Web Luminosity Data Applications for Alpha Generation

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Abstract

This paper investigates investment applications of Web Luminosity, a measure of the ubiquity of a company's brands in relevant internet citations. Web Luminosity is important in this research because of its relevance to brand loyalty. Long considered an intangible, brand loyalty is now routinely factored into investment analysts' calculations of the intrinsic value of relevant firms. To do so, many models use brand loyalty proxy metrics interpolated from financial statements. With today's technologies those data are processed instantly and distributed widely, so that much of the competitive edge previously documented in studies is currently difficult to translate into alpha. The other traditional brand loyalty data source is focus groups; they are time-consuming, costly, and may contain sampling bias. Web Luminosity, derived from a corporation's total relevant brand citations on the internet, makes use of a free global focus group proxy, the internet. To do this, extensive mapping and lexicography files are needed to extract only pertinent data. Transforming web luminosity data for a company into an investment signal requires several more analytic steps and a comprehensive framework to determine the signal's relevance and efficacy. This white paper documents that process, then proceeds to the testing phase. First, investment signals are tested to demonstrate their effectiveness in differentiating groups of positive future performers from negative future performers, thus identifying efficacy in long-short portfolios. Then, a core long-only US Large Cap portfolio application is illustrated.

Why is Brand Loyalty Important to Investors?

Brand loyalty is one of the first intangible assets recognized in academic literature. The academic interest derives from the value that brand loyalty generates to companies in terms of:

- A substantial entry barrier to competitors,
- An increase in the firm's ability to respond to competitive threats,
- Greater sales and revenue, and
- A customer base less sensitive to the marketing efforts of competitors.

A practical example of brand loyalty being helpful in providing superior investment returns comes from Peter Lynch of Fidelity Magellan fame. Peter Lynch advocated "liking a store, a product, or a restaurant is a good reason to get interested in a company and put it on your research list"[1] for selecting equities with enough brand loyalty to warrant further fundamental analysis. Peter Lynch also credits brand loyalty as a significant intangible when he argued that

[1] Lynch, Peter. *One Up on Wall Street.* New York: Simon & Schuster, 1989. ISBN 0-7432-0040-3. pp. 16.

“the alert shopper has a chance to get the message about retailers earlier than Wall Street does”[2] while managing the Magellan Fund at Fidelity Investments from 1977 to 1990. During that time the average annual return experienced by Magellan’s shareholders was over 29% and it is renowned for having, "the best 20-year return rate of any mutual fund in history."[3]

Jack Treynor[4] agreed, and then extended it in more blatantly economic terms; arguing that, "Brand loyalty manifests itself in consumers’ willingness to pay a higher price for the brand they prefer." He then went on to say, "The importance of brand loyalty stems from the anxiety of consumers at a point when the industry is unstable and certain brand names hold a better reputation for the quality of their product than others in the industry." Treynor used rates of change in sales among competitors in attempting to interpolate proxies for brand loyalty. Lev[5] demonstrated that analysts restricting their analyses to traditional financial statements systematically underestimate the intrinsic value of companies comprising more than 50% of the market capitalization of the S&P 500 by failing to account for significant intangibles such as brand value and intellectual property. Damodoran[6] picked up on Lev’s thesis to estimate the value of these intangibles. Chen, Doerpinghaus, and Yu[7] later demonstrated the specific impact of brand loyalty on positive changes in franchise value and profitability.

As more investors became aware of the impact that this intangible asset could have on future corporate revenue streams, more of them used small focus group data and derived proxies from financial statements to consider this metric in stock selection. Any opportunity to extract alpha would have to come from being able to discern changes in brand loyalty before the next financial statements were reported.

The Internet as a Global Focus Group

An alternative approach made possible by the internet is the use of "Big Data" in cyberspace to create a passive "focus group". Such a de facto "focus group" may consist of literally hundreds of millions of globally dispersed consumers on a daily basis, while simultaneously collecting brand name citations via “web scraping” for tens of thousands of brand names. With so vast a landscape, it is easy for an amateur web-scraper to get lost in the weeds, collecting more useless

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[2] Lynch, Peter. *Beating the Street.* New York: Simon & Schuster, 1993. ISBN 0-671-75915-9. pp. 118.

[3] Reiff, Nathan. "The Greatest Investors: Peter Lynch." *Investopedia,* https://www.investopedia.com/university/greatest/peterlynch.asp. May 2017.

[4] Treynor, Jack. "The Investment Value of Brand Franchise. "*Financial Analysts Journal* 55, no. 2, 1999, pp. 27-34.

[5] Lev, Baruch. Intangibles: Management, Measurement, and Reporting. *Brookings Institution Press*, 2000.

[6] Damodaran, Aswath. "The Value of Intangibles." *Working Paper,* NYU Stern School of Business, September 2009.

[7] Chen, Xuanjuan, Helen Doerpinghaus, and Tong Yu. *Franchise Value and Firm Profitability: The Case of Property-Liability Insurance Industry*. Working Paper, Kansas State University, 2010.

than usable data. It is important to understand and how to apply the necessary IT tools and resources. And subsequently, to design algorithms and engineering approaches that efficiently capture the relevant data that you do need to develop trading signals, while ignoring the rest of the noise out there.

Capturing these Data from Cyberspace

Selecting the best method for capturing data from cyberspace requires a thorough understanding of the kinds of data being collected and how it will be used. For example, the needs and environment of a political campaign differ substantially from those of an investment manager. A political campaign might be scanning the web in an effort to find out which of their candidate's soundbites is getting the most traction with the media. In such an environment the political campaign doesn't need years of prior sampling, nor does it have to be especially sensitive to copyright or intellectual property (IP) ownership issues – since the material collected will be used internally, non-competitively and only over a very short term.

On the other hand, investment managers who are analyzing the merits of the various equities in their portfolios need to collect and store data in a manner that permits comparisons over extended periods of time. The extended time periods are necessary both to (a) understand how a given cyber based metric (e.g., a brand's daily Web Luminosity) is varying over multi-quarter or multi-year time frames (e.g., thereby inferring consumer brand loyalty) and (b) for "back testing" the efficacy of the investment strategies that are using those metrics. And investment managers have an additional burden: they need to be highly sensitive to copyright and IP ownership issues if they have any hope of satisfying their in-house compliance officers.

In practice compliance issues place major restrictions on the places where data may be captured and how it can be stored. Nearly all material on the web is copyrighted intellectual property. And nearly every website has "terms of use" that restrict how the contents of the website can be used without the explicit permission of the site's owner. Furthermore, collecting material via access credentials or unauthorized hacking opens a number of issues concerning the extent to which the material might be considered "privileged." One example of a service provider running afoul of website copyright protection is the case of American Airlines vs. FareChase[8].

There are strategies that can deal with some of these concerns. One of these strategies involves the lexicographic analysis of the publicly available portions of cyberspace within the confines of "fair use" as defined by the United States Copyright Act of 1976, 17 U.S.C. § 107. This particular strategy does not replicate, distribute or store any of the raw materials encountered. The only data collected is disassembled, aggregated, sorted, and tallied into lists of common language words that are themselves in the public domain – a compiled dictionary from which the

[8] "American Airlines, FareChase Settle Suit". The Free Library. 2003-06-13.

individual original copyrighted web materials (and their intellectual property content) cannot be reconstructed.

Developing a Lexicon to "Cross the Rubicon"

Fortunately, investment managers can utilize such a dictionary – since the word tallies can tell them just how often a given word has been encountered on a daily basis. Savvy investment managers realize that among the words within the dictionary are words that are used as brand names by thousands of publicly traded corporations. It is also helpful to have a strong knowledge of search engines and their optimization algorithms as detailed by Pershave and Dezhgosha[9].

The lexicographic strategy requires formidable IT resources. The "Big Data" in cyberspace is truly big; at last reckoning the web contains over 20 zettabytes of data (that's a 20 followed by 21 zeros) – or roughly 5 terabytes for each and every global online user, enough data to fill several trillion dollars of hard drives. Any collection approach is necessarily time constrained; no collection approach can visit all of this ever-expanding data in a reasonable amount of time. Tarp and Gouws[10] documented that a delicate balance is required to maintain lexicons that have enough translation algorithms to succeed without experiencing overload. However, carefully engineered approaches can provide statistically rigorous and unbiased samples – provided that they have access to industrial strength bandwidths.

The software utilized is typically highly proprietary and expensive to produce. The "web scraping" portion must be very lean and highly tuned to this particular lexicographic task. The subsequent statistical analysis also has to be designed to deal with substantial scale and noise issues. For example, it can be challenging to have statistical confidence in all points of a data series where the largest values (e.g., the number of global online citations of a brand name such as "Facebook" or "fb.com") can differ by ten orders of magnitude from the lowest values (e.g., the citation counts for a regional bank).

Furthermore, noise is introduced into the data series by something that we all experience: fluctuating bandwidth. If we desire daily data resolutions, sample sizes are necessarily constrained by the daily "web scraping" window and are therefore materially impacted by each day's effective bandwidth. Unfortunately, even "industrial strength" bandwidth is subject to daily or hourly traffic saturation and network latency issues. And in the longer run, today's bandwidth is not what we experienced several years ago, and it will almost certainly not be what we will be

[9] Peshave, Monica, and Kamyar Dezhgosha. "How search engines work and a web crawler application." *Working Paper*, Department of Computer Science, University of Illinois, Springfield USA (2005).

[10] Tarp, Sven and Rufus H Gouws. "Information overload and data overload in lexicography." International Journal of Lexicography, Volume 30, Issue 4, 1 December 2017, pp. 389–415.

experiencing several years from now. Extracting a statistically robust signal from dramatically fluctuating sample sizes can be a significant technical challenge.

Note that the lexicographic strategy also avoids the parsing challenges encountered by those who attempt to discern the sentiment of web postings. Parsing sentiment from social media postings can be a nightmare of double or triple negatives, hyperboles, non-standard emoticons, demographic biases and snarky comments. But even without sentiment per se, the lexicographic approach can identify short term spikes in the occurrences of a given brand name – allowing such spikes to be referred to analysts for interpretation. Kaplan and Haenlein[11] document some of these obstacles. More recently, Batrinca and Treleaven[12] report some progress in this area using cluster algorithms.

The lexicographic strategy also requires a database that maps brand names to the corporations that own them. The materiality of brand names can change over time, and the corporations that they belong to can change even faster. Arora and Bhalla[13] documented the importance and obstacles involved in maintaining lexicons that keep up with shifts in search engine terminologies.

A brand name mapping database is a moving target that can require substantial resources to keep it both accurate and current. The good news is that if you are consistent in applying your quality control mechanisms to ensure your lexicon is still current and accurate, the data you collect will allow you to stay accurate and consistent when you aggregate relevant brand citation data at the corporate level.

Defining Web Luminosity

Understanding the nature of corporate citation data is crucial. Citation rates vary over time due to a number of factors: the organic growth (or contraction) of the power of their brands, various seasonal factors, and events that catch the public's attention. Therefore, algorithms must be applied to a moving sample window of citation days to compensate for spikes and other noise so that on any given day, each corporation has a characteristic level of citations. Web Luminosity is defined as this characteristic level of citations.

Web Luminosity can be thought of as the magnitude or scale of a company's presence on the web. As a scalar number, it is a feature or characteristic of the company's relevant brands in the

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[11] Kaplan, Andreas M. and Michael Haenlein. "Users of the world, unite! The challenges and opportunities of Social Media. " *Business Horizons*, Volume 53, Issue 1, January–February 2010, pp. 59-68.

[12] Batrinca, Bogdan and Philip C. Treleaven "Social media analytics: a survey of techniques, tools and platforms." *AI & SOCIETY*, February 2015, Volume 30, Issue 1, pp. 89–116.

[13] Arora, Palvi and Tarun Bhalla. "A Synonym Based Approach of Data Mining in Search Engine Optimization." *International Journal of Computer Trends and Technology*– Volume 12, Number 4, Jun 2014, pp. 201 – 205.

aggregate at any given time. As a time series, the numbers can infer the dynamic nature of consumer loyalty to a company's brands – a key input in the investment decision-making process provided that the data are scrubbed, classified, scaled, and analyzed correctly. Two important considerations used in gauging the usefulness of Web Luminosity data to be incorporated into investment signals are relevance and industry signal strength.

Signal Relevance

Signal Relevance, another key term, is defined as the correlation of on-line brand citation rates (i.e., Web Luminosity) to revenue. For corporations in industries that are closely engaged with consumers, Web Luminosity will often be positively correlated to revenues. This was illustrated in greater detail in a working paper by Davis[14].

For other corporations, especially in non-consumer oriented industries, there is generally very little correlation between Web Luminosity and revenues. We refer to the correlation of citation rates to revenue as the "Signal Relevance" for a given corporation. However, these scalar numbers need context to increase usefulness to investors. Signal Relevance is best understood and implementable in a strategy when aggregated on an industry by industry basis.

High-Signal Industries vs. Low-Signal Industries

Corporate Web Luminosity generally depends on both the number of customers it has and the frequency of its interactions with those customers. Some corporations (e.g., AMGN or LMT) simply do not interact directly with consumers at all, and have very low Web Luminosity. Other corporations (e.g., MCD or JACK) have large scale consumer operations and transact relatively frequently with those customers – creating much higher Web Luminosity as a by-product of those interactions.

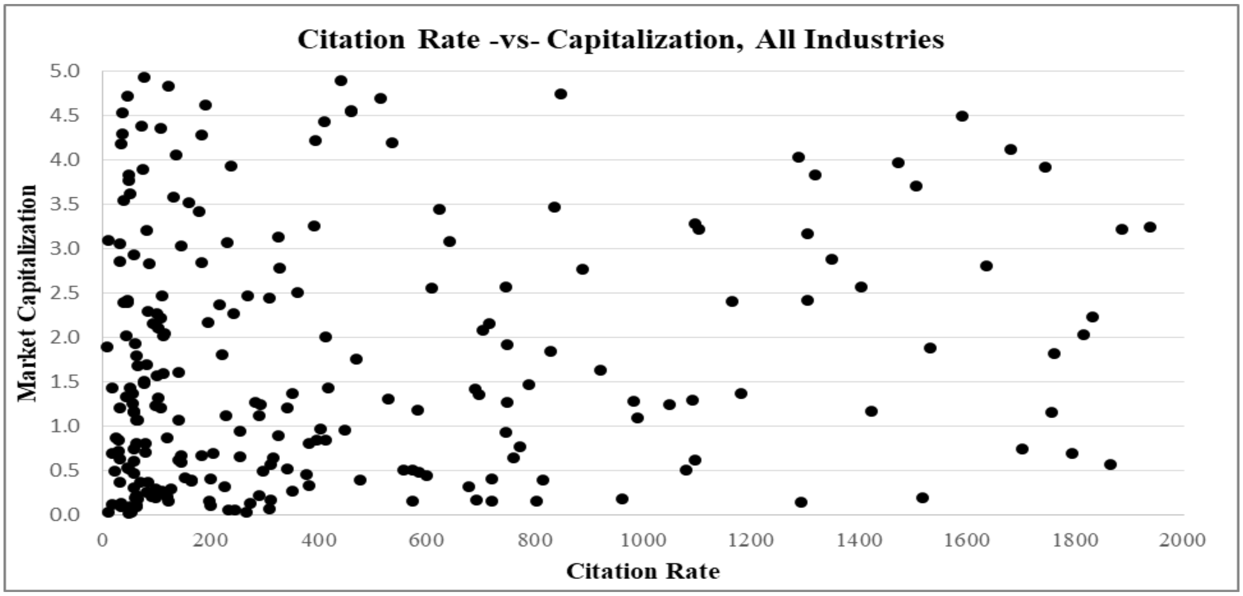
Corporations are often classified and grouped by both the industry in which they are engaged and the scale of their market capitalization. It is important to understand how such classifications impact the availability and usefulness of the brand name citations (i.e., Web Luminosity) that can be found in cyberspace. When comparing the number of times that consumers interact with MCD and AMGN, it is obvious that their respective industries are a critical factor in the vast differences in their brand citation rates. Similarly, when comparing brand citation rates for MCD and JACK, it is clear that the scale of consumer operations, using market capitalization as a crude but available proxy, is likely the major factor in MCD's substantially higher Web Luminosity.

[14] Davis, Richard C. "BrandLoyalties.com Basic Concepts." *Working Paper*, Consumer Metrics Institute and BrandLoyalties.com, http://brandloyalties.com/BrandLoyalties_White_Paper_-_Basic_Concepts.pdf, December 2017.

If we plot all corporate brand citation rates (disregarding their respective industries) against their market capitalizations, we would see a scatter diagram similar to Exhibit 1 – where a random sample of corporations shows no significant relationship or dependency between brand citation rates and capitalization:

<u>Exhibit 1</u>

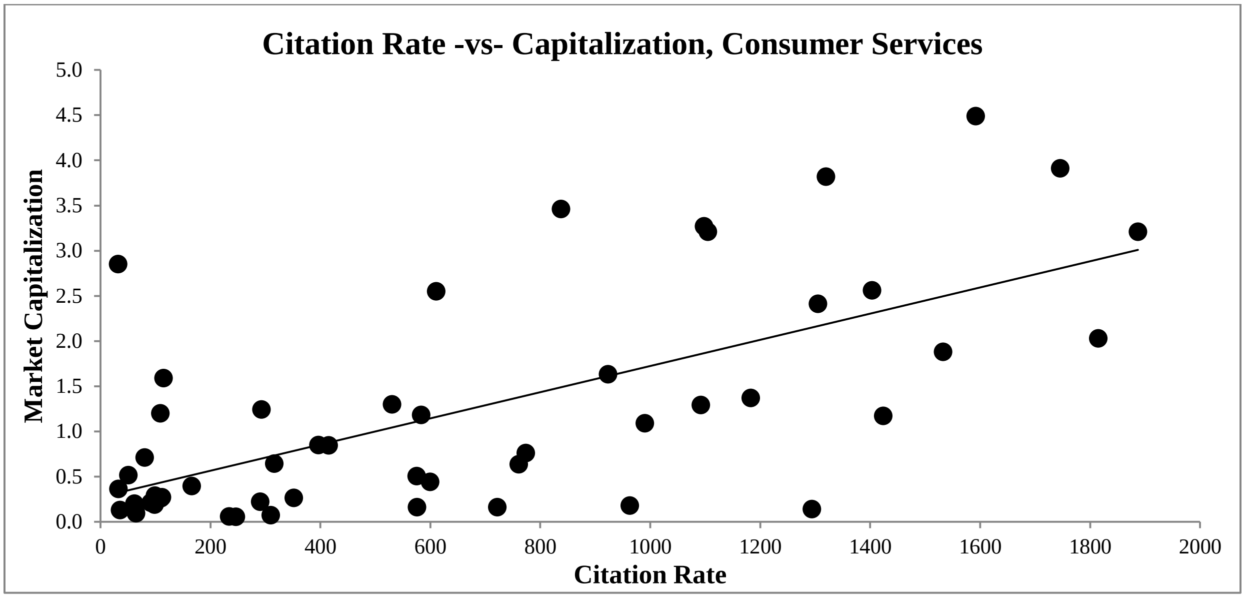
Brand Name Citation Rates –vs– Capitalization, All Industries



Source: BrandLoyalties, Inc.

However, if we reorganize those same corporations into subsets and eliminate companies not directly engaged in consumer services, a clearer picture emerges. Exhibit 2 demonstrates a better defined empirical relationship between brand citation rates and capitalization. Now, a regression line with far less noise can be plotted:

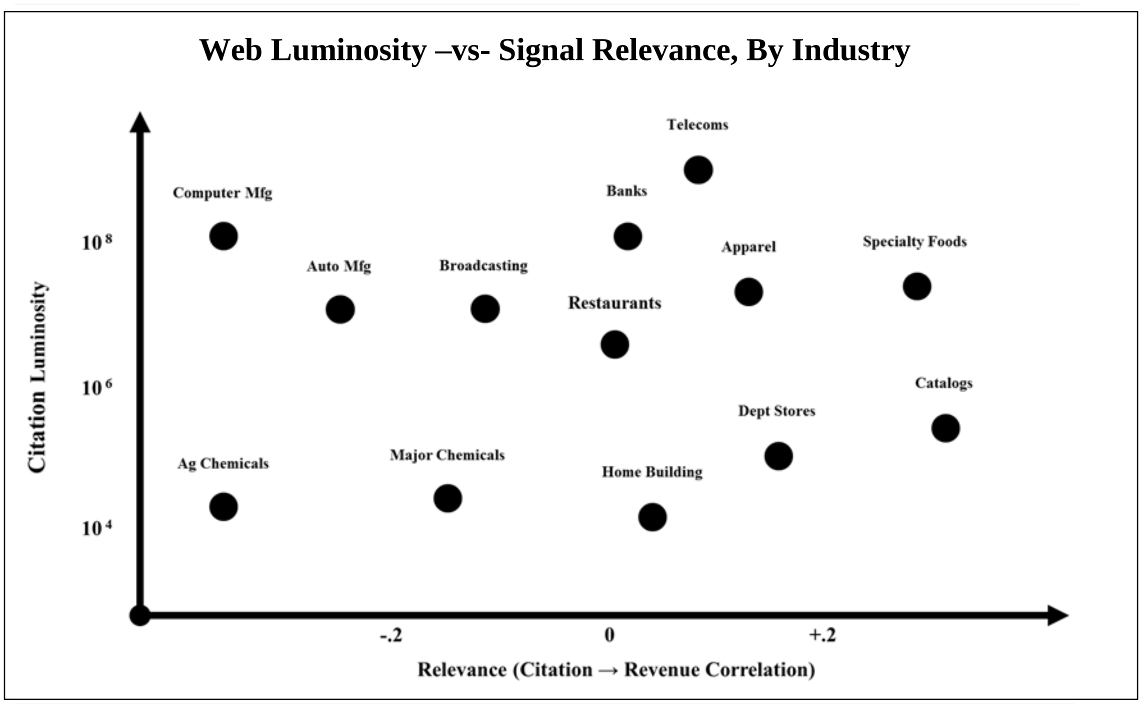
Exhibit 2



Source: BrandLoyalties, Inc.

From this kind of analysis we can confirm the intuitively obvious: the corporation's principal industry is the key determinant for the citation metrics. Yet within a single industry, an increased scale of consumer operations can materially impact brand citation rates, as shown in Exhibit 3:

Exhibit 3



Source: BrandLoyalties, Inc.

The industries with the most valuable signal relevance based business intelligence generally reside in the upper right portion of the chart. Although the computer manufacturers in the upper left portion of the chart have substantial Web Luminosity, most of that luminosity is support related and only a fraction of the brand citations are created by revenue generating activities. Each corporation has a unique luminosity and signal relevance profile, and the industry averages plotted in Exhibit 3 mask significant company-by-company profile variances within each industry. We have found that, in general, the corporations with the highest signal relevance are engaged in the production or marketing of consumer discretionary goods that require minimal post-purchase support.

In order to avoid spurious "false positive" correlations between citation rates and revenue, it is important to understand a plausible causality between the two variables. The industry groupings provide a macro way to think about that causality: a high correlation between consumer citations and revenue is more plausible for a fast food chain than it is for an agricultural chemical producer. For this reason corporate "industry" classifications are helpful to determine both the availability and the usefulness of the data in cyberspace.

Exhibit 4

Corporations with high citation rate to revenue correlation over trailing 8 quarters

	Corporation	Correlation
DSW	DSW Inc.	95.29%
JWN	Nordstrom, Inc.	94.35%
HTZ	Hertz Global Holdings, Inc.	94.11%
BKS	Barnes & Noble, Inc.	91.71%
LUX	Luxottica Group SpA	86.03%
PIR	Pier 1 Imports, Inc.	83.57%
PCMI	PC Mall, Inc.	83.45%
PERF	Perfumania Holdings, Inc.	83.09%
DV	DeVry, Inc.	81.02%
JCP	J.C. Penney Co., Inc.	77.73%

Source: BrandLoyalties, Inc.

In these cases, the real-time brand citation rate metrics over the current corporate quarter can be a plausible proxy for as-yet unreported revenues as shown in Davis[15]. Citation metrics are anticipatory for two reasons: first, the activity being captured in cyberspace is at the leading edge of the distribution channel and, in many cases, even prior to consumer transactions; and secondly, formal earnings reports necessarily lag revenue transactions. For research driven tactical managers, daily revenue proxies can provide a source for alpha generation.

Exhibit 5

Corporations lacking material citation rate to revenue correlation over trailing 8 quarters

Corporation		Correlation
ANTM	Anthem Inc.	3.73%
THC	Tenet Healthcare Corp.	3.23%
LLY	Eli Lilly and Company	2.76%
TEVA	Teva Pharmaceutical Industries Limited	0.68%
RHT	Red Hat Inc.	0.62%
INTC	Intel Corporation	-0.14%
QCOM	QUALCOMM Incorporated	-0.21%
CELG	Celgene Corporation	-0.80%
BMY	Bristol-Myers Squibb Company	-0.94%
NSC	Norfolk Southern Corporation	-3.90%

Source: BrandLoyalties, Inc.

Other corporations do not exhibit consistent material correlations between brand citation share and revenue, examples of which are shown in Exhibit 5. These corporations are generally not heavily involved with the production or marketing of discretionary goods directly to consumers. For these corporations citation share metrics do not provide meaningful proxies for unreported revenues.

BrandLoyalties' Signal Scores

For this paper we have used data from BrandLoyalties, Inc., a provider of proprietary consumer brand loyalty signals derived from a time series of corporate Web Luminosity scores. Their daily signals reflect Web Luminosity share growth over the trailing 90 days and include quantitative

[15] Davis, Richard C., " "Big Data" Meets "Smart Beta" ", *The Journal of Index Investing*, Summer 2015, pp. 39 – 50.

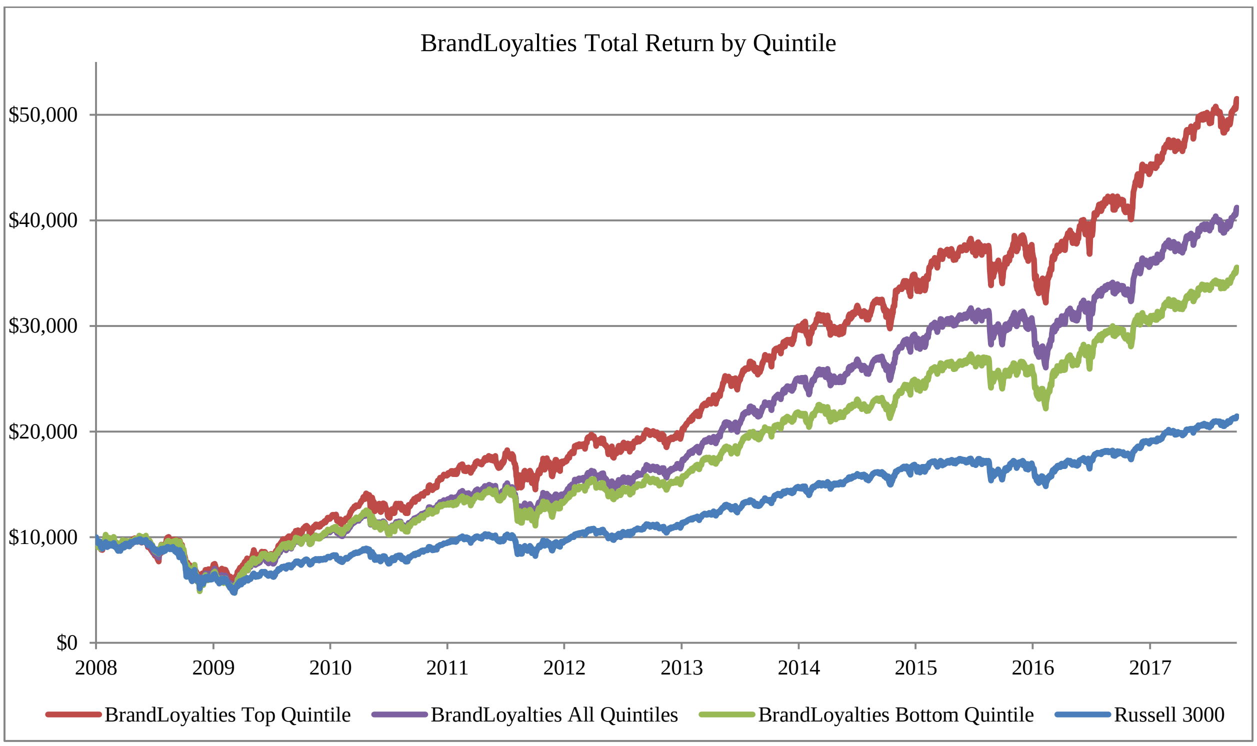
assessments of the relevance of those signals to real-time corporate revenues. They have provided these signals to a select client base of hedge funds and institutional investors since 2012.

Suitability for hedge funds

One of the classic litmus tests for the potenial usefulness of an alternative data set for a hedge fund is to test the performance of top quintile scores against bottom quintile scores. For this test, the universe was grouped into quintiles according to BrandLoyalties' signal score. Each quintile was rebalanced quarterly from the beginning of 2008 through September 30, 2016. The graph in Exhibit 6 shows the spread between top quintile companies in the universe and bottom quintile companies.

Exhibit 6

Graphical Performance of Top Quintile vs. Universe vs. Bottom Quintile Data



Source: BrandLoyalties, Inc.

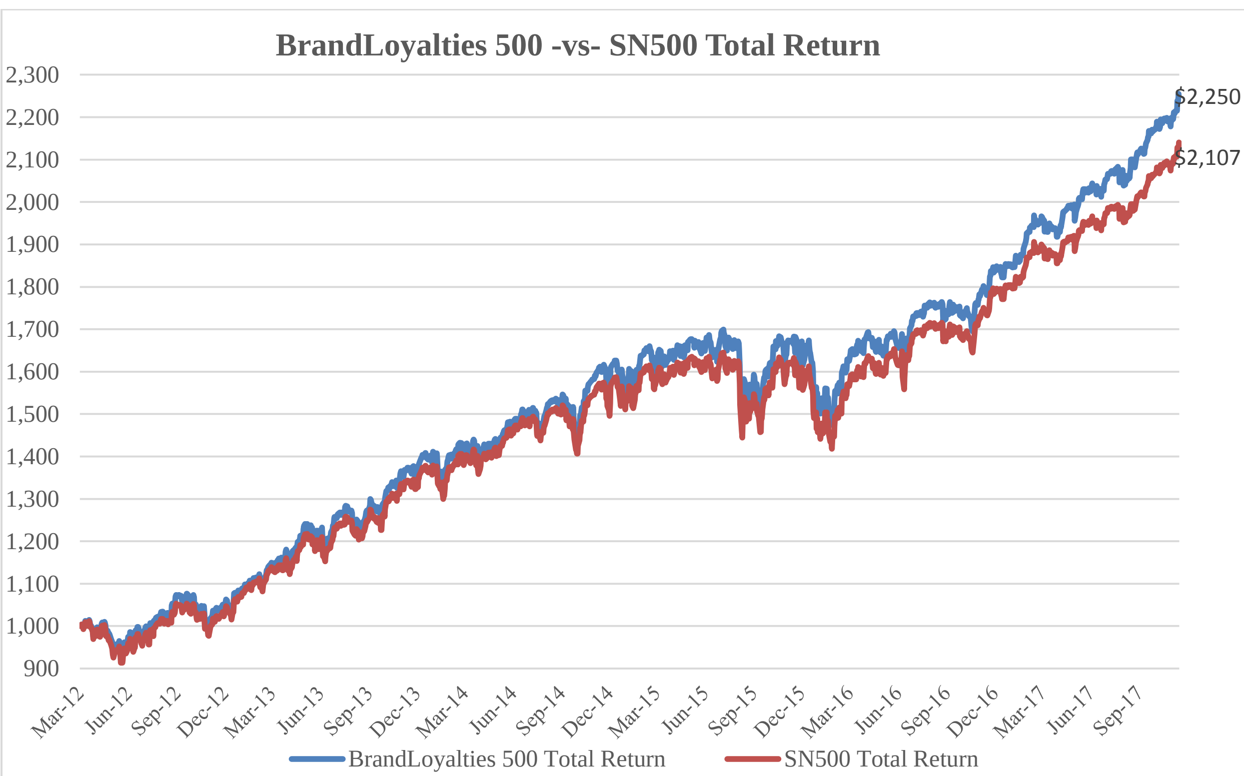
Suitability as a source of incremental alpha for long-only core US Large Cap portfolios

This is less of a made-to-order challenge for signals derived from "Big Data" than the quintile comparison. As we have detailed, there are more companies and industries that do not have brands with high luminosity scores than those that do. Therefore, there will be many stocks in a core portfolio that will receive a neutral rating because their BrandLoyalties, Inc. score is not meaningful. Nevertheless, we wanted to test if the stocks that had clear BrandLoyalties, Inc. signals during the period were sufficient to add incremental alpha to an index of the largest 500 stocks domiciled in the US as represented by S-Network Global Indexes' market-cap weighted SN500 Index.

To produce a BrandLoyalties, Inc. enhanced version of the 500-stock portfolio, an algorithm was applied. First, all 500 stocks were reduced in weight by 50% for the preliminary round. Then the weights were increased for stocks in the top three quintiles by twice the original weight, 1.5 times the original weight, and back up to the full weight respectively. The weights from the second round were added together. Then the weights of the entire portfolio were increased proportionally until the weights for all the stocks summed to 100%. The 500 stocks were rebalanced quarterly with stocks entering and exiting the index with no survivorship bias.

The result for the 5-year period was a superior return for the BrandLoyalties, Inc. enhanced SN500 portfolio by 138 basis points, 17.66% to 16.28% during the 5-year period. The results in Exhibit 7 show that a strategy based upon Web Luminosity can add value to a benchmark portfolio even when meaningful scores exist on only slightly more than half of the companies in the benchmark index.

<u>Exhibit 7</u>



Summary

This paper defines corporate Web Luminosity as the sum of characteristic levels of brand citations for a company's relevant brands. Defining Web Luminosity is much easier than capturing it and determining its relevance. The many issues involved in creating a lexicon, corporate brand maps and rules to collect the relatively few terabytes of potentially usable information from the zettabytes of information available daily are daunting but achievable. IT tools and resources, algorithms and engineered approaches must be carefully applied to identify the nuggets of helpful data available from the vast tableau of the web. Then, even when a researcher believes he or she has captured something of value, data cleansing and categorization are ongoing activities. In fact, the changing dynamics of how these data appear, how access to them can be obtained, and how they will be consumed are far greater than those that have been involved in the past two centuries of financial statement analyses. Furthermore, Web Luminosity is only helpful in predicting the future direction of corporate revenue streams for companies in certain industries, generally consumer-oriented industries where brand loyalty can be a major differentiating factor.

From an investment perspective, the hypothesis was confirmed that the analytic metrics extracted from the techniques could add differentiable signals that could create superior returns during the specific periods for which data were available. This was done by comparing the performance of companies with top quartile signals derived from the luminosity data with those having bottom quartile signals. Next, we compared a cap-weighted portfolio of the 500 largest US-listed stocks with a portfolio with a modified weighting scheme engineered to increase weighting to companies with above-average signal strength. Although the differentiation here is more subtle, it is consistent and impressive given that all the same stocks were utilized. These results may be used as starting points for new strategies that could potentially provide even more impressive investment results.

Disclosure: Global Finesse LLC was engaged and received compensation to perform independent analyses and write this research paper based on our findings for BrandLoyalties, Inc. The client provided these data and gave us full access to its history and derivations as covered under a confidentiality agreement. Thus, while the authors believe these data and the analyses contained within to be accurate and consistent, we disclose that we did not ourselves derive or validate the raw luminosity data utilized in these analyses. Global Finesse LLC is a consulting firm that does not sponsor, manage or sell any investment vehicle.

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