Brand Value and Long-Run Stock Returns

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Abstract

Using Interbrands' data as well as a novel text-based measure of brand value, we find that an equal-weighted portfolio of best brands earns a monthly excess return of at least 25 bps. This result is not due to firm characteristics, industry composition, small-cap stocks, or organization capital. The excess returns are driven by companies that develop their brands internally (i.e., not by acquisitions) and analysts underestimate future earnings of brand names in their forecasts. We highlight serious limitations of measuring brand value using past advertising expenses and find no abnormal returns associated with this (input) measure of brand value.

Keywords: Brand Value, Intangible Assets, Excess Returns, Undervaluation

A truly great business must have an enduring "moat" that protects excellent returns on invested capital.

The dynamics of capitalism guarantee that competitors will repeatedly assault any business "castle" that is earning high returns. Therefore, a formidable barrier such as [...] possessing a powerful world-wide brand (Coca-Cola, Gillette, American Express) is essential for sustained success.

Warrant Buffett's letter to shareholders, 2007

A great company is not a great investment if you pay too much for the stock.

The Intelligent Investor of Benjamin Graham

Because almost all investors think these attributes [valued brands and stellar reputations] make for great investments, demand for companies with these characteristics is supersized, which bids up current prices and depresses future returns.

Wall Street Journal, June 10, 2019, titled "Warren Buffett Likes 'Wide Moat' Stocks. Should You?"

1. Introduction

Firm value derives not only from tangible assets (e.g., property, plants, machines) but also from intangibles. Intangible assets are generally categorized as knowledge capital (including human capital) and brand capital. Modern corporations are increasingly investing in intangible assets and the role of these assets in explaining firm value has grown significantly over the last few decades.[1] In recent years, the portion of overall corporate capital stock that is intangible is estimated to be about 50% (Corrado and Hulten 2010; Gulen et al. 2021; Ewens et al. 2020). Moreover, Belo et al. (2022) estimate that, on average, between 70% and 80% of firm value comes from intangible capital.

In this paper, we investigate the stock market valuation of the most visible intangible asset, namely brand capital. Intangible capital, by its nature, is difficult to measure and value, and our focus on brand capital is motivated by three main observations. First, brand capital constitutes a significant portion (between 10% and 23%, on average) of firm value (Belo et al. 2022; Vitorino 2014). Second, unlike other forms of intangible capital, there is a clear and indisputable link between having a more recognized brand name and higher firm value. Specifically, top brands charge higher prices (Keller 2013; Kaul and Wittink 1995; Ailawadi et al. 2003), have more loyal customers (Chaudhuri and Holbrook 2001), enjoy durable advantages over competitors and face lower threats from entrants (Bronnenberg et al. 2012), have lower financial constraints and higher cash flow stability (Larkin 2013) and elicit greater customer interest in trying, adopting, and personally promoting a new branded product (Keller 1993). Third, unlike other forms of intangible capital that may not be readily and directly observable by market participants, brand

[1] See Gutierrez and Philippon (2017), Corrado et al. (2009), Haskel and Westlake (2017); Ewens et al. (2020).

names are highly visible. As a result, while one might expect other intangibles to be underpriced (in case of mispricing), brand value is likely to be overpriced due to the popularity of top brands (Frieder and Subrahmanyam 2005).

We find that an equal-weighted portfolio of Interbrand's yearly list of Best Brands (BB) in the U.S. earns a monthly excess return of 25 to 35 basis points (bps) from 2000 to 2020. These figures exclude the short-term market reaction to the BB list announcement and are remarkably robust across various factor models and hence not driven by exposures to (risk) factors such as size, value, momentum, profitability, quality, expected growth. In addition, the results remain virtually unchanged after controlling for the exposure to intangible-related factors proposed in the literature (Eisfeldt and Papanikolaou 2013; Peters and Taylor 2017). Moreover, the excess returns are not driven by micro-cap stocks and as a result a (capped) value-weighted BB portfolio earns significant abnormal returns (20 to 25 bps per month). The BB's excess return from Fama-MacBeth regressions controlling for a host of characteristics (including organization capital) is 35 bps per month, with an associated cumulative excess return of 116% in our sample.

Theoretically, whether the stock market fully values brand capital or whether it over- or underestimates it is ambiguous. As explained above, scholars have documented the positive effects of brand name on firm value. Indeed, one of the most widely known bits of advice offered by Warren Buffett is to pick stocks of companies with a sustainable "economic moat," a term that typically refers to companies with strong brands. However, great (strong-brand) companies might not necessarily make great investments. If the stock market is efficient and fully incorporates the value of brands in current stock prices (Fama 1970), top brands should have the same risk-adjusted returns as other companies. In fact, precisely because top brands are great companies and this is known to market participants, top brands might be overvalued, leading to negative excess returns for these companies in the future. In addition, higher reputation of brand names might be associated with higher investor base, lower risk and lower cost of capital (Cao et al. 2015), also leading to lower expected returns for investors.

In contrast, companies with high brand value may be undervalued in the stock market for the following two reasons. First, accounting rules treat investments in creating and enhancing brands as operating expenses, and hence they are fully expensed in the year they are incurred, and no associated (brand) asset is created in the balance sheet. This leads to lower accounting earnings and book value of equity. As a result, a fair price for a company that invests significantly in its brand capital would make it look (misleadingly) overvalued according to common valuation metrics such as price-to-earnings (PE) or market-to-book (MB) ratios. Second, while it may be easy to observe and incorporate some benefits of a strong brand (e.g., higher margins) into current valuations, many other long-term beneficial effects of a brand name for the firm's value could be underestimated, which is in fact the underlying assumption behind the famous advice of Warren Buffett mentioned earlier.

To investigate the mechanism behind the excess returns and to further diminish a potential concern that the results we document are driven by other factors correlated with brand value, we conduct two main analyses.[2] First, we exploit the accounting differences in treatment of internally developed versus acquired intangibles. While the former is fully expensed and do not show up in the balance sheet, the latter is capitalized. As a result, companies that develop their brand internally would appear (misleadingly) to be too expensive according to common valuation metrics such as PE or MB ratios. Indeed, we find that the excess returns are statistically significant *only* for companies that develop their brands internally. Any alternative hypothesis should also explain why there is no excess return for brand names with relatively large stock of acquired intangible assets. Second, we study earnings surprises and find that analysts tend to underestimate earnings of BBs in their forecasts. Higher intangible brand value manifest itself in larger positive surprises in future tangible outcomes (i.e., earnings), leading to higher stock prices and higher returns to brand names. We also show that keeping the original portfolio rather than rebalancing it according to the most current list of BBs leads to significantly lower returns, suggesting that brand value is indeed not a permanent characteristic and that the results are unlikely to be driven by an omitted variable correlated with the original set of brand names.

We also propose and study the excess return to a novel text-based measure of brand value (another output measure) constructed from textual analysis of firms' annual reports since 1996. We find that a portfolio of top brands according to this text-based measure earns significantly higher excess returns than the one we reported for the Interbrand's sample. Indeed, if the stock market undervalues brand value, one would expect that the undervaluation be larger when there is less coverage and attention. This independent analysis reassures us that the results we document are unlikely to be driven by another factor than the brand name, allows for constructing portfolios

[2] We note that both in our factor models and in Fama-MacBeth regressions, we control for the role of other intangible capital. Hence, higher knowledge or human capital does not explain our results.

with a larger set of brands than what is available via Interbrand, and serves as an out-of-sample test.

The extant literature typically measures intangible capital using *input* measures such as past accounting data of cumulated expenditures on research and developments, selling, general, and administrative expenses, or advertising expenses (in case of brand capital), and assuming a constant depreciation rate (Belo et al. 2022; Eisfeldt et al. 2022; Peters and Taylor 2017; Belo et al. 2014; Vitorino 2014; Hasan et al. Forthcoming). Despite all merits of such measurement,[3] we focus on the BB list, an *output* measure of brand capital, compiled yearly by Interbrand. The BB list is more suitable for the purpose of our study for two main reasons. First, while an input (accounting) measure of brand capital could be readily estimated, it requires to have the input measure, i.e., advertising expenses. Since this is not a mandatory item to be disclosed, about half of BBs would drop out of analysis due to not reporting advertising expenses. Examples of these companies in 2020 are Apple, Microsoft, General Electric, IBM, Caterpillar, Disney, Kellogg, HP, American Express, Constellation Brands, Adobe, Cisco, Starbucks, and Tesla. A study of brand value excluding these top brands could well reach to misleading results. Second and even more importantly, accounting measures are backward looking and uninformative regarding the quality of the investments. The BB list, in contrast, is forward looking and much more reactive to changes in the market values of brand names, i.e., when a brand loses huge value (e.g., Motorola) or when a brand gains significant value in a short period of time (e.g., Zoom). Relatedly, some companies manage to create a valuable brand while spending almost nothing on traditional advertising (e.g., Tesla). These companies would correctly show up among BBs while being categorized as having very low brand capital according to advertising expenses.[4] For all these reasons, it is more appropriate to study whether the stock market fully values brand capital using an *output* measure (e.g., the BB list) than a measure based on cumulated past advertising expenses (an input measure). Indeed, we find no excess return when we use the input measure of brand value. Somewhat similar results are shown in Cohen et al. (2013) where they find that while firms with higher R&D investments do not earn any excess returns, a subsample of firms that are better able to convert R&D to cash flows (based on their past track record) earn abnormal returns of 11% per year.

[3] For example, to compute a measure of book equity that includes intangibles, one must use investments in intangibles (input measures). This is for consistency reasons, since book equity is an input measure.

[4] In addition, advertising is one out of numerous means companies have in hand to improve their brand value.

The closest paper to ours is Belo et al. (2014), in which the authors investigate the relation between brand capital *intensity* (constructed from past advertising expenditures) and firm risk using a structural model. The general idea in that paper is that companies with a high *share* of brand capital (to their assets or employees) are low productivity firms since their stock of brand capital is too large. Because investments to build the stock of brand capital (i.e., advertising) is irreversible, firms with high brand capital intensity are riskier and hence have higher expected returns in equilibrium. Our paper complements Belo et al. (2014) in two important ways. First, our analysis is focused on output measures of brand value, which we argued in detail above why it is a more appropriate measure than the input measure for testing the stock market valuation of brand names. Second and more importantly, companies with high brand capital intensity, the focus of the theory in Belo et al. (2014), are *not* brand names. Top ten companies with highest share of brand capital to assets in 2020 are Everquote, Parts ID, Contextlogic, Zovio, Casper Sleep, Smiledirectclub, Skillz, Cargurus, Curiositystream, and Blue Apron Holding, which are clearly not brand names. In contrast, top valuable brands in our analysis in 2020 include Apple, Amazon, Microsoft, Coca-Cola, Disney, Nike, Facebook, McDonald's, Intel, and IBM. Consistently, brand capital intensity has a very low correlation (-0.07) with Interbrand's brand value and not surprisingly including it in our regressions has virtually no effect on our coefficient of interest. Hence, our paper is complementary to Belo et al. (2014) as we have a different theoretical argument (applied to brand names, not low productivity firms with too much advertising expenses) requiring us to use a completely different measure and study distinct set of companies.

More generally, our paper contributes to the growing literature that studies the asset pricing implications of intangible capital such as R&D expenditures and patents (Eberhart et al. 2004; Lev and Sougiannis 1996; Hirshleifer et al. 2013; Cohen et al. 2013; Fitzgerald et al. 2021), selling, general, and administrative expenses (Banker et al. 2019), trademarks (Hsu et al. 2022), customer satisfaction (Aksoy et al. 2008; Fornell et al. 2016), organization capital (Eisfeldt and Papanikolaou 2013), and employee satisfaction (Edmans 2011; Boustanifar and Kang 2022). Most previous papers have studied input measures of intangible capital constructed from SG&A, R&D, or advertising expenses. Our focus on an output measure of brand capital is similar to papers that consider employee satisfaction rather than investments on employees (Edmans et al.

2020; Boustanifar and Kang 2022) or patent citations (and success in converting R&D to sales) instead of investments on R&D (Zhen et al. 1999; Hirshleifer et al. 2013; Cohen et al. 2013).

While we control for extensive set of factors and characteristics and we provide evidence on the mechanism behind our results, there are several alternative potential explanations. First, investments in intangibles might be riskier (e.g., whether advertising leads to higher brand value is uncertain), and therefore these companies could have higher expected returns. This cannot be the explanation since not only we control for investments on advertising, but also our measure of brand value is an output measure identifying companies that do actually have high brand value. The second potential explanation is that companies with high brand value might be those with high organization (human) capital and as argued in Eisfeldt and Papanikolaou (2013), these companies are riskier (with higher expected returns) since their shareholders do not own a significant part of firm assets (i.e., human capital). In contrast, we study the value of brand names, a type of intangible capital owned by the firm. If anything, one would expect that companies with high brand value have lower risk due to their customer loyalty that makes them less vulnerable to macroeconomic shocks. Our regressions also control for organization capital and hence our results are unlikely to be driven by possible correlations between brand value and other intangible capital. Finally, a mispriced omitted and unobserved variable correlated with brand value could potentially be an explanation. To be qualified, such an unobserved variable should also vary systematically across brand names developed internally and those acquired externally. In addition, professional analysts should also systematically underestimate the positive effect of that omitted variable on future earnings. While certainly not impossible to come up with such an unobserved omitted variable and relate it to brand value and excess returns, we find it an unlikely explanation. As we do not have a natural experiment that exogenously assigns different brand values to firms, our paper joins a long list of related studies whose results are subject to non-causal interpretation (Edmans 2011; Hirshleifer et al. 2013; Hsu et al. 2022; Cohen et al. 2013; Gompers et al. 2003; Yermack 2006).

The remainder of this paper unfolds as follows. Section 2 describes our data and measurements and provides descriptive statistics. Section 3 explains our empirical methodology and results. Section 4 investigates the reasons behind outperformance of the BB portfolio. Section 5 studies abnormal returns to alternative measures of brand value. Finally, Section 6 concludes our work.

2. Data, measurement, and descriptive statistics

2.1. Best Brands (BB) List

The main data source in this paper is the annual list of top brands (Best Global Brands) produced by Interbrand, which provides the most well-known and widely used brand valuation method. In fact, the first brand valuation model was developed by John Murphy, the founder of Interbrand, in the 1980s. Murphy realized the need to develop a brand valuation methodology following the wave of mergers and acquisitions in the 1980s. As Murphy himself put it, in the 1980s, there was "a huge buying and selling of branded-goods businesses where what was essentially being bought and sold was brands, but nobody knew how to value brands" (Holdsworth 2001). In 1988, Interbrand developed a proprietary methodology for brand valuation. In 1989, the company evaluated the Pillsbury brand for Grand Metropolitan PLC's acquisition of Pillsbury Co., which is recognized as the first official brand valuation and is considered as a milestone achievement in the branding industry (Arvidsson 2011).

Interbrand's valuation methodology (as will be explained shortly) relies on the idea of measuring incremental future earnings to the branded company that are due to its brand, rather than other firm characteristics such as product quality. This method of computing brand market value essentially estimates the intrinsic value of a brand name (by discounting its future expected cash flows), which is considered the most reasonable way of estimating the market value of a brand (Damodaran 2009). This is also precisely how marketing scholars define brand equity. For instance Simon and Sullivan (1993) define brand equity as "the incremental cash flows which accrue to branded products over and above the cash flows which would result from the sale of unbranded products."[5] A classic example illustrating brand equity is the significantly higher price of a branded medicine versus a generic version, even though the two products are identical. For example, even for a product such as aspirin that has been off patent for more than 100 years, Bronnenberg et al. (2015) find that the price of the branded version produced by Bayer is five times greater than the unbranded products.

Interbrand was also the first company to have its methodology certified as compliant with the requirements of ISO 10668 (requirements for monetary brand valuation). Moreover, its valuation

[5] Prior works have documented a significant brand premium across different categories of products, including automobiles (Sullivan 1998), S&P 500 index funds (Hortaçsu and Syverson 2004), online books (Smith and Brynjolfsson 2001), and consumer packaged foods (Bronnenberg et al. 2015).

estimates have been found to be relevant and sufficiently reliable for use in financial reporting statements. As a result, Interbrand's (brand) valuation methodology is recognized widely by businesses, standard-setting authorities, academic and regulatory bodies, as well as accountancy and legal practices. Finally and importantly, Interbrand's data on top brands have been available since 2000, which is significantly longer than alternatives. A long time series covering different market conditions, i.e., booms and crises, is crucial for making conclusions that are reliable and generalizable, particularly since we are studying the long-term stock market valuation of brands. For example, in the dotcom bust of the early 2000s many technology companies with valuable brands were significantly and negatively affected, and therefore an analysis that excludes this crisis may generate biased results.

To be included in the Interbrand assessment, a company must meet a number of criteria. Specifically, the brand needs to be global (i.e., at least 30% of its revenue must come from outside the brand's home region and the company must have a presence in Asia, Europe, and North America), have publicly available data on the brand's financial performance, be visible (the brand must have a public profile and sufficient awareness across major economies of the world), and have the expectation of positive long-term economic profits (the return must be above the brand's cost of capital).

To estimate the value of a brand, Interbrand follows a three-step process. First, it estimates the economic profit of the company or the after-tax operating profit of the brand, minus the cost of capital needed to generate the brand's revenue. In the second step, Interbrand estimates the Role of Brand Index (RBI), which measures the portion of purchases attributable to the brand as opposed to other factors such as price or product features. Depending on the brand, the RBI is determined by commissioned market research, benchmarking against Role of Brand scores from other brands in the same industry, or expert panel assessment. Multiplying the estimated economic value (estimated in Step 1) by the RBI (computed in Step 2) leads to "brand earnings," which is an estimate of future extra earnings the branded company is expected to earn compared to an otherwise similar company without the brand name. In the third and final step, brand earnings is discounted using a measure of brand strength. Brand strength is computed using 10 (internal and external) factors such as leadership, engagement, and relevance, that are all measured relative to other brands in the industry. Overall, brand strength measures the ability of the brand to create loyalty, and therefore sustainable demand and profit into the future.

Starting in 2000, Interbrand began publishing an annual list of BBs. The initial list included 75 global brands in 2000 but it was increased to 100 brands in 2001 onwards. Up to 2007, the lists were published in July or August; subsequently, the announcement date was moved to late September or October. As we are interested in the long-term effect of brand value and whether the stock market overvalues or undervalues it, our BB portfolio is formed (or rebalanced) in the first day of the month following the announcement date. The few weeks of delay between the list announcement and our portfolio formation/rebalancing allows sufficient time for the market to react to the news. Therefore, our analysis effectively allows the market to price in the effect of the brand value announcement and then investigates whether the stock market fully incorporates the impact of brand capital on future returns.

2.2. Descriptive Statistics of Best Brands (BBs)

It is important to note that the BB list that is published is based on brands, not companies. That is, multiple brands from the same company (e.g., Google and YouTube from Alphabet Inc., Coca-Cola and Sprite from the Coca-Cola Company, and KFC and Pizza Hut from Yum! Brands, Inc.) could show up separately as top brands in the same year. Our analysis is at the stock level and hence we map brands to stocks. Whenever we present data and analysis based on brand values, we sum brand values of the same company and use that as the brand value for the company (e.g., the sum of the Google and YouTube brands is treated as the brand value of Alphabet). This implies that the list of stocks in each year will be lower than the list of brands. Moreover, we focus on US companies for which we have stock price data from the Center for Research in Security Prices (CRSP), which means that private companies are excluded from the sample.[6] Table 1 reports the number of BBs included in our analyses per year. The average number of companies included in the BB portfolio annually is 47. The number of companies in the portfolio is comparable with that of prior studies that have a similar empirical set-up as this paper (Hong and Kacperczyk 2009; Yermack 2006; Edmans 2011). We note that our text-based analysis reported later will have 100 firms in the portfolio per year. Table 1 also reports statistics on the number of companies that are added and dropped from each list compared to the previous

[6] Private companies such as Wrigley Company, Levi Strauss & Co., and The Wall Street Journal are not included in the portfolio. Further, companies that are listed in the US stock market as ADRs—such as Anheuser-Busch InBev, Honda Motors, and HSBC Holdings—also are not included in the portfolio.

one. As expected, the list of BBs tends to be quite stable (i.e., a top brand in one year will most likely stay within the top brands the following year), but we do have companies entering and leaving the list. On average, three new brands enter the list each year and two brands leave the list, presumably due to negative shocks to the brand value. For example, Motorola failed to adopt to changes in the telecommunications industry from the wireless telephone to the smartphone and was dropped from the BB list in 2009. Overall, of all companies in the original BB list (2000), 29% had dropped out of the list by 2010 and 45% had dropped out by 2020.

Table 2 reports counts of brand names by industry. The number within parentheses following each company name reports how many years (out of a total 21 years) each firm was part of the BB list. As shown, some companies have always been part of the list (e.g., Microsoft, Amazon, Apple, HP, McDonald's, Coca-Cola, Nike). In contrast, some other companies that were among the top brands in earlier years had dropped out of the list in later years (e.g., Motorola, Merrill Lynch, Xerox) and some newer brands were added to the list over the past decade that were not part of the list previously (e.g., Salesforce, Netflix).

Figure 1 and Figure 2 present the information reported in Table 2 in a graphic form. Specifically, Figure 1 plots the number of BBs per industry (48 Fama-French classification) in our sample. The figure has two clear messages: (a) BBs have been present in 27 (out of 48) industries including Computer Software, Computers, Business Services, Consumer Goods, Hotels, Banking, Electronic Equipment, Machinery, Automobiles, Food Products, Aircraft, and Petroleum and Tobacco Products, to name a few; and (b) there are relatively large cross-sectional differences in terms of number of BBs per industry. Industries with the most BBs include Computer Software, Computers, Business Services, Consumer Goods, and Restaurants and Hotels, whereas the ones with the lowest numbers are Recreation, Aircraft, Petroleum and Natural Gas, Insurance, and Personal Services.

To illustrate the evolution of industry affiliation of the BBs, Figure 2 shows the number of brands per industry by year. For better visual presentation, the cells are color-coded where the darker cells indicate larger numbers. As shown, there are industries where the presence of BBs has been very stable over time—including Consumer Goods, Restaurants and Hotels, and Banking— whereas industries such as Computer Software and Business Services have been accommodating increasingly more BBs.

Table 3 presents summary statistics of BBs for the first year (in Panel A) and the last year (in Panel B) of our sample. BBs are clearly large companies with a mean (median) market cap of \$288bn (\$143bn) in 2020. In comparison, the NYSE 80th, 90th, and 95th percentile breakpoints in 2020 are \$17bn, \$37bn, and \$79bn, respectively. The minimum market value in 2020 is \$15.3bn, while the maximum is \$2.3tn, hence a very skewed size distribution.

To better illustrate the size distribution of BBs and its evolution over time, Figure 3 plots the percentage of BBs in each NYSE size category per year. As shown, about 90% of BBs have market capitalizations that are larger than the 80th percentile NYSE size breakpoint. We rarely observe a BB with a size below the 50th NYSE breakpoint. Therefore, we present most of our empirical results based on a BB equal-weighted portfolio, since it is essentially impossible that our equal-weighted results would be driven by micro-cap stocks. We will investigate below the robustness of our results with respect to the exclusion of very small stocks and using the value-weighted portfolio. We will show that the straight value-weighted portfolio is dominated by a few extremely large companies and hence we also report the results when we cap the weights of stocks in the portfolio.

Table 3 also show that intangible assets constitute, on average, about 21% of total assets of BBs in 2020, with a large variation ranging from 0% to 54%. It is important to note that intangible assets (e.g., brand values, customer relationships) reported in the balance sheets are almost entirely those that have been obtained via acquisitions. This is because, except in very specific situations, accounting rules do not allow capitalizing intangible assets that are developed within the firm. In one of our empirical analyses, in order to shed light on the mechanism behind the return predictability, we exploit this different accounting treatment of internally developed versus externally acquired intangibles.

In addition, as shown in Table 3, BBs spend, on average, 11.92% (7.74%) of their gross profit on advertising in year 2000 (2020). The average ratio masks a significant variation across BBs. There are some BBs that spends relatively little on advertising (e.g., Accenture, Cisco, Deere & Company), whereas some others devote more than 15% of their gross profit to advertising (e.g., The Walt Disney, Colgate-Palmolive, Nike). It should be noted that many firms do not report advertising expenses separately. In 2000 (2020), out of 38 (46) BBs we have advertising expenses for only 28 (38) of them. Examples of companies that did not report advertising expenses in 2020 are Apple, Tesla, General Electric, and American Express.[7]

Following Eisfeldt and Papanikolaou (2013) and Belo et al. (2014), we also compute organization capital and brand capital to total assets for the BBs. As shown in Table 3, in 2020, BBs have an average organization capital to assets of 1, with a huge variation from 0.29 to 2.24. Similarly, the average brand capital to assets is 0.16 with a very large variation from almost zero (0.02) to 0.55. These clearly show, not surprisingly as explained above, that top brand names are very different from each other according to the input measure of brand capital.

To understand the (non-risk-adjusted) returns of the BB portfolio, we study the performance of a $1000 initial investment in the BB portfolio compared to the same investment in two benchmarks: characteristics-matched (in terms of size, book-to-market, and momentum) and industry-matched portfolios from September 2000 to December 2020. We find that the BB portfolio has significantly outperformed these two benchmarks. The average monthly return of the BB, industry-matched, and characteristics-matched portfolios are 0.96%, 0.86%, and 0.79%, respectively. The corresponding cumulative returns of these portfolios throughout our sample are 653%, 511%, and 411%, respectively.

Our detailed empirical analysis in the next session investigates whether the BB portfolio is associated with any excess return after controlling for common (risk) factors that are known to be related to stock returns.

3. Empirical Methodology and Results

Having documented detailed characteristics and descriptive statistics of the BBs and their returns compared to some benchmarks, we turn to statistical analysis to evaluate how much (if anything) of the BB portfolio's return could be considered abnormal. Specifically, in this section, we conduct empirical analyses using factor models as well as Fama-MacBeth regressions to control for characteristics that are known to be related to the cross-section of stock returns.

[7] These firms report marketing, promotional and advertising costs as an element of selling, general and administrative expense. We checked their annual filings manually, and indeed there is no number reported for advertising expenses. In case of Tesla, the company report that "advertising costs were immaterial for the years ended December 31, 2020, 2019 and 2018."

We focus on long-run stock returns (rather than valuation ratios or event studies) for several reasons. First, studying stock returns is much less subject to causality issues. For example, a correlation between higher brand value and higher profitability/valuation could simply be due to better performance causing higher brand value, i.e., reverse causality. However, since the effect of performance should already be incorporated into the current stock price, a better-performing firm should not have higher *future* returns. Second, focusing on stock returns allows us to estimate excess returns after controlling for (risk) factors that should be associated with higher returns such as size, value, momentum, profitability, quality, and expected growth. Finally, given the evidence that the market does not fully incorporate intangibles (Lev and Sougiannis 1996; Aboody and Lev 1998; Chan et al. 2001; Edmans 2011; Hirshleifer et al. 2013; Boustanifar and Kang 2022), event studies or valuation ratios would underestimate the effect of brand values. Indeed, Dutordoir et al. (2015) find a positive abnormal return for companies listed in the top brand list in a short-term event-study setup. By forming our portfolio in the month after the announcement, the excess returns we report are above and beyond the short-term market reaction to the announcement.

3.1. Time Series Factor Regressions

The most common practice used in empirical finance to estimate abnormal returns connected with a particular strategy/portfolio is to use factor regressions. Generally speaking, in these set-ups, we run regressions of excess returns of the portfolio on known (risk) factors that affect returns. A general equation for such a regression is:

$$ER_t = \alpha + \sum \beta_k \cdot Factor_{k,t} + \varepsilon_t \qquad (1)$$

where ER_t is the excess returns over the risk-free rate, $Factor_{k,t}$ represents the known factors (depending on the choice of model), and β_k is the factor loading on each long-short factor portfolio return. The coefficient α measures abnormal returns that cannot be associated with exposure of the portfolio to any of the factors.

We use several of the most recent factor models (in addition to Carhart model) to estimate abnormal returns. Specifically, we use the 5-factor model of Fama and French (2018) plus momentum (Fama-French 6-factor), q-factor model of Hou et al. (2014), q5-factor model of Hou, Mo, et al. (2020), and the "AQR" 6-factor model (Frazzini and Pedersen 2014; Asness et al. 2019). The Fama and French 6-factor model adds profitability (*RMW*) and investment (*CMA*) to the Carhart model. The q-factor model consists of factors for market (*R_MKT*), size (R_ME), investment (*R_IA*), and profitability (*R_ROE*). The q5-factor model augments the q-factor model with expected investment growth (*R_EG*). It is important to note that many strategies that generate significant abnormal returns in the Fama-French 6-factor framework have insignificant alphas in the q-models (Hou, Mo, et al. 2020), highlighting the necessity of estimating abnormal returns using the q-models as well to make sure that the excess returns are not driven by exposure to factors in the q-models. Finally, we also consider the *AQR* model including the following factors: market (*MKT*), size (*SMB*), value (*HML*), momentum (*UMD*), betting against beta (*BAB*), and quality minus junk (*QMJ*).

We use all five of the asset pricing models mentioned above (Carhart, Fama-French 6-factor, q-factor, q5-factor, and *AQR* models) to test whether the BB portfolio is associated with any significant positive or negative abnormal returns. Unless otherwise stated, the results we report are based on the equal-weighted portfolio (as BBs tend to be very large companies), but we do investigate the robustness of these results using alternative methodologies in the next section. The standard errors for coefficients are calculated using the Newey and West (1987) method to allow for residuals to be heteroskedastic and serially correlated.

The results of different factor model regressions are reported in Table 4. We use five different factor models and hence there are five different columns, each corresponding to one model. This table documents a positive and significant excess return associated with the BB portfolio that is remarkably robust across all the factor models. For example, the Carhart 4-factor and Fama-French 6-factor alphas are 32 and 29 bps per month (with t-statistics of 3.39 and 3.03), respectively. The lowest estimated alpha is in the q5 model, which is 25 bps per month (t-statistic 2.11). Our most conservative estimate yields an average excess return to the BB portfolio of 3% per year, or a cumulative excess return of 83.9% during our 21-year sample.

As shown, the BB portfolio has a negative and significant exposure to the momentum factor (*MOM* in Carhart and FF6 and *UMD* in *AQR*). In addition, the BB portfolio has a positive and significant loading on the quality factor of the *AQR* model (*QMJ*) and the expected growth factor of the q-5 model (*EG*). We note that the latter is constructed based on operating cash flow and implicitly measures the effect of some intangible investments since it includes R&D expenditures (Hou, Mo, et al. 2020).

Overall, the results of Table 4 strongly suggest that the BB portfolio generates a positive, sizable, and statistically significant excess return, after controlling for common (risk) factors including size, value, momentum, profitability, quality, and expected growth. It is important to highlight that these excess returns are above and beyond any positive short-term market reaction to the BB list announcement due to the fact that, as explained above, the BB portfolio is formed several weeks after the list announcement to allow for the market to price in the news.

3.2. Sensitivity of the BB Portfolio to Weighting Method

Our main analysis in this paper is focused on an equal-weighted BB portfolio. It is well known that the estimated excess returns could be sensitive to the choice of an equal- versus value-weighted portfolio (Fama and French 2008; Hou, Xue, et al. 2020), given the disproportionate effects that "micro" stocks may have on the returns of equal-weighted portfolios. In our set-up, however, this should not be a significant source of concern because, as shown in Figure 3, we rarely have any stock with a market cap below the NYSE 50th size breakpoint. To be more precise, we do not have any BB with a size below the NYSE 30th percentile in any single year during the sample, while there are three occasions (in 2000, 2001, and 2003) where one of the companies in the BB portfolio has a size that lies between the NYSE 30th and 50th percentile breakpoints. Instead, as also highlighted in Fama and French (2008), the characteristics of value-weighted portfolios are dominated by a few very large firms, and this is particularly the case in our context. For example, in 2020, the largest BB has a market capitalization of $2.3tn, compared to the median of "only" $143bn. In other words, the distribution of market capitalization has a few outliers that a value-weighted portfolio is going to be dominated by only a handful of gigantic stocks, which is clearly not a balanced portfolio.

We investigate whether our results are driven by small-cap stocks in two ways. First, we continue to use the equal-weighted BB portfolio but exclude smaller stocks, i.e., those with a market cap below the NYSE 50th percentile breakpoint. In the second approach, we create value-weighted portfolios that assign small weights to smaller stocks and hence lower their influence on portfolio returns. Specifically, in the presence of extremely large stocks in the portfolio (as in our situation), to construct a tradable but balanced portfolio one could use capped value-weighted portfolios in which the market caps are winsorized at a threshold such as the NYSE 80th percentile (Jensen et al. 2021). We follow this practice to create a BB value-weighted portfolio where the market caps for computing weights are winsorized at the NYSE 90th percentile breakpoint. This effectively means that we assume that the BBs with market capitalizations larger than the NYSE 90th percentile breakpoint have market caps equal to the NYSE 90th percentile. In this way, smaller companies will have small weights in the portfolio and no one stock will dominate the portfolio. We then form our value-weighted portfolio according to this assumption and run the factor regressions. Table 5 reports the results, together with the original excess returns we estimated previously for the sake of comparison. As shown and as was expected, excluding small stocks does not have any effect on our estimates of excess returns to the BB equal-weighted portfolio. However, the abnormal returns from the straight value-weighted portfolio are much smaller in magnitude and statistically insignificant. Obviously, the difference between the results of equal- and value-weighted portfolios are not due to inclusion of small stocks, as shown before. On the contrary, the difference comes from the fact that the value-weighted portfolio is dominated by few very large companies. Indeed, the excess returns to the capped value-weighted portfolio is quite similar both in size (between 20 and 29 bps per month) and statistical significance to the ones of the equal-weighted portfolio.

Overall, these results show that the positive and significant abnormal returns to the BB portfolio are robust to using a capped value-weighted portfolio and are not due to the influence of small stocks.

3.3. Controlling for Characteristics: Fama-MacBeth Regressions

In the previous section, we used factor models to study the abnormal returns of our BB portfolio after controlling for factors from several of the most recent and well-known models in empirical asset pricing. One potential concern related to the factor regression results is that differences in characteristics of BBs (eg., size, market-to-book ratio, profitability, etc.) compared to other firms could be the reason behind the abnormal returns we document. While factors such as size, value, and momentum are included as covariates in the factor regressions, these characteristics could still have explanatory power, as argued in Daniel and Titman (1997). In addition, the factor regression set-up does not allow us to control for many characteristics at the same time. To address this issue, we use the Fama and MacBeth (1973) methodology (FM). Specifically, we start with the universe of ordinary common stocks in CRSP (share codes of 10 and 11) and retain in our analysis all companies with a market cap above $1 million and a stock price of more than $1. Using all these stocks, we then run the following regression:

$$R_{it} = \alpha_0 + \alpha_1 BB_{it} + \alpha_2 Z_{it} + \varepsilon_{it} \qquad (2)$$

where R_{it} is the raw (or industry-adjusted) return on stock *i* in month *t*, BB_{it} is the dummy variable which has a value of 1 if the stock is among the most recent BB list and 0 otherwise. Z_{it} is the set of characteristics variables and α_1, which is the coefficient of interest, measures the abnormal return associated with the companies in the BB list.

We use characteristics from Brennan et al. (1998), and add to them further characteristics variables that have more recently been used in the literature. Characteristics from Brennan et al. (1998) include: the log of market cap in month t-2 (*SIZE*); the log of the book-to-market ratio, which is recalculated each July (*BM*); the total dividend per share of the last 12 months to current price (*YIELD*); the logs of the compounded returns in month t-3 to month t-2 (*RET2-3*), month t-6 to month t-4 (*RET4-6*), and month t-12 to month t-7 (*RET7-12*); the log of dollar trading volume in month t-2 (*DVOL*); and the log of price at the end of month t-2 (*PRICE*). Additional new characteristics we include are *ASSET GROWTH* (the annual growth rate of total assets, representing firm investments), *ROE* (return on equity), *PROFITABILITY* (cash-based operating profitability as in Ball et al. (2016)), *EARN SURP* (earnings surprise), *LEVERAGE* (total debt to total assets), *R&D* (log of expenses on research and developments), and *ADVERTISING* (log of expenses on advertising), and *ORG CAP* (log of organization capital constructed as in Eisfeldt and Papanikolaou (2013)). As firms with high brand value might also have high knowledge or human capital, including organization capital as a characteristic is important to isolate the incremental effect of brand value.

Table 6 reports the results of FM regressions where the unit of observation is a stock-month, and the dependent variable is the raw stock return in Columns 1-3 and industry-adjusted returns in Columns 4-6. We use three specifications (for each dependent variable) that gradually add more characteristics. In the first specification (Columns 1 and 4), we use the characteristics used in Brennan et al. (1998), while the second specification (Columns 2 and 5) adds further characteristics including *ASSET GROWTH*, *ROE*, *EARN SURP*, *LEVERAGE*, *R&D*, and *PROFITABILITY*. The third specification (Columns 3 and 6) adds *ADVERTISING* and *ORG CAP*.

The results of Table 6 Column 1 show that BBs have excess returns of 42 bps per month in our basic specification, which is reduced to 34 bps after controlling for a host of recently proposed characteristics (Column 2). In Column 3 and after controlling for organization capital, we still estimate an excess return of 27 bps for BBs, which is sizable, statistically significant and in the same range as what was estimated using factor regressions in Table 4.

As we documented in detail in Section 2, although BBs come from many different industries, there is significant variation in terms of the number of BBs across industries. One may wonder how much of the excess returns is due to the particular industry composition of BBs. Columns 4-6 of Table 6 investigate this question using similar FM regressions as before, but with industry-adjusted returns as the dependent variable. As shown, the estimated monthly excess return in the full specification is 25bps (in Column 6), which shows that industry composition plays no role in in explaining the excess returns to BBs.

One important point to highlight is that organization capital stock we include in regressions does embed brand capital stock (or the book value of investments in advertising) in it. Having said that, we provide in Appendix Table 1 the results of Fama-MachBeth regressions with alternative specifications. Specifically, we include brand capital and brand capital to assets (or brand capital intensity) instead or in addition to organization capital variables. We note that brand capital is computed using cumulating past advertising expenditures similar as in Belo et al. (2014). As shown, if anything, the excess return estimates to brand names become larger.

The last specification in Appendix Table 1 adds an additional variable, *DOMESTIC*, which is a dummy variable indicating whether the firm is local (=1) or global (=0). We add this as one might be concerned that BBs are international companies, and these companies might have higher return than local companies. The variable *DOMESTIC* is constructed using Compustat (geographic) Segment data. Companies whose geographic segment includes only the USA are considered local. As shown, indeed local companies tend to have lower returns, but including of this variable has virtually no effect on the coefficient of interest, which remains 39bps both in the third and fifth specification.

Overall, after controlling for all characteristics, BBs have, on average, significant excess returns of at least about 25 to 30 bps per month.

3.4. Time Series of Excess Returns

Having documented significant average excess returns to BBs, one might wonder if the average excess return is driven by a few outlier months during which (for whatever reason) the returns to BBs were extremely large. In addition, it would be interesting to see if the excess returns come from the early part of the sample and have disappeared since. To address these points, we estimate month-by-month excess returns using FM methodology. We first note that the average of monthly excess returns (the coefficients on *BB* reported in Table 6) are very close to the median numbers. For example, the median monthly excess return is 0.31, which is in the very close to the average excess return estimated in Table 6 Column 3. In the industry-adjusted specification (corresponding to Column 6 of Table 6), the median monthly excess return is 0.28, compared to the average of 0.25. Overall, the fact that the mean and median statistics are close to each other strongly rejects the existence of influential outlier months.

To further understand the time series of excess returns, Figure 4 plots the cumulative monthly abnormal return series estimated using the FM regressions corresponding to Column 3 of Table 6. As shown, the cumulative excess return series moves up and down (as expected), but with a clear upward trend. The cumulative excess return is 116% during the entire sample. This shows that the excess returns do not only come from the start of the sample or a particular period.

Using FM regressions as above, we conduct two further analyses to better understand the excess returns in different periods. First, we estimate the excess returns in different economic conditions. Specifically, we study the following periods: (a) the dotcom crash from April 2000 to October 2002, (b) the boom leading to the financial crisis from November 2002 to July 2008, (c) the financial crisis from August 2008 to March 2009, (d) post-financial crisis and the period of sovereign debt crisis from April 2009 to December 2013, and (e) the last period from January 2014 to December 2020. The estimated monthly excess returns in these periods are 48, 34, 20, 60, and 16 bps, respectively. These results are consistent with the idea that brand names not only do well in good times (due to, for example, stronger demand, having high pricing power, and facing lower threat of entrants) but also in bad times as they typically have more loyal customers.

In our second sub-sample analysis, we estimate excess returns in periods of 5-year long during our sample, namely 2000-2005, 2006-2010, 2011-2015, and 2016-2020. The corresponding excess returns are 56, 34, 25, and 22 bps, respectively. These results confirm our previous findings that the excess returns are not due to specific events or a particular year during our sample.

4. Why Does the BB Portfolio Outperform?

In this section we conduct several additional tests to better understand why the BB portfolio generates significant excess returns over the long term.

4.1. Does Yearly Rebalancing Add Value?

As shown in Section 2, brand values tend to be persistent, and hence the BB portfolio composition does not dramatically change from one year to another. Having said that, as we also reported earlier, there are reasonable movements into and out of the BB list such that about half of the companies included in the list in 2001, which is the first year with 100 top brands, dropped out of the list by 2020. If the stock market undervalues the value of brand names, we should expect to see a higher return to the BB portfolio that takes into account time series changes in the BB list versus the one that invests in the original list and never rebalances. Relatedly, investigating this will help us understand whether the excess returns come only from the original set of companies that were included in earlier lists (and remain there) or whether new information about top brands and the development of brand values matters for the portfolio returns.

To investigate this issue, we estimate the excess returns to a portfolio that invests in the 2001 list and never rebalances and compare them with the results we estimated in the previous sections using an annually rebalanced portfolio.[8] If there is additional value derived from additions and removals from the BB list in subsequent years, we should observe a lower excess return from the portfolio that does not rebalance compared to the original BB portfolio that is rebalanced based on each year's list. Figure 5 shows the excess returns, using all of the five factor models, of a portfolio of the 2001 BB list (not rebalanced) together with our originally constructed BB

[8] We use the 2001 list, since in the 2000 list there were only 75 brand names announced while from 2001 onward the list increased to 100 top brands. However, our conclusion remains the same when we use the 2000 list.

portfolio (with yearly rebalancing) used in Table 4. As we demonstrate, ignoring the stocks added or dropped from the lists in the portfolio construction reduces the excess returns across all five models significantly. For instance, in the Fama-French 6-factor model, taking into account new information (addition/removals of brands) in subsequent lists increases the excess returns almost twofold from 15 to 29 bps per month. These results strongly suggest that a significant portion of the abnormal returns to the BB portfolio comes from yearly rebalancing of the BB portfolio that removes (includes) the brands that have lost (gained) significant value since the year before.

We also investigate whether there is important information in changes in the magnitude of brand values. Specifically, thus far our investment strategy has been based on the "signal" of the company being listed as a top brand. To understand whether excess returns are associated with stocks with higher dollar brand value, in unreported regressions, we use the FM methodology but instead of a dummy variable (=1 if top brand and =0 if not), we use the log of Interbrand's estimated brand value as our main variable of interest. The estimated coefficient on this variable is also positive and statistically significant, showing that companies with higher brand value also have had higher excess returns. These results are reported in Appendix Table 2.

To sum up, our findings strongly support the idea that taking into account updates to the brand values and newer BB lists is very important for the magnitude of excess returns we have documented.

4.2. Exposure to Intangible Factors

As BBs are most likely companies with overall high intangible assets, one might wonder whether exposure of the BB portfolio to intangible (or intangible-related) factors proposed in the literature explains the abnormal returns we document. First, we note that we have already reported the abnormal returns using the q5 model, in which the expected growth factor is supposed to capture intangible assets (Hou, Mo, et al. 2020). We note that this factor is generated using operating cash flows (including R&D expenses), while excluding the potential effect of SG&A on generating revenue. As shown in Table 4, indeed the BB portfolio has a positive and significant exposure to the expected growth factor, which suggests that BB portfolios tend to be more focused on companies with high intangible assets, as expected. Controlling for the expected growth factor reduces the excess returns from 0.35 per month in q4 to 0.25 per month in q5. In fact, the best-performing model in terms of explaining the excess returns of the BB portfolio is the q5 model. Having said that, even controlling for the expected growth factor of the q5 model leaves significant abnormal returns to the BB portfolio unexplained.

Another recent strand of literature has argued that the book value of equity should also include the value of intangibles that are missing from the balance sheet (Lev 2018; Eisfeldt and Papanikolaou 2013; Eisfeldt et al. 2022; Lev and Srivastava 2020; Park 2022). This literature has also argued that the deteriorating quality of book assets as a fundamental value (due to the omission of intangibles) is at least partially responsible for the underperformance of the value factor during the past decade (Eisfeldt et al. 2022; Park 2022). In addition, this literature has shown that an HML factor that takes into account intangibles prices assets with lower pricing errors and significantly outperforms the traditional HML factor. Eisfeldt et al. (2022) also find that an active manager can implement a profitable long-short strategy by going long "intangible" HML and short traditional (i.e., Fama-French) HML. Therefore, one may wonder if the exposure of our portfolio to such an intangible HML could be responsible for the excess returns to the BB portfolio.

To address this point, we replace the value factor in our factor regressions with alternative value factors proposed in the literature that account for intangibles. In particular, we use three such intangible value factors. (1) The HML^{INT} factor constructed by Eisfeldt et al. (2022) essentially follows the same methodology as the Fama-French HML, with the main difference that it estimates firm-level stocks of intangible assets, as in Eisfeldt and Papanikolaou (2013), and adds these to the book equity of the firm. In this method, intangible assets are measured by applying the perpetual inventory method to flows of all SG&A and R&D expenses (B^{INT}). This method also sorts the factor within industries to remove the effect of different accounting practices across industries in terms of reporting items such as SG&A and R&D. (2) HML^{IME} is differentiated in terms of a firm-sorting method by applying the INT/M variable sorting method instead of B^{INT}/M. (3) $\text{HML}^{\text{PTINT}}$ includes only 30% of SG&A plus 100% of R&D as investment in intangibles, following Peters and Taylor (2017).[9]

Table 7 reports the excess returns of the BB portfolio using the Carhart, FF6, and *AQR* models in which the HML factor is replaced with either HML^{INT}, HML^{IME}, or $\text{HML}^{\text{PTINT}}$. For the sake

[9] We note that some have criticized these practices of estimating intangible values because they are based on "one-size-fits-all mechanical rules of thumb, such as treating 30% of SG&A as investments and assuming the same life of SG&A investments across all industries" (Iqbal et al. 2021).

of comparison, we also report the original excess returns estimated using these models, which were reported in Table 4. As shown, the excess returns remain virtually the same regardless of which HML factor we use.

We also investigate whether the exposure to organization capital factor as in Eisfeldt and Papanikolaou (2013) explains the abnormal returns to BB portfolio. To do so, we add this factor to all of our factor models (Carhart, FF6, q, q5, and AQR). We find a negative and statistically significant loading of BB portfolio on this factor. Consequently, the monthly BB excess return in all models increases both in size and statistical significance (e.g., from 29 with t-stat of 3.03 to 32 basis points with t-stat of 3.29 in FF6) when we control for organization capital factor. These results are not reported for the sake of brevity.

In Fama-MachBeth regressions reported in Table 6 and Appendix Table 1, we also included organization capital and the input measure of brand capital (including these variables as a proportion of total assets), none of which has any significant effect on the excess return estimates to the BB portfolio. Overall, our results strongly reject the hypothesis that exposure to intangible-related factors proposed in the literature or the role of other intangible assets (R&D, knowledge capital, etc.) explain the outperformance of the BB portfolio. If anything, controlling for those factors slightly increases the excess returns.

4.3. Influence of Computer Software Companies

As shown in Figure 1, a large fraction of BBs belongs to Computer Software industry (CS). A natural question is whether the excess returns are driven solely by companies in this sector. To address this question, we conduct two tests. First, we add a dummy variable in FM regressions that gets the value of 1 for CS companies and 0 otherwise. Second, we run FM regressions after dropping CS companies from the sample. Table 8 reports the results. As shown, the coefficient on BB dummy remains sizable and statistically significant in both analyses and across different specifications (between 0.22 and 0.41), showing that the BB excess returns are not driven only by companies in Computer Software industry.

4.4. Internally versus Externally Generated Intangibles

So far, we have shown that the BB portfolio has a significant excess return that is not explained by exposure to common risk factors. As discussed earlier, one reason for this could be that the balance sheets of companies do not typically reflect their brand values and hence companies with valuable brands would look misleadingly overvalued according to valuation ratios such as the MB. To investigate this channel directly, we exploit the different accounting treatments of internally developed versus acquired brands.

Generally accepted accounting principles (GAAP) requires that expenditures on internally generated intangibles be expensed as incurred, while it permits firms to capitalize expenditures on acquired identifiable intangibles such as brand names.[10] This means that any intangible assets that are listed on a company's balance sheet were most likely gained as part of the acquisition of another business, or they were purchased outright as individual assets. This differential treatment of internally versus externally generated intangibles has been shown to negatively affect the informativeness of reported numbers to external users (Amir and Lev 1996; Lev and Sougiannis 1996). In addition, not showing the value of internally developed intangible assets has been demonstrated to mislead even sophisticated investors and financial analysts, resulting in systematic mispricing of securities for intangible-intensive firms (Aboody and Lev 1998; Eberhart et al. 2004; Lev and Gu 2016).

Therefore, if the lack of information about the value of intangibles on the balance sheet causes mispricing of these assets (a brand's value, in our case), we should expect lower excess returns to BBs that rely more on building their intangible assets externally (by acquisitions) rather than internally. In fact, there is a relatively large heterogeneity in terms of intangible intensity of BBs based on the assets reported on their balance sheets. For example, the ratio of intangible to total assets (as reported on the balance sheet) is more than 50% for companies such as Kraft Heinz, Kellogg's, Pfizer, or Visa, while this ratio is 0 (or close to 0) for companies such as Netflix, Harley-Davidson, Apple, or Nike. This means that the former group of companies develops their brands more externally, for which we expect a significantly lower excess return.

To test this hypothesis, we run FM regressions as before, but with two (instead of one) dummy variables: one representing those with high intangible intensity as reported in their

[10] An asset is identifiable when it can be separated from the business, or when it arises from a contractual or other legal right. For instance, organization capital or customer relationships are not identifiable assets.

balance sheet (HIGH INT BB) and the other for those with low intangible intensity (LOW INT BB). HIGH INT BB is a dummy variable and, in each year, gets a value of 1 for BBs whose intangible assets as the fraction of their total assets are higher than the median and 0 otherwise. LOW INT BB are the rest of BBs that their share of intangible assets is lower than the median in each year. The estimated coefficient on HIGH INT BB shows whether BBs that have been acquiring a lot of their intangibles externally (and hence their balance sheet carries a relatively large amount of intangible assets) have higher or lower excess returns than those BBs who are mostly relying on internal brand developments. We expect a lower excess return for HIGH INT BB than for LOW INT BB.

Table 9 report the results. As shown, the estimated coefficients on HIGH INT BB are positive but much smaller in magnitude than the coefficients on LOW INT BB. For example, as reported in Columns 1-2, the excess return to BBs with high intangible intensity is about half of the excess returns to those with low intangible intensity and marginally significant. When we include organization capital (Column 3), the coefficient on High INT BB drops significantly to 0.07 (t-stat of 0.42) whereas the coefficient on LOW INT BB increases from 0.51 to 0.63 (t-stat of 2.89). A similar pattern appears when we examine industry-adjusted returns (Columns 4-6). This finding that the average positive excess return to BBs almost entirely comes from those BBs that develop their brands internally—and hence their balance sheets show relatively low intangible assets— suggests that lack of reporting of brand values on the balance sheets could be responsible for part of the excess returns we have documented for the BB portfolio.

The abovementioned result is consistent with Chen et al. (2017), who find that intangible-intense Israeli businesses that are listed in the country and follow IFRS (hence capitalizing the development portion of their R&D) have price informativeness that is an order of magnitude higher than similar Israeli companies that are listed in the US and follow GAAP (hence expensing R&D completely). Importantly, they also report that before IFRS was adopted in Israel (2007), the share price informativeness of the two groups of firms (Israel-listed and US-listed) was practically identical. Similarly, Oswald et al. (2017) find that R&D capitalization in the UK has informative value. In addition, Aboody and Lev (1998) exploit the only exception in the U.S to the immediate expensing of R&D, i.e., capitalization of software development costs, and show that these cumulative software assets reported on the balance sheets are associated with higher stock prices. Moreover, Kallapur and Kwan (2004) find that announcements of brand capitalization (following acquisitions) in a sample of firms with high intangible assets do indeed result in abnormally high (positive) returns.

We note that even for acquired brands, the value that is reported on the balance sheet is the transaction value. It remains unchanged even if the brand value increases significantly over time. This is why even if a company has built its brand completely from acquisitions, the market could still misprice the brand value since the value that is reflected on the balance sheet could be significantly different from the true value. Sinclair and Keller (2017) highlight the importance of providing more information about brand value and its development over time for investors to make more informed decisions.

4.5. Earnings Surprises

As discussed in the introduction, one reason that companies with high brand values could be undervalued is the complexity of taking into account future benefits of brand names. For example, while it is relatively easy to forecast the future earnings of a well-known brand such as Apple from the sales of its iPhones or iPads, such a well-known brand could easily market a completely new product (e.g., Apple Watch, Apple Car) due to its reputation and the loyalty of customers to its products, something that is much harder to forecast. Valuable brands also have higher market power and could more easily increase the prices of their products, leading to higher earnings. If the market underestimates the future earnings potentials of brand names, these companies would earn long-term excess returns, as realized future profits would be larger than expected.

In order to test this channel, we study earnings surprises. We follow closely the prior literature (Giroud and Mueller 2011; Edmans 2011) and run the following regressions:

$$Earnings\ Surprise_{it} = b_0 + b_1 BB_{it} + b_2 Z_{it} + \varepsilon_{it} \tag{3}$$

Earnings Surprise is measured using one-year, two-year, or five-year surprises. One- and two-year earnings surprises are computed as the actual earnings per share (EPS) minus the median analyst forecast from Institutional Brokers' Estimate System (IBES), deflated by the stock price. Following the prior literature, we also remove observations when the forecast error is large, i.e., greater than 10% of the price. A five-year surprise is the actual five-year EPS growth minus the median analysts' long-term growth forecast.[11] BB_{it} is an indicator variable for whether the company was included in the most recent BB list. Z_{it} is a set of control variables including size and market to book ratios. We also include year and industry fixed effects in all regressions.

The findings are shown in Table 10. Panels A, B, and C report the results for one-year, two-year, and five-year earnings surprises, respectively. As shown, we find robust evidence across all specifications that earnings surprises are significantly larger for BBs than other firms. We note that these effects are robust even after controlling for size, BM ratio, and year and industry fixed effects. These results are consistent with the idea that even professional analysts tend to underestimate the power of brand names in generating future profits, which effectively contributes to long-term excess returns for investors in these companies.

5. Alternative Measures of Brand Value

5.1. A Text-based Measure of Brand Value

In this section, we construct a novel (and parsimonious) measure of brand value using textual analysis of companies' annual filings. Our approach is based on the simple premise that companies with a strong brand speak more about "brand" in their annual filings. As an example, while a typical company in 2020 mentions *brand* or *brands* only 3 times in its annual filing, these words appear 210 times in Nike, 119 times in Marriott, and 96 times in Coca-Cola's annual filings.

We first download the universe of annual filings from the SEC EDGAR platform since 1996, when digitalized filings became mandatory. We parse each filing and count the number of times *brand* (singular or plural) appears in the filing. Then, we exclude companies with *Brand* or *Brands* in their name, but our results are similar when we include them.[12] We then merge it with CRSP and Compustat and study the excess returns of portfolios invested according to this text-based measure of brand value. This independent analysis helps us creating top brand portfolios

[11] To make sure that at the time of the forecast, analysts know the prior earnings, the consensus forecast is taken four months after the previous fiscal year-end. Note that almost all 10K reports are filed within three months after the fiscal year-end.
[12] Most of these companies are those with a large portfolio of brands such as Constellation Brands Inc. Therefore, indeed it's important that our results are robust to including them.

including more companies than what available from Interbrand and it will also serve us as an out-of-sample test in the period immediately preceding the Interbrand sample.

To be included in the text-based top brands portfolio in each year, the company should satisfy the following two criteria: (a) it should be ranked amongst top 100 companies in terms of *brand* frequency and (b) it should have a market capitalization of at least $5 bn. The latter condition is to make sure that we do not include small-cap stocks in the portfolio. Having said that, this condition is not crucial, and the results are robust when we use alternative cutoff points such as $1bn or $500m. The portfolio has 386 unique firms during the whole sample from 1996 to 2020.

We first analyze the output of text-based brand value to check the validity of the proposed measure. Indeed, we find that companies that are known to have valuable brands show up on the top. For example, companies such as Coca-Cola, Nike, Marriott, American Express, Gap, McDonald's, Colgate-Palmolive, Altria Group, Starbucks, Mattel, Kellogg, and Bristol-Myers Squibb appear amongst top brands in almost every year. Other usual suspects such as Kraft Heinz, Mastercard, Visa, Microsoft, Procter & Gamble, Hilton, Booking Holdings, Raph Lauren, Harley-Davisdon, Kellogg, McDonalds, Starbucks, and PayPal also appear often amongst top brands. Interestingly, well-known brands but those that are not typically considered as valuable brands according to accounting metrics (e.g., those with little or no advertising expense) also appear in our top brands portfolio. Some examples include Twitter, Alphabet, LinkedIn, Square, Salesforce, Tesla, Pinterest, Uber, Lyft, Snap, and Grubhub.[13]

Companies in this text-based brand portfolio are from diverse industries (39 out of 49 Fama-French industries). Only in 2020, the portfolio includes companies from 26 industries including Apparel, Recreation, Food products, Restaurants and Hotels, Beer & Liquor, Retail, Candy & Soda, Consumer Goods, Computer Software, Entertainment, Business Services, Wholesale, Tobacco products, Machinery and Medical equipment, among others. To sum up, while much more could be done to properly select a group of top brands, we keep this parsimonious

[13] For example, below are some excerpts from Tesla's annual filing in 2010 (italics are ours), in which the word *brand* was repeated 45 times: "Our intent is to …strengthen Tesla *brand*, ". "Our principal marketing goals are to … build long-term *brand* awareness and manage corporate reputation". "To date, we have limited experience with marketing activities as we have relied primarily on the internet, word of mouth and attendance at industry trade shows to promote our *brand*. To further promote our *brand*, we may ..." "The strength of our *brand* has been highlighted by independent authorities. For example, in November 2009, Advertising Age selected us as one of "America's hottest *brands*" in a special report highlighting the year's 50 top *brands*."

approach, which yields a reasonable outcome. The noise in the data will work against us finding any significant result.

We follow similar approach as in Interbrand sample but since in this case we are using companies' filings as the input data, we rebalance the portfolio at the end of June each year (following the common practice in the literature that uses accounting data). This text-based measure of brand value allows us to extend the sample time series significantly to have about 5 more years of data starting from 1996.

Table 11 reports the results of time-series factor regressions for the text-based top brands portfolio across all models. Panel A shows the results corresponding to the Interbrand sample, while Panel B reports them for the full sample starting from 1996. As shown, if anything, the results are stronger than what we reported in Table 4 using Interbrand data. If the stock market undervalues brand names that are publicly announced and receives huge coverage from the media (Interbrand list), one would expect such undervaluation be higher in companies with significant brand value that receive less attention and coverage. Consistently, we also find that using the extended data starting 1996 leads to higher excess returns (with minimum of 58 bps per month in FF6). Finally, the advantage of using this text-based measure of brands is that we can also form a larger portfolio, for example, including top 200 (instead of 100) companies. We find robust results and with larger magnitudes (e.g., FF6 alpha of 37 bps with t-stat of 5.56 in 2000-2020), again consistent with the fact that companies with valuable brands that receive less attention from the media might be more prone to undervaluation.

Overall, we find consistent and reassuring results using a novel and parsimonious measure of brand value based on textual analysis of companies' annual filings. Specifically, we find that (a) a portfolio of top brands based on this measure also earns significant excess returns and (b) these excess returns are larger compared to using publicly announced Interbrand data.

5.2. Book Value of Brand Capital

The most common method researchers use to estimate the stock of intangible capital is the perpetual inventory method, in which intangible value is computed using cumulative relevant expenses with a constant depreciation rate (Peters and Taylor 2017). This method is applied to estimate the stock of brand capital using advertising expenses (Belo et al. 2022; Belo et al. 2014).

As explained in the introduction, using the book value of brand capital could lead to misleading results (in our setup) for several reasons: (a) many top brands (e.g., about half of top brands in 2020's Interbrand list) do no report advertising expenses, (b) advertising expense is an input measures and uninformative of the quality of the investment in brand, (c) it is backward looking and not responsive to sudden changes in brand value, and (d) valuable brands could be (are) made with almost zero (traditional) advertising (e.g., Tesla), and (e) advertising is only one out of numerous types of expenses that help building a stronger brand.

Despite these shortcomings, we closely follow prior literature to choose relevant parameters and measure the book value of firm-level brand capital, and then we study the excess return to portfolios based on this measure. Specifically, we use CRSP/Compustat merged data starting from 1975; before 1975 very few firms were reporting advertising expenses. We also use the depreciation rate of 20% for the stock of brand value. To estimate the initial stock, the annual growth rate of 10% for advertising expenses is used. Then, we form a portfolio invested each year in companies ranked amongst top 100 in terms of book value of brand capital in the preceding year and rebalanced at the end of June. While our theoretical arguments for potential undervaluation of brands have no particular prediction related to companies with low level of brand capital (hence our focus in this paper on long-only portfolios), in this section we also show results of a portfolio which is long in the top quintile minus short in the bottom quintile of book value of brand capital to be in line with prior literature that uses the book value of brand capital as a source of risk (a type of investment with adjustment cost) in a structural model (Belo et al. 2014).

Table 12 reports the results of time-series factor regressions using both long and long-short equal-weighted portfolios according to book value of brand capital. Columns 1-4 show results corresponding to Interbrand period (2000-2020), whereas columns 5-8 report them for the full available sample (1975-2020).[14] As shown, in the long-only portfolio, we find positive and significant Carhart alpha of around 30 bps (columns 1 and 5). However, these excess returns turn out to be only due to strong exposure of the portfolio to profitability and investment factors. Specifically, after controlling for investment and profitability factors, the excess returns drop

[14] We only report Carhart and FF6 results for brevity, but other factor models yield similar results as FF6.

significantly in magnitude and become statistically insignificant (columns 2 and 6). In the long-short portfolio, the Carhart alphas are also insignificant.[15]

Overall, we do not find evidence supporting the idea that companies with high book value of brand capital earn higher excess returns after controlling for recent factors such as profitability and investment. This suggest that unlike companies with valuable brands using Interbrand data (as measured using an *output* and forward-looking metric), firms with high stock of brand capital (an *input* and book value metric) do not appear to be undervalued in the stock market after controlling for investment and profitability factors. This result highlights important differences, discussed earlier, between input and output measures of intangible assets.

6. Conclusion

In this paper, we hypothesize and find supporting evidence that stock market does not fully incorporate the long-term impact of an important and visible intangible capital, namely brand value. A portfolio of top brands in the U.S. earns a sizable and statistically significant excess return (25 to 35 bps per month during the period 2000-2020) that is robust across different models and after controlling for firm characteristics and industry affiliations.

Our results are interesting and perhaps somewhat surprising since, unlike other measures of intangible assets that might not be easily observable by the market, brand names are highly visible and as a result are expected to be prone to overvaluation. However, treating of investments on brand equity (not only advertising but all other efforts to improve reputation and brand value) as an expense as well as difficulty of forecasting all long-term benefits of having a recognized brand make companies with valuable brands prone to undervaluation. Consistently, we find that the excess returns are largest when the brand is developed internally (as externally acquired brands are capitalized) and analysts tend to underestimate earnings of companies with valuable brands in their forecasts.

[15] We find similar patterns using value-weighted portfolios. The corresponding alphas (t-stat) in Columns 1-4 of Table 12 are 0.26 (2.85), 0.11 (1.32), 0.74 (2.72), and 0.01(1.02), respectively.

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Figure 1. Counts of Best Brands' Stock, by Industry

This figure shows total counts of Best Brands' Stocks in each Fama-French 49 industry category during our sample, from September 2000 to December 2020.

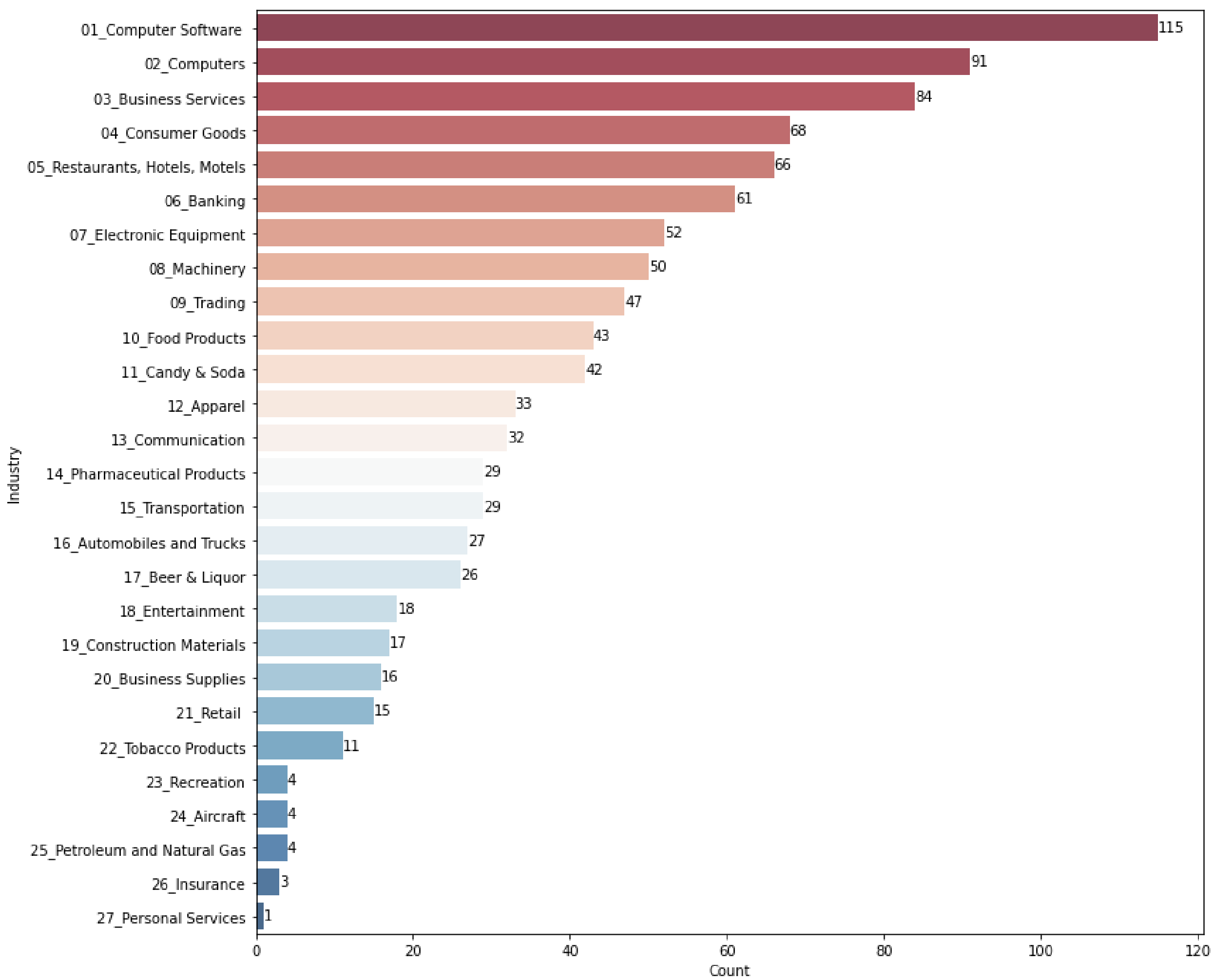

Figure 2. Evolution of Best Brands' Industry Affiliations

This figure shows the number of Best Brands' Stocks by industry and year. The darker the cell color, the larger the number.

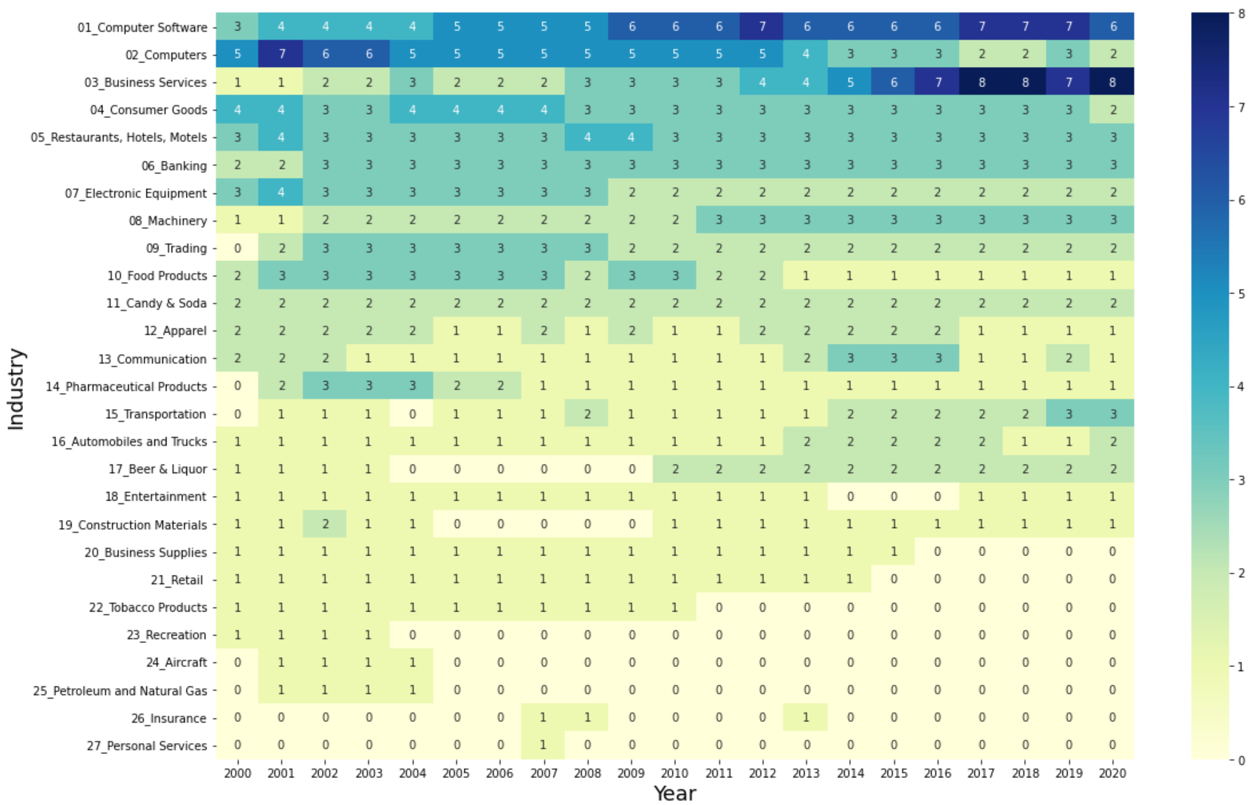

Figure 3. Size distribution of BBs' across time

This figure plots the percentage of number of Best Brands' firms that belong to each NYSE size category for each year from 2000-2020. The categories are between 50th and 80th percentiles (large caps), between 80th and 95th percentiles (mega caps) and above 95th percentile (giga caps). NYSE different percentile breakpoints are taken from Ken French website.

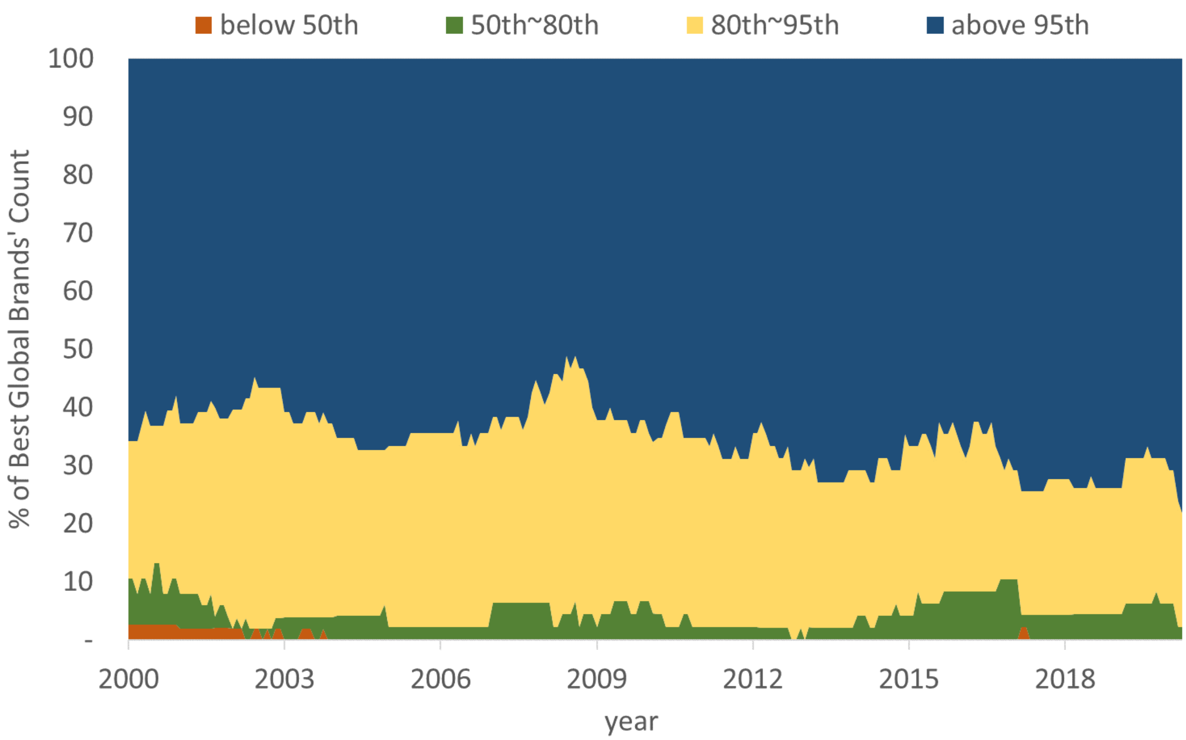

Figure 4. Cumulative excess returns of BBs

This figure plots the monthly cumulative excess returns of BBs during our sample. The excess returns are estimated using Fama-MacBeth regressions similar to the one in Column 2 of Table 6. The sample includes 244 months ranging from September 2000 to December 2020.

Figure 5. Does yearly portfolio rebalancing add value?

This figure plots the monthly excess returns of the BB portfolio which is rebalanced yearly following the announcement of each Interbrand list of top brands (i.e., BB portfolio). In addition, the figure plots the excess return of a portfolio that invest in the 2001 list of top brands and do not change the portfolio composition during the rest of the sample.
We report alphas using five different factor models including Carhart four-factor, Fama-French 5-factor plus momentum (FF6), q, q-5, and AQR 6-factor model. The factors in FF6 are market (Mkt), size (SMB), value (HML), momentum (MOM), profitability (RMW), and investment (CMA). The q-model has market, size (R_ME), investment (R_IA), and profitability (R_ROE), and the q5 models adds to these the expected investment growth factor (R_EG). The AQR model includes the market, size, value, and momentum (UMD), and adds to them betting against beta (BAB) and quality minus junk (QMJ) factors.

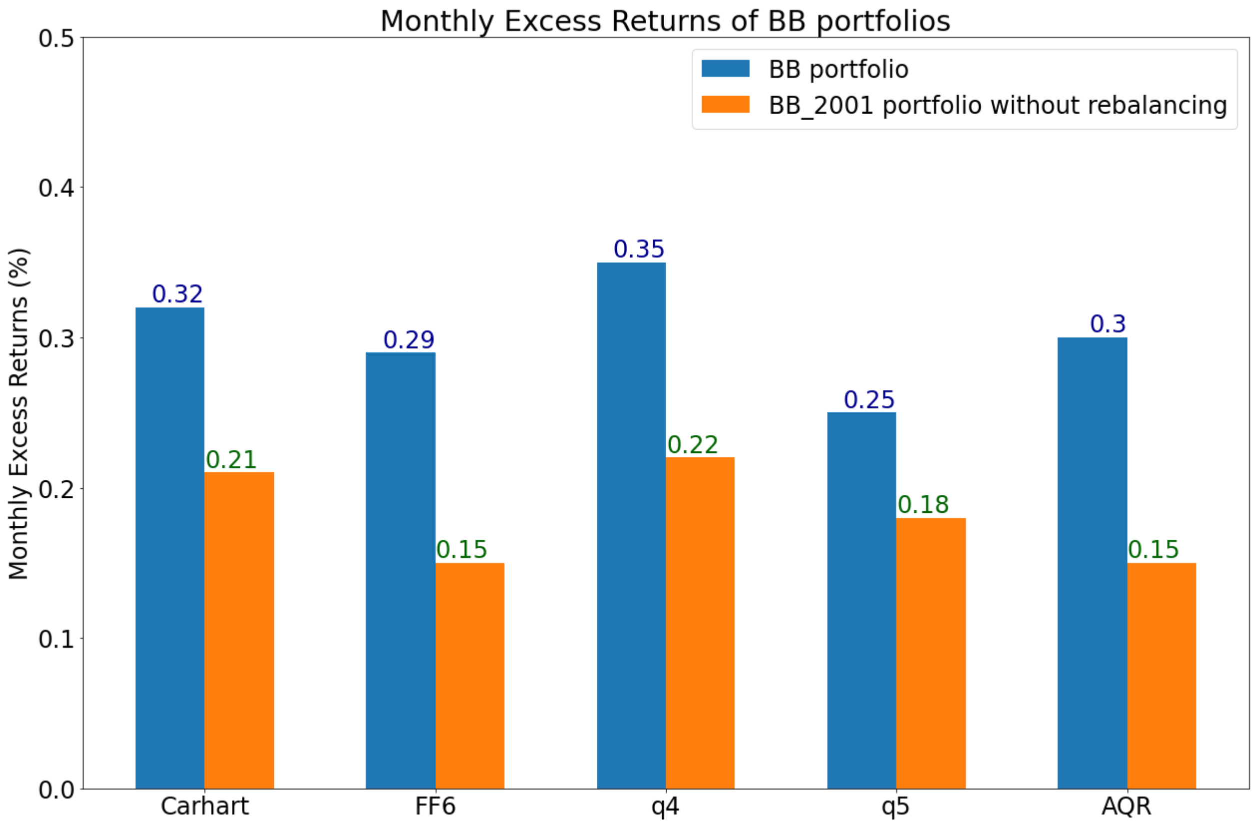

Table 1. Summary statistics on number of BBs used in the paper

This table reports (in Column 2) the number of BB stocks per year that are included in the BB portfolio, i.e., those that had returns available on CRSP for at least one month during the portfolio formation periods of each year. Column 3 shows the number of companies that are added to the list and Column 4 report the number of added companies as a fraction of total number of companies in the list. Columns 5 and 6 repeat the similar statistics (the raw number and the proportion) for companies that are dropped from the list in each year.

Year of list	**# of BB Stocks**	**# Added**	**(%)**	**# Dropped**	**(%)**
2000	38				
2001	51	13	(25.5)	0	(0.0)
2002	53	6	(11.3)	4	(7.8)
2003	51	0	(0.0)	2	(3.8)
2004	49	2	(4.1)	4	(7.8)
2005	45	3	(6.7)	7	(14.3)
2006	45	1	(2.2)	1	(2.2)
2007	47	3	(6.4)	1	(2.2)
2008	46	4	(8.7)	5	(10.6)
2009	45	4	(8.9)	5	(10.9)
2010	46	3	(6.5)	2	(4.4)
2011	45	1	(2.2)	2	(4.3)
2012	48	3	(6.3)	0	(0.0)
2013	48	3	(6.3)	3	(6.3)
2014	48	1	(2.1)	1	(2.1)
2015	48	1	(2.1)	1	(2.1)
2016	48	2	(4.2)	2	(4.2)
2017	47	2	(4.3)	3	(6.3)
2018	46	0	(0.0)	1	(2.1)
2019	48	2	(4.2)	0	(0.0)
2020	46	2	(4.3)	4	(8.3)
Average	**47**	**3**	**(5.8)**	**2**	**(5.0)**

Table 2. Best Brands, by industry

This table reports the brand names counts in each industry group. The numbers in the industry column indicate the total count of stock-years for best brands in that industry. The numbers in Brands column show how many years each company was listed as part of best brands. In cases in which one firm has multiple brands, the firms were counted as one stock such as Microsoft/LinkedIn, Google/YouTube, Facebook/Instagram, HP/Compaq, AOL/Time, Gillette/Pampers/Duracell, KFC/Pizza Hut, and Coca-Cola/Sprite.

Industry	Brands
Computer Software (115)	Amazon.com (21), Microsoft/LinkedIn (21), Oracle (19), Google/YouTube (16), Yahoo! (13), Adobe (12), Facebook/Instagram (9), Salesforce (4)
Computers (91)	Apple (21), HP/Compaq (21), Xerox (16), Dell (14), IBM (14), Sun Microsystems (3), Compaq (2)
Business Services (84)	Accenture (19), eBay (17), Visa (13), MasterCard (9), IBM (7), AOL/Time (5), Hewlett Packard Enterprise (5), PayPal (5), Disney (4)
Consumer Goods (68)	Colgate (21), Harley-Davidson (19), P&G(Gillette/Pampers/Duracell) (18), Kodak (8), Estee Lauder (1), Xerox (1)
Restaurant, Hotels, Motels (66)	McDonald's (21), Starbucks (21), KFC/Pizza Hut (20), Hilton (2), Burger King (1), Marriott International (1)
Banking (61)	American Express (21), Citigroup (21), JPMorgan (19)
Electronic Equipment (52)	Cisco (21), Intel (21), Motorola (9), Texas Instruments (1)
Machinery (50)	GE (21), Caterpillar (19), Deere & Company (10)
Trading (47)	Goldman Sachs (20), Morgan Stanley (19), Merrill Lynch (8)
Food Products (43)	Kellogg's (21), Heinz (13), Kraft (7), Campbell’s (2)
Candy & Soda (42)	Coca-Cola/Sprite (21), Pepsi (21)
Apparel (33)	Nike (21), Polo Ralph Lauren (12)
Communication (32)	MTV (17), Discovery (7), AT&T (3), Disney (3), PayPal (1), Zoom (1)
Pharmaceutical Products (29)	Johnson & Johnson (19), Pfizer (6), Merck (4)
Transportation (29)	UPS (16), FedEx (11), UBER (2)
Automobiles and Trucks (27)	Ford (21), Chevrolet (3), Tesla (3)
Beer & Liquor (26)	Jack Daniel’s (15), Corona (11)
Entertainment (18)	Disney (14), Netflix (4)
Construction Materials (17)	3M (12), Gillette/Duracell (5)
Business Supplies (16)	Kleenex (16)
Retail (15)	GAP (15)
Tobacco Products (11)	Marlboro (11)
Recreation (4)	Barbie (4)
Aircraft (4)	Boeing (4)
Petroleum and Natural Gas (4)	ExxonMobil (4)
Insurance (3)	AIG (2), Berkshire Hathaway (Heinz) (1)
Personal Services (1)	Hertz (1)

Table 3. Descriptive statistics of BBs

Panel A of this table shows the descriptive statistics of BBs in the first year (Panel A) and the last year (Panel B) of our sample. The BB list is announced yearly by Interbrand. Accounting data are from Compustat. Market values are from CRSP, and accounting variables are from Compustat. Organization capital and brand capital are constructed from SG&A and advertising expenses, respectively, and based on perpetual inventory method as in Eisfeldt and Papanikolaou (2013) and Belo et al. (2014).

Panel A: Descriptive statistics on BBs' characteristics, 2000

	#firms	Mean	Median	Std.	Min	Max
Market Cap ($ bn)	38	84.56	44.41	112.36	0.50	571.61
Market/book	38	13.51	6.17	21.32	0.73	97.43
Dividend yield (%)	38	3.69	1.05	12.22	0.00	94.46
Gross profits to total assets (%)	36	44.28	46.32	21.46	7.65	101.66
Capex to revenue (%)	38	6.95	5.11	4.99	1.34	23.53
Operating cash flows to revenue (%)	38	14.10	12.53	9.41	-3.29	60.74
Intangibles as a % of total assets (%)	38	13.58	7.81	15.60	0.00	75.02
Advertising Expense to gross profit (%)	28	11.92	9.71	7.12	3.25	29.10
Organization capital to total assets	20	1.56	1.51	1.02	0.17	3.63
Brand capital to total assets	12	0.33	0.26	0.24	0.11	0.80

Panel B: Descriptive statistics on BBs' characteristics, 2020

	#firms	Mean	Median	Std.	Min	Max
Market Cap ($ bn)	46	288.30	143.09	431.36	14.20	2,255.97
Market/book	43	7.69	5.21	17.40	-26.36	94.55
Dividend yield (%)	45	1.63	1.60	1.33	0.00	5.27
Gross profits to total assets (%)	38	32.54	32.68	13.83	10.48	65.14
Capex to revenue (%)	46	5.50	4.07	3.99	0.00	18.31
Operating cash flows to revenue (%)	45	21.38	20.95	19.48	-38.72	78.43
Intangibles as a % of total assets (%)	46	21.03	16.39	17.68	0.00	54.03
Advertising Expense to gross profit (%)	38	7.74	4.95	6.65	0.39	22.61
Organization capital to total assets	35	1.01	0.90	0.57	0.29	2.24
Brand capital to total assets	23	0.16	0.08	0.15	0.02	0.55

Table 4. Excess returns of BB portfolio

This table reports time-series factor regression results of BB equal-weighted portfolio. The dependent variable is the monthly return of BB portfolio in excess of the risk-free rate. We report the results for five factor models, hence five columns in the table. The factor models used are Carhart four-factor, Fama-French 5-factor plus momentum (FF6), q, q-5, and AQR 6-factor model. The factors in FF6 are market (Mkt), size (SMB), value (HML), momentum (MOM), profitability (RMW), and investment (CMA). The q-model has market, size (R_ME), investment (R_IA), and profitability (R_ROE), and the q5 models adds to these the expected investment growth factor (R_EG). The AQR model includes the market, size, value, and momentum (UMD), and adds to them betting against beta (BAB) and quality minus junk (QMJ) factors. Newey-West standard errors are calculated, and the t-statistics are reported in parentheses. The sample is from September 2000 to December 2020. *, **, and *** indicate significance levels at 10%, 5%, and 1%, respectively.

Dependent Variable:	Excess return				
	(1)	(2)	(3)	(4)	(5)
Model:	Carhart	FF6	q	q5	AQR
α	0.32***	0.29***	0.35***	0.25**	0.30***
	(3.39)	(3.03)	(3.01)	(2.11)	(2.80)
β_{MKT}	0.99***	1.00***	1.01***	1.04***	1.04***
	(31.77)	(30.01)	(26.47)	(25.37)	(28.61)
β_{SMB}	-0.02	-0.02			-0.01
	(-0.55)	(-0.34)			(-0.19)
β_{HML}	-0.02	-0.04			-0.01
	(-0.54)	(-0.75)			(-0.21)
β_{MOM}	-0.18***	-0.18***			
	(-4.21)	(-4.29)			
β_{RMW}		0.05			
		(0.78)			
β_{CMA}		0.01			
		(0.14)			
β_{R_ME}			-0.07**	-0.05	
			(-1.96)	(-1.19)	
β_{R_IA}			0.04	0.02	
			(0.41)	(0.25)	
β_{R_ROE}			-0.23**	-0.30***	
			(-2.53)	(-3.22)	
β_{R_EG}				0.20**	
				(2.43)	
β_{UMD}					-0.16***
					(-4.09)
β_{BAB}					-0.07**
					(-2.02)
β_{QMJ}					0.18**
					(2.61)
# obs	244	244	244	244	244

Table 5. Sensitivity of excess returns of BB portfolio to micro and mega-cap stocks

This table reports the sensitivity of the excess return of equal-weighted BB portfolio with respect to (a) excluding relatively smaller (below NYSE 50th percentile) BBs and (b) value-weighted instead of equal-weighted BB portfolio. We provide excess return estimates for both the straight and capped (at the 90^{th} NYSE size percentile) value-weighted results. We report the excess return using five factor models, hence five columns in the table. The factor models used are Carhart four-factor, Fama-French 5-factor plus momentum (FF6), q, q-5, and AQR 6-factor model. The factors in FF6 are market (Mkt), size (SMB), value (HML), momentum (MOM), profitability (RMW), and investment (CMA). The q-model has market, size (R_ME), investment (R_IA), and profitability (R_ROE), and the q5 models adds to these the expected investment growth factor (R_EG). The AQR model includes the market, size, value, and momentum (UMD), and adds to them betting against beta (BAB) and quality minus junk (QMJ) factors. Newey-West standard errors are calculated, and the t-statistics are reported in parentheses. The sample is from September 2000 to December 2020. *, **, and *** indicate significance levels at 10%, 5%, and 1%, respectively.

Dependent Variable:	Excess return				
	(1)	(2)	(3)	(4)	(5)
Model:	Carhart	FF6	q	q5	AQR
α original estimates (equal-weighted)	0.32***	0.29***	0.35***	0.25**	0.30***
	(3.39)	(3.03)	(3.01)	(2.11)	(2.80)
α excluding small caps (size < NYSE 50^{th} pct breakpoint)	0.30***	0.29***	0.34***	0.24**	0.29***
	(3.31)	(3.00)	(2.97)	(2.10)	(2.75)
α straight value-weighted	0.12	0.14	0.16	0.02	0.11
	(1.26)	(1.45)	(1.54)	(0.19)	(1.08)
α capped value-weighted (capped at NYSE 90^{th} pct breakpoint)	0.25***	0.23***	0.29***	0.20*	0.24***
	(3.00)	(2.83)	(2.94)	(1.93)	(2.64)
# obs	244	244	244	244	244

Table 6. Excess returns of the BB portfolio: Fama-MacBeth regressions

This table presents the results of Fama-MacBeth regressions. The dependent variable in Columns 1-3 is raw return while it is industry-adjusted return in Columns 4-6. Within each set, there are three specifications: the first specification includes characteristics used in Brennan et al. (1998). The second specification adds further important characteristics used in more recent literature. The last specification adds log of advertising expenses. Our variable of interest is the dummy variable (BB) which is an indicator variable for stocks in the BB list. SIZE is the log of market cap in month t-2, BM is the log of book-to-market ratio, YIELD is the ratio of dividends in the previous fiscal year to the market value at calendar year-end, RETn1-n2 (for different n1 and n2) are the logs of cumulative compounded returns between t-n2 and t-n1. DVOL is the log of dollar trading volume in month t-2, PRICE is the log price in month t-2, ASSET GROWTH is the annual growth rate of total assets, ROE is the return on equity, PROFITABILITY is the cash-based operating profitability, EARN SURP is the earning-per-share (EPS) minus EPS twelve month ago minus drift scaled by the standard deviation of that expression. Drift is the average earnings growth over the past two years. LEVERAGE is total liabilities over total assets. R&D and ADVERTISING are log of these expenses. ORG CAPITAL is the log of organization capital computed similar as Eisfeldt and Papanikolaou (2013). Newey-West standard errors are calculated, and the t-statistics are reported in parentheses. The sample is from September 2000 to December 2020. *, **, and *** indicate significance levels at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep var:	Stock return			Industry-adjusted return		
BB	0.42***	0.34***	0.27**	0.29***	0.20*	0.25**
	(3.10)	(2.65)	(2.17)	(2.65)	(1.94)	(2.25)
SIZE	0.17*	0.07	-0.18	0.13	0.04	-0.16
	(1.83)	(0.63)	(-1.32)	(1.51)	(0.44)	(-1.16)
BM	0.02	0.06	-0.07	-0.00	0.04	-0.07
	(0.12)	(0.52)	(-0.55)	(-0.00)	(0.44)	(-0.71)
YIELD	-0.01	-0.01	-0.01**	-0.01	-0.01*	-0.01**
	(-0.97)	(-1.51)	(-2.20)	(-1.26)	(-1.73)	(-2.47)
RET2-3	-0.67**	-0.80**	-0.24	-0.74**	-0.86***	-0.37
	(-2.11)	(-2.53)	(-0.69)	(-2.52)	(-2.98)	(-1.08)
RET4-6	-0.78**	-0.85**	-0.61	-0.80**	-0.86**	-0.63*
	(-2.11)	(-2.41)	(-1.64)	(-2.30)	(-2.50)	(-1.78)
RET7-12	-0.58**	-0.62***	-0.52**	-0.63***	-0.65***	-0.59***
	(-2.48)	(-2.81)	(-2.35)	(-2.76)	(-3.09)	(-2.67)
DVOL	-0.15*	-0.11	-0.10	-0.10	-0.07	-0.05
	(-1.84)	(-1.34)	(-1.16)	(-1.30)	(-0.92)	(-0.60)
PRICE	-0.70***	-0.66***	-0.55***	-0.71***	-0.68***	-0.58***
	(-3.62)	(-3.48)	(-3.06)	(-3.57)	(-3.45)	(-3.08)
ASSET GROWTH		0.24***	0.14		0.23***	0.13
		(5.79)	(1.63)		(5.46)	(1.54)
ROE		-0.02	-0.01		-0.02	-0.02
		(-1.26)	(-0.84)		(-1.54)	(-1.19)
PROFITABILITY		0.65**	0.94***		0.54	0.87***
		(1.98)	(3.55)		(1.58)	(2.74)
EARN SURP		0.05***	0.06***		0.05***	0.06***
		(4.52)	(6.41)		(4.62)	(6.63)
LEVERAGE		0.85***	0.34		0.69***	0.24
		(3.04)	(0.94)		(3.03)	(0.83)
R&D		0.06**	0.04		0.06***	0.05***
		(2.17)	(1.45)		(4.70)	(3.13)
ADVERTISING			0.01			-0.01
			(0.29)			(-0.32)
ORG CAPITAL			0.27***			0.22***
			(3.10)			(3.05)
CONSTANT	2.51***	2.88***	5.22***	1.70**	2.04**	3.86***
	(2.60)	(2.98)	(3.90)	(1.97)	(2.38)	(2.82)
Observations	604,556	604,556	482,983	604,556	604,556	482,983
R-squared	0.05	0.06	0.07	0.04	0.05	0.07

Table 7. Excess returns of BB portfolio: Controlling for intangible factors

This table reports the excess returns of equal-weighted BB portfolio when we use intangible-adjusted value factors (HML^{INT}, HML^{IME}, and HML^{PTINT}) instead of traditional value factor. HML^{INT} is an intangible-augmented value factor which was introduced by (Eisfeldt et al. 2022). This approach is correcting the book equity by including the intangible assets measured by applying the perpetual inventory method to flows of SG&A expenses (B^{INT}). HML^{IME} is differentiated in terms of firm-sorting method by applying the INT/M variable sorting method instead of B^{INT}/M. HML^{PTINT}, alternatively, includes only 30% of (SG&A minus R&D) plus 100% of R&D as investment in intangible following Peters and Taylor (2017). Excess returns in each case are reported for all different models which include HML factor in it. Newey-West standard errors are calculated, and the t-statistics are reported in parentheses. The sample is from September 2000 to December 2020. *, **, and *** indicate significance levels at 10%, 5%, and 1%, respectively.

Dependent Variable:	Excess return		
	(1)	(2)	(3)
Model:	Carhart	FF6	AQR
α original estimates	0.32***	0.29***	0.30***
	(3.39)	(3.03)	(2.80)
α using HML^{INT}	0.31***	0.30***	0.30***
	(3.51)	(3.31)	(2.92)
α using HML^{IME}	0.30***	0.29***	0.29***
	(3.33)	(3.26)	(2.89)
α using HML^{PTINT}	0.32***	0.30***	0.30***
	(3.49)	(3.18)	(2.87)
# obs	244	244	244

Table 8. Influence of Computer Software companies on BB excess returns

This table presents the results of Fama-MacBeth regressions, similar as those reported in Table 6. In columns 1-3, we add COMP SOFT, which is a dummy variable indicating companies in the Computer Software industry. In columns 4-6, we drop all companies in Computer Software industry from the regression sample. Within each set, there are three specifications: the first specification includes characteristics used in Brennan et al. (1998). The second specification adds further important characteristics used in more recent literature. The last specification adds log of advertising expenses. Our variable of interest is the dummy variable (BB) which is an indicator variable for stocks in the BB list. SIZE is the log of market cap in month t-2, BM is the log of book-to-market ratio, YIELD is the ratio of dividends in the previous fiscal year to the market value at calendar year-end, RETn1-n2 (for different n1 and n2) are the logs of cumulative compounded returns between t-n2 and t-n1. DVOL is the log of dollar trading volume in month t-2, PRICE is the log price in month t-2, ASSET GROWTH is the annual growth rate of total assets, ROE is the return on equity, PROFITABILITY is the cash-based operating profitability, EARN SURP is the earning-per-share (EPS) minus EPS twelve month ago minus drift scaled by the standard deviation of that expression. Drift is the average earnings growth over the past two years. LEVERAGE is total liabilities over total assets. R&D and ADVERTISING are log of these expenses. ORG CAPITAL is the log of organization capital computed similar as Eisfeldt and Papanikolaou (2013). Newey-West standard errors are calculated, and the t-statistics are reported in parentheses. The sample is from September 2000 to December 2020. *, **, and *** indicate significance levels at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep var:	Stock return					
BB	0.41***	0.33***	0.27*	0.30**	0.22*	0.24**
	(3.02)	(2.64)	(1.94)	(2.46)	(1.96)	(2.26)
COMP SOFT	0.07	0.04	0.06			
	(0.69)	(0.44)	(0.62)			
SIZE	0.17*	0.06	-0.18	0.18*	0.07	-0.34**
	(1.80)	(0.62)	(-1.32)	(1.94)	(0.71)	(-1.97)
BM	0.02	0.06	-0.07	0.02	0.06	-0.12
	(0.13)	(0.52)	(-0.55)	(0.18)	(0.49)	(-1.20)
YIELD	-0.00	-0.01	-0.01**	-0.01	-0.01	-0.01
	(-0.93)	(-1.48)	(-2.11)	(-1.06)	(-1.54)	(-0.96)
RET2-3	-0.67**	-0.80**	-0.24	-0.67**	-0.82**	-0.63
	(-2.10)	(-2.52)	(-0.67)	(-2.08)	(-2.56)	(-1.14)
RET4-6	-0.77**	-0.85**	-0.61	-0.78**	-0.87**	-0.97**
	(-2.09)	(-2.40)	(-1.62)	(-2.06)	(-2.38)	(-2.00)
RET7-12	-0.59**	-0.62***	-0.52**	-0.59**	-0.61***	-0.35
	(-2.50)	(-2.83)	(-2.37)	(-2.46)	(-2.72)	(-1.42)
DVOL	-0.14*	-0.11	-0.10	-0.16*	-0.12	-0.03
	(-1.82)	(-1.33)	(-1.14)	(-1.94)	(-1.42)	(-0.31)
PRICE	-0.70***	-0.66***	-0.55***	-0.69***	-0.65***	-0.57**
	(-3.61)	(-3.47)	(-3.03)	(-3.65)	(-3.48)	(-2.27)
ASSET GROWTH		0.24***	0.14		0.28***	0.23
		(5.84)	(1.63)		(5.50)	(1.37)
ROE		-0.02	-0.01		-0.01	-0.13**
		(-1.22)	(-0.82)		(-0.42)	(-2.24)
PROFITABILITY		0.64**	0.93***		0.59*	1.42***
		(1.97)	(3.52)		(1.78)	(2.89)
EARN SURP		0.05***	0.06***		0.05***	0.10***
		(4.55)	(6.47)		(5.12)	(4.12)
LEVERAGE		0.85***	0.34		0.82***	-0.18
		(3.06)	(0.95)		(2.98)	(-0.60)
R&D		0.06**	0.04		0.06*	0.03
		(2.10)	(1.40)		(1.96)	(0.73)
ADVERTISING			0.01			0.00
			(0.25)			(0.06)
ORG CAPITAL			0.27***			0.33***
			(3.10)			(3.19)
CONSTANT	2.52***	2.88***	5.21***	2.48***	2.86***	6.53***
	(2.60)	(2.97)	(3.85)	(2.63)	(2.99)	(3.87)
Observations	604,556	604,556	482,983	561,714	561,714	444,749
R-squared	0.05	0.06	0.07	0.05	0.06	0.07

Table 9. Reported intangibles and BB excess return

This table repeats the results of Fama-MacBeth regressions as in Table 6 but reports the excess returns separately for BBs that have relatively high intangibles (HIGH INT BB) versus those with relatively low intangibles (LOW INT BB) as reported in their balance sheet. The dependent variable in Columns 1-3 is raw return while it is industry-adjusted return in Columns 4-6. Within each set, there are three specifications: the first specification includes characteristics used in Brennan et al. (1998). The second specification adds further important characteristics used in more recent literature. The last specification adds log of advertising expenses. Our variable of interest is the dummy variable (BB) which is an indicator variable for stocks in the BB list. SIZE is the log of market cap in month t-2, BM is the log of book-to-market ratio, YIELD is the ratio of dividends in the previous fiscal year to the market value at calendar year-end, RETn1-n2 (for different n1 and n2) are the logs of cumulative compounded returns between t-n2 and t-n1. DVOL is the log of dollar trading volume in month t-2, PRICE is the log price in month t-2, ASSET GROWTH is the annual growth rate of total assets, ROE is the return on equity, PROFITABILITY is the cash-based operating profitability, EARN SURP is the earning-per-share (EPS) minus EPS twelve month ago minus drift scaled by the standard deviation of that expression. Drift is the average earnings growth over the past two years. LEVERAGE is total liabilities over total assets. R&D and ADVERTISING are log of these expenses. ORG CAPITAL is the log of organization capital computed similar as Eisfeldt and Papanikolaou (2013). Newey-West standard errors are calculated, and the t-statistics are reported in parentheses. The sample is from September 2000 to December 2020. *, **, and *** indicate significance levels at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep var:		Stock return			Industry-adjusted return	
LOW INT BB	0.60***	0.51***	0.63***	0.49***	0.39***	0.62***
	(3.24)	(3.03)	(2.89)	(4.08)	(3.06)	(3.77)
HIGH INT BB	0.29*	0.22	0.07	0.17	0.08	0.05
	(1.94)	(1.37)	(0.42)	(1.14)	(0.54)	(0.34)
SIZE	0.18*	0.07	-0.18	0.13	0.04	-0.16
	(1.83)	(0.63)	(-1.31)	(1.51)	(0.45)	(-1.15)
BM	0.02	0.06	-0.07	0.00	0.04	-0.07
	(0.12)	(0.53)	(-0.54)	(0.00)	(0.44)	(-0.71)
YIELD	-0.01	-0.01	-0.01**	-0.01	-0.01*	-0.01**
	(-0.97)	(-1.51)	(-2.20)	(-1.25)	(-1.72)	(-2.45)
RET2-3	-0.67**	-0.80**	-0.24	-0.74**	-0.86***	-0.36
	(-2.11)	(-2.53)	(-0.68)	(-2.52)	(-2.98)	(-1.08)
RET4-6	-0.78**	-0.86**	-0.62	-0.80**	-0.86**	-0.63*
	(-2.11)	(-2.41)	(-1.64)	(-2.30)	(-2.51)	(-1.79)
RET7-12	-0.59**	-0.62***	-0.52**	-0.63***	-0.65***	-0.59***
	(-2.48)	(-2.81)	(-2.35)	(-2.76)	(-3.09)	(-2.67)
DVOL	-0.15*	-0.11	-0.10	-0.10	-0.07	-0.05
	(-1.85)	(-1.34)	(-1.17)	(-1.30)	(-0.92)	(-0.61)
PRICE	-0.70***	-0.66***	-0.55***	-0.71***	-0.68***	-0.59***
	(-3.62)	(-3.48)	(-3.07)	(-3.58)	(-3.45)	(-3.09)
ASSET GROWTH		0.24***	0.14		0.23***	0.13
		(5.80)	(1.63)		(5.47)	(1.54)
ROE		-0.02	-0.01		-0.02	-0.02
		(-1.26)	(-0.84)		(-1.54)	(-1.19)
PROFITABILITY		0.65**	0.94***		0.54	0.87***
		(1.98)	(3.55)		(1.58)	(2.74)
EARN SURP		0.05***	0.06***		0.05***	0.06***
		(4.52)	(6.41)		(4.62)	(6.63)
LEVERAGE		0.84***	0.34		0.69***	0.23
		(3.02)	(0.93)		(3.01)	(0.82)
R&D		0.06**	0.04		0.06***	0.05***
		(2.17)	(1.44)		(4.68)	(3.09)
ADVERTISING			0.01			-0.01
			(0.30)			(-0.32)
ORG CAPITAL			0.27***			0.22***
			(3.11)			(3.06)
CONSTANT	2.52***	2.88***	5.22***	1.71**	2.04**	3.86***
	(2.60)	(2.98)	(3.90)	(1.97)	(2.38)	(2.82)
Observations	604,556	604,556	482,983	604,556	604,556	482,983
R-squared	0.05	0.06	0.07	0.04	0.05	0.05

Table 10: Earnings surprises

This table reports the results of regressions of earnings surprises on an indicator variable for whether the company was in the most recent Best Brand list (BB), and other control variables (book-to-market ratio and size). The dependent variable in Panel A (B) is the actual EPS minus the I/B/E/S median analyst forecast 8 (20) months before the end of the forecast period, scaled by the stock price. In Panel C, long-term earnings growth surprise is the actual five-year annualized EPS growth rate minus the median analyst long-term growth forecast. All coefficients are multiplied by 1000. All regressions include year and industry fixed effects as well as a constant.

	(1)	(2)	(3)
Panel A: 1-year earnings			
BB	2.19***	2.29***	1.80***
	(3.96)	(3.94)	(2.59)
BM		0.10	0.11
		(0.62)	(0.70)
SIZE			0.48
			(1.62)
# obs	71,090	61,884	61,884
Panel B: 2-year earnings			
BB	3.74***	3.89***	2.09***
	(3.10)	(3.12)	(2.55)
BM		0.35	0.39
		(1.29)	(1.46)
SIZE			1.82***
			(3.25)
# obs	49,755	43,579	43,579
Panel C: Long-term earnings			
BB	3.70***	1.43***	1.31***
	(4.43)	(2.69)	(2.33)
BM		1.65***	1.63***
		(5.63)	(5.57)
SIZE			2.12***
			(3.19)
# obs	13,832	11,848	11,845

Table 11. Excess return to a text-based measure of brand value

This table reports time-series factor regression results of an equal-weighted BB portfolio constructed using textual analysis of companies' annual filings. To be included in the portfolio, a company must meet the following two criteria: (a) ranked amongst top 100 companies in each year according to the frequency of the following words in their annual filing: Brand, Brands, Branding, Branded, and (b) has a market capitalization greater than or equal to $5 bn. The latter is not crucial and only for making sure that the results are not driven by tiny-cap stocks. In Panel A, we report results using the same sample as Interbrand reported in Table 4 (only alphas are reported for brevity) and in Panel B we run regressions for the full sample for which digitalized company filings from SEC EDGAR platform could be obtained, i.e., 1996-2020. The dependent variable is the monthly return of BB portfolio in excess of the risk-free rate. We report results for five different factor models, hence five columns in the table. Newey-West standard errors are calculated, and the t-statistics are reported in parentheses. *, **, and *** indicate significance levels at 10%, 5%, and 1%, respectively.

Dep Var:	Excess return				
	(1)	(2)	(3)	(4)	(5)
Model:	Carhart	FF6	q	q5	AQR
Panel A: Interbrand sample (2000-2020)					
α	0.51***	0.32***	0.47***	0.46***	0.31***
	(4.89)	(4.14)	(3.63)	(4.36)	(3.64)
# obs	244	244	244	244	244
Panel B: 1996-2020					
α	0.65***	0.58*	0.63**	0.64***	0.52**
	(3.36)	(1.97)	(2.45)	(2.66)	(1.99)
β_{MKT}	0.95***	0.97***	1.04***	1.03***	1.07***
	(16.75)	(30.27)	-16.02	-17.19	-14.36
β_{SMB}	-0.01	0.09			-0.08
	(-0.09)	(1.38)			(-0.64)
β_{HML}	0.03	0.00			0.22**
	(0.25)	(0.00)			-1.97
β_{MOM}	-0.15***	-0.15***			
	(-3.19)	(-3.73)			
β_{RMW}		0.24**			
		(2.27)			
β_{CMA}		-0.16			
		(-0.48)			
β_{R_ME}			-0.10	-0.10	
			(-1.06)	(-1.07)	
β_{R_IA}			0.11	0.11	
			(0.59)	(0.59)	
β_{R_ROE}			-0.16	-0.15	
			(-1.38)	(-1.18)	
β_{R_EG}				-0.02	
				(-0.22)	
β_{UMD}					-0.14**
					(-2.48)
β_{BAB}					0.04
					(0.75)
β_{QMJ}					0.20*
					(1.76)
# obs	300	300	300	300	300

Table 12. Brand capital and excess returns: Using the book value (an input measure)

This table reports time-series factor regression results of equal-weighted portfolios sorted according to stock of firm level brand capital, as commonly measured using the perpetual inventory method. The results are reported using two different portfolios: Top 100 brands in each year (Columns 1,2, 5, and 6), and a long-short portfolio which is long in stocks ranked on the top quintile of brand capital and short in the bottom quintile (Columns 3, 4, 7, and 8). The table also report the result corresponding to our sample period (Columns 1-4) as well as going back to 1975, the year before which very few firms were reporting advertising expenses. The dependent variable is the monthly return of the corresponding portfolio in excess of the risk-free rate. We report the results for only two of factor models for brevity: Carhart and Fama-French 5-factor plus momentum (FF6). The factors in FF6 are market (Mkt), size (SMB), value (HML), momentum (MOM), profitability (RMW), and investment (CMA). Newey-West standard errors are calculated, and the t-statistics are reported in parentheses. *, **, and *** indicate significance levels at 10%, 5%, and 1%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample:	Interbrand sample (2000-2020)				1975-2020			
Portfolio:	High *Book* Brands		High - Low		High *Book* Brands		High - Low	
Model:	Carhart	FF6	Carhart	FF6	Carhart	FF6	Carhart	FF6
α	0.30**	0.12	0.26	-0.24	0.26***	0.12	-0.04	-0.39**
	(2.49)	(1.23)	(0.94)	(-0.95)	(3.08)	(1.40)	(-0.19)	(-2.03)
β_{MKT}	0.97***	1.03***	0.04	0.18***	0.10***	1.03***	0.14***	0.19***
	(27.68)	(39.59)	(0.63)	(3.07)	(35.63)	(39.56)	(2.99)	(4.06)
β_{SMB}	0.26***	0.30***	-0.56***	-0.37***	0.10*	0.17***	-0.80***	-0.55***
	(4.20)	(4.76)	(-3.11)	(-2.96)	(1.69)	(3.97)	(-7.61)	(-6.95)
β_{HML}	0.12*	-0.03	0.58***	0.28***	0.20***	0.07	0.54***	0.34***
	(1.82)	(-0.57)	(5.03)	(2.72)	(3.20)	(1.31)	(3.63)	(3.63)
β_{MOM}	-0.21***	-0.23***	-0.03	-0.11*	-0.19***	-0.21***	-0.03	-0.09
	(-4.75)	(-5.72)	(-0.35)	(-1.97)	(-4.39)	(-5.46)	(-0.31)	(-1.21)
β_{RMW}		0.22***		0.82***		0.27***		0.85***
		(3.23)		(6.95)		(3.81)		(9.64)
β_{CMA}		0.27***		0.22		0.23***		0.15
		(4.33)		(1.26)		(3.81)		(0.97)
# obs	244	244	244	244	546	546	546	546

Appendix Table 1. Fama-MacBeth regressions: Alternative specifications

	(1)	(2)	(3)	(4)	(5)
Dep var:	Stock return				
BB	0.38**	0.41**	0.39**	0.44**	0.39**
	(2.33)	(2.50)	(2.51)	(2.59)	(2.50)
SIZE	-0.18	-0.21	-0.37**	-0.25*	-0.37**
	(-1.25)	(-1.41)	(-2.06)	(-1.72)	(-2.06)
BM	-0.02	-0.05	-0.13	-0.13	-0.13
	(-0.24)	(-0.56)	(-1.29)	(-1.40)	(-1.28)
YIELD	-0.01	-0.01	-0.01	-0.00	-0.01
	(-0.75)	(-0.49)	(-0.90)	(-0.26)	(-0.90)
RET2-3	-0.69	-0.65	-0.55	-0.62	-0.55
	(-1.32)	(-1.21)	(-1.06)	(-1.16)	(-1.07)
RET4-6	-1.06**	-1.02**	-0.92**	-0.98**	-0.93**
	(-2.43)	(-2.39)	(-2.12)	(-2.28)	(-2.12)
RET7-12	-0.44**	-0.42*	-0.36	-0.45**	-0.35
	(-1.99)	(-1.96)	(-1.63)	(-2.04)	(-1.62)
DVOL	-0.01	-0.00	-0.01	-0.01	-0.01
	(-0.09)	(-0.05)	(-0.13)	(-0.07)	(-0.12)
PRICE	-0.65**	-0.68**	-0.61**	-0.73**	-0.61**
	(-2.33)	(-2.39)	(-2.26)	(-2.55)	(-2.27)
ASSET GROWTH	0.23*	0.29*	0.17	0.39***	0.17
	(1.67)	(1.94)	(1.18)	(2.62)	(1.17)
ROE	-0.09*	-0.10*	-0.09*	-0.12**	-0.09*
	(-1.67)	(-1.85)	(-1.72)	(-2.08)	(-1.71)
PROFITABILITY	1.30***	1.31***	1.21***	1.26***	1.21***
	(2.97)	(3.02)	(2.80)	(2.92)	(2.78)
EARN SURP	0.07***	0.07***	0.07***	0.07***	0.07***
	(3.93)	(3.98)	(3.93)	(3.97)	(3.93)
LEVERAGE	0.30	0.28	-0.10	0.23	-0.10
	(1.12)	(1.05)	(-0.32)	(0.87)	(-0.32)
R&D (log)	0.05	0.05	0.04	0.07*	0.04
	(1.33)	(1.41)	(0.91)	(1.68)	(0.91)
ADVERTISING (log)	0.01	0.16**	0.05	0.16**	0.05
	(0.19)	(2.51)	(0.68)	(2.53)	(0.68)
BRAND CAP (log)	0.12*		0.00		0.00
	(1.83)		(0.04)		(0.04)
BRAND CAP/ASSETS		-0.37**		0.20	
		(-2.33)		(0.84)	
ORG CAP (log)			0.33***		0.33***
			(3.20)		(3.20)
ORG CAP/ASSETS				-0.19***	
				(-6.25)	
DOMESTIC					-0.52**
					(-2.21)
CONSTANT	4.93***	4.98***	6.58***	5.97***	6.59***
	(3.36)	(3.36)	(3.68)	(4.19)	(3.68)
Observations	160,146	160,146	160,146	160,146	160,146
R-squared	0.09	0.09	0.09	0.09	0.09

Appendix Table 2. Fama-MacBeth regressions using continuous brand value

This table uses log brand value reported by Interbrand as the variable of interest (instead of a dummy variable indicating top brands).

	(1)	(2)	(3)	(4)	(5)	(6)
Dep var:		Stock return			Industry-adjusted return	
BRAND VALUE	0.05***	0.04**	0.05***	0.04***	0.03**	0.03**
	(2.89)	(2.57)	(2.66)	(2.87)	(2.31)	(2.30)
SIZE	0.17*	0.06	-0.18	0.13	0.04	-0.17
	(1.79)	(0.61)	(-1.33)	(1.48)	(0.43)	(-1.17)
BM	0.02	0.06	-0.07	0.00	0.04	-0.07
	(0.12)	(0.52)	(-0.54)	(0.00)	(0.44)	(-0.71)
YIELD	-0.01	-0.01	-0.01**	-0.01	-0.01*	-0.01**
	(-0.97)	(-1.51)	(-2.23)	(-1.26)	(-1.74)	(-2.49)
RET2-3	-0.68**	-0.80**	-0.25	-0.74**	-0.86***	-0.37
	(-2.11)	(-2.53)	(-0.69)	(-2.52)	(-2.98)	(-1.08)
RET4-6	-0.78**	-0.85**	-0.61	-0.80**	-0.85**	-0.63*
	(-2.11)	(-2.41)	(-1.63)	(-2.30)	(-2.50)	(-1.78)
RET7-12	-0.58**	-0.62***	-0.52**	-0.63***	-0.65***	-0.59***
	(-2.48)	(-2.81)	(-2.35)	(-2.76)	(-3.09)	(-2.67)
DVOL	-0.15*	-0.11	-0.09	-0.10	-0.07	-0.05
	(-1.83)	(-1.33)	(-1.13)	(-1.29)	(-0.91)	(-0.58)
PRICE	-0.70***	-0.66***	-0.55***	-0.71***	-0.68***	-0.58***
	(-3.61)	(-3.48)	(-3.06)	(-3.57)	(-3.44)	(-3.08)
ASSET GROWTH		0.24***	0.14		0.23***	0.13
		(5.80)	(1.62)		(5.46)	(1.53)
ROE		-0.02	-0.01		-0.02	-0.02
		(-1.26)	(-0.85)		(-1.55)	(-1.20)
PROFITABILITY		0.65**	0.94***		0.54	0.87***
		(1.99)	(3.57)		(1.58)	(2.75)
EARN SURP		0.05***	0.06***		0.05***	0.06***
		(4.53)	(6.41)		(4.63)	(6.64)
LEVERAGE		0.85***	0.34		0.69***	0.24
		(3.03)	(0.94)		(3.02)	(0.84)
R&D		0.06**	0.04		0.06***	0.05***
		(2.16)	(1.45)		(4.67)	(3.09)
ADVERTISING			0.01			-0.01
			(0.26)			(-0.36)
ORG CAPITAL			0.27***			0.22***
			(3.10)			(3.05)
CONSTANT	2.53***	2.89***	5.23***	1.72**	2.05**	3.88***
	(2.62)	(2.99)	(3.91)	(2.00)	(2.40)	(2.83)
Observations	604,556	604,556	482,983	604,556	604,556	482,983
R-squared	0.05	0.06	0.07	0.04	0.05	0.05