Same Same but Different? The Predictive Power of Association Types in Brand Buzz for Investor Returns

Stefan Fischer
University of Goettingen, stefan.fischer@wiwi.uni-goettingen.de

Welf Weiger
University of Goettingen, welf.weiger@wiwi.uni-goettingen.de

Maik Hammerschmidt
University of Goettingen, maik.hammerschmidt@wiwi.uni-goettingen.de

Same Same but Different? The Predictive Power of Association Types in Brand Buzz for Investor Returns

Short Paper

Stefan F. Fischer
University of Goettingen
stefan.fischer@wiwi.uni-goettingen.de

Welf H. Weiger
University of Goettingen
welf.weiger@wiwi.uni-goettingen.de

Maik Hammerschmidt
University of Goettingen
maik.hammerschmidt@wiwi.uni-goettingen.de

Abstract

Brand buzz sentiment–the favorability of public communications about the brand–has become a major source to gauge brand reputation and predict investor returns. In this research, the authors build a prediction model of investor returns by empirically elaborating on its intricate relations with two novel sentiment measures by integrating brand reputation literature with brand buzz research. Accordingly, investor returns are conceptualized as a function of the favorability of buzz associated with the brand's ability to deliver its outputs (brand ability buzz sentiment) and the favorability of buzz associated with the brand's societal impact (brand responsibility buzz sentiment) along with their interaction, respectively. Deploying support vector machine learning and panel vector autoregression, preliminary evidence suggests that brand ability buzz sentiment but not brand responsibility buzz sentiment drives investor returns, yet their interaction inhibits investor returns. The proposed model outperforms extant prediction models of investor returns.

Keywords: Brand buzz sentiment, brand reputation, support vector machine, panel vector autoregression, abnormal stock returns

Introduction

Brand buzz sentiment refers to the favorability of the entire public communications pertaining to a brand (Hewett et al. 2016). With communications occurring increasingly through digital media these days and advances in information technology, brand buzz sentiment has received widespread attention as a popular proxy for brand reputation because it reveals the associations that are held in memory for the brand by the broader public and in doing so complements conventional, less readily available, less granular and more expensive information sources (Schweidel and Moe 2014).

Consider, for example, the United Airlines Flight 3411 incident in 2017. The violent removal of a passenger from a fully boarded, overbooked flight which went viral almost instantaneously spawned an unusual number of unfavorable associations regarding the brand's ability to deliver its services. The resulting drop of brand ability buzz sentiment led to a decrease in investor returns of −4% within only two days (Shen 2017). However, this effect may not exclusively be caused by sentiment associated with the brand's ability to cater to the needs of its customers. In another incident in which a passenger was violently removed from a Southwest Airlines plane for speaking Arabic aboard, brand buzz sentiment dropped due to the increase in unfavorable associations regarding the brand's social responsibility. Even though at a different magnitude, speed, and duration, this drop in brand responsibility buzz sentiment led to the same decrease in investor returns (Stack 2016).

Prior research on the relation between brand buzz sentiment and investor returns has largely neglected to differentiate brand buzz sentiment in terms of the revealed brand associations as illustrated in the real-world examples above. Instead, prior studies have merely considered the average favorability of all brand-related communications regardless their dominant association type for predicting investor returns. However, not accounting for this associative context may lead to biased predictions of investor returns . For instance, the sentiment of brand buzz from online product reviews, which is overtly dominated by ability associations, has consistently been found to have a positive effect on investor returns (Luo and Zhang 2013; Luo et al. 2013; Tirunillai and Tellis 2012; Chen et al. 2011). In contrast, there has been mixed evidence in support of a positive link for the sentiment of brand buzz obtained from other sources than product reviews. For example, in stock message boards, brand buzz sentiment is less characterized by ability associations but rather dominated by responsibility associations (Jiang et al. 2014). However, for sentiment from stock message boards, prior research has identified positive effects (Das and Chen 2007; Chen et al. 2014; Wysocki 1998), negative effects (Zhang et al. 2012), and null effects (Tumarkin and Whitelaw 2001; Antweiler and Frank 2004). In sum, the extant empirical findings suggest that predictions of investor returns by brand buzz sentiment may vary by the type of brand association they convey. Thus, conventional brand buzz sentiment may over- or underestimate future investor returns and thus be biased. Yet, no study has disentangled the effect brand buzz sentiment has on investor returns while considering different brand association types.

The goal of this short paper is to empirically elaborate on how separating brand buzz sentiment into brand ability buzz sentiment and brand responsibility buzz sentiment may inform the prediction of investor returns. Given the anecdotal evidence from both research and practice summarized above, we expect that brand buzz sentiment as well as its inherent association types are positively related with future investor returns. However, we further consider that the latter may not only inform the prediction of investor returns in isolation but interaction because different association types are likely to simultaneously appear in brand buzz sentiment. For instance, every year since 2012, WestJet's viral "Christmas Miracle" image videos spawn favorable ability and responsibility associations in brand buzz simultaneously (Bender 2013; WestJet 2018). In summary, we expect that separating brand buzz sentiment in two generic association types and considering their respective interaction yields additional explanatory power in predicting investor returns.

This research contributes to the theory and practice of brand buzz in several aspects. Conceptually, we integrate traditional brand reputation literature with research on brand buzz sentiment to introduce two novel concepts of brand buzz sentiment: brand ability buzz sentiment, which refers to the favorability of brand-related communications that are primarily associated with the brand's reputation to deliver its outputs and brand responsibility buzz sentiment, which denotes the favorability of brand-related communications that are primarily associated with the brand's willingness to improve the well-being of society at large. We argue that this separation of brand buzz sentiment parallels two generic types of brand associations identified in brand reputation literature (e.g., Brown and Dacin 1997; Luo and Bhattacharya 2006; Berens et al. 2005) and yields additional predictive value inherent to brand buzz sentiment. Analytically, we provide a scalable and widely-applicable, sequential approach for identifying the dominant type of association per brand-related communication through linear support vector machine (SVM) learning and for measuring the sentiment for both generic associative types of brand buzz which allows us to classify more than 3.2 mio. single, real-world communications with an accuracy of 85%. Empirically, using daily data on eight corporate U.S. airline brands for a period of 398 trading days, we determine and compare the prevalence, duration, and magnitude of investor returns from conventional brand buzz sentiment as well as brand ability buzz sentiment and brand responsibility buzz sentiment along with their respective interaction. Our preliminary results suggest that predictions of investor returns based on our proposed model outperforms extant models based on conventional brand buzz sentiment by 62% in the short- and 39% in the long-run. Moreover, the predictive power of brand buzz sentiment may primarily root in brand ability buzz sentiment since brand responsibility buzz explains merely a fraction of variance. Interestingly, we find empirical evidence for a negative interaction between brand ability buzz sentiment and brand responsibility buzz sentiment. Managerially, our research not only provides more accurate investor return predictions from brand buzz sentiment but also allows for actionable implications in that it unmasks the boundary of its predictive value: while an increase in brand buzz sentiment may generally underestimate future investor returns as compared with brand ability buzz sentiment, it may overestimate investor returns if it stemmed from an increase in both ability and responsibility buzz sentiment.

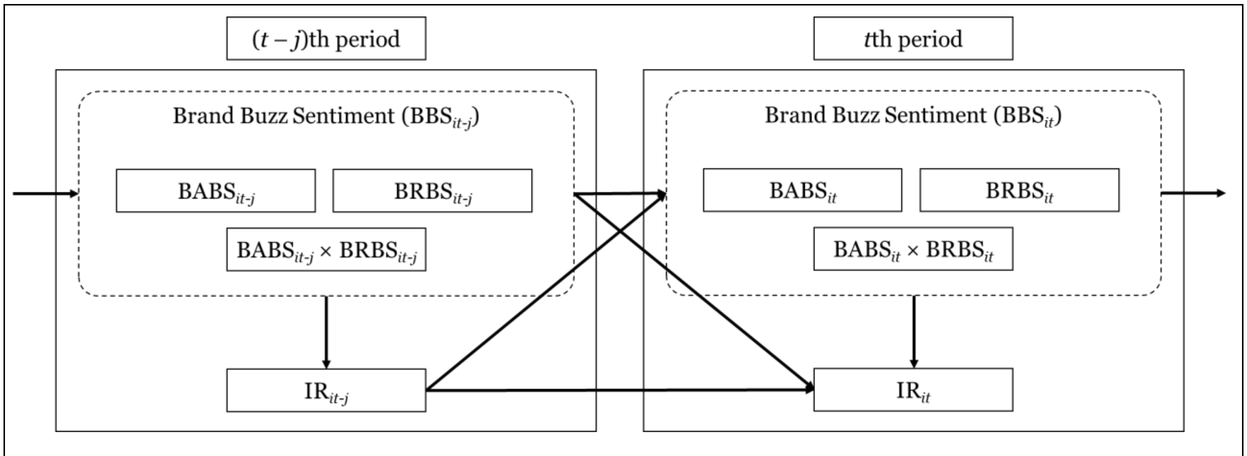

Figure 1. Modified Research Model

Empirical Methodology

Research Design

Our research framework considers the relationships between brand ability buzz sentiment, brand responsibility buzz sentiment, their interaction and investor returns (see Figure 1). In order to empirically elaborate on these intricate relations and to be able to relate to extant literature, we select the U.S. airlines industry because it is a well-established research context in marketing and finance (e.g., Luo and Homburg 2008). In 2017, domestic passenger enplanements rose by three percent as compared to 2016 reaching an all-time high of 741.6 million in the U.S. (Bureau of Transportation Statistics 2018). Thus, airlines promise to draw sufficient brand buzz and thus represent a fruitful data source for our study (Tirunillai and Tellis 2012). Adopting further sampling criteria of previous studies (Luo et al. 2013; Tirunillai and Tellis 2012), we selected eight airlines (American Airlines, Delta Air Lines, Hawaiian Airlines, JetBlue Airways, SkyWest Airlines, Southwest Airlines, Spirit Airlines, United Airlines) that (1) earn the majority of corporate sales with passenger air transportation services, (2) under their corporate brand identity, and (3) within the U.S.; (4) were publicly listed on one of the U.S. stock exchanges (NASDAQ/NYSE/AMEX) throughout the sampling period from January 4, 2016 through August 1, 2017; (5) had not undergone any identity changes during that period; (6) together account for at least 70% of domestic market share and (7) a cross-section of different market segments (low-cost vs. full service airlines) in order to be representative for the entire industry.

Sentiment Measures

To capture our brand buzz sentiment measures, we utilized automated textual analysis and followed the workflow described in Berger et al. (2019) which comprises three steps.

Step 1: The acquisition and pre-processing of brand buzz data started with collecting historic buzz on the sampled brands generated from English-speaking sources within North America through Alterian SM2. SM2 is a leading digital media monitoring and analytics tool that has been applied in previous research (e.g., Hsu and Lawrence 2016). Its data warehouse comprises over 50 billion digital communications from over half a million sources from a cross-section of digital channels (e.g., blogs, forums, news) worldwide dating back to January 2016 (Hsu and Lawrence 2016). In line with Hewett et al. (2016), we constructed a standardized search algorithm comprising and combining several brand identities such as the corporate brand name along with common misspellings (e.g., misplaced space characters), stock references (e.g., cash tag), the name of the respective chief executive officer, along with Twitter handles (e.g., @americanair) and common hashtags (e.g., #neverflydelta). Following an iterative process, we checked carefully that each brand-specific search algorithm accounted for idiosyncrasies of each brand content-wise, yet was as consistent as possible across brands structure-wise. Whenever a search term was found to be equivocal but essential, we added additional excludes or slightly diverted from the cross-sectional standard. For instance, during data collection we learned that the search term "sky west" also hit on tweets on a book titled "Sky: Child, Interrupted" by William Dale West. We thus excluded phrases from SkyWest's search algorithm that uniquely hit on communications about the book and were unrelated with the airline such as "autistic" or "@skywest1515". As a result, we retrieved over 3.2 mio. communications about the eight airlines from SM2's data warehouse. For each communication, we retrieved the full content along with a favorability score based on SM2's basic sentiment model and several descriptive statistics such as the time and date. We then removed non-meaningful information such as HTML tags and removed stop words before we finally reduced the remaining words into their common stem using freely available, standard libraries of the Natural Language Toolkit (NLTK 2019).

Step2: The automated identification of the associative type of a communication deploys a linear SVM which has been successfully applied to and advised for a variety of comparable classification tasks (e.g., Homburg et al. 2015; Tirunillai and Tellis 2012). For this purpose we draw on the libraries of libsvm (Fan et al. 2005) and liblinear (Fan et al. 2008) that have been wrapped through C and Cython and made publicly available by SciKit (2019) through Python.

For training the SVM, we began with crafting a dictionary of words for a naïve pre-classification. Basically, we started with extracting words from the manual of the investment research firm Kinder, Lydenberg, and Domini Research and Analytics Inc.'s (KLD) database. The KLD database has been widely adopted in brand reputation literature and summarizes brand associations in six dimensions: community, diversity, environment, governance, product, and employee (Fombrun 1998; Servaes and Tamayo 2013). We further supplemented the resulting dictionary with allocating a list of the most frequently mentioned words across all sampled communications to the respective KLD dimension.

We next had each communication naively pre-classified into either of the six KLD dimension by counting the number of words of each dimension being mentioned in the respective communication. In the second step of the SVM classification phase, we randomly selected 200 pre-classified communications about the Delta Air Lines brand per KLD dimension. A human coder, who was not informed about the goal of our research, read the KLD manual in order to classify each of the 1,200 communications (200 communications x 6 KLD dimensions) to either one of the KLD dimensions or to none at all without revealing the result of the naive pre-classification. Across the six KLD dimensions, the human coder could successfully classify at least 120 communications.

Finally, we trained the linear SVM based on these 720 communications and let it classify any communications into either one of the six KLD dimensions automatically. Following Homburg et al. (2015) we split the 720 naively pre-classified and human validated communications at a rate of 85:15 into a training sample (n=612) and a validation sample (n=108). We built the SVM using stratified tenfold cross-validation as described in Homburg et al. (2015) and calculated the classification accuracy over these ten stratified training samples as well as between the training sample and the validation sample. Overall, the linear SVM model with which we classified each communication into either one of the six KLD dimensions achieved an accuracy score of 85 % indicating that on average 17 out of 20 communications are coded accurately.

Step 3: In calculating the sentiment measures, we follow common practice to scale the difference between favorable and unfavorable communications pertaining to the brand by its sum (e.g., Luo et al. 2013). We adopt the sentiment model of SM2 which had each communication readily classified into either positive, negative or neutral favorability. For conventional brand buzz sentiment (BBS), we consider every brand-related communication on a given day. For brand ability buzz sentiment (BABS), we consider only those favorable and unfavorable associations about the brand which have been classified into either the employee or the product dimension of KLD exclusively by the linear SVM and thus is primarily dominated by brand ability associations. In doing so, we follow the common practice of brand reputation literature (e.g., Berens et al. 2005). In service industries, the ability of the brand to deliver its outputs is inherently related to employee-related associations as well as product-related associations. For measuring brand responsibility buzz sentiment (BRBS), we consider any favorable and unfavorable communications about the brand which has been classified into either the community, environmental, governance, or diversity of KLD exclusively by the linear SVM and thus is primarily dominated by brand responsibility associations.

Prediction Models of Investor Returns

Following prior literature (Dewan and Ramaprasad 2014; Song et al. 2019), we employ panel vector autoregression (PVAR) for our empirical analysis. PVAR is exceptionally suited for studying intricate and dynamic relations between a system of endogenous time-series variables within highly granular and large size panel settings (Holtz-Eakin et al. 1988; Luo et al. 2013). The PVAR approach proceeds in four steps.

Step 1: PVAR requires all endogenous variables to be stationary and to not being cointegrated over time. Thus, we conduct augmented Dickey-Fuller tests on all endogenous variables per brand (Luo et al. 2013; Tirunillai and Tellis 2012). Since the resulting test statistics ranged from −15.91 to −8.70 and are below the critical value −3.98, we can reject the null hypothesis of any endogenous variable to be evolving over time at the 99% confidence level and parcel out any possible cointegration among them.

Step 2: We specify three PVAR models based on the formula below as follows (e.g., Song et al. 2019).

$$y_{it} = \sum_{j=1}^{p} \Gamma_j \, y_{it-1} + x_{it} + f_i + e_{it}$$

Depending on the respective prediction model of investor returns (IR), y_{it} is either a two-variable vector $\{BBS, IR\}$ in Model 1 a three-variable vector $\{BABS, BRBS, IR\}$ in Model 2, or a four-variable vector $\{BABS, BRBS, BABS, BRBS, IR\}$ in Model 3 denoting the endogenous treatment of the brand buzz sentiment measures and investor returns for brand i on trading day t which allows them to be explained by both past variables of themselves and past variables of each other (Luo et al. 2013). In line with extant research, we choose the abnormal stock returns obtained by performing the Fama-French four factor regression over a rolling window of 250 trading days as a clean and precise measure of investor returns that has been adjusted for common risk factors and thus allows for a fair comparison of investor returns across brands (Luo and Homburg 2008; Luo et al. 2013). Γ_j are 2 × 2 matrices of slope coefficients for the endogenous variables vector in Model 1, which extends to 3 × 3 matrices for Model 2, and 4 × 4 matrices for Model 3, respectively. For all respective prediction models, the optimal number of lags denoted as p has been identified to be 1 based on multiple information criteria following previous studies and comprising the Schwartz's Bayesian information criterion, Hannan-Quinn's information criterion, and Hansen's J statistic (Abrigo and Love 2016; Luo et al. 2013).

Regardless the respective prediction model, we control for a comprehensive set of common covariates through x_{it} which is the ten-variable vector $\{MON, TUE, WED, THU, ROA, EPS, AEF, ADV, NWOM, VOL\}$: MON, TUE, WED, and THU are dummy variables that control for day-of-week time fixed effects (French 1980); ROA denotes the brand's return on assets as measured by the ratio of operating income to total asset per quarter as obtained from Compustat (Luo et al. 2013); EPS refers to the brand's earnings per share less extraordinary items retrieved from Compustat on the quarterly level (Nam and Kannan 2014); AEF is the mean of analyst's earnings forecasts for the brand as available from I/B/E/S (Nam and Kannan 2014); ADV represents the brand's quarterly advertising expenditure and is measured by scaling its selling, general, and administrative expenses by its total assets as obtained from Compustat (Nam and Kannan 2014); $NWOM$ denotes negative word-of-mouth from traditional, offline channels and is the number of customer complaints about the brand filed with the U.S. Department of Transportation scaled by the brand's total current assets as obtained from Compustat on the quarterly level (Luo and Homburg 2008), and VOL refers to brand buzz volume and is measured as the natural logarithm of the total number of daily communications about the brand as pulled out of SM2' data warehouse (Nam and Kannan 2014). Finally, f_i denotes brand specific fixed effects using Helmert's forward mean-differencing procedure and e_t is the mean zero error term (Arellano and Bover 1995).

Step 3: To address multicollinearity concerns among the estimated PVAR parameters arising from the underlying panel data structure, prior research has suggested OIRF estimates for hypothesis testing (Leeflang et al. 2017). From the estimated PVAR parameters, we generate orthogonalized impulse response function (OIRF) estimates and corresponding standard errors by simulating the fitted PVAR model by Monte Carlo simulation with 1,000 runs to test the statistical significance of parameters at the 95% level. We chose orthogonal transformation to correct for contemporaneous correlation in the white-noise residuals. We do so to predict immediate, next day investor returns following an one unit shock (one standard deviation) in sentiment which was the minimum time for the effects to be statistically significant (wear-in time), and to predict the cumulative investor returns following an one unit shock in sentiment over a period of 11 consecutive trading days which was the common time period across all variables to reach their asymptote (wear-out time) (Luo et al. 2013; Tirunillai and Tellis 2012).

Step 4: Finally, we compute forecast error variance decomposition (FEVD) estimates to compare each type of brand buzz sentiment for its predictive value, i.e., how much variance in investor returns it explains. In accordance with step 3, we established this relative predictive value based on immediate, next day FEVDs and cumulative, eleven day FEVDs trailing an unit shock in sentiment using Monte Carlo simulations with 1,000 runs (Luo et al. 2013; Tirunillai and Tellis 2012).

Preliminary Findings

Table 1 summarizes the pairwise correlations between the endogenous variables of the PVAR models. As expected, the correlation among the sentiment measures and their previous day representation are all positive and statistically significant at the 1% level which underscores the appropriateness of the PVAR approach. Interestingly, conventional BBS is stronger correlated with BABS than BRBS although the communications are almost evenly distributed between BABS and BRBS across all brands in the sample.

Table 1. Pairwise Correlation between Endogenous Variables

	1	2	3	4	5	6	7	8
1. IR_t	1.000							
2. IR_{t-1}	*−0.021*	1.000						
3. BBS_t	*0.004*	*0.017*	1.000					
4. BBS_{t-1}	*0.005*	*0.004*	0.534	1.000				
5. $BABS_t$	*0.014*	*−0.001*	0.912	0.494	1.000			
6. $BABS_{t-1}$	*0.014*	*0.014*	0.494	0.912	0.514	1.000		
7. $BRBS_t$	*0.001*	*0.033*	0.667	0.372	0.393	0.271	1.000	
8. $BRBS_{t-1}$	*−0.015*	*0.001*	0.385	0.666	0.285	0.393	0.404	1.000

Correlations in italics are not significant. All other correlations are significant at the 99% level.

Table 1. A Pairwise Correlation between Endogenous Variables

Next, we present the preliminary results of the PVAR procedure described in the previous section in Table 2. Following the convention in extant empirical literature to express FEVDs in percent and OIRF estimates along with their standard errors in basis points (e.g., Tirunillai and Tellis 2012). To determine the significance of OIRF estimates at the 95% level, we check whether their confidence interval spans zero (not significant) or does not span zero (significant), respectively (Lütkepohl 2007). As summarized in Table 2, BBS and BABS have a significant positive predictive relationship with immediate investor returns (25.55 and 28.03 basis points) and cumulative investor returns (34.69 and 36.16 basis points). Both, BBS and BABS, further explain nontrivial portions of variance in immediate investor returns (0.45% and 0.66%) and cumulative investor returns (0.94% and 1.06%). However, BRBS does not significantly predict investor returns neither immediately nor cumulatively. Although the portion of variance in investor returns being explained by the interaction effect of BABS and BRBS is considerably small (0.08% immediately and 0.25% cumulatively), its predictive relationship with immediate as well as cumulative investor returns is both statistically and economically significant (−12.93 and −17.89 basis points). To further check these effects for temporal causality, we performed Granger Causlity tests on the optimal lag (Luo et al. 2013; Tirunillai and Tellis 2012). The test results largely support the PVAR findings: BBS and BABS are granger causing investor returns at the 95% level, whereas BRBS is not granger causing investor returns directly, but in interaction with BABS at the 90% level.

Table 2. Results for Investor Returns Prediction Models						
Panel A. Immediate, Next Day Investor Returns Prediction						
	Model 1		Model 2		Model 3	
	OIRF	FEVD	OIRF	FEVD	OIRF	FEVD
BBS	25.55 (6.48)	0.45%				
BABS			28.03 (6.36)	0.66%	27.12 (5.87)	0.65%
BRBS			$6.32^{n.s.}$ (5.50)	0.08%	$5.70^{n.s.}$ (5.23)	0.05%
BABS x BRBS					−12.93 (5.14)	0.08%
Panel B. Cumulative, Eleven Day Investor Returns Prediction						
	Model 1		Model 2		Model 3	
	OIRF	FEVD	OIRF	FEVD	OIRF	FEVD
BBS	34.69 (10.27)	0.94%				
BABS			37.03 (9.49)	1.13%	36.16 (9.39)	1.06%
BRBS			$10.12^{n.s.}$ (6.81)	0.08%	$10.39^{n.s.}$ (7.18)	0.08%
BABS x BRBS					−17.89 (7.14)	0.25%
OIRF estimates and standard errors are expressed in basis points. Significance is denoted based on their confidence intervals. If the confidence interval spans zero, it is not significant at the 95% level as denoted by superscript n.s. FEVDs are expressed in percent.						

Table 2. Results for Investor Returns Prediction Models

Conclusion

Our proposed prediction model of investor returns, i.e., Model 3, outperforms the conventional one, i.e., Model 1, in terms of explaining variance in immediate (cumulative) investor returns by more than 62% (38%). The effect of BBS on investor returns is positive and primarily driven by BABS which achieves comparable OIRF estimates in the short-and long-run. Although findings from Model 2 suggest that BBS underestimates immediate and cumulative investor returns by roughly 3 basis points, findings from Model 3 indicate that BBS may overestimate immediate (cumulative) investor returns by more than 11 (16) basis points if an increase in BBS is not exclusively rooted in BABS but BABS and BRBS concurrently.

Overall, this preliminary study served well in providing insights on the proposed research questions. However, it is not free from limitations guiding our future steps. First, we aim to extend our sample across different industries and different types of firms. Although the single industry context is quite common in prior brand buzz research and considering firms with highly identical business models limits biases from unobserved heterogeneity in panel settings with small n, cross-industry, cross-firm type settings promise higher generalizability. Second, we have so far not differentiated between favorable and unfavorable associations per type of brand buzz sentiment. Prior research, however, suggests that unfavorable associations may yield a stronger effect on investor returns than favorable associations. Third, although ability and responsibility constitute two generic types of associations held for the brand which have received widespread attention in brand reputation literature, it may be interesting to consider a more nuanced typology of brand associations in order to leverage the high granularity of brand buzz sentiment for predicting investor returns.

References

Abrigo, M. R. M., and Love, I. 2016. "Estimation of panel vector autoregression in Stata," *The Stata Journal* (16:3), pp. 778–804.
Antweiler, W., and Frank, M. Z. 2004. "Is All That Talk Just Noise? The Information Content of Internet Stock Message Boards," *Journal of Finance* (59:3), pp. 1259–1294.
Arellano, M., and Bover, O. 1995. "Another look at the instrumental variable estimation of error-components models," *Journal of Econometrics* (68:1), pp. 29–51.
Bender, A. 2013. "The Real 'Christmas Miracle' Of WestJet's Viral Video: Millions In Free Advertising," (accessed March 11, 2019). https://www.forbes.com/sites/andrewbender/2013/12/12/the-realchristmas-miracle-of-westjets-viral-video-millions-in-free-advertising/#3344587b22be
Berens, G., Riel, C. B. M. Van, and Bruggen, G. H. Van. 2005. "Corporate Associations and Consumer Product Responses: The Moderating Role of Corporate Brand Dominance," *Journal of Marketing* (69:3), pp. 35–48.
Berger, J., Humphreys, A., Ludwig, S., Moe, W. W., Netzer, O., and Schweidel, D. A. 2019. "Uniting the Tribes: Using Text for Marketing Insight," Journal of Marketing (forthcoming).
Brown, T. J., and Dacin, P. A. 1997. "The Company and the Product: Corporate Associations and Consumer Product Responses," *Journal of Marketing* (61:1), pp. 68–84.
Bureau of Transportation Statistics 2018. "2017 Annual and December U.S. Airline Traffic Data," (accessed April 16, 2019). https://www.bts.dot.gov/newsroom/2017-annual-and-december-us-airline-trafficdata
Chen, Y., Liu, Y., and Zhang, J. 2011. "When Do Third-Party Product Reviews Affect Firm Value and What Can Firms Do? The Case of Media Critics and Professional Movie Reviews," *Journal of Marketing* (76:2), pp. 116–134.
Chen, H., De, P., Hu, Y. J., and Hwang, B.-H. 2014. „Wisdom of Crowds: The Value of Stock Opinions Transmitted Through Social Media," *The Review of Financial Studies* (27:5), pp. 1367–1403.
Das, S. R., and Chen, M. Y. 2007. "Yahoo! for Amazon: Sentiment Extraction from Small Talk on the Web," *Management Science* (53:9), pp. 1375–1388.
Dewan, S., and Ramaprasad, J. 2014. "Social Media, Traditional Media, and Music Sales," *MIS Quarterly* (38:1), pp. 101–121.
Fan, R.-E., Chang, K.-W., Hsieh, C.-J., Xiang, X.-R., and Lin, C.-J. 2008. "LIBLINEAR : A Library for Large Linear Classification," *Journal of Machine Learning Research* (9), pp. 1871–1874.
Fan, R.-E., Chen, P.-H., and Lin, C.-J. 2005. "Working Set Selection Using Second Order Information for Training Support Vector Machines," *Journal of Machine Learning Research* (6), pp. 1889–1918.
Fombrun, C. J. 1998. "Indices of Corporate Reputation: An Analysis of Media Rankings and Social Monitors ' Ratings," *Corporate Reputation Review* (1:4), pp. 327–340.
French, K. R. 1980. "Stock Returns and the Weekend Effect," *Journal of Financial Economics* (8:1), pp. 55–69.
Hewett, K., Rand, W., Rust, R. T., and van Heerde, H. J. 2016. "Brand Buzz in the Echoverse," *Journal of Marketing* (80:3), pp. 1–24.
Holtz-Eakin, D., Newey, W., and Rosen, H. S. 1988. "Estimating Vector Autoregressions with Panel Data," *Econometrica* (56:6), pp. 1371–1395.
Homburg, C., Ehm, L., and Artz, M. 2015. "Measuring and Managing Consumer Sentiment in an Online Community Environment," *Journal of Marketing Research* (52:5), pp. 629–641.
Hsu, L., and Lawrence, B. 2016. "The role of social media and brand equity during a product recall crisis: A shareholder value perspective," *International Journal of Research in Marketing* (33:1), pp. 59–77.
Jiang, S., Chen, H., Nunamaker, J. F., and Zimbra, D. 2014. "Analyzing firm-specific social media and market: A stakeholder-based event analysis framework," *Decision Support Systems* (*67*), pp. 30–39.
Leeflang, P. S. H., Wieringa, J. E., Bijmolt, T. H. A., and Pauwels, K. H. 2017. *Advanced Methods for Modeling Markets*, Philadelphia, CA: Springer.
Luo, X., and Bhattacharya, C. B. 2006. "Corporate Social Responsibility, Customer Satisfaction, and Market Value," *Journal of Marketing* (70:4), pp. 1–18.
Luo, X., and Homburg, C. 2008. "Satisfaction, Complaint, and the Stock Value Gap," *Journal of Marketing* (72:4), pp. 29–43.

Luo, X., and J. Zhang. 2013. “How Do Consumer Buzz and Traffic in Social Media Marketing Predict the Value of the Firm?,” *Journal of Management Information Systems* (30:2), pp. 213–238.
Luo, X., Zhang, J., and Duan, W. 2013. “Social Media and Firm Equity Value,” *Information Systems Research* (24:1), pp. 146–163.
Lütkepohl, H. (2007). *New introduction to multiple time series analysis* (2nd ed.), Berlin: Springer.
Nam, H., and Kannan, P. K. 2014. “The Informational Value of Social Tagging Networks,” *Journal of Marketing* (78:4), pp. 21–40.
NLTK. 2019. “Natural Language Toolkit,” (accessed January 20, 2019). https://www.nltk.org/
Schweidel, D. A., and Moe, W. W. 2014. “Listening In on Social Media: A Joint Model of Sentiment and Venue Format Choice,” *Journal of Marketing Research* (51:4), pp. 387–402.
SciKit. 2019. "Support Vector Machines," (accessed January 23, 2019). https://scikitlearn.org/stable/modules/svm.html#svm-classification
Servaes, H., and Tamayo, A. 2013. “The Impact of Corporate Social Responsibility on Firm Value : The Role of Customer Awareness,” *Management Science* (59:5), pp. 1045–1061.
Shen, L. 2017. “United Airlines Stock Drops $1.4 Billion Afetr Passenger Removal Controversy,” (accessed August 31, 2019). https://fortune.com/2017/04/11/united-airlines-stock-drop/
Song, T., Huang, J., Tan, Y., and Yu, Y. 2019. “Using User- and Marketer-Generated Content for Box Office Revenue Prediction: Differences Between Microblogging and Third-Party Platforms,” *Information Systems Research* (30:1), pp. 191–203.
Stack, L. 2016. “College Student Is Removed From Flight After Speaking Arabic on Plane,” (accessed March 12, 2019). https://www.nytimes.com/2016/04/17/us/student-speaking-arabic-removed-southwestairlines-plane.html
Tirunillai, S., and Tellis, G. J. 2012. “Does Chatter Really Matter? Dynamics of User-Generated Content and Stock Performance,” *Marketing Science* (31:2), pp. 198–215.
Tirunillai, S., and Tellis, G. J. 2014. “Mining Marketing Meaning from Online Chatter: Strategic Brand Analysis of Big Data Using Latent Dirichlet Allocation,” *Journal of Marketing Research* (51:4), pp. 463–479.
Tumarkin, R., and Whitelaw, R. F. 2001. “News or noise? Internet message board activity and stock prices,” *Financial Analysts Journal* (57:3), pp. 41–51.
WestJet. 2018. “WestJet Christmas Miracle - Uniting Through Traditions,” (accessed March 12, 2019). https://www.westjet.com/en-ca/about-us/christmas-miracle
Wysocki, P. 1998. “Cheap talk on the web: The determinants of postings on stock message boards,” Working Paper 98025, University of Michigan Business School, Ann Arbor, MI.
Zhang, Y., Swanson, P. E., and Prombutr, W. 2012. “Measuring Effects on Stock Returns of Sentiment Indexes,” *The Journal of Financial Research* (35:1), pp. 79–114.