash flows that investors may expect from such apparent mean-level brand improvements (Aaker and Jacobson 2001). Indeed, if there are increases in dispersion and quality heterogeneity, investors would question the brand's true performance, restraining their responses to brand rating enhancements. In contrast, when such brand rating enhancements are accompanied by decreases in dispersion, investors would then be more certain of the brand's rating improvement and take these expected effects into account. This suggests that investors react less positively to changes in brand rating in the presence of increasing (vs. decreasing) dispersion, weakening the brand rating–firm value relationships.

H_{3a}: The positive relationship between changes in brand rating and abnormal returns is negatively moderated (i.e., weaker) when brand dispersion increases.

H_{3b}: The negative relationship between changes in brand rating and firm idiosyncratic risk is positively moderated (i.e., weaker) when brand dispersion increases.

DATA

Measures for Brand Rating and Dispersion

The data source is the BrandIndex provided by YouGov Group, which specializes in online panels and monitors global and local brands in the United States, the United Kingdom, and Germany, inter alia. For the U.S. market, YouGov daily monitors approximately 1,025 brands in 20 industry sectors by surveying approximately 5,000 consumers from all relevant demographic groups (from a panel size of 1.5 million consumers). For the U.K. markets, it tracks approximately 1,100 brands in 20 sectors by surveying approximately 2,000 consumers (panel size of 230,000) each day. For the German markets, it monitors approximately 500 brands in 20 industry sectors by surveying approximately 1,000 consumers (panel size of 100,000) daily.[6] Our large panel size is advantageous because it can be more representative of the brand user universe and capture the "wisdom of the crowd" (Tirunillai and Tellis 2012). In addition, the daily level of our brand data is beneficial because it can more quickly reflect the changes in brand user perceptions. When sales data are not available at the disaggregated daily level, brand perceptions can inform managers how brands are working and enable them to address the opportunities dynamically.

Our measure of brand dispersion from the YouGov data reflects the variance in brand ratings across consumers (i.e., heterogeneity). Conceptually, the construct of brand dispersion could apply to the within-brand variability in performance from usage occasions, variability in the mean across consumers, or both. The YouGov measure may reflect an unknown mix of both, which could cloud the analyses and constrain the discussion of analysis results to be more speculative. Still, YouGov's large panel size and random selection of respondents suggests that the data more likely reflect between-subject (rather than within-subject) variance.[7]

More specifically, the BrandIndex consists of six indicators:

- Perceived brand quality: "Which of the brands in the sector do you associate with good or poor quality?"
- Perceived brand value: "Which of the brands do you associate with good or poor value-for-money?"
- Perceived brand satisfaction: "Would you identify yourself as a recent satisfied or an unsatisfied customer of any of these brands?"
- Perceived brand recommendation: "Which brands would you recommend to a friend? Or suggest avoiding?"
- Perceived brand affect: "For which brands do you have a 'generally positive' or 'generally negative' feeling?"
- Perceived brand workplace reputation: "Which of the brands would you be proud/embarrassed to work for?"

YouGov collects the data in the following manner: First, for a given industry sector, the respondents select all brands for which they agree to the positive question (e.g., good brand quality). Then, they select all brands for which they agree to the negative question (e.g., poor brand quality). The rest of the brands are then rated as neutral. Thus, for each brand, three responses are possible: positive, negative, and neutral. Brand competition effects are also controlled for because respondents rate the competing brands within one sector simultaneously. Furthermore, to reduce common method bias from the same survey respondent, YouGov measures the brand perception indicators independently across respondents. That is, any respondent is asked about his or her perception of only one brand indicator for a particular sector rather than for all six brand indicators for the same industry. The indicator–industry combination is randomized.

For each of the six indicators, we calculated the raw brand rating scores by taking the differences of the number of respondents who agree with the positive judgments and the number of respondents who agree with the negative judgments divided by the total number of respondents (= number of positive + negative + neutral respondents). The raw dispersion score for each indicator is the associated standard deviation. Pairwise correlations for the raw values of brand dispersion and brand rating are positive and large, ranging from .217 to .607. Thus, we applied principal com-

[5]The literature stream (Aaker and Jacobson 1994, 2001; Bharadwaj, Tuli, and Bonfrer 2011; Rego, Billett, and Morgan 2009) has previously examined main effects of brand rating improvements on returns and risks; thus, we do not formally hypothesize them here.

[6]To ensure that the brand responses represent the general population, we weighted or apportioned respondents by age, race, gender, education, income, and geography (region) using census data.

[7]For perspectives on within-subject variance, see Chandrashekaran et al. (2007); Grewal, Chandrashekaran, and Citrin (2010); and Rust et al. (1999).

ponent analysis (PCA) with a Varimax rotation for each country. This analysis extracts two factors with eigenvalues larger than one in each country. These factors account for 81.5%–83.2% of the variance, while commonalities of all indicators range between .692 and .907. For each country, the six rating scores load on the first factor (loadings range between .764 and .942), whereas the six dispersion scores always load on the second factor (loadings range between .843 and .933). Thus, the first underlying factor represents the final measure of brand rating, and the second factor represents the brand dispersion variable.[8]

YouGov provided data for all available 2,369 brands surveyed between January 1, 2008, and August 31, 2011. The sample covers single- and multiple-brand firms. To ensure that the brand rating and dispersion variables are not biased by small sample sizes, we excluded all observations with less than 30 respondents per country, brand, and indicator. In addition, to ensure that the results are not biased by too short a time series, we included only those brands that had at least 500 consecutive daily observations. Then, we associated all brands with their owners. We had to exclude 59% of the originally available 2,369 brands because they did not belong to publicly listed firms, changed owners during the covered time frame, or did not have a sufficiently long time series. Ultimately, we obtained a sample of 960 brands, with 508–925 time-series observations for each brand. Thus, the final total number of brand–day observations is 730,818, for which we matched the brand dispersion and rating data with firm stock performance data to test the hypotheses. For examples of the brand dispersion and brand rating data, see Appendix B. Table 1 presents descriptive statistics and correlations.

Measures for Stock Market Performance

According to prior research on the marketing–finance interface, stock market performance is often measured by return and risk (Campbell, Grossman, and Wang 1992; Luo and Bhattacharya 2009). To estimate abnormal return, we must parcel out a multitude of broad-market systematic risk factors using the four-factor financial benchmark model (Carhart 1997; Fama and French 1993). Although the use of daily data yields more precise estimates, daily stock price movements can be autoregressive and nonsynchronous. This can have a severe influence on the precision of risk-factor loading estimates. To control for such lagged effects, we include four periods of lagged risk covariates in the expected return model as Lewellen and Nagel (2006) propose. Thus, we get the following four-factor financial benchmark model after correcting for high-frequency (daily) stock returns:

$$(1)\qquad R_{it} - R_{rf,t} = \alpha_i + \sum_{\tau=0}^{4}\Big[\beta_{i\tau} \times \big(R_{m,t-\tau} - R_{rf,t-\tau}\big) + s_{i\tau} \times SMB_{t-\tau} + h_{i\tau} \times HML_{t-\tau} + u_{i\tau} \times UMD_{t-\tau}\Big] + \varepsilon_{it},$$

where $R_{rf,t}$ is the risk-free rate and $R_{m,t-\tau}$ is the average market return, $SMB_{t-\tau}$ is the size premium–related market risk, $HML_{t-\tau}$ is the growth premium–related market risk, and $UMD_{t-\tau}$ is the momentum-related market risk (Jegadeesh and Titman 1993). In addition, τ represents the current day (τ = 0) and previous four days (τ = 1, 2, 3, and 4), and ε_{it} denotes the error term. Data for $R_{m,t-\tau}$, $R_{rf,t-\tau}$, $SMB_{t-\tau}$, $HML_{t-\tau}$, and $UMD_{t-\tau}$ are from Kenneth R. French's data library. We used a rolling window of 250 trading days before the target day to estimate factor coefficients and residuals to measure the time-varying abnormal return and idiosyncratic risk.

Abnormal return is calculated as the difference between the raw return and expected return, that is, $AR_{it} = R_{it} - E(R_{it})$, where $E(R_{it})$ is the expected return as defined in Equation 1. Idiosyncratic risk is calculated by the standard deviation of the model residual ε_{it} in Equation 1 (Luo and Bhattacharya 2009). Furthermore, because stock-trading volume indicates stock liquidity and investor interest in the firm's shares (Grullon, Kanatas, and Weston 2004; Luo 2008), we enter trading volume as the endogenous stock value variable in the vector autoregressive (VAR) model. We measure trading volume as the total number of shares traded scaled by the number of shares outstanding to control for firm size effects (Campbell, Grossman, and Wang 1992).

Measures for Control Variables

We also examine possible sources for heterogeneity affecting the estimated effects of brand rating and dispersion on stock market performance. Thus, we control for various industry-, firm-, and brand-level variables (e.g., Mizik and Jacobson 2009; Morgan and Rego 2009) as exogenous controls in VAR models. Appendix C provides details.

MODELS

Analysis Strategy

We begin by presenting straightforward, model-free evidence for brand dispersion's stock market impact. We then employ a dynamic modeling framework using VAR models for our empirical hypotheses testing (Dekimpe and Hanssens 1999). Vector autoregressive modeling is an established modeling technique in marketing and finance research, and researchers have frequently applied it for similar research questions (e.g., Joshi and Hanssens 2010). The introduction to the Web Appendix (www.marketingpower.com/jmr_webappendix) provides a road map for all additional models and tests.

Dynamic VAR Model

The VAR methodology controls for endogeneity, seasonality, nonstationarity, serial correlation, reverse causality, and complex feedback loops (Luo 2009; Pauwels 2004). Specifically, VAR models at least partially account for endogeneity bias by enabling all endogenous variables to affect one another in a fully interactive modeling system with direct, feedback, autocorrelation, and crossover effects between brand rating and dispersion. For example, regarding direct effects, because branding effects may accumulate with delayed responses over time, VAR models capture not only short-term or immediate effects but also the dynamics of long-term or cumulative effects through the generalized impulse response functions. With respect to the feedback

[8]We tested the robustness of this factor structure by conducting PCA for each brand. Additional results support this two-factor structure, as Web Appendix A (www.marketingpower.com/jmr_webappendix) illustrates. We also tested the robustness of this procedure using a less restrictive sample size requirement. The minimum sample size for such analyses is 100 (Netemeyer, Bearden, and Sharma 2003); thus, we included more brands with at least 100 daily observations and increased the sample to 772,784 brand–day observations. Furthermore, we applied a filter technique to control day-to-day measurement error. The results are robust (see Web Appendixes B and C).

Table 1

DESCRIPTIVE STATISTICS AND PAIRWISE CORRELATIONS (CONTEMPORANEOUSLY AND ONE-DAY LAG)

Variable Name	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*
1. $Return_t$	1													
2. $Return_{t-1}$	–.041***	1												
3. $Risk_t$	.023***	.149***	1											
4. $Risk_{t-1}$	–.001	.023***	.154***	1										
5. $Volume_t$	.032***	.022***	.052***	.029***	1									
6. $Volume_{t-1}$	.006***	.032***	.111***	.051***	.791***	1								
7. $Rating_t$	.000	.001	–.001	.001	–.002*	.000	1							
8. $Rating_{t-1}$	.001	.000	–.002*	–.001	–.001	–.002*	–.494***	1						
9. $Dispersion_t$	–.002**	.000	.000	–.001	.001	.000	–.452***	.226***	1					
10. $Dispersion_{t-1}$	.001	–.002**	.000	.000	.001	.001	.223***	–.452***	–.491***	1				
11. $Rating_t \times Dispersion_t$	.000	.000	.006***	.005***	–.010***	–.010***	–.001	.024***	.000	–.027***	1			
12. $Rating_{t-1} \times Dispersion_{t-1}$	–.002*	.000	.004***	.006***	–.010***	–.010***	–.021***	.000	.028***	–.001	.308***	1		
13. $Awareness_t$	.002*	–.002**	.001	–.002**	.003**	.000	.003***	–.001	.018***	–.005***	–.003***	.002	1	
14. $Awareness_{t-1}$	–.004***	.002*	.002**	.001	.000	.003**	.000	.003***	–.010***	.018***	.001	–.003***	–.493***	1
M	.000		.000		.009		.000		.000		–.032		.000	
Mdn	.000		.000		.006		.000		.000		–.007		.000	
Max	2.510		.086		1.317		2.437		2.611		1.591		.553	
Min	–.711		–.098		.000		–2.025		–2.198		–3.558		–.575	
SD	.030		.000		.015		.261		.272		.096		.060	

*$p < .10$.
**$p < .05$.
***$p < .01$.
Notes: N = 730,818 brand–day observations. Nonstationary variables in first differences (idiosyncratic risk, brand rating, brand dispersion, rating × dispersion, brand awareness).

effects, to the degree that consumers follow stock markets, it could be that in some cases, consumers' judgments of brands such as Apple are informed by what they have heard about its stock price. In addition, there could be crossover effects because higher ratings may lead to higher variance (Godes and Mayzlin 2004). Using generalized forecast error variance decomposition (Pesaran and Shin 1998), we estimate the relative contribution of brand rating and dispersion to the prediction of firm value.

We specify the following VAR model with exogenous variables formalizing the relationships between brand rating, brand dispersion, and stock performance variables:

$$(2)\quad \begin{bmatrix} \text{Abnormal return}_{it} \\ \Delta\text{Idiosyncratic risk}_{it} \\ \text{Trading volume}_{it} \\ \Delta\text{Brand rating}_{it} \\ \Delta\text{Brand dispersion}_{it} \\ \Delta\text{Rating}_{it} \times \Delta\text{Dispersion}_{it} \end{bmatrix} = \sum_{n=1}^{p} \begin{bmatrix} \gamma_{11}^{n} & \cdots & \gamma_{16}^{n} \\ \vdots & \ddots & \vdots \\ \gamma_{61}^{n} & \cdots & \gamma_{66}^{n} \end{bmatrix} \begin{bmatrix} \text{Abnormal return}_{i,t-n} \\ \Delta\text{Idiosyncratic risk}_{i,t-n} \\ \text{Trading volume}_{i,t-n} \\ \Delta\text{Brand rating}_{i,t-n} \\ \Delta\text{Brand dispersion}_{i,t-n} \\ \Delta\text{Rating}_{i,t-n} \times \Delta\text{Dispersion}_{i,t-n} \end{bmatrix} + \begin{bmatrix} \phi_{11} & \cdots & \phi_{1,15} \\ \vdots & \ddots & \vdots \\ \phi_{61} & \cdots & \phi_{6,15} \end{bmatrix} \begin{bmatrix} x_1 \\ \vdots \\ x_q \end{bmatrix} + \begin{bmatrix} \varepsilon_{\text{Abnormal return, it}} \\ \varepsilon_{\text{Idiosyncratic risk, it}} \\ \varepsilon_{\text{Trading volume, it}} \\ \varepsilon_{\text{Brand rating, it}} \\ \varepsilon_{\text{Brand dispersion, it}} \\ \varepsilon_{\text{Rating} \times \text{Dispersion, it}} \end{bmatrix}.$$

In line with the Granger causality and panel unit root tests, the stationary endogenous variables of Abnormal return and Trading volume enter the VAR model unchanged. (Web Appendix D shows the results for brand dispersion's impact on trading volume [see www.marketingpowewr.com/jmr_webappendix].) Idiosyncratic risk, brand rating, and brand dispersion are nonstationary and enter the model in first differences. In addition, the use of changes in brand dispersion and brand rating is consistent with the efficient market hypothesis, which asserts that because a stock price reflects all public information, only unexpected information about the firm (or changes in brand variables) can move stock prices. We model the interaction term brand rating × brand dispersion as a product of changes in rating and dispersion for each lag n. The off-diagonal terms of the matrices ($\gamma_{k\ell}^{n}$)($k \neq \ell$) estimate the direct, indirect, or crossover effects among all endogenous variables, and diagonal elements ($k = \ell$) estimate autoregressive effects. The vector (x_q) comprises exogenous variables controlling for time trends; seasonality; and brand-, firm-, and industry-level covariates. For each brand-level VAR model, we chose the optimal lag order (n) according to Schwartz's Bayesian information criteria.

To test the asymmetric effects of upside versus downside dispersion, we analyzed a VAR model allowing for such asymmetry:

$$(3)\quad \begin{bmatrix} \text{Abnormal return}_{it} \\ \Delta\text{Idiosyncratic risk}_{it} \\ \text{Trading volume}_{it} \\ \Delta\text{Brand rating}_{it} \\ \Delta\text{Upside dispersion}_{it} \\ \Delta\text{Downside dispersion}_{it} \end{bmatrix} = \sum_{n=1}^{p} \begin{bmatrix} \gamma_{11}^{n} & \cdots & \gamma_{16}^{n} \\ \vdots & \ddots & \vdots \\ \gamma_{61}^{n} & \cdots & \gamma_{66}^{n} \end{bmatrix} \begin{bmatrix} \text{Abnormal return}_{i,t-n} \\ \Delta\text{Idiosyncratic risk}_{i,t-n} \\ \text{Trading volume}_{i,t-n} \\ \Delta\text{Brand rating}_{i,t-n} \\ \Delta\text{Upside dispersion}_{i,t-n} \\ \Delta\text{Downside dispersion}_{i,t-n} \end{bmatrix} + \begin{bmatrix} \phi_{11} & \cdots & \phi_{1,15} \\ \vdots & \ddots & \vdots \\ \phi_{61} & \cdots & \phi_{6,15} \end{bmatrix} \begin{bmatrix} x_1 \\ \vdots \\ x_q \end{bmatrix} + \begin{bmatrix} \varepsilon_{\text{Abnormalreturn, it}} \\ \varepsilon_{\text{Idiosyncratic risk, it}} \\ \varepsilon_{\text{Trading volume, it}} \\ \varepsilon_{\text{Brand rating, it}} \\ \varepsilon_{\text{Upside dispersion, it}} \\ \varepsilon_{\text{Downside dispersion, it}} \end{bmatrix}.$$

In measuring upside (downside) brand dispersion, the BrandIndex data set has only three possible responses: positive, negative, and neutral. Thus, we used the percentage of positive respondents and the standard deviation formula for binary variables to calculate the upside dispersion: $\text{Dispersion}^{\text{upside}} = \sqrt{\%\text{positive} \times (1 - \%\text{positive})}$ (see, e.g., Wooldridge 2010, p. 561). Similarly, we used the percentage of negative respondents and the standard deviation formula for binary variables to calculate the downside dispersion: $\text{Dispersion}^{\text{downside}} = \sqrt{\%\text{negative} \times (1 - \%\text{negative})}$. In addition, because the BrandIndex data set has six indicators, we have six upside and six downside dispersion items. Then, applying PCA, we obtained two underlying factors. The factor loaded by the six upside dispersion items is the final measure for the upside brand dispersion, and the other factor loaded by the six downside dispersion items is the final measure for the downside brand dispersion.

From the VAR estimation results, we calculate the immediate and cumulative responses using generalized impulse response functions (Dekimpe and Hanssens 1999), which are not sensitive to the causal ordering of variables. We calculated confidence intervals (CIs) and t-test results for the average immediate and cumulative effects using the means and standard errors of effects obtained from the 960 brand-level VAR models. Similarly, we calculated the relative impact of brand metrics using the generalized forecast error variance decomposition.

To decide on the correct specification of brand-level VAR models, we applied (1) pairwise Granger causality tests, (2) various individual and panel unit roots tests, and (3) Pedroni panel cointegration tests. This procedure ensures that estimated coefficients can be compared across brand-level models. Thus, after estimating VAR models for 960 brands over the sampled days, we can evaluate the performance effects of brand dispersion (Srinivasan et al. 2009).[9]

Granger Causality Tests

The Granger causality test (Granger 1969) examines whether one variable is temporally causing a second variable after accounting for lagged values of the second variable.

[9]Drawing on Pauwels et al. (2004) and Srinvisan et al. (2009), we estimate the model for each brand (and do not aggregate the brands on a firm level). It would be ideal to estimate the model $\text{Stock Performance}_{\text{Brand i}} = \alpha + \beta X_{\text{Brand i}} + \varepsilon$ for each brand. Stock performance variables, however, are only available on an aggregated corporate level. The stock performance variables cannot be split into Brand i and Non–Brand i parts. However, it seems reasonable to assume that $\text{Stock Performance}_{\text{Non–Brand i}}$ (i.e., stock performance that is not associated with a particular Brand i) and X are uncorrelated. Thus, the estimated coefficient vector β is unbiased (see footnote 5 in Srinivasan et al. 2009).

Only when a focal variable Granger-causes at least one other variable *and* is Granger-caused by other variables do we treat it as endogenous in our VAR model. As Web Appendix E (www.marketingpower.com/jmr_webappendix) illustrates, the results suggest that both dispersion and rating Granger-cause abnormal return ($p < .05$) and idiosyncratic risk ($p < .01$). The interaction term of dispersion and rating Granger-causes risk and weakly Granger-causes abnormal returns ($p < .10$). We also conducted additional Granger tests and found robust results with 5, 10, 15, and 20 lags as well as with Bonferroni correction. Overall, we conclude that all focal variables are indeed endogenous.

Panel Unit Root and Cointegration Tests

Panel and individual unit root test results suggest that abnormal return is stationary because it does not have a unit root. However, panel unit root tests deliver a mixed picture regarding the other variables (see Table E2, Panel A, in Web Appendix E at www.marketingpower.com/jmr_webappendix). For risk, the majority of panel unit root tests indicate the nonstationary, evolving nature of risk. This is confirmed by the various individual unit root tests (see Table E2, Panel B, in Web Appendix E). Regarding the changes in brand variables, the majority of panel unit root tests indicate stationarity as well. Given the large N and T dimensions in our data set, we apply the panel-ν statistic of the Engle–Granger-based Pedroni panel cointegration test that tends to have the best power relative to other statistics (Pedroni 2004). Using lag length selection (based on the Schwarz information criterion), Newey–West bandwidth selection, and degree-of-freedom-corrected Dickey–Fuller residual variances, the results provide no indication that variables are cointegrated ($p > .10$). Thus, we use first differences of all evolving variables in the VAR model.

RESULTS

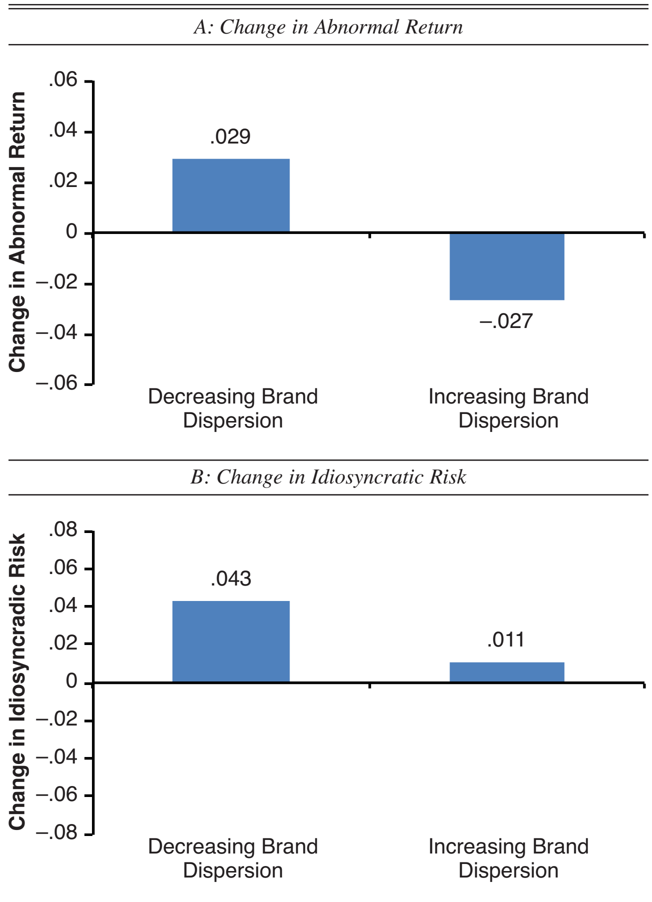
Model-Free Evidence

Table 1 reports the simple zero-order correlations. In our data, there is a significant negative correlation between dispersion$_t$ and returns$_t$ ($p < .05$) and between dispersion$_{t-1}$ and returns$_{t-1}$ ($p < .05$). In addition, the rating–dispersion interaction term$_t$ is positively correlated with risk$_t$ ($p < .01$), and the rating–dispersion interaction term$_{t-1}$ is positively correlated with risk$_{t-1}$ ($p < .01$), as we expected. Figure 1, Panel A, illustrates that the bar with increasing (decreasing) dispersion has a lower (higher) return. Thus, these results provide initial model-free evidence for H_{1a} that increases in brand dispersion have a negative impact on abnormal returns. In addition, Figure 1, Panel B, shows that the bar with increasing dispersion has a lower risk, whereas the bar with decreasing dispersion has a higher risk, providing initial evidence for $H_{1b(alt)}$.

Figure 2, Panel A, shows that increasing downside dispersion reduces abnormal returns (the line with negative slope), but increasing upside dispersion has almost no effect on returns (the flat line). Thus, these results provide model-free evidence for H_{2a}, the asymmetric effects between upside versus downside dispersion for returns. Because the two lines have almost the same slope in Figure 2, Panel B, there seem to be no asymmetric effects for idiosyncratic risk.

Figure 1

MODEL-FREE EVIDENCE FOR THE EFFECTS OF BRAND DISPERSION

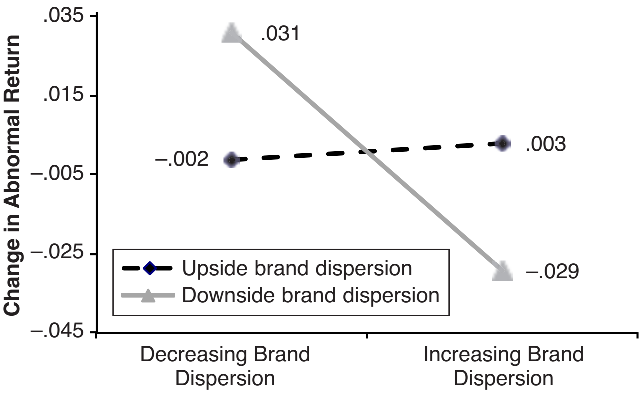


Notes: All variables are adjusted by periodwise industry means.

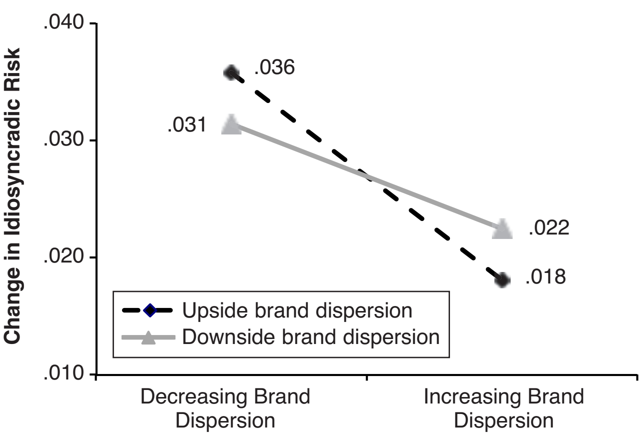
Figure 3 plots the cell means of the four possible combinations of (2 × 2) changes in dispersion and brand rating after adjusting industry means to allow for meaningful comparison across industries. Results suggest that the benefits of increased ratings depend on whether dispersion is decreasing. For example, firms can gain the maximum abnormal return benefit (.056) when rating increases and dispersion decreases. Conversely, the worst scenario (–.040) occurs when rating decreases and dispersion increases. As Figure 3, Panel A, shows, when dispersion increases (as opposed to decreases), the slope for the correlation between brand rating and returns becomes substantially smaller (i.e., a flatter line), although it is still positive. These results provide evidence for H_{3a} that dispersion weakens the positive relationship between changes in brand rating and abnormal returns. Regarding risk, Figure 3, Panel B, suggests that when dispersion increases (as opposed to decreases), the negative slope for the correlation between brand rating and risks becomes substantially smaller; that is, weaker risk-reduction benefits of brand rating result when dispersion increases. Thus, dispersion tempers the risk-reduction benefits of brand rating, as we hypothesized in H_{3b}. Web Appendix F (see www.marketingpower.com/jmr_webappendix) shows for Figure 3 the analysis of variance results of quadrant analysis for brand rating and dispersion.

Figure 2
MODEL-FREE EVIDENCE FOR THE EFFECTS OF UPSIDE AND DOWNSIDE BRAND DISPERSION

A: Change in Abnormal Return



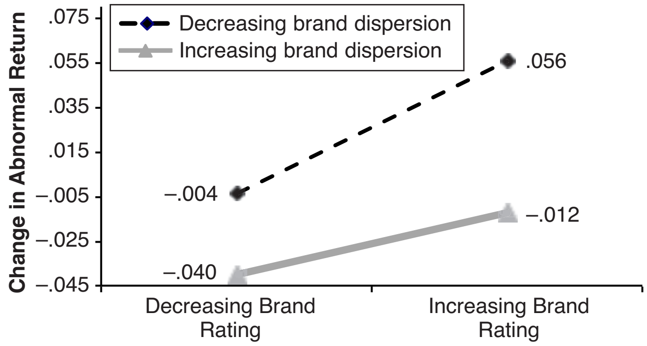
B: Change in Idiosyncratic Risk



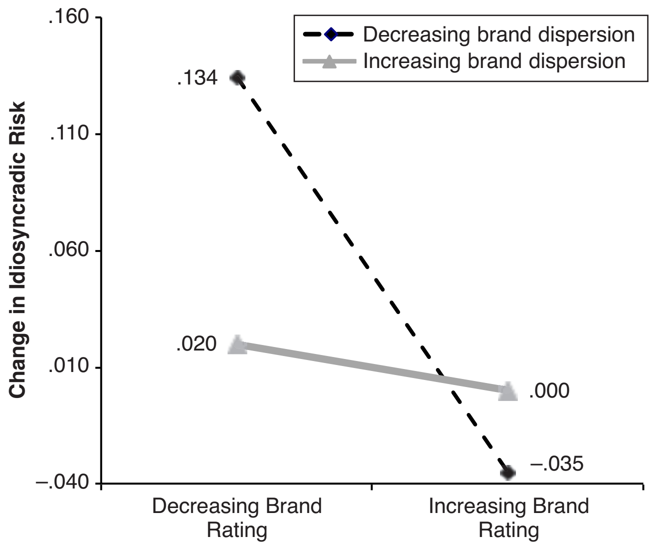
Notes: All variables are adjusted by periodwise industry means.

Figure 3
MODEL-FREE EVIDENCE FOR THE INTERACTION BETWEEN BRAND RATING AND DISPERSION

A: Change in Abnormal Return



B: Change in Idiosyncratic Risk



Notes: All variables are adjusted by periodwise industry means.

Results for VAR Models and Dynamics

Analyzing the dynamic effects among the endogenous VAR variables can help researchers gauge how the brand metrics drive stock market performance over time. Concretely, we compare short-term (immediate) and long-term (cumulative) elasticities. We define the immediate impact as the effect on performance on day t + 1 from one unit of unexpected shock (1 SD) in the brand variables on day t. The accumulated elasticities reach the asymptotic levels in equilibrium within ten days (Luo 2009; Pauwels 2004). Table 2 presents results for the immediate and cumulative effects of brand dispersion and rating on performance. This table shows mean, standard deviation, and t-value estimates from the brand-level VAR models and impulse response functions. To ensure that estimated effect sizes are not contaminated by outliers, we calculated the t-values for 95% Winsorized means (i.e., 95% CIs).

Results for Brand Rating

Our results are largely consistent with those in prior research. As Table 2 reports, the immediate impact of the unexpected shock in brand rating on return has the predicted sign (.001) but is not significant ($p > .10$). The cumulative impact of brand rating is significant with the expected sign (.002; $p_{incl\_outliers} < .10$ and $p_{Winsorized} < .05$). As such, with large-scale, daily-level brand index data, our findings provide more empirical evidence for previous results on the positive associations between stock returns and brand equity (Aaker and Jacobson 2001).

In addition, we find that the immediate effects of brand rating on risk (–.002; $p < .05$) have the expected signs and are significant. Thus, our study with high-frequency daily brand data extends previous research that supports risk-reduction effects of brand quality with low-frequency yearly data (Bharadwaj, Tuli, and Bonfrer 2011; Rego, Billett, and Morgan 2009). The cumulative impact of brand rating on risk has the expected sign (–.001) but is not significant ($p > .10$). This might come as a surprise at first glance, but it can be partially explained by the interaction between mean-level brand rating and dispersion, as we discuss subsequently.

Table 2

IMMEDIATE AND CUMULATIVE IMPACT OF BRAND METRICS ON STOCK PERFORMANCE (N_{BRANDS} = 960)

			Equal-Weighted Individual Effects				Inverted SE-Weighted Individual Effects[a]		
Impulse	*Response*	*Hypothesis (Expected Sign)*	*M*	*SE*	*t-Value (Including Outliers)*	*t-Value (95% Winsorized)*	*M*	*SE*	*z-Value*
Immediate Effects									
Brand rating	Return		.001	.031	1.126	1.099	.001	.001	.81
Brand dispersion	Return	H_{1a} (–)	–.002*	.030	–1.842*	–1.942*	–.002	.001	–1.90*
Rating × dispersion	Return	H_{3a} (–)	–.000	.038	–.388	–.284	.000	.001	.17
Brand rating	Risk		–.002**	.030	–2.120**	–2.212**	–.002	.001	–1.83*
Brand dispersion	Risk	H_{1b} (+/–)	–.002*	.030	–1.859*	–2.030**	–.001	.001	–1.06
Rating × dispersion	Risk	H_{3b} (+)	.005***	.044	3.299***	3.370***	.003	.002	2.18**
Cumulative Effects (Ten Days)									
Brand rating	Return		.002*	.025	1.911*	1.989**	.002	.001	1.75*
Brand dispersion	Return	H_{1a} (–)	–.002**	.024	–1.994**	–2.096**	–.002	.001	–1.97**
Rating × dispersion	Return	H_{3a} (–)	.001	.074	.293	.375	.002	.003	.77
Brand rating	Risk		–.001	.026	–.967	–.811	–.000	.001	–.02
Brand dispersion	Risk	H_{1b} (+/–)	–.003***	.025	–3.523***	–3.882***	–.003	.001	–2.84***
Rating × dispersion	Risk	H_{3b} (+)	.024***	.103	7.152***	7.364***	.019	.004	5.19***

*$p < .10$ (two-tailed).
**$p < .05$ (two-tailed).
***$p < .01$ (two-tailed).
[a]Individual effects are aggregated using a multilevel model with cluster-robust standard errors (brands are nested within firms). Furthermore, brand-level observations (respectively, firm-level observations) are weighted by the inverse of standard errors of effects (for a similar approach, see Bezawada and Pauwels 2013; Srinivasan et al. 2004).
Notes: Average effects from the VAR models and impulse response functions. Total number of brand–day observations is 730,818.

Results for the Direct Effects of Brand Dispersion

Next, we test H_{1a} and H_{1b} with regard to the direct effect of an unexpected change in dispersion on return and risk with VAR results (see Table 2). The immediate dispersion–return elasticity is negative and significant (–.002; $p < .10$). Furthermore, the cumulative dispersion–return elasticity is also negative and significant (–.002; $p < .05$), thus in strong support of H_{1a}'s prediction that increases in dispersion have a negative impact on abnormal returns.

In addition, the immediate dispersion–risk elasticity (–.002; $p < .05$) and cumulative dispersion–risk elasticity are negative (–.003; $p < .01$), in support of $H_{1b(alt)}$. Thus, dispersion's direct effects on stock prices are significant. That is, higher dispersion is associated with lower returns and lower risk in both the short run and long run after accounting for endogeneity, nonstationarity, seasonality, reverse causality, and complex feedback loops.[10]

Although these effects seem small in magnitude, the monetary impact can be substantial depending on the market capitalization of the firm. An unexpected shock by one standard deviation in dispersion lowers returns by .002 standard deviations. For the average firm with $36.9 billion in market capitalization, this means a net loss of $2.2 million after ten days, all else held constant.[11]

Figure 4 depicts the results of the impulse response functions for the impact of an unexpected change in dispersion on return (Panel A) and risk (Panel B). The dotted lines represent the one standard deviation CI for the impact. We find that the effect of dispersion on returns reaches its peak on the first day and then decays toward equilibrium. We do not find substantial shifts after five days. The impact on risk peaks after two days reverses on day three and diminishes after that toward equilibrium.

Results for Asymmetrical Effects

To investigate differences in upside versus downside dispersion, we separated the two and reestimated the VAR models. Similar to prior branding literature (Rego, Billett, and Morgan 2009) and customer satisfaction literature (Tuli and Bharadwaj 2009), we find evidence that downside dispersion has a stronger negative impact on returns than upside dispersion (see Table 3). The immediate and cumulative downside dispersion–return elasticities are significantly negative (–.003, $p < .05$, and –.002, $p < .10$, respectively), whereas the immediate and cumulative upside dispersion–return elasticities are not significant ($p > .10$). This suggests that downside dispersion seems to have more negative impact on return than upside dispersion. These relatively larger effects of downside dispersion are consistent with the literature on negativity bias and loss-aversion theory (Luo and Homburg 2007; Tellis and Johnson 2007). Regarding risk, however, both types of dispersion have an almost equal significantly negative cumulative impact on risk (–.005 and –.004, respectively; $p < .05$). Thus, we find evidence for an asymmetrical effect on return but not for risk. These findings provide empirical support for H_{2a}.

Results for Indirect Effects of Brand Dispersion-Interactive Effect with Brand Rating

We now turn to H_{3a-b}, regarding the impact of the interaction between brand dispersion and brand rating (see Table

[10]These findings are robust if we aggregate individual effects by using a multilevel model with cluster-robust standard errors (brands are nested within firms) and weight brand-level observations by the inverse of standard errors of effects (for a similar approach, see Bezawada and Pauwels 2013; Srinivasan et al. 2004).

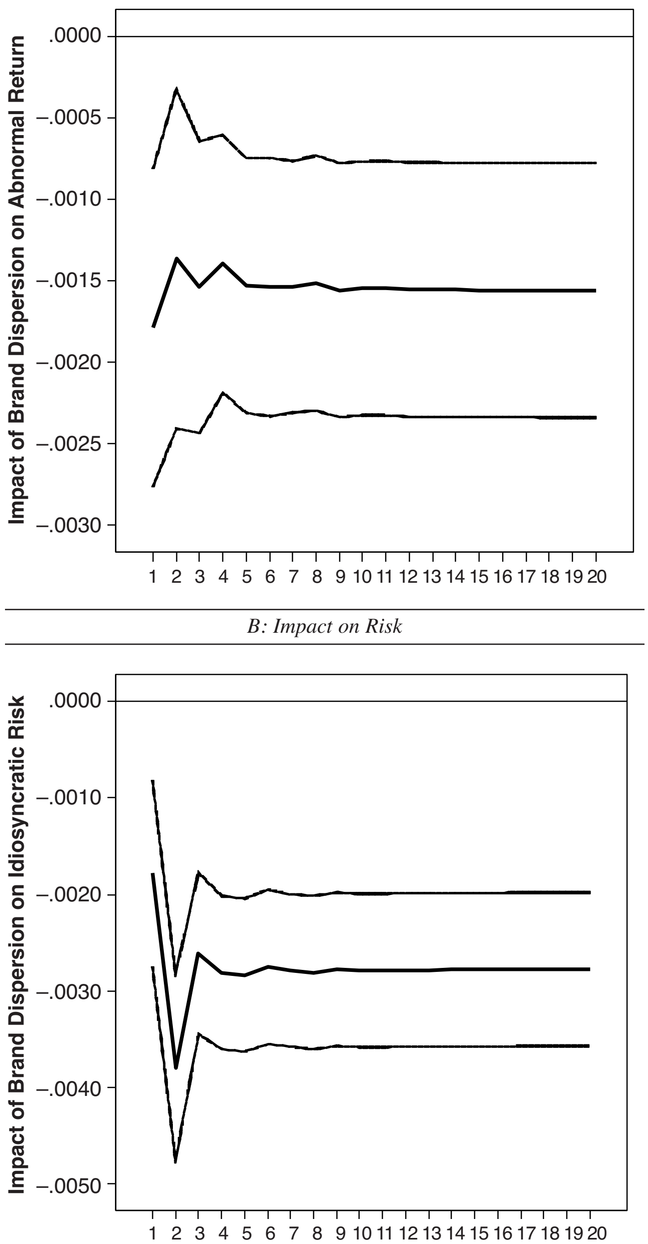
[11]These effect sizes are comparable to Tirunillai and Tellis (2012), who report an accumulated value $3.3 million for a unit shock in user-generated content on abnormal stock returns after 15 days.

Figure 4

IMPULSE RESPONSE FUNCTIONS FOR THE EFFECTS OF BRAND DISPERSION ON RETURN AND RISK

A: Impact on Return

B: Impact on Risk



Notes: Dotted lines represent the ±1 SD CI

2). For the impact of the interaction effect on return, we cannot reject the null hypothesis, because immediate effects (–.000) and cumulative effects (.001) are not significant (p > .10), thus rejecting H_{3a}.[12] However, we find that the immediate impact of this interaction on risk has the expected sign (.005) and is significant (p < .01). In addition, the cumulative impact on risk has the expected sign (.024) and is significant (p < .01), thus in strong support of H_{3b}. These findings suggest that brand dispersion affects the main effect of brand rating on risk. The risk-mitigation benefit of brand rating becomes stronger if dispersion decreases but significantly weaker if dispersion increases.

[12]We explore the variation of these effects across industries, firms, and brand covariates in Web Appendix G (www.marketingpower.com/jmr_webappendix).

Additional Results and Robustness Checks

Brand awareness confounding. YouGov requests that respondents not rate every brand; rather, they are instructed to pick brands from one industry sector that are rated positively on an attribute and then to pick brands from the same sector that are rated negatively. This introduces brand awareness confounding bias, because unfamiliar brands are less known and, thus, not selected by respondents. To rule out this confound, we control for brand awareness effects with an indicator measuring whether the respondents have heard anything positive or negative about a brand. The results in Web Appendix B (www.marketingpower.com/jmr_webappendix) suggest that our conclusion is robust to this brand awareness confound.

Monthly level analyses. Because investors may not be fully aware of daily changes in brand dispersion, we conducted additional results with monthly frequencies. We have adjusted all model variables by monthly industry means. Given the nested data structure (periods are nested within brands, brands are nested within firms, and firms are nested within industries), we applied a multilevel modeling technique. We also control for other variables including profitability, cash flow, market share, total assets, analyst coverage, analyst recommendations, percentage of strategic stock holdings, and industry competition. Because Granger causality tests suggest that financial performance variables are interrelated, we add abnormal return, idiosyncratic risk, and trading volume as additional control variables to reduce endogeneity bias. Although the interaction between dispersion and rating is insignificant, we find that main effects of brand dispersion on return (–.013; p < .05) and risk (–.021; p < .01) remain stable, consistent with H_{1a} and $H_{1b(alt)}$ (see Web Appendix H at www.marketingpower.com/jmr_webappendix).

Single-branded results. We also conducted more analyses with only single-brand firms and found robust results of our key hypotheses. This subsample consisted of 213 firms. The cumulative effects of dispersion on return (mean coefficient = –.005, SE = .003; p < .10) and risk (mean coefficient = –.006; SE = .004; p < .10) are consistent with H_{1a} and $H_{1b(alt)}$. Furthermore, the brand rating × dispersion–risk elasticity (mean coefficient = .023; SE = .005; p < .01) are consistent with H_{3b}.

Relative effects between brand dispersion and brand rating. Recall that we use the generalized forecast error variance decomposition technique (Pesaran and Shin 1998) to compare the relative importance of dispersion, rating, and the interaction term. As Figure 5 reports, the results show the extent to which our brand metrics account for the variation in returns (Panel A) and risk (Panel B). Our results provide an answer to Keller and Lehmann's (2006, p. 746) call for research to examine which matters more. In all three cases, we observe that brand dispersion and brand rating are almost equally important, whereas the interaction is less important in explaining the variability in firm returns but is more important in risk.

IMPLICATIONS

This study ushers in brand dispersion, an important new metric for research on branding, marketing strategy, and the

Table 3

IMMEDIATE AND CUMULATIVE IMPACT OF UPSIDE AND DOWNSIDE BRAND DISPERSION ON STOCK PERFORMANCE

Impulse	Response	Hypothesis (Expected Sign)	M	SE	z-Value	Random Effects SD (Firm)	SD (Residual)
Immediate Effects							
Brand rating	Return		.000	.001	.06	.012	.037
Upside dispersion	Return		–.000	.001	–.33	.009	.037
Downside dispersion	Return	H_{2a} (–)	–.003	.001	–2.50**	.012	.036
Brand rating	Risk		–.002	.001	–1.48	.010	.034
Upside dispersion	Risk		–.001	.001	–1.08	.009	.035
Downside dispersion	Risk	H_{2b} (–)	–.002	.001	–1.48	.011	.033
Cumulative Effects (Ten Days)							
Brand rating	Return		–.001	.002	–.37	.015	.042
Upside dispersion	Return		.000	.001	.13	.011	.043
Downside dispersion	Return	H_{2a} (–)	–.002	.001	–1.68*	.013	.041
Brand rating	Risk		–.005	.002	–2.45**	.018	.060
Upside dispersion	Risk		–.005	.002	–2.20**	.017	.061
Downside dispersion	Risk	H_{2b} (–)	–.004	.002	–2.07**	.021	.056

*p < .10 (two-tailed).

**p < .05 (two-tailed).

Notes: Daily data; N_{brands} = 1,108; T_{min} > 100. Total number of firm– or brand–day observations is 772,784. Average effects from the VAR models and impulse response functions are shown. We aggregated individual effects using a multilevel model with cluster-robust standard errors (brands are nested within firms). Furthermore, brand-level observations (respectively, firm-level observations) are weighted by the inverse of standard errors of effects (for a similar approach, see Srinivasan et al. 2004).

marketing–finance interface. Using a high-frequency data set for 960 brands with 730,818 brand–day observations, our findings corroborate brand dispersion's dual impact: it directly affects firm value and indirectly tempers the effects of brand rating on stock market performance. We reveal the novel finding that dispersion has Januslike effects on firm value, in that it is consistently related to lower abnormal returns but a beneficial reduction in risks. Furthermore, we discover that dispersion may explain as much variability of future returns as brand rating and that the interplay between brand dispersion and rating accounts for a substantial variability of future risk with long-lasting performance implications. These findings are robust and drawn from a large-scale, multiyear, multicountry data set. The strength of this empirical evidence provides assurance to researchers and managers that the dispersion of brand ratings should be as salient a concern as brand rating mean levels.

Why does brand dispersion still have an effect even if investors may not have access to those exact BrandIndex variance data? We speculate that the BrandIndex variance can be a manifestation of some other brand cues that are more widely observable through brand communications, news reports, social media postings, Google searches, and daily online chatter. For example, variance in brand ratings may be manifested by firms' brand announcements that are inconsistent or likely to divide consumers into lovers and haters (e.g., Southwest's early boarding fee, Starbucks's breakfast sandwiches). Moreover, news coverage would reflect brand variance. For example, some Apple loyalists turned into brand haters as a result of the removal of Google Maps from the Apple ecosystem, and Starbucks's customers greeted the arrival of VIA coffee with mixed emotions (Felten 2009). Finally, recent studies (Luo, Zhang, and Duan 2012; McAlister, Sonnier, and Shively 2012; Tirunillai and Tellis 2012) demonstrate that investors constantly scan brand-related information (WOM volume and variance) on social media platforms and quickly impound such more observable brand intelligence into stock prices.

Theory Contributions

Our study offers several implications for theory. First, it exposes the role of brand dispersion in marketing strategy explanations of firm value. Our findings are crucial because previous branding research has neglected dispersion, even though it can have direct bearing on firm shareholder wealth. Dispersion can indicate cross-consumer inconsistency and consumer polarization, and downside dispersion is strongly associated with negative returns. These findings offer original insights into brand management theory and justify Keller and Lehmann's (2006) point that standard deviations or variance in branding ratings are also vitally important.

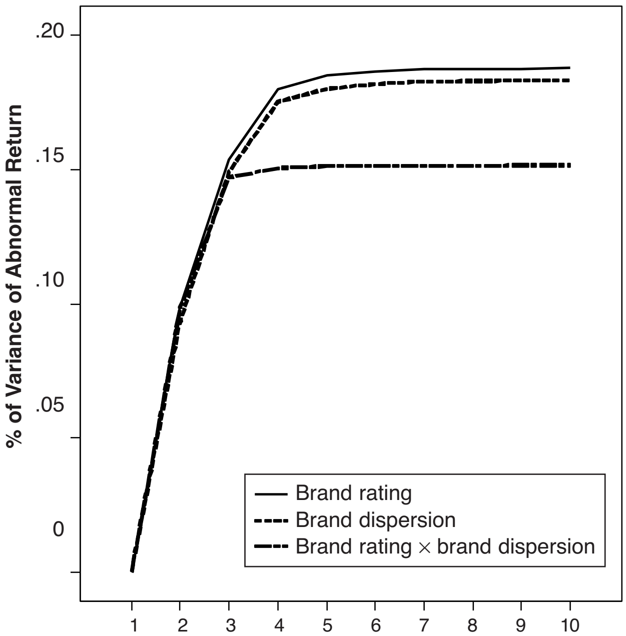
Brand dispersion's contrasting role advances the branding literature, because scholars have paid inadequate attention to how a brand can have competing effects on firm value. We find that dispersion simultaneously has both good effects on risk and bad effects on returns. This lower-returns–lower-risk result provides a more complex perspective on the translation of market-based brand assets into financial value and indicates the potential for opposing relationships among the firm value drivers (Srivastava, Shervani, and Fahey 1998).

In addition, the asymmetric effects between upside and downside dispersion generate new insights. We find evidence that downside dispersion has a stronger negative impact on returns than upside dispersion. This finding provides additional import because firms often underappreciate the contribution of their bottom customers (Homburg, Steiner, and Totzek 2009). In addition, we find symmetrical results for upside versus downside dispersion on firm risk, in support of the role of both brand dispersion and rating in affecting idiosyncratic firm risk. Moreover, this symmetry in upside versus downside dispersion on firm risk supports the practice of hypothesizing and testing both components (Rego, Billet, and Morgan 2009; Tuli and Bharadwaj 2009) rather than limiting theorizing and empirical analysis to the downside.

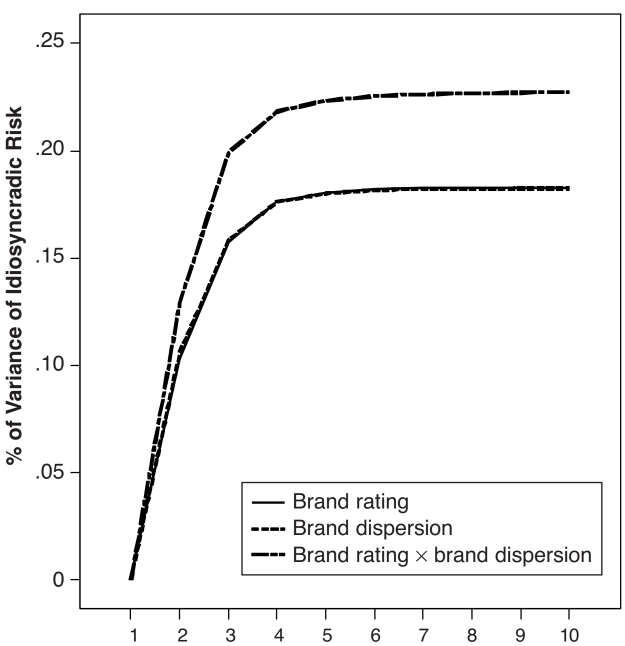
Furthermore, the interaction effects between brand dispersion and brand rating provide more nuanced evidence on the role of brand assets in generating competitive advantage

Figure 5
AVERAGE EXPLAINED VARIANCE OF RETURN AND RISK BY BRAND METRICS (GENERALIZED FORECAST ERROR VARIANCE DECOMPOSITION)

A: Variance in Return



B: Variance in Risk



(see, e.g., Morgan and Rego 2009). These brand benefits are more likely to accrue to those firms that improve their brand perceptions while decreasing dispersion. Failure to incorporate dispersion and its interplay with mean brand ratings can lead to biased (over- or under-) estimates of the contribution of brands to firm stock performance.

Thus, there appear to be more intricate and dynamic associations between brand ratings (means) and stock market performance than those identified previously. Indeed, for research on the financial value of brand attributes (Mizik and Jacobson 2008), our findings indicate the importance of including dispersion and its interplay with mean brand ratings. Failing to support the value relevance of any attribute may reflect investor uncertainty about the firm's ability to deliver the attribute, not necessarily that the attribute is not value relevant itself per se.

Finally, for the WOM literature, our study supports efforts to move beyond volume and valence and incorporate second moment information (dispersion). Recent investigations on WOM have focused on online rating dispersion and the interactions between the mean and variance of such ratings (Sun 2012). We add that the WOM of brand lovers and haters might extend across a disparate, heterogeneous community (Godes and Mayzlin 2004) and thus may be more impactful than discussions centered on a narrow, homogeneous population. Indeed, dispersion may indicate whether the product is mainstream or niche or suggest the WOM's precision (Nam, Manchanda, and Chintagunta 2010), thus more fully accounting for the influence of WOM.

Managerial Relevance

Managers should pay significant attention to dispersion and adopt it as a brand metric because it can limit the rewards the firm may earn from brand rating improvements. Dispersion also has the ability to negatively affect firm value, because it can signal inconsistency, disagreement, and consumer polarization. However, dispersion is not all bad, in that it can also lead to lower idiosyncratic risk.

Prudent marketers may take advantage of brand dispersion information. For example, they should not only pursue brand lovers (e.g., top-two box) but should also engage with brand haters (e.g., bottom-two box) to understand negative consumption experiences to reverse the "vicious cycle of negative consumer voice and word-of-mouth" (Luo 2009, p. 150). Our findings indicate the relative importance of such downside dispersion in this regard. Thus, firms should pay close attention to brand haters for more productive brand management. Incorporating dispersion, especially the influence of downside dispersion, may enhance the predictive validity of quantitative models linking brand equity to customer lifetime value (Stahl et al. 2012).

Indeed, a singular focus on mean-level brand ratings may produce biased and inaccurate assessments of brand value. With low dispersion, brand rating improvement leads to more returns, thus underestimating the power of brand equity if dispersion is ignored. Conversely, with high dispersion, brand rating's impact on returns can be lower, thus overestimating the power of brand equity if dispersion is ignored. In this sense, without considering dispersion, brand managers may be over- (under-)rewarded for brand rating improvements if there is an increase (decrease) in dispersion. Therefore, brand manager compensation and promotion practices should be adjusted to take such effects into account.

For the investment community, we highlight the value relevance of dispersion. Dedicated and privileged investors with earlier or more accurate dispersion information might profit from it because increasing brand variance diminishes stock values. Managers and investors should acknowledge that dispersion's role in cueing that brand rating information may not be credible. The heterogeneity in brand ratings can also be reflective of inconsistent brand communications, which can affect the brand's financial value (McKay and Vranica 2003).

LIMITATIONS AND FURTHER RESEARCH

Several limitations must be borne in mind when considering our results. First, our data set does not provide the precise mechanisms by which the investment community becomes aware of such daily changes in dispersion. We present some evidence that investors would pay attention to BrandIndex data, but this could be supported by future studies through surveys.

Second, dispersion in brand ratings may occur for reasons internal (e.g., brand inconsistency) or external (e.g., competitor activity, shifts in customer preferences) to the firm. Our data did not have measures for the drivers of dispersion. Behavioral investigation of the causes of dispersion is warranted. Further research is also needed to isolate the relative effects of manageable versus unmanageable dispersion. In addition, day-to-day changes in dispersion may be affected by sampling variation, which would introduce some noise. Furthermore, dispersion may reflect that a firm has successfully transformed its positioning or targeted a new consumer group; therefore, understanding these effects to long-term horizons would also be valuable.

In addition, a limitation of the YouGov data is that respondents evaluate each brand with only positive, negative, and neutral options. Ratings on an interval scale across all brands would distinguish moderate ratings and allow for a finer measure of dispersion. Moreover, research shows that the attributes we used (e.g., satisfaction, recommendation, attractiveness as employer) to evaluate brand quality are different, whereas we combined those attributes into a single factor. Further studies of dispersion with various brand perception dimensions are called for. Finally, our focus here is on cross-consumer heterogeneity in brand ratings with YouGov's data. Within-consumer variability over time is also important; therefore, there is a need to explore within-subject dispersion more fully (Rust et al. 1999).

CONCLUSION

In conclusion, this study documents initial evidence for the role of brand dispersion. Downside dispersion yields negative abnormal returns, and if unmanaged, dispersion can severely impair the benefits of brand rating enhancements. However, dispersion benefits the firm by reducing risk. We hope this study opens a new window of opportunity and spurs research to further explicate this important new brand metric.

Appendix A

DOES DAILY BRAND RATING INFORMATION CONTAIN BUSINESS-RELEVANT NEWS THAT MATTERS FOR INVESTORS? SOME ANECDOTIC EVIDENCE

References	*Contents*
The Wall Street Journal (Bialik 2010)	Brand performance indicators that rely on telephone polls, such as the American Customer Satisfaction Index and Interbrand, have the drawback of longer lead times (respectively appearing only quarterly and once a year). Online polling systems such as the BrandIndex have the advantage of collecting information about brand perceptions from a similar amount of respondents with much shorter lead times. Therefore, such brand rating can track consumer reaction to events such as the BP oil spill or Toyota product recall almost simultaneously (reflecting the reaction of stock prices to such events).
Bloomberg (Jordan 2010)	Using Twitter data from February to December 2008, Bollen, Mao, and Zeng (2010) show that sentiments expressed online could predict future Dow Jones Industrial Average index values with 87.6% accuracy. From this research, Derwent Capital Markets initiated a hedge fund using Twitter posts to make investments on the basis of social media mood and its connections to stock market movements (FTSE 100, FTSE 250, and Dow Jones Industrial Average indexes as well as oil, gold and other precious metals and currencies).
Forbes BrandIndex blog (Marzilli 2011; http://blogs.forbes.com/brandindex/)	News about brands (e.g., Facebook, Lenovo, Amazon.com, Apple) are associated with the daily BrandIndex rating, indicating the BrandIndex rating contains valuable information about recent and potential business developments.
YouGov press releases and regulatory reports (YouGov 2006, 2007, 2008a, b); *Financial Times* (Johnson 2008)	YouGov has several direct platforms for distributing its BrandIndex data directly to the financial community. In 2006, it created a joint venture with Execution, a European stockbroker, to provide financial institutions with a competitive edge through primary research into consumer trends through its BrandIndex. As YouGov's chief executive officer said, "The speed and accuracy of our research has already resulted in a positive response to our products from the investment community" (YouGov 2006). This service evolved into YouGovAlpha in 2007, a dedicated market research agency with services tailored to the specific needs of fund managers and investment professionals (YouGov 2007). A March 2008 earnings announcement revealed that customers of BrandIndex data included Privero Capital, a hedge fund (YouGov 2008).
The Washington Post (Tse and Ahrens 2008), *Fortune* (Cendrowski 2012)	Many "brand investors" recognize the value of a strong and iconic brand. Jensen Investment Management chairman and portfolio manager Robert Millen explains, "Brands themselves are what one might call soft assets.... Once you've built that strength and you continue to feed it and support it over time, then you get ... pricing power that allows the business to maintain margins.... Secondly, you get repeat business. And those two things lead to consistent earnings" (Tse and Ahrens 2008). Jensen's statement is corroborated by the finding that some hedge and investment funds use BrandIndex data.
Fresh Networks (Stratmann 2011), Venture Beat (Byrne 2011)	Consulting and analytics companies report that daily brand buzz and brand popularity (measured by, e.g., consumer sentiment in social media, number of Facebook fans) can be a lead indicator for stock price performance.
Globe Newswire (Krebsbach and Brady 2012)	Bazaarvoice's study shows that brand-related conversations are associated with stock prices. The report is based on an analysis of 26 million tweets, each of which mentioned at least one of 13 brands from the BrandZ Global 100 Brands list, including Adidas, Clinique, Colgate, Gillette, Hugo Boss, Nike, Pampers, Pepsi, Ralph Lauren, Samsung, Intel, Tesco, and Sony. There was a positive correlation of .91 between Twitter volume and closing stock prices.
RightTrade (2012), HedgeChatter (www.hedgechatter.com), SNTMNT (http://www.sntmnt.com/brands/)	Several firms have emerged (beginning in 2009) to provide real-time sentiment monitoring for investors (e.g., HedgeChatter, SNTMNT, RightTrade, DCM Capital). For example, RightTrade provides investors with a measure of real-time media sentiment from newspapers, trade press, blogs, and newswires—providing "dynamic monitoring of companies, people, products, topics, brand and reputation" (RightTrade 2012). HedgeChatter is a platform that uses natural language processing and text analytics to monitor keywords, trends, conversations, and social media sentiment across a range of social media sites, enabling investors to sort through this value-relevant information.

Appendix B

EXAMPLES OF BRANDS WITH RELATIVELY HIGH/LOW BRAND RATING AND DISPERSION

A: Coverage: United States + United Kingdom + Germany (GDP weighted)

	Brand Rating	
Brand Dispersion	*Low*	*High*
Low	easyJet, Bing, Air France, Thomas Cook, Mazda	Deutsche Lufthansa, Amazon.com, Intel, FedEx, Bridgestone
High	McDonald's, Starbucks, T-Mobile, BP, Acer	Coca-Cola, Microsoft, Hewlett-Packard, Nike, Apple

B: Selected Top and Bottom Brands by Industry

	Brand Rating		*Brand Dispersion*	
Industry	*Top*	*Bottom*	*Top*	*Bottom*
Airlines	Southwest airberlin Condor	Ryanair AeroMexico easyJet	Ryanair Delta XXX[a]	Air Canada Air New Zealand Tuifly
Automotive	Michelin Goodyear Honda	Fiat Kia Smart	Toyota Ford Fiat	Continental Mitsubishi Cooper Tires
Banks and financial services	Visa Mastercard Maestro	XXX[a] Ocean Finance Goldman Sachs	XXX[a] Chase Wells Fargo	EuroHypo SEB Zions Bank
Food and beverage	Cheerios Pillsbury Thorntons	SunnyD Milwaukee's Best Keystone	SunnyD Nestlé Stella Artois	Purdey's Green Mountain Odwalla
Health and pharmaceutical	Johnson & Johnson Neosporin Advil	Viagra Cialis Avandia	Tylenol Viagra Tums	Femara Strattera Aventis
Industrial goods	UPS FedEx TNT	Deutsche Post Lincoln Electric DHL	Deutsche Post GE UPS	Lincoln Electric Lennox Milwaukee
Insurance	Aflac MetLife Zurich	AIG United Healthcare Progressive	Geico Allstate Progressive	Allianz AXA Mercury
Information technology	Google HP Microsoft	1&1 Norton Gateway	Dell Norton Hotmail	Ricoh Flickr Lenovo
Media and entertainment	Discovery Channel Animal Planet Food Network	MTV MSNBC BET	Fox News Channel NBC MSNBC	CNET.com Versus Univision
Oil and gas	Shell Aral Chevron	BP ExxonMobil Texaco	BP Aral Shell	OMV Murco Fina
Personal and household goods	Craftsman Sony Clorox	Kappa Bush Brylcreem	Lynx George Nike	Duofold Albert Nipon Volcom
Retail	Marks & Spencer Amazon.com Lowes	WeightWatchers Primark 99 Cents Only	Primark Wal-Mart Tesco	Lucy Arden B. Conn's
Telecommunications	O2 Verizon Wireless Vodafone	Deutsche Telekom Comcast Tele2	Deutsche Telekom BT AT&T	Madasafish Cable & Wireless U.S. Cellular
Travel and leisure	Olive Garden Marriott Courtyard	Paddy Power Bingo Mecca Bingo Ladbrokes Bingo	McDonald's KFC Taco Bell	Kona Grill Noah's Bagels Cosi
Utilities	NaturEnergie eprimo SW Düsseldorf	RWE npower EON	RWE EON Yello Strom	SW Düsseldorf eprimo Sainsbury's Energy

[a]For reasons of confidentiality, these brands have been made anonymous.

Notes: Selected brands fall below/above the respective mean values for brand rating and dispersion; their position in the table does not necessarily indicate their actual rank.

Appendix C
CONTROL VARIABLE OVERVIEW

Variable	*Source*	*Operationalization*	*Rationale*
Return on assets (ROA)	Datastream	Ratio of firm's operating income to book value of total assets.	Captures firm profitability.
ROA variability	Datastream	Standard deviation of ROA across the past five years.	Greater ROA variability is associated with lower credit worthiness and higher risk because it indicates uncertainty (higher volatility) in future cash flows (Tuli and Bharadwaj 2009).
Assets	Datastream	Natural log of total assets.	Controls for firm size effects (Rao, Agarwal, and Dahlhoff 2004).
Market-to-book value	Datastream	Market value of equity divided by book value.	Indicates the importance of intangible assets (Morgan and Rego 2009).
Leverage	Datastream	Ratio of total long-term debt to the sum of long-term debt and market value of equity of a firm.	Captures the firm's ability to repay debt and financial distress (Kisgen 2006; Luo 2007; Luo and Bhattacharya 2009).
Strategic stock holdings	Datastream	100% of common stock minus the free float (Ferreira and Laux 2007).	The percentage of shares that is not available to the ordinary stock market but rather held by strategic investors that own each at least 5% of shares. Such investors are usually institutional investors such as pension funds, trusts, or banks. Captures investor heterogeneity.
Industry sector	Dow Jones/FTSE	We assigned each brand and firm to its appropriate industry sector, applying the Industry Classification Benchmark (ICB).	Control for industry effects. The ICB is a standard industry classification taxonomy.
Number of segments	Dow Jones/FTSE	Each brand was assigned to one of the 114 subsectors of ICB. We summed the number of sectors for each firm (Rego, Billett, and Morgan 2009).	Indicates the scope of a firm's product-market coverage, which controls for diversification effects (Morgan and Rego 2009).
Brand country-of-origin	Coded	We assigned each brand and firm according to the country of the firm's headquarters.	Captures country-level effects.
Corporate branding	Coded	Coded 0/1 if the corporate name is dominant when selling the products and services (e.g., FedEx, McDonald's).	Controls for any branding strategy effects (Rao, Agrawal, and Dahloff 2004).
House-of-brands	Coded	Coded 0/1 if the firm does not use its corporate brand for labeling its multi-brand products and services (e.g., Unilever, Diageo).	Controls for any branding strategy effects (Rao, Agrawal, and Dahloff 2004).
Intrafirm brand competition in segment	Dow Jones/FTSE	Number of brands a firm operates within the same sector based on the 114 subsectors of ICB.	On the one hand, brand proliferation can induce cannibalization, competition, and diluted marketing effects. On the other hand, the more brands a firm operates, the more brand management synergies exist (Morgan and Rego 2009).
Interfirm brand competition in segment	Datastream	Herfindahl industry concentration index (HHI), which is the sum of squared market shares of the firms in the industry derived from sales revenue based on the 114 subsectors of ICB.	$HHI_j = \Sigma_i^I s_{ij}^2$, where s_{ij} is the ratio of firm's sales to the total sales of industry j to which firm i belongs. The lower the HHI, the higher the industry competition (Hou and Robinson 2006).

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