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The performance of global brands in the 2008 financial crisis: A test of two brand value measures

Johny K. Johansson [a], Claudiu V. Dimofte [b,*], Sanal K. Mazvancheryl [c]

[a] McDonough School of Business, Georgetown University, Washington DC 20057, United States
[b] San Diego State University, San Diego CA 92182, United States
[c] Kogod School of Business, American University, Washington DC 20016, United States

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A B S T R A C T

Previous literature has argued that high brand equity helps stabilize financial returns and reduce share price volatility. This research investigates how some of the strongest brands in the U.S. market fared in terms of financial performance during the Fall 2008 stock market downturn. Initial results using a financially based measure of brand value (Interbrand) show that, counter to expectations, these top brands did not outperform the market as a whole. However, the findings are in the hypothesized direction when an alternative, consumer-based brand equity measure (EquiTrend) is used to replicate the analysis. After first employing the three Fama–French factors to evaluate stock performance, we assess the added brand equity effect using both aforementioned measures. The consumer-based measure shows a significant incremental effect on stock performance after controlling for risk and financial fundamentals. Furthermore, this positive effect also applies to share volatility and firm betas. None of these effects hold for the financially based measure.

1. Introduction

Relating marketing indicators to financial indicators of stock market performance and shareholder value has been the focus of several recent publications in the academic marketing literature (e.g., Mizik & Jacobson, 2009b; O'Sullivan, Hutchinson, & O'Connell, 2009; Srinivasan & Hanssens, 2009). These analyses have shown that some of the firm's customer-level assets, such as *customer satisfaction*, *customer equity*, and *brand equity*, have a significant impact on financial performance (Fornell, Mithas, Morgeson, & Krishnan, 2006; Krasnikov, Mishra, & Orozco, 2009; Kumar & Shah, 2009). Specifically, the brand equity of a firm brand has been shown to have a significant positive impact on stock market performance. For example, Barth, Clement, Foster, and Kasznik (1998) used a sample of 1204 brand value estimates from 1991 to 1996 and found them to be positively related to stock prices and returns. Madden, Fehle, and Fournier (2006) juxtaposed a portfolio of 111 firms' brands from the Interbrand list of most valuable brands between 1994 and 2001 to a benchmark market portfolio and observed higher returns and lower risk for the Interbrand set. Finally, Rego, Billett, and Morgan (2009) used data from 252 EquiTrend listed firms between 2000 and 2006 to show that high brand equity reduces volatility and, thus, the risk associated with a brand's stock.

Despite the published research on the topic, there is no strong agreement in the marketing literature on how to define and measure brand equity. Two basic approaches can be distinguished. Brand equity can be measured either at the consumer level (Aaker, 1996) or at the financial markets level (Simon & Sullivan, 1993). Researchers following the consumer-level approach view brand image, consumer affinity, and customer loyalty as the main drivers of brand value (e.g., Aaker, 1996, Keller, 2007). Examples of commercially available, customer-based brand measures include Harris Interactive's EquiTrend measure and Young & Rubicam's Brand Asset Valuator. Alternatively, researchers employing financially based measures (e.g., Madden et al., 2006) focus on financial metrics, such as projected revenues and return on investment, to determine a brand's net present value. Commercially available monetized values of brands include the Interbrand Brand Value measure and Millward Brown's BrandZ. Whereas the consumer-based approach defines brand equity according to levels of consumer engagement, the financially based approach essentially translates intangible assets into financial figures by assessing a brand's ability to generate future earnings.

It is not a priori obvious that the two approaches will concur in terms of what brands are more valuable. In fact, the two corresponding measures employed in this research (EquiTrend and Interbrand)

* Corresponding author. Tel.: +1 619.594.0209.
E-mail addresses: johanssj@georgetown.edu (J.K. Johansson), cdimofte@mail.sdsu.edu (C.V. Dimofte), sanal@american.edu (S.K. Mazvancheryl).

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only correlate at $r=.22$ (*ns*) during 2008 ($N=50$). Previous literature does not explain the reasons for such a low correlation. For example, brands ranked high according to consumer mindset measures supposedly command deep customer loyalty and are highly visible in consumer markets. These benefits ensure steady revenue levels and reduce firm idiosyncratic risk as well as its cost of capital (Rego et al., 2009). Alternatively, brands that fare well on financial markets-based measures tend to belong to firms with greater revenue streams and more predictable earnings (i.e., the so-called "large cap firms"). Large cap firms have a wider shareholder base and more prominent research coverage among analysts (Brennan & Subrahmanyam, 1996; Chordia, Subrahmanyam, & Anshuman, 2001). Thus, both types of measures suggest lowered risk and possibly higher returns for high equity brands. To date, no empirical comparison of the two types of measures has been undertaken. The purpose of this research is to present one such comparison.[1]

The effect of brand equity on stock performance has been shown to be particularly beneficial in an economic downturn, when firms face reduced consumer demand (Deleersnyder, Dekimpe, Sarvary, & Parker, 2004) and thus earn lower revenues and profits (Srinivasan, Lilien, & Sridhar, 2011). In an economic crisis, firms with high brand equity would thus be more likely to sustain revenues than firms with lower equity. Furthermore, because investors are likely to search for less risky investments in such an environment, high equity brands should become particularly attractive as "safe harbor." One would therefore expect the share prices of the strongest brands to lose less than those of weaker brands in an economic downturn. The financial crisis of 2008 and the stock market downturn in the Fall of 2008 (i.e., the September to December period when the market lost over 30% of its value) offer an ideal opportunity to test this general hypothesis.

In what follows, we analyze the stock market performance of 50 of the Interbrand Top 100 global brands from September to December of 2008. The 50 brands selected represent the subset where brand and stock market shares are directly related, and for which we have corresponding EquiTrend measures. We compare the Fall 2008 stock returns for the selected brands against the rest of their industries and the overall market. Initial results are consistent but not encouraging: shares of the highly rated brands did not drop significantly less than the market. The study then uses the three-factor Fama–French model (Fama & French, 1993) to account for differences in market-based risk for the 50 brands. The model shows that brands scoring the highest on brand equity as measured by EquiTrend do in fact show superior performance, in line with the basic hypothesis. We then introduce the financial fundamentals in order to avoid spurious inferences and to identify the incremental contribution from EquiTrend brand equity. For each of three dependent variables (stock returns, volatility, and betas) we investigate the additional explanatory power of brand value by introducing the Interbrand and the EquiTrend scores associated with each stock. Throughout the analyses we test for omitted variables and model misspecification by introducing additional variables and testing alternative functional forms (including an explicit consideration of the Fama–French market factors). Results are robust: within the sample, the EquiTrend measure is more successful than the Interbrand measure in identifying the brand equity that matters.

The rest of the article is organized as follows: the next sections develop the hypotheses and describe the data and the methodology used. A subsequent section presents the results and interpretation of the findings. The paper concludes with a discussion section, which includes an explanation of the differential impact of the two measures.

[1] This research does not claim that either consumer mindset-based or financial market-based measures are superior at capturing the brand equity construct. We simply undertake an empirical exercise, wherein we juxtapose one representative measure from each camp to assess their relative predictive power on stock performance.

2. Hypothesis development

The year 2008 offers a dramatic example of a financial crisis. Over that year, the S&P 500 Index lost 38.5% and the Dow Jones Industrials (DJI) average dropped 33.8%. The vast majority of stocks (almost 9 out of 10 of those in the broader S&P 1500 Index and more than 90% of those in the S&P 500) lost value during the year. On average, losing stocks dropped more than 40% of their value and almost $7 trillion in market value was wiped out. Shares of large firms with value-priced stocks, generally considered a safer part of the market, lost 38% of their value as measured by the Vanguard Value exchange traded fund. The 4-month period from early September through the end of December was particularly turbulent and included notable events such as the federal takeover of Fannie Mae and Freddie Mac, Lehman Brothers' bankruptcy, and AIG's $85 billion bailout. The Volatility Index (VIX) of the Chicago Board Options Exchange, known as the market's "fear index," reached an intraday all-time high of 89.53 during the year's 4th quarter.

For the comparison of the two brand equity measures during the crisis, we focus on the critical period between September and December of 2008 (see Figure 1). If brand equity lowers risk, the effect should manifest itself most clearly in this time of great turbulence. The key comparison to make is which of the two measures better protected stock returns in this period.

2.1. Hypotheses

Brand equity is the added value that a brand name and its associated logo confer upon a product or service. For example, Aaker defines brand equity as "a set of brand assets and liabilities linked to a brand, its name and symbol, that add or subtract from the value provided by a product or service to a firm and/or that firm's customers" (Aaker, 1991, p.15). The assets and liabilities "can be usefully grouped into five categories: *brand loyalty*, *name awareness*, *perceived quality*, *brand associations* in addition to perceived quality, and *other proprietary brand assets*—patents, trademarks, channel relationships, etc." (Aaker, 1991, p.16).

A "strong" brand is one that can sustain and raise high positive brand equity over time, maintaining customer loyalty and successfully defending itself against competitive encroachment (Aaker, 1996). A brand that possesses high equity should be able to sustain both a price premium and a relatively stable revenue stream. The awareness associated with high equity will reduce consumer search costs and should facilitate repeat purchases (Kamakura & Russell, 1993). Further, the loyal consumer will be less susceptible to competitor appeals and will do less comparison shopping. In addition, the association of brand equity with high perceived quality will increase customer satisfaction and reduce the incentive to consider brand substitution (Berthon, Hulbert, & Pitt, 1999; Chaudhuri & Holbrook, 2001; Oliver, 1997).

Past research demonstrating the positive relationship between brand equity and share prices also suggests that investors recognize the positive effects (e.g., Aaker & Jacobson, 1994; O'Sullivan et al., 2009). This recognition is partly attributed to reputation, as investors tend to prefer well-known brands and brands with higher advertising spending (Joshi & Hanssens, 2010; McAlister, Srinivasan, & Kim, 2007). The share prices of high equity brands will rise to incorporate the advantages and the volatility of the shares should decrease to reflect the lower risk (Rego et al., 2009). Although the evidence on the extent to which the stock market prices efficiently incorporate high brand equity is still tentative (Mizik & Jacobson, 2008; O'Sullivan et al., 2009; Srinivasan, Pauwels, Silva-Risso, & Hanssens, 2009), the effect on the risk reduction is well established

Fig. 1. Timeline of events during the Fall 2008 financial crisis.

(Rego et al., 2009; Srinivasan & Hanssens, 2009; Tuli & Bharadwaj, 2009).

Research has shown that scoring highly on brand equity measures is associated with reduced systematic and unsystematic risk in the stock market (e.g., Rego et al., 2009; Srinivasan & Hanssens, 2009). Systematic risk refers to the variability in a firm's stock returns due to the variation in the market as a whole. Unsystematic risk is the variability due to factors specific to the firm. Strong brand equity will help insulate the brand from market-level declines (Rego et al., 2009). One would therefore expect brands scoring highly on brand equity measures to show less sensitivity to market drops. This would mean that the market beta as computed during the crisis should be lower for high equity brands. Formally put:

H1. High equity brands will show lower betas than low equity brands in a downturn.

Brand assets are firm-specific, and thus their effect should be unique to the specific brand. This suggests that their effects are primarily idiosyncratic and distinct (see Aaker, 1996; Keller & Lehmann, 2006). Because brand equity values are sustained over time (Aaker & Jacobson, 1987), a reasonably efficient stock market would incorporate such advantages in share prices (see Rego et al., 2009). High brand equity simply means higher stock values. However, the stable earnings of stronger brands may make high equity brands particularly attractive during a severe downturn. High equity brands would then show more resistance to market-level shocks than other brands (Rego et al., 2009). This suggests that the volatility of brands scoring highly on brand equity measures during a crisis would be lower. Formally put:

H2. High equity brands will show lower volatility than low equity brands in a downturn.

The reduction in beta and volatility associated with high brand equity would then suggest that brands scoring highly on brand equity measures would show less of a drop in share values in a downturn. Formally put:

H3. The decline in stock returns will be lower for high equity brands than for low equity brands in a downturn.

3. Data

3.1. Stock returns

The typical measure of a stock's performance over a period is its return, usually calculated as the percent change of its share price over the period. We used COMPUSTAT daily closing prices on the NYSE, ASE, or NASDAQ for the period between September 1 and December 31, 2008. The return was then computed as the share price at the end of December 31, minus the price at the end of September 1, and divided by the price at the end of September 1. To obtain percentages, we multiplied by 100.[2] Our basic expectation was that firms with strong brands (i.e., with high scores on brand equity measures) would show less of a drop in returns over the four-month period.

3.2. Share volatility

The volatility of the stocks during the period was calculated using standard methods. Counting the trading days when the markets were open during the four months yielded a time series of 85 daily prices for each firm. From these prices, we computed 84 daily returns for each firm. The standard deviation of this series of returns was then used as a measure of share volatility. Our basic expectation was that shares of brands scoring highly on brand equity measures would show lower volatility.

3.3. The betas

Finally, to calculate the firm's reaction to the market drop during the period, we first computed the daily returns in the S&P 500 index for the period. Following the CAPM model, we then regressed daily returns against the market returns minus the risk-free returns to estimate the "beta" of the stock (Fama, 1970; Fama & French, 1993). Because we posit that high brand values insulate firms from a down market, we expected that the betas for firms with brands scoring highly on brand equity measures to be below 1.0 and the betas for firms with brands scoring lower on brand equity measures to be above 1.0, suggesting greater vulnerability to market swings.[3]

3.4. Brand equity

The brands selected for the study were all part of the "100 Best Global Brands" ranking published by Interbrand[4] in September

[2] A common alternative measure involves taking the natural logarithm of price at the end of the period minus the natural logarithm of price at the beginning of the period. The two procedures yield very similar results.

[3] Whether the beta and the volatility measures as calculated here are truly measures of "risk" is of course debatable. As risk measures, they should in principle be computed before the actual crisis occurred. They are useful here mainly as indicators of the degree to which the brand shares reacted to the overall market (the betas) and the degree to which brand equity might have made share prices relatively stable (volatility).

[4] See www.interbrand.com for the full list of the 100 brands. The rankings were based on brand data collected during the 12 months prior to June 30, 2008. How Interbrand scores are calculated is explained in Appendix A. Interbrand scores are valued in U.S. dollars and termed "brand values," not strictly measures of "brand equity."

Table 1a
Sample of 50 brands with brand scores.

Brand	Interbrand value[a]	EquiTrend value[b]	Brand	Interbrand value[a]	EquiTrend value[b]
AIG	7.02	41.41	IBM	59.03	61.09
Amazon.com	6.43	67.84	ING	3.77	60.69
American Express	21.94	53.88	Intel	31.26	66.17
Apple	13.72	60.24	J. P. Morgan	10.77	53.13
Avon Products	5.26	51.48	Johnson & Johnson	3.58	75.30
BP	3.91	57.86	Kellogg's	9.71	68.22
Canon	10.88	65.98	Marriott	3.50	62.59
Cisco	21.31	60.17	McDonald's	31.05	65.18
Citibank	20.17	51.92	Microsoft	59.01	71.40
Coca-Cola	66.67	71.20	Morgan Stanley	8.70	44.05
Colgate	6.44	67.58	Motorola	3.72	59.08
Daimler-Benz	25.58	55.75	Nike	12.67	62.90
Dell	11.70	62.66	Nokia	35.94	55.99
Disney	29.25	66.92	Oracle	13.83	50.29
eBay	7.99	63.39	Panasonic	4.28	62.29
FedEx	3.36	67.08	Pepsi	13.25	69.98
Ford	7.90	55.90	Philips	8.33	61.48
Gap	4.36	54.47	Research in Motion	4.80	54.07
GE	53.09	70.60	SAP	12.23	45.88
Google	25.59	73.53	Sony	13.58	67.62
Harley Davidson	7.61	47.50	Starbucks	3.88	57.64
Heinz	6.65	79.27	Toyota	34.05	63.52
Honda	19.08	57.68	UPS	12.62	72.83
HP	23.51	64.89	Visa	3.34	71.31
HSBC	13.14	49.73	Yahoo!	5.50	71.92

[a] Brand values in billions of U.S. dollars (see Appendix A).
[b] Brand equity scores (see Appendix B).

2008. We then acquired the corresponding scores for the same brands from Harris Interactive's EquiTrend database. Those scores were released in June 2008.[5] Thus, while the selected brands were all part of the Interbrand top 100 brands, they were not necessarily part of the top EquiTrend brands.

Not all 100 brands in the Interbrand list could be included. Privately owned firms are not listed in the stock market, a fact that eliminated a few leading brands (e.g., IKEA). Some strong brands are part of a firm's larger portfolio (e.g., Gillette belongs to Procter & Gamble), making it difficult to relate brand value to share price. For practical reasons and because the financial crisis was felt first and most acutely in the U.S., we also limited the data to shares listed on the U.S. stock exchanges, NYSE, ASE, and NASDAQ. Nevertheless, a number of non-U.S. brands were included. The final sample of 50 observations included 7 European, 5 Japanese, and 38 North American brands. Table 1a presents the 50 brands and their associated Interbrand and EquiTrend scores.

4. Preliminary results

The initial analysis compared the average drop for the 50 brands over the four-month period to that of the market and their respective industries over the same timeframe. We used a simple average of the 50 brands and compared this to the equal weight S&P 500 index (EW S&P 500). The common S&P 500 index uses weights proportional to the individual stock's market capitalization. Because the daily market caps varied widely during the crisis, creating noise in the data, we opted for the simpler average.[6]

For the portfolio consisting of these particular 50 stocks, the results were not in line with our hypothesis that these brands would beat the market. During the period between September 1 and December 31, 2008, the EW S&P 500 dropped 34.65%. The average drop during the same period for the 50 firms in our sample was higher at 35.62%. A t-test showed the difference to be non-significant ($p = .69$) but still surprising because it is in the "wrong" direction. We decided to eliminate the 8 brands representing institutions from the exposed financial sector, which produced slightly better results, with a drop of 32.28% for the remaining 42 brands; however, this result was not significantly better than the market ($p = .27$). In any case, this test is inappropriate because the S&P index of course includes the financial firms.[7]

We then tested a weighted average of the 50 brands against the common weighted S&P 500 index. The weighted S&P 500 index dropped 30.27% during the four months, slightly less than the equal weights index. The weighted average for the portfolio of 50 brands with their relative market capitalization as the weights showed a mean drop of 32.92%, which was still in the "wrong" direction but not significant ($p = .64$). Eliminating the financial brands showed some improvement. The weighted average drop for the non-financial brands was 30.10%, approximately the same and slightly better than the market (though not significantly so). The damage incurred by the financial brands was clearly an important driver in the weak overall performance.[8]

We then examined possible industry effects. The 50 brands may have come from particularly exposed industries, as was the case for the financial institutions. Industry effects in stock market analyses are often captured by using a dummy variable for each industry (e.g., Rego et al., 2009). In the present case, where the sample was limited in size and several industries were represented by very few brands, such a procedure was not feasible. Instead, using Google Finance, we grouped the 50 brands into 30 industries. The number of firms in an industry varied considerably, from as few as 4 (air couriers) to as many as 392 (regional banks). We then used the Wharton Research Data Service (WRDS), which draws on Compustat, to extract the share prices for each of the brands in the industry from September 1 to December 31, 2008. The percentage return was computed for each brand in the industry. A weighted average was then used to calculate the mean daily return for the industry in the period, the weights based on the "market cap" of the firm (its share price multiplied by the number of shares outstanding). The result was 30 time series of 84 observations each for the mean industry returns during the period. These data allowed us to estimate "industry betas" by regressing industry returns against the S&P 500. We also computed an adjusted set of industry mean returns, where in turn each of the 50 brands was excluded from the computation (to control for the fact that when one firm is a large player in an industry with few firms, its returns will dominate the industry average).

The mean drop for the 30 industries (excluding the focal brand) was 29.76%, close to the market using the weighted S&P 500 index. The industries were not unrepresentative or unique. Remarkably, brands scoring highly on Interbrand dropped more than their respective industries, where many weaker brands were presumably represented. The correlation between the returns of the 50 firms and the industry returns was positive but low ($r = .07$, $p = .63$),

[5] The EquiTrend score calculation is described in detail in Appendix B.

[6] For an evaluation of the differences between the two S&P indices, see Zeng et al. (2010). Weighted results were also computed in several instances, especially at the beginning of the analysis to determine whether the results changed much. The results were very similar and are available upon request. For the period under investigation, the two S&P indices correlated at $r = .99$.

[7] There is a potential confound in the fact that the market index contains many of the Interbrand stocks. The S&P 500 includes 36 of the 50 brands in Table 1 (the foreign brands are excluded). We eliminated those 36 brands from the S&P 500 index to recompute the index. The results reported here were virtually unchanged. They are available upon request.

[8] A natural question here is whether the analysis should only cover the non-financial brands. The problem with such an approach is that the S&P 500 index does include the financial brands as well. Also, 13 of the top 100 Interbrand brands in 2008 were financial brands.

suggesting that the brands scored highly by Interbrand were not greatly influenced by what happened in their industries overall.

5. Analyzing risk and returns

5.1. Methodology

Although it was surprising to find the 50 brands performing worse than the market as a whole, the analysis needed to control for the particular risk factors of those brands. Although they all belonged to the Interbrand top 100, various risk factors may have made these stocks particularly vulnerable. To control for this, we applied the Fama–French three-factor model, which is a well-established method for conducting financial analysis of marketing effects (Fama & French, 1993; Srinivasan & Hanssens, 2009). The Fama–French three-factor model explains daily returns for a stock as a function of three risk-related factors: the overall market return adjusted for the risk-free (Treasury bill) return ($R_m - R_{rf}$), the difference in returns for small versus big stocks (SMB), and the difference in returns for high book-to-market versus low book-to-market stocks (HML). To calculate the risk characteristics of each stock, we used the period from May 1 to August 31, 2008, the four months immediately preceding the crisis (see Fig. 1). Data on the three daily factors during that period were downloaded from Kenneth French's publicly available online database. The time series of 86 daily returns for each individual stock was then regressed on the three factors using the Newey-West heteroscedasticity and autocorrelation-consistent covariance matrix estimator (Newey & West, 1987) to calculate the standard errors and t-statistics. We also used 3 lags, following the Newey and West (1994) optimum lag method (see Appendix C for details, including estimation equations and the properties of the relevant error terms).

This approach generated the beta and the SMB and HML coefficients for each stock over the four-month period preceding the crisis. Analogous to the two-step Fama and MacBeth (1973) method, which has been widely used in the empirical analysis of the cross section of stock returns of financial panel data sets (Jagannathan & Wang, 1998; Shanken, 1992), these coefficients were then used as regressors to explain the cross-sectional differences in the subsequent 4 months between September 1 and December 31, 2008. In this period, all 50 stocks faced a similar market crisis. However, the reaction in their share prices should have differed depending on the estimated Fama–French coefficients, which capture the reaction of share prices to market swings. Thus, to the extent that the observed share drops simply reflected systematic market and risk factors, the share drops should not be attributed to idiosyncratic factors, including brand equity. To test whether brand equity still played a role, in a subsequent step we introduced the brand equity scores for each brand as an additional regressor. If the systematic risk factors were sufficient to explain the differences in share drops over the period, there would be no added role for brand equity.

In the cross-sectional analysis, we also introduced and tested other idiosyncratic variables that may explain observed differences in return drops and eliminate any brand equity effect. To this end, we largely followed Rego et al. (2009) in identifying several relevant "financial fundamentals."[9] These financial fundamentals are described next (see Table 1b for relevant summary statistics).

- *Age*. Older firms are more established and have already proven capable to withstand disruption across time. In a sense, they are "survivors" that will be more likely to attract investors in a downturn. Following Rego et al. (2009), this variable was coded as "1" for firms less than 25 years old, "2" for firms between 25 and 50 years old, and "3" for firms 50 years or older.[10]
- *Leverage*. Leverage was computed as the ratio of long-term debt plus current liabilities to total equity and referred to the degree to which borrowed funds were used to operate a business. The debt/equity ratio should have a negative effect on returns in a crisis, when high leverage likely exposes investors to greater equity risk (Ferreira & Laux, 2007).
- *Credit rating*. The firm's credit rating is one signal of how risky the stock is. Stronger ratings should provide confidence to investors (both bond holders and equity holders) in an economic downturn.

Table 1b
Descriptives for the 50 brands.[a]

Brand	Change%	Beta	Volatility	DOB	Leverage	Credit R.	Diversif.
AIG	−92.85	2.30	15.78	1967	89.97	8.75	1
Amazon.com	−37.01	1.16	5.68	1994	81.54	6.25	1
American Express	−54.34	1.39	6.53	1850	92.64	8.25	2
Apple	−48.64	.94	5.06	1976	42.67	8.00	1
Avon Products	−44.53	.85	4.81	1886	86.88	8.00	1
BP	−13.46	1.12	5.23	1889	59.91	9.00	2
Canon	−27.70	1.06	5.29	1937	30.30	9.00	2
Cisco	−31.37	1.02	4.54	1984	41.43	8.25	2
Citibank	−64.89	1.86	11.59	1812	94.81	8.75	1
Coca-Cola	−13.06	.68	3.40	1886	86.96	8.25	1
Colgate	−10.66	.64	3.23	1806	76.30	8.75	2
Daimler-Benz	−34.99	1.35	6.49	1886	71.70	7.75	2
Dell	−50.84	.82	4.83	1984	86.11	7.75	2
Disney	−30.06	1.11	4.91	1923	47.40	8.00	1
eBay	−42.00	1.00	4.90	1995	23.83	7.75	2
FedEx	−24.24	.83	4.31	1971	43.33	7.00	2
Ford	−49.22	1.31	9.25	1903	97.48	4.75	1
Gap	−32.00	.98	5.28	1969	45.47	6.25	2
GE	−43.22	1.11	5.35	1892	84.46	10.00	2
Google	−33.87	.89	4.46	1998	10.44	10.00	2
Harley Davidson	−58.44	.84	6.19	1903	58.01	8.25	1
Heinz	−27.76	.58	3.04	1869	81.51	7.00	2
Honda	−31.93	1.05	5.69	1948	62.85	8.25	2
HP	−21.11	.83	4.26	1939	56.57	8.00	2
HSBC	−37.98	.85	4.35	1865	94.25	8.75	2
IBM	−28.92	.73	3.32	1911	76.36	8.25	1
ING	−65.13	1.52	8.95	1991	96.99	8.75	1
Intel	−35.08	.98	4.61	1968	23.16	8.25	2
J. P. Morgan	−19.13	1.42	7.68	1823	92.11	8.75	2
Johnson & Johnson	−16.59	.63	2.99	1886	46.49	10.00	1
Kellogg's	−20.82	.57	2.83	1906	77.84	7.25	2
Marriott	−33.14	1.10	5.58	1971	83.65	7.00	1
McDonald's	−1.14	.60	2.97	1948	48.01	8.00	2
Microsoft	−28.27	.96	4.49	1975	50.15	10.00	1
Morgan Stanley	−61.16	2.59	14.25	1935	97.01	8.25	2
Motorola	−53.42	1.32	6.41	1928	55.63	7.00	1
Nike	−16.64	.88	4.65	1964	37.11	8.25	1
Nokia	−36.20	.98	5.13	1865	53.89	8.00	2
Oracle	−17.73	.96	4.43	1977	51.29	8.00	1
Panasonic	−39.82	.97	5.23	1918	42.81	8.75	1
Pepsi	−21.15	.58	3.04	1898	50.23	8.25	2
Philips	−39.64	1.02	5.13	1891	40.22	7.75	2
Research in Motion	−68.11	.94	6.47	1984	28.63	7.00	1
SAP	−34.54	.94	4.64	1972	37.26	9.00	2
Sony	−41.96	1.00	5.16	1946	70.19	7.75	1
Starbucks	−39.90	.99	4.93	1985	55.77	7.00	1
Toyota	−26.33	1.10	4.83	1937	61.41	9.00	2
UPS	−15.15	.73	3.52	1907	68.80	8.75	1
Visa	−30.06	.92	4.70	1958	110.54	8.25	1
Yahoo!	−34.93	.92	5.56	1994	21.95	6.75	1

[a] Variables as described in the Methodology section.

[9] One might question whether the financial fundamentals provide the proper modeling framework, since the market was not in equilibrium during the crisis. One might also wonder whether financial fundamentals played any role in share prices (see Johnson & Kwak, 2010). Still, to avoid spurious inferences they need to be considered.

[10] Analyses employing the continuous age variable find identical results.

Table 2a
Three regression models of share returns[a] ($N=50$).

Dependent variable: percent return, Sept. 1–Dec. 31, 2008			
Independent	Estimated standardized coefficients (sig. levels in parentheses)		
Variables	Base model	Interbrand	EquiTrend
Beta	−.601 (.000)	−.606 (.000)	−.495 (.000)
SMB coeff.	.221 (.061)	.208 (.076)	.142 (.213)
HML coeff.	−.243 (.039)	−.198 (.103)	−.130 (.283)
Brand score		.148 (.194)	.306 (.023)
Adj. R^2	*.44*	*.44*	*.50*
AIC	*404.41*	*404.49*	*400.24*
BIC	*412.06*	*527.12*	*409.80*

[a] The Beta, SMB, and HML regressors are coefficient estimates from the four-month period May 1 to August 31, 2008, immediately preceding the Fall 2008 period analyzed here. AIC and BIC criteria both favor the EquiTrend model. In addition, F-tests comparing the performance of the brand equity models to the base model show that the addition of Interbrand did not improve the model fit ($F(1, 45)=2.55$, $p=.11$), but the addition of EquiTrend did so significantly ($F(1, 45)=5.58$, $p<.02$). In this research, we follow the convention of using two-tailed tests unless otherwise stated.

Table 2b
Regression models of share returns for unanticipated Interbrand changes ($N=45$).

Dependent variable: percent return, Sept. 1–Dec. 31, 2008		
Independent	Estimated standardized coefficients (sig. levels in parentheses)	
Variables		
Beta	−.561 (.000)	−.569 (.000)
SMB coeff.	.200 (.114)	.191 (.127)
HML coeff.	−.230 (.150)	−.203 (.204)
Unanticipated Interbrand change	.121 (.395)	.082 (.571)
Interbrand score		.156 (.206)
Adj. R^2	*.43*	*.45*

For our study, credit rating was coded using data from the Standard & Poor's 2008 credit rating score on a 10-point scale ranging from “10” for an AAA rating to “1” for DDD.[11]

- *Diversification*. Diversification captures the number of different industries in which the firm operates. The more businesses in which the firm operates, the lower is potentially its stock's risk. Following Rego et al. (2009), this variable was coded “1” for a single industry firm and “2” for a firm with more diversification.

The estimation method closely drew on standard cautions in financial analysis. The wide-ranging size differences between the brands easily lead to unequal variances in the observations (heteroscedasticity) and suggested the use of generalized least squares analyses. The size differences also created a need to reduce the influence of extreme observations and outliers (see Barth et al., 1998). To address these problems, we employed the feasible generalized least squares (FGLS) regression approach using the STATA statistical package. FGLS uses the square of the residuals from the initial OLS results as the diagonal entries in the variance-covariance matrix. This matrix is then used for a generalized least squares estimation, each observation weighed in inverse proportion to the square of its residual in order to control for heteroscedasticity and the impact of outliers (Judge, Griffiths, Hill, Luetkephol, & Lee, 1985). The resulting coefficients are both efficient and consistent.

5.2. Stock returns and brand values

We first analyzed the role of high brand values in the return performance of the 50 stocks.

We began by using the three Fama–French terms (i.e., the beta and the SMB and HML coefficients for each stock over the four-month period preceding the crisis, as described above) to control for the influence of systematic risk factors (see Table 2a). Not surprisingly, these factors captured the returns performance of the 50 stocks associated with our brands well. To assess the possible incremental effect of brand equity beyond these factors, we introduced the two brand value measures in turn, as extra predictors of stock returns. Whereas the addition of Interbrand did not significantly affect these returns, EquiTrend performed much better. The introduction of EquiTrend scores significantly improved the adjusted R-square and produced the best model fit according to both the Akaike (AIC) and Bayesian (BIC) information criteria for model selection. Thus, we found that during the Fall 2008 crisis, firms with higher EquiTrend brand scores had higher returns (or less negative returns) than their systematic riskiness would have suggested. This is consistent with the notion that brand equity lowers unsystematic risk.

The EquiTrend scores did not change for any brand during the four-month period, but stocks with higher brand scores performed better than the stock's systematic risk would have predicted. These results offer support for the “safe harbor” interpretation, the notion that investors move towards stocks with higher brand scores in a crisis. No such effect was observed for the high Interbrand stocks. However, the Interbrand scores for 2008 were made public on September 19, 2008, and it would therefore be possible that they contained unanticipated changes that affected the performance of the stocks. To assess this possibility, we calculated the change in Interbrand scores between 2007 and 2008 and re-ran the analysis for Interbrand changes as well as 2008 scores. The results again showed no significant impact from Interbrand scores. Given the slightly smaller sample size ($N=45$), the results were not conclusive. However, the direction of the results was consistent: Interbrand scores did not influence investors significantly (see Table 2b).

We tested the above results for spuriousness by assessing what other brand idiosyncratic factors may have played a role. Omitted variables could possibly account for the brand equity effect uncovered. Table 2c presents the results of three alternative models, which include industry performance as well as the firm-specific variables described in the methodology section.

As the results in Table 2c show, none of the financial fundamentals significantly explained share price performance over the period. Firm age is a marginally positive factor, suggesting that older firms may have better weathered the storm. There is clearly a possibility of multicollinearity obscuring any single variable's impact, but that matters less because the emphasis here is upon the incremental impact of the brand value scores. It is clear that the improvement from Interbrand scores is small and non-significant.[12] In contrast, the EquiTrend scores do suggest a significant positive effect of high brand equity. Once again, the introduction of EquiTrend scores significantly improves the adjusted R-square and produces the best model fit. Even with the financial fundamentals accounted for, high EquiTrend scores give the associated brands a significant boost.

We attempted other model specifications to further test for the possibility of omitted variable bias. The objective was to see whether the Interbrand scores would enter significantly and whether the EquiTrend effect could be eliminated. For example, we tested

[11] We are aware of the role of imperfect credit ratings in the crisis (e.g., Lowenstein, 2010). Nevertheless, to be prudent from a statistical standpoint, the credit scores need to be accounted for. In fact, in the Fall of 2008, investors were apparently very much influenced by faulty credit ratings.

[12] Note that because the included 50 brands all have relatively high scores on the Interbrand measure, this does not mean that Interbrand scores overall have no impact on share prices. This is not an analysis of the complete range of Interbrand scores, and thus is not an assessment of the scores' validity.

Table 2c
Three extended regression models of share returns[a] ($N=50$).

Dependent variable: percent return, Sept. 1–Dec. 31, 2008			
Independent	Estimated standardized coefficients (sig. levels in parentheses)		
Variables	Base model	Interbrand	EquiTrend
Beta	−.504 (.001)	−.504 (.001)	−.401 (.007)
SMB coeff.	.347 (.015)	.330 (.030)	.258 (.061)
HML coeff.	−.266 (.071)	−.243 (.135)	−.153 (.311)
Industry change	.070 (.545)	.069 (.555)	.052 (.633)
Age	.247 (.086)	.234 (.127)	.250 (.067)
Leverage	−.092 (.530)	−.104 (.486)	−.102 (.459)
Credit rating	.152 (.245)	.128 (.380)	.118 (.335)
Diversification	−.104 (.383)	−.107 (.378)	−.097 (.388)
Brand score		.049 (.724)	.296 (.033)
Adj. R^2	*.44*	*.43*	*.59*
AIC	*410.16*	*411.88*	*406.36*
BIC	*427.37*	*431.00*	*425.48*

[a] AIC and BIC criteria both favor the EquiTrend model. Furthermore, F-tests comparing the performance of the brand equity models to the base model show that the addition of Interbrand did not improve the model fit ($F(1, 40)=.22$, $p=.64$), but the addition of EquiTrend did so significantly ($F(1, 40)=4.79$, $p<.04$).

whether the portion of revenues coming from the North American or other global markets could significantly affect firm performance. Neither of the two variables entered the models significantly. The international diversification of the revenue stream did not greatly matter, showing that the crisis was indeed a global one. We also tested whether financial firms receiving funds from the Trouble Asset Relief Program (TARP) in November 2008 showed a significantly different pattern, again finding no particular shifts in brand effects. The initial results remained robust.

5.3. Share volatility and brand values

The next step in the analysis was to assess the impact of brand value on stock volatility. The hypothesis here was that brands scoring high on brand equity measures would show less volatility.

The volatility in the market, measured as the standard deviation of the S&P 500 for the daily returns across the four months from September 1 to December 31, 2008, was 4.07% for the weighted S&P 500 measure and 4.24% for the EW S&P 500 index.[13] Notably, the 50 selected brands showed a higher degree of volatility at 5.52%, which was significantly more than the market ($p<.001$). The average volatility of the 30 industries in that period was 4.82%, which was significantly higher ($p<.02$) than the market but also significantly lower than the selected brands ($p<.03$). Selecting out the financial brands yielded a reduction, with an average volatility of 4.81% for the 42 brands, which was still significantly higher than the market ($p<.001$) but not significantly higher than their respective industries at 4.58%. Contrary to expectations, stocks with high brand values actually showed higher volatility than the others in the market and in their industries.

We then ran three regressions of volatility against the financial fundamentals alone; after, we ran one regression with the Interbrand values and one regression with the EquiTrend values added (see Table 3). Interbrand scores did not lower volatility significantly, although the negative effect was in the hypothesized direction of lowering risk. In contrast, the EquiTrend measure showed a strong, significant impact and clearly helped reduce volatility.

[13] Volatility figures are often annualized. For consistency, we use the four-month measure here.

Table 3
Three regression models of share price volatility[a] ($N=50$).

Dependent variable: standard deviation of share price changes, Sept. 1–Dec. 31, 2008			
Independent	Estimated standardized coefficients (sig. levels in parentheses)		
Variables	Base model	Interbrand	EquiTrend
Industry volatility	.350 (.011)	.337 (.014)	.244 (.034)
Age	−.303 (.034)	−.277 (.052)	−.142 (.196)
Leverage	.393 (.008)	.398 (.007)	−.033 (.823)
Credit rating	.047 (.711)	.092 (.485)	−.083 (.434)
Diversification	.123 (.336)	.133 (.296)	.024 (.817)
Brand score		−.178 (.178)	−.482 (.000)
Adj. R^2	*.26*	*.27*	*.48*
AIC	*224.31*	*223.73*	*207.36*
BIC	*235.78*	*237.11*	*220.75*

[a] AIC and BIC criteria both favor the EquiTrend model. Further, F-tests comparing the performance of the brand equity models to the base model show that the addition of Interbrand did not improve the model fit ($F(1, 43)=2.22$, $p=.14$), but the addition of EquiTrend did so significantly ($F(1, 43)=19.35$, $p<.001$).

5.4. Firm betas and brand values

We next examined the firms' market betas and the related industry betas. We expected the firms scoring high on brand equity measures to show lower betas.

We calculated the 4-month betas for the firms and the industries using the 84 daily returns in the period from September to December, 2008.[14] The average beta for the 50 firms over the four months was $\beta=1.04$, which was not significantly different from 1.0 ($p=.49$), suggesting that these firms tended to follow the market, on average. The 30 industry-to-market betas averaged 1.10, which was not significantly different from the market ($p=.12$). The higher volatility of the financial brands, however, was clearly reflected in the average betas. Selecting out the financial firms resulted in an average firm beta of .93, which was significantly lower than 1.0 ($p<.03$). The non-financial industries similarly lowered their average beta to 1.06, not significantly different from 1.0. The 8 financial brands had an average beta of 1.61, with an average industry beta of 1.34, which were both significantly higher than 1.0. In terms of the betas, the non-financial firms were significantly less sensitive to the market, while their industries were slightly more exposed.

We next ran the three beta regressions with financial fundamentals included. The results were in line with the previous analyses (see Table 4). The Interbrand coefficient estimate was very low, while the EquiTrend scores again showed strong significance, which helped to insulate the stocks from downward market swings.

6. Results summary

6.1. The top 50 brands

Contrary to expectations, the 50 brands selected from the Top 100 Global Brands did not perform better than the market in the Fall 2008 crisis. The returns of the 50 brands did not outperform the market but instead were slightly worse than the market average (although not significantly so). Hypothesis 3 is not supported. The 50 brands also performed worse than their industry peers, and the results suggest that these leading brands did not necessarily move with their respective industries.

[14] The industry data used in these beta regressions did not exclude the focal brands. We wanted the betas to reflect the full set of firms in each industry. To follow standard procedure, we also used the weighted S&P 500 measure as the market index. Betas are typically calculated for longer periods of time, such as a year, but we wanted to focus on the four months specifically. Still, the correlation between the Fall 2008 betas and the betas published for the whole 2008 year was a very high $r=.99$.

Table 4
Three regression models of the brand betas[a] ($N=50$).

Dependent variable: firm-to-market betas, Sept. 1–Dec. 31, 2008			
Independent	Estimated standardized coefficients (sig. levels in parentheses)		
Variables	Base model	Interbrand	EquiTrend
Industry beta	.186 (.165)	.187 (.164)	.083 (.519)
Age	−.519 (.001)	−.531 (.001)	−.500 (.000)
Leverage	.311 (.033)	.313 (.033)	.242 (.078)
Credit rating	−.024 (.853)	−.039 (.769)	−.028 (.816)
Diversification	.247 (.060)	.241 (.069)	.215 (.080)
Brand score		.064 (.634)	−.344 (.009)
Adj. R^2	*.25*	*.23*	*.34*
AIC	*44.62*	*45.90*	*38.66*
BIC	*56.09*	*59.28*	*52.05*

[a] AIC and BIC criteria both favor the EquiTrend model. Furthermore, F-tests comparing the performance of the brand equity models to the base model show that the addition of Interbrand did not improve the model fit ($F(1, 43)=.61$, $p=.44$), but the addition of EquiTrend did so significantly ($F(1, 43)=7.24$, $p<.01$).

The results for volatility and betas were also inconsistent with previous research. The 50 brands showed higher volatility and higher betas than the market, which was not significant in either case but still demonstrated a trend toward higher riskiness. Excluding the financial brands from the set showed the expected pattern with both volatility and betas, which indicated lower sensitivity for non-financial brands than for brands from the financial sector. However, because the S&P 500 market indices also include the financial brands, the overall results reject both H1 and H2.

6.2. Interbrand

The results were inconsistent with the argument that stocks of high-value brands (according to Interbrand) provide a safe haven for investors during turbulent financial times. During the Fall 2008 stock market drop, brands with high Interbrand scores did not perform better than the market. If anything, they performed worse. They also underperformed relative to the industries they belong to, where less prominent global and local brands were included. Controlling for financial fundamentals and other related variables showed no significant impact on the 50 brands' financial performance from brand values.

In terms of volatility, similarly surprising results were obtained. The 50 brands were more volatile than both the market and their industries, against expectations that high brand equity would reduce risk. As for betas, the 50 brands did not perform significantly worse than the market or their industries, but they did not do better either. Eliminating the financial firms lowered the betas significantly below 1.0. However, once financial fundamentals were controlled for, the Interbrand effect was not significant.

6.3. EquiTrend

The EquiTrend results generally show a much more positive picture of brand equity. Among the 50 brands, higher brand equity according to EquiTrend performed according to our initial hypotheses. Not only did high EquiTrend scores help lower volatility and the betas significantly, but the scores also showed a significantly positive impact on the share prices over the period. Brand equity as measured by EquiTrend helped lower riskiness and also helped limit overall losses in the Fall 2008 crisis.

It is important to note here that the 50 brands were selected from Interbrand's Top 100 global list. If EquiTrend is superior to Interbrand, a selection of top EquiTrend brands would presumably outperform the market. To test this conjecture, we selected the top 50 EquiTrend brands from the industries previously analyzed. The simple average drop of these 50 brands between September and December of 2008 was 29.48%. This was significantly less than the EW S&P 500 drop of 34.65% ($p<.02$), which supports our present findings.

7. General discussion

This section will first address several issues of methodology and assess whether the observed results are valid and reliable. We will then discuss the possible explanations for the divergent results for the two brand equity measures.

7.1. Sample selection

The sample of 50 brands selected is small and of limited representativeness. One omission consists of the brands from conglomerate firms such as P&G and Unilever; another is the limit of shares listed on American stock exchanges; and a third is the exclusion of privately held firms. These brands are clearly not representative of the entire brand universe, whether in the U.S. or elsewhere. Nevertheless, the selected brands do include some of the most prominent global brands, and the aim was to evaluate how the best brands performed in the crisis. If these brands did not compare well to the vast majority of brands, it is difficult to believe that brand value is very important in stock market performance.

7.2. Measure selection

One measurement issue was the shift between equal weight and market cap weighted performance measures. We provided both in several instances. The main argument in favor of weighted measures is the use of market cap weights in the typical S&P comparisons. However, because equal weights have been shown to be preferable when markets are inefficient in pricing factors (e.g., Zeng, Dash, & Guarino, 2010,) and because they avoid introducing additional noise when weights fluctuate widely, equal weights may be preferable in this instance. In any case, as our findings show, the results are very similar.

7.3. Financial brands

The results clearly indicate that the Fall 2008 crisis hit financial firms the hardest. This is of course well known. The question is whether our results are mainly a result of including the financial institutions in our analysis. We think there is very little choice, given that our benchmark market indicators all include some or all of the financial firms. Nevertheless, we have shown that our results, even without the financial firms, fall into the same pattern. However, with a smaller sample size the statistical significance tends to be lower.

7.4. Time period

The chosen 4-month time period is limited. The cutoff dates of September 1 and December 31 2008 are necessarily arbitrary, although they did encompass the main portion of the crisis. The cutoff two weeks before the Lehman bankruptcy seemed logical because it was considered a significant event and because we wanted to include a period sufficiently long for the aftermath to play out. Once a longer period is addressed, many other factors need to be considered. However, we wanted to examine financial performance in a period where the market was clearly not in equilibrium and thus brand effects could enter prominently. Doing so, however, imposes a limit on the generalizability of the analysis; in equilibrium, the brand effect question revolves mainly around whether brands are properly valued by the market (see Mizik & Jacobson, 2009a).

7.5. Misspecification

The regression results could possibly be affected by misspecification, including omitted variables. Several additional financial and related variables were tested. As noted earlier, foreign sales percentage was assessed, as was the use of TARP funds. We introduced alternative transformations of the financial fundamentals, including curvilinear relationships, by adding squared terms. We tested log transformations for the Interbrand independent variable and also used the Interbrand rankings instead of the dollar values. We also expanded on the brand scores by introducing “brand leadership” variables, drawing on the market share rank for the brands in their respective industries. Because no significant changes appeared in the brand equity effects, we retained the simple results presented in the tables.

7.6. Estimation method

The separate brand estimations during the calibration period (May 1–August 31, 2008) followed standard Newey–West methods for time series analysis. The feasible least squares method used for the cross-sectional analysis addresses some of the typical problems in cross-sectional stock data. It controls for heteroscedasticity and limits the influence of extreme observations and outliers (Judge et al., 1985). The introduction of industry averages helps control intra-industry error correlations, which are likely because different industry sectors are not necessarily affected to the same extent by a downturn. The results were stable across methods (OLS versus robust regression versus FGLS) and did not seem to be attributable to any method problems. In these data, the uncovered effects persist.

7.7. Brand equity

If the results hold, how can one explain why the EquiTrend brand equity scores possess more diagnostic information than the Interbrand brand value measure? Our first test was to check how the two measures correlated; as previously mentioned, the correlation was a meager $r=.22$ (*ns*). We next checked the degree to which the measures favored or discriminated against certain types of businesses. Brands are likely to be more important in some sectors than in others, for example, perhaps more important in the consumer goods sector than in the business-to-business sector (see Fischer, Voelckner, & Sattler, 2010). In particular, we asked whether the assessment of brand equity in financial institutions showed some systematic bias between the two measures. Financial institutions averaged a score of 53.27 in the EquiTrend measure, which was significantly lower ($p<.03$) than the average of 63.00 for the non-financial brands. However, the Interbrand measure showed a similar difference, from \$17.5 billion for non-financials to an \$11.1 billion average for financial brands, which was not significant at $p=.29$ but directionally consistent. We tried other splits (consumables versus durables, services versus products, B2B versus B2C) but the results were similar. The measures do not appear to differ in their assessment of brand equity by industry.

How strongly financial measures of brand equity should correlate with consumer-based measures is unclear. As we have observed, both measures have been used in past research to identify brand equity effects in the stock market, but there is no published empirical research directly comparing the two. Some previous research has put forward dimensions of brand value similar to the Interbrand-EquiTrend distinction. For example, Kamakura and Russell (1993) presented a dichotomy composed of Brand Value (quality perceptions discounted for price and advertising expenditure levels) and Brand Intangible Value (consumer brand name associations). Similarly, Francois and MacLachlan (1995) distinguished between measures of “brand equity,” which are largely financially oriented, and measures of “brand strength,” which tend to originate in consumers' brand experiences and reactions. The value of financially based data as a measure of “brand equity” is questioned by Aaker (1996, p. 314), who notes that Interbrand scores are brand *values*, not *equity* measures. Overall, there seems to be agreement in the literature that financial and customer-based measures tap into different brand dimensions, whether they are called brand equity or brand value. The low correlation found here clearly supports this assumption.[15]

8. Conclusion

The likely explanation for the differing performance of the two measures lies in the way equity is captured. The EquiTrend brand equity measure assesses consumer allegiance to a brand and is thus largely exogenous to the stock market. In contrast, Interbrand brand values partially rely on financial projections, which are necessarily predicated on specific assumptions about future growth. If the assumptions used to generate financially projected brand values no longer hold, the calculated brand values will not surprisingly be misleading. In contrast, the customer-based measures would point to a sustainable edge in the marketplace, even in, or perhaps particularly in, a down economy.

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Appendix A. Interbrand value calculations

The Interbrand formula deducts the following from total company earnings: (1) brand sales costs, (2) marketing costs, (3) overhead costs, including depreciation, (4) a charge for capital employed, and (5) taxes. The result of these deductions is then adjusted to account for the role of the brand in driving demand to determine what proportion of intangible earnings is attributable to the brand. The resulting brand earnings are then further adjusted by brand strength.

Brand strength involves several factors: (1) leadership (25%), or the brand's ability to dominate a market (positive factor); (2) stability (15%), assessing how long the brand has been established (positive factor); (3) market volatility (10%), accounting for the risk of new technology and low entry barriers (negative factor); (4) reach (25%), or the geographic spread of brand sales (positive factor); (5) trend (10%), capturing the upward/downward trajectory of the brand; (6) support (10%), assessing the consistency of marketing support (positive factor); and (7) legal protection (5%), dealing with the firm's problems in protecting the brand name across markets (negative factor). These factors are combined according to the percentage weights in a brand strength index, which is used to derive a discount factor for projected future earnings. A strong brand with a high index score will yield strong future earnings and thus have a small discount rate (around the 5% typical of a low-risk investment). A weaker brand will have a higher discount rate, reflecting the higher risk associated with its future earnings. The resulting net present value for each brand produces its Interbrand score and associated ranking.

Source: Lindemann (2003).

[15] That said, note that in this research, the data only address one specific aspect of the two measures: how they fared during the 2008 financial market collapse. We are reluctant to make general statements on the overall usefulness of the two metrics (in either absolute or relative terms), as both have a demonstrated value in several other respects.

Appendix B. Equitrend value calculations

The EquiTrend brand equity score is a consumer survey measure that has been collected annually since 1989 for a representative selection of brands in the U.S. market. In 2008, over 20,000 U.S. consumers were surveyed online, and the total number of brands rated was 1170 (each brand received approximately 1000 ratings). In the EquiTrend methodology, the data are weighted to be representative of the entire U.S. population of consumers ages 15 and over on the basis of age by sex, education, race/ethnicity, region, and income. A brand's equity score is determined by first combining *Familiarity*, *Quality*, and *Purchase Intent* ratings at the individual respondent level. The brand's total equity score is then aggregated across all respondents with some familiarity with the brand, and the result is indexed on 100. As with Interbrand, the top scores are publicly disseminated, but the brands in the top lists do not overlap consistently. EquiTrend scores for the complete set of brands are available commercially.

Source: www.harrisinteractive.com

Appendix C

Following the two-step Fama and MacBeth (1973) method, we first estimated the three-factor Fama–French regression model on the four-month period from May 1 to Aug 31, 2008 immediately preceding our analysis period (see Fig. 1). This resulted in 85 daily observations for each brand. The regressions were run separately for each of the 50 brands.

$$\left(R_{it}-R_{rf,t}\right) = \alpha_i + b_i\left(R_{m,t}-R_{rf,t}\right) + s_i SMB_t + h_i HML_t + \varepsilon_{it} \quad (1)$$

where

- R_{it} stock return for brand i on day t,
- $R_{rf,\,t}$ the risk-free rate of return on day t,
- $R_{m,\,t}$ the market rate of return on day t,
- SMB_t the difference in returns for small versus big stocks on day t,
- HML_t the difference in returns for high versus low book-to-market stocks on day t,
- i 1, 2, 3,…50 brands,
- t 1, 2, 3,…86 trading days.

The error-term for Eq. (1) has the following properties:

$E(\varepsilon_{it})=0$;$E(\varepsilon_{it}^2)=\sigma_i^2$; and$E(\varepsilon_{it}\varepsilon_{i,\,t-1})\neq 0$ for some finite time period t, indicating possible serial correlation. To correct for serial correlation, we used the Newey–West estimator (Newey & West, 1987) to obtain autocorrelation-consistent estimates. We used the automatic lag selection approach suggested by Newey and West (1994), which led to a lag-length of 3 periods (days) resulting in 83 usable daily observations for the period under consideration.

In the next step, we estimated the following cross-sectional model of 50 brands for Fall 2008 (i.e., Sep. 1–Dec 31, 2008):

$$DP_i = \beta_0 + \beta_1\left(\hat{b}_i\right) + \beta_2(\hat{s}_i) + \beta_3\left(\hat{h}_i\right) + \beta_4(B_i) + \eta_i \quad (2)$$

where

DP_i the percentage change in share price for brand during Fall 2008;

$\hat{b}_i$, $\hat{s}_i$ and $\hat{h}_i$are the coefficient estimates from Eq. (1);

- B_i brand value for brand i (Interbrand or EquiTrend score);
- η_i error term for brand i.

This error-term has the following properties:

$E(\eta_i)=0$; $E(\eta_i^2)=\vartheta^2$; and $E(\eta_i\eta_j)\neq 0$ for $i\neq$j, allowing that returns may be correlated across individual brands. To correct for heteroscedasticity, we used the Feasible GLS (FGLS) estimation technique to yield consistent estimates (note that even though$\hat{b}_i$, $\hat{s}_i$, and $\hat{h}_i$are the coefficient estimates from Eq. (1), the errors in these time series estimates are uncorrelated with the cross-sectional error termη_i).

Finally, we also estimated extended versions of the model in Eq. (2) using additional control variables, including *Age*, *Leverage*, *Credit rating*, and *Diversification* (as described in the Methodology section).

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