An Open Access Journal
• ISSN: 10683844

Multicultural Education
Research Article

Homepage: www.MC-caddogap.com

Social Media and Customer-Based Brand Equity: An Empirical Investigation in Retail Industry

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ABSTRACT

As customer-brand engagement progressively shifts to digital domains, understanding social media effects in branding has become a vital issue. Social media effectiveness is especially important for the US retail sector due to intense competition among retailers for consumer attention and engagement on digital channels. Yet, the research on the effectiveness of social media in the retail industry remains sparse. Thus, the purpose of this paper is to investigate how social media affects US retailers' customer-based brand equity (CBBE) which is an important indicator of brand success. Using a dataset of 15,717 retailer-day observations, the authors empirically test the dynamics between owned and earned social media and CBBE using panel vector auto regression (PVAR). The authors find strong impacts of owned and earned social media on CBBE across the board. However, they find that owned social media harms CBBE of retailers dealing in hedonic and high involvement products. Whereas owned social media helps general retailers in building CBBE, it reduces CBBE of specialty retailers.

ARTICLE INFO

Keywords:
customer-based brand equity; owned social media; earned social media; high/low involvement; utilitarian/hedonic goods; retail industry

Article History:
Received: 31 August 2018;
Accepted: 17 September 2018;

1. INTRODUCTION

Over the last two decades, customer-based brand equity (CBBE) has emerged as one of the key marketing concepts for academics and practitioners alike (Keller1993). CBBE is defined as the differential effect of brand knowledge on consumer response to the brand's marketing (Keller1993) . There now exists a robust body of literature on creating, measuring, and managing CBBE in traditional marketing settings (Keller2016). As consumer-brand engagement progressively shifts to digital domains, understanding the effectiveness of social media marketing strategies has become vital for brand management. Recently, researchers have started examining how social media activities affect consumer mindset metrics (Colicev et al.2018;Liu and Lopez2016;Lovett and Staelin2016) and consumer behavior (De Vries et al.2017). Yet, limited research exists on the link between social media and CBBE. Understanding this connection is important for two related reasons. First, although research has shown that social media is associated with firm value, it's unclear whether this relationship is predictive or causal. Since CBBE is an important determinant of firm value (Rego et al.2009) , investigating the social media–CBBE link will help illuminate the mechanism underlying the relationship between social media and firm value. Second, a strong social media–CBBE link will underscore the potential of social media to create enduring customer value (Kumar2015) and thus complement the recent research on value-relevance of digital marketing.

We seek to bridge this research gap by investigating how owned and earned social media affect CBBE. Whereas owned social media (OSM) refers to brand-owned digital assets, such as corporateFacebook pages, earned social media (ESM) refers to voluntary, user-generated brand mentions and recommendations that a company does not directly generate or control. Empirically, we focus on the retail industry because its context presents several advantages for our study. First, social media usage is pervasive in the US retail industry with 91% of American retailers active on two or more social networks as of 2014 (Yesmail2014). Second, social media profoundly affects retailer business with the recent social media report suggesting that social media influences purchase decisions of 32% of consumers (Deloitte2014). Furthermore, 71% percent of retail executives believe that social media has a significant impact on their businesses (Larson and Dolan2013). Yet, the research on the effectiveness of social media in the retail industry remains sparse (Rapp et al.2013). Despite the interest in social media, both B2C and B2B retailers continue to focus on one-directional communications with more obsolete communication tools (e.g., email) (Järvinen et al.2012). Third, CBBE is particularly crucial for profitable retailer operations due to the intense competition in the sector (Ailawadi and Keller2004) . As more and more retailers incorporate social media spending in their marketing budgets, understanding how social media impacts CBBE will help retailers in long-term marketing planning.

Accordingly, we investigate the following two research questions: (1) How are owned and earned social media associated with retailers' CBBE, and (2) which factors moderate this association? To that end, we use high-frequency daily data for 39 retailers and estimate a panel vector autoregression model with exogenous variables (PVAR) to uncover the relationships between earned and owned social media and CBBE.

By doing so, we make three contributions to the marketing theory and practice. First, we are among the first few to show the effect of social media on CBBE, which is an important market-based asset. As CBBE is a key determinant of cash flows and long-term firm value (Regoet al.2009), our research implies potentially causal effect of social media on firm value. Thus, this study advances the research stream on key performance indicators for social media marketing, the role of web analytics as well as the return on investment on social media (Sauraet al.2017). Accordingly, marketers can use social media simultaneously for improving consumer sentiments in the short term and for enhancing CBBE, customer equity, customer experience, and consequent firm value in the long term (Lemon and Verhoef2016). Second, our study underscores the relevance of social media for highly competitive retail sector where creating and sustaining CBBE is a major and costly challenge (Ailawadi and Keller2004) . Third, our analysis pinpoints the conditions under which social media is most effective for retailers. We find that social media emerges as an important driver of CBBE for general retail and high involvement products. Finally, we find that owned social media plays a beneficial (harmful) role for utilitarian (hedonic) and high involvement products.

The manuscript proceeds as follows: in Section2, we provide the conceptual framework of this research, in terms of the effects of owned and earned social media on customer-based brand equity. We also introduce the key moderating variables: utilitarian and hedonic goods, high and low-involvement goods, and retail categories. We describe the data and its unique characteristics in Section3. We adopt a Panel Vector-Autoregressive (PVAR) modeling approach that we describe in Section4and report the results in Section5. We conclude in Section6with the discussion of the results, the implication of the study, and suggestions for future research.

2. CONCEPTUAL FRAMEWORK

2.1 *Customer-Based Brand Equity(CBBE)*

CBBE is a higher-level construct composed of five dimensions comprising brand awareness, brand associations, brand activity, brand attitude, and brand attachment (Keller2013, p. 129). We argue that owned and earned social media affect CBBE by affecting some or all of its five components.

2.2 *Owned Social Media andCBBE*

Due to their expertise in content creation, brands can generate informative content that notifies customers about new products, promotions, and brand-related corporate news. Such content typically is aimed to increase brand awareness (Risius and Beck2015;Universal McCann2013). Consumers' brand attitude is more positive towards brands that regularly disclose relevant brand-related information (Hewett et al.2016). For example, brands may provide objective characteristics and independent quality ratings of their products. This information stimulates consumers to scrutinize the brands' products closely (Gohet al.2013), leading to higher trust in the brands.

Brands often respond to customer requests and complaints on owned social media, thereby simultaneously satisfying the concerned customers and showcasing service efficiency and effectiveness of the brands to other customers and non-customers. AUniversalMcCann(2013) study reports that 65% of consumers who get a response to their complaints (or who manage to help others) feel more valued as consumers and are more likely to recommend the brand to others. Finally, two-way social media communication may improve customer engagement through co-creation (Arnouldet al.2009), allowing users to develop and share new ideas and suggest improvements in brands' products and services. These actions help build brand communities, which in turn engender brand attachment (Keller et al.1998;Muniz and O'Guinn2001) and brand loyalty (Arnould et al.2009).

2.3 *Earned Social Media and CBBE*

Previous research argues that both the volume and valence of earned social media convey complimentary information to consumers. The volume of earned social media refers to the quantity of consumer interactions with a brand and includes "likes", "shares", and "comments" on the brand's posts or other consumers' brand-related posts on social media. The valence of earned social media refers to positive or negative sentiment.

Babic´ et al.(2016) andGoh et al.(2013) document that the mere availability of consumers' opinions has an influence on other consumers, regardless of the valence of opinions. A large body of literature has also discussed how social media communications (e.g., earned social media volume) generate brand-related electronic word-of-mouth (eWOM) that ultimately impacts consumer perceptions of brand's products (Pauwelset al.2016). In this stream of research, earned social media acts as a "lead" (Saura et al.2017) that a consumer can follow by further inquiring of brand products, accessing the brand's website, downloading a product catalog, or requesting more information from a brand by compiling a questionnaire. For example,Palos-Sanchez et al.(2018), in the context of mobile marketing, show that number of likes, the number of shares, and the characteristics of the posts and their links, influence promotional and recruitment actions. In this respect, earned social media allows eWOM to quickly spread through a consumer's social network, generating multiple brand impressions and leading to higher brand awareness (Peters et al.2013) and even to a favorable shift in consumer perceptions and brand attitudes (Duan et al.2008;Tirunillai and Tellis2012), thereby affecting CBBE. Overall, it can be argued that earned social media volume creates brand-related "leads" and impressions that have a positive effect on CBBE and indirectly affect brand sales (through CBBE).

Other studies have shown that, besides earned social media volume, the sentiment of the earned social media affects product sales by altering customers' quality expectations and attitudes toward a brand (Tang et al.2014) for different types of content such as reviews (Godes and Mayzlin2004) and comments on social media (Schweidel and Moe2014). Thus, we expect earned social media valence to also affect CBBE.

2.4 *Moderating Variables*

The effects of owned and earned social media on CBBE are likely to be dependent on several firm-, product-, and consumer-level factors. For brevity, we study one firm-level factor and two product-level factors that are important for the context of this study.Bart et al.(2014) show that the impact of mobileadvertising on consumers varies depending on whether the advertised product is deemed utilitarian or hedonic and whether the product requires high or low purchase involvement. We expect earned social media to have a higher impact on high involvement products because consumers perceive earned social media to be more credible than owned social media (deleted for peer-review). ANielsen(2013) study reports that 92% of consumers trust recommendations from the people in their social network (e.g., Facebook friends), 70% consumers trust online reviews (e.g., other consumers on Facebook), while only 47% trust traditional advertising.

At the firm level, we consider three common types of retail operations: general, specialty, and restaurants. Our choice of these categories is partly driven by data availability. Therefore, we do not have a priori expectations about magnitudes of the effects of owned and earned social media across these categories.

3. DATA

3.1 *Data and Sample*

Our sample includes 39 retailers for whom sufficiently long time-series data are available. A few examples of these retailers are Albertsons, Amazon, BestBuy, and CVS. The final data set is obtained by merging social media data with data on CBBE. Table1provides the description and sources of these variables. The final data set is a balanced panel of 39 retailers spanning 403 days (13 November 2012 through 20 December 2013), resulting in 15,717 retailer-day observations.

We collect social media data from Facebook, which has been adopted by a majority of retailers (Yesmail2014) and used in previous research (John et al.2016). We purchased Facebook data from a third-party provider that archives Facebook data using automated web technologies.

Owned Social Media

We use the number of daily posts made by a brand on its corporate Facebook page as a measure of owned social media.

Earned Social Media

We use the number of likes, shares, and comments on a brand's Facebook posts as a measure of earned social media volume. To preserve model parsimony, we apply principal component analysis (PCA) to these metrics and use the factor scores as a measure of earned social media volume. Each of the social media metrics has a high loading only on one factor and each factor has adequate reliability as measured by Cronbach's alpha. To measure positive and negative earned social media valence, we perform sentiment analysis on 580,513 user comments on 39 brands' Facebook posts. We apply Naïve Bayes classifier to extract sentiment from each post for a given brand on a given day. For a discussion on text mining algorithms for social media data we refer toKübler et al.(2017).

Customer-Based Brand Equity(CBBE)

The data to construct our measure of CBBE comes from YouGovBrandIndex panel, which monitors multiple brands in multiple industries by surveying 5000 randomly selected consumers (from a panel of 5 million) daily. To assure representativeness, YouGov weights the sample by age, race, gender, education, income, and region. YouGov administers the same set of questions on each brand assuring consistency for each metric. In any survey, individuals respond to only one measure for each industry, thereby reducing common method bias and measurement error. YouGov data has been previously used in the marketing literature (Colicev et al.2016;Hewett et al.2016).

The data collection of YouGov can be described as follows. For each item, a minimum of 100 respondents per day are randomly drawn from the panel and provided with a set of up to 30 brands for a pre-selected industry. In the first step, respondents select those brands (per click) that they know (aware of). These answers are recorded to construct the brand Awareness metric. Those brands that were not selected in first step are eliminated. This ensures that the following questions are answered only for those brands that respondents know. Next, only those brands that were selected in the first step can appear for the following questions. However, only one question (e.g., brand impressions) will appear for a given respondent. After the respondent has answered one question, he or she will terminate the survey for that sector. This helps reduce common method bias and measurement error. Although panelists might be re-invited after a period of two weeks, they will be blocked for the respective sector and brand item they have answered before for a period of at least two months. This is important to eliminate repeated measurement as a source for demand effects and serial correlation in brand metrics. Brand competition effects are also controlled for because respondents rate the competing brands within one sector simultaneously.

We proxy for five CBBE dimensions with five YouGov measures.YouGov has a direct measure for brand awareness which relates to the extent to which brand is recognized by consumers. Brand associations are typically the qualities of attributes that consumers associate with the brand. "Perceived value" proxies for brand associations. Brand activity relates to consumer purchase considerations. Thus, YouGov's "purchase considerations" proxies for brand activity. Brand attitudes are overall brand impressions and brand attachment measures the extent of satisfaction with the brand. YouGov's "brand impression" proxies for brand attitude, and "satisfaction" proxies for brand attachment. At the aggregate brand level, YouGov metrics range between −100 and +100. We perform panel-level PCA on the five YouGov metrics, which resulted in only one factor with eigenvalue greater than 1 (capturing 69% variance). We use this factor as our measure of CBBE.

Control Variables

We include YouGov's "advertising awareness" metric as a proxy for the effectiveness of brands' advertising (De Vrieset al.2017). To control for impactful brand-related events, we include YouGov's "buzz" metric, which captures whether people have heard anything positive or negative about the brand through news, advertising, or offline WOM.

Table 1. Measures and Data Sources.

Variable	Description	Source
CBBE	Customer-Based Brand Equity composed of five dimensions: awareness, perceived value, purchase consideration, brand impression and customer satisfaction	YouGov
Earned Social Media Volume	The number of likes, shares, and comments on a brand's Facebook post	Proprietary Data Source
Owned Social Media	The number of daily posts made by a brand on its corporate Facebook page	
Negative ESM Valence	The number of negative user posts on brands' Facebook page.	
Positive ESM Valence	The number of positive user posts on brands' Facebook page.	
Advertising Awareness	Whether YouGov survey respondents have seen any brand related advertising in the past two weeks.	YouGov
Buzz	Whether YouGov survey respondents have heard anything positive or negative about a brand in the past two weeks.	

We provide the sample composition in Table2.

Table 2. Brand Sample.

Major Retail Category	Industry Classification (YouGov Group)	Brands
General Retail	Department store	Dillard's, JC Penney, Kohl's, Macy's, Sears
	Supermarket	Albertsons, Kroger, Publix, Safeway, Target, Walmart, Wholefoods
	Warehouse store	Costco, Sam's Club
Restaurants	Dine-in restaurant	Applebee's, Chili's, Little Caesars, Olive Garden, Outback Steakhouse, Red Lobster
	Fast food restaurant	Burger King, Domino's, KFC, McDonalds, Pizza Hut, Starbucks, Subway, Taco Bell, Wendy's
Specialty	Clothing store	Gap, Nordstrom
	e-commerce	Amazon, Priceline, eBay
	Electronics retailer	Best Buy
	Footwear store	Adidas
	Pharmacy	CVS, Rite Aid, Walgreen's

3.2 *Moderators*

Hedonic/Utilitarian and High-Low Involvement categories

We determined hedonic/utilitarian and high/low involvement attributes of the 39 retailers in the sample by conducting a survey on Amazon mTurk. We followed the procedure outlined in Bart et al.(2014) and measured these attributes on a 2-item 7-point bipolar scale. Next, using median splits we divided our sample into following four subgroups: utilitarian-high involvement brands (UHI) (seven brands, e.g., Sears, Amazon.com), utilitarian-low involvement brands (ULI) (twelve brands, e.g., RiteAid, CVS), hedonic-high involvement brands (HHI) (eleven brands, e.g., Gap, Red Lobster), and hedonic-low involvement brands (HLI) (nine brands, e.g., Subway, Starbucks).

Retailing Categories

We split the sample into three broad retailing categories: general, specialty, and restaurants. General retail category comprises 14 brands from department stores (e.g., Macy's), supermarkets (e.g., Kroger), and warehouse stores (e.g., Costco). Specialty retail category comprises 10 brands from clothing stores (e.g., Gap), electronics retailers (e.g., Best Buy), footwear stores (e.g., Adidas), and pharmacies (e.g., Rite Aid). Finally, the restaurants category comprises 15 brands from dine-in restaurants (e.g., Applebee's) and fast food restaurants (e.g., McDonalds).

4. METHODOLOGY

4.1 *Panel Vectro Auto regression*

We adopt PVAR model (Holtz-Eakinet al.1988), which allows for unobserved brand-level heterogeneity and accounts for potential endogeneity by: (a) jointly estimating the system of equations via Generalized Method of Moments (GMM) that uses past lags as instruments (Young2017), allowing dynamic feedback loops between endogenous variables, (c) controlling for the effects of exogenous variables, and (d) controlling for non-stationarity, serial correlation, and reverse causality that may lead to spurious regression problem (Granger and Newbold1986). We useAbrigo and Love (2016)'s PVAR routine in Stata and take following methodological steps.

Our analysis consists of several methodological steps which we present in Table3and discuss in detail in this section.

Table 3. Analysis steps in the Panel Vector Auto regression Modeling Approach.

MethodologicalStep	RelevantLiterature	ResearchQuestion
1. Unit Root Tests, Cointegration andStability		
Panel Grangercausalitytest	(Baltagi2013;Granger1969)	What is the temporal causality among variables?
Panel UnitRootTests	(Baltagi2013)	Are variables stationary or evolving? Panel
VARLagSelection	(AndrewsandLu2001;Hansen1982)	WhatisthecorrectlagforthepanelVAR?
2. Model of Dynamic Interactions		
Panel Vector autoregressive(PVAR)model	(Abrigo andLove2016; Holtz-Eakin et al.1988)	How do owned and earned social media and CBBE interact? What is the effect of an impulse in endogenous variable on all the other variables?
3. Impulse responsefunctions(IRF)	(Pesaran andShin1998)	

4.2 Panel Granger Causality

Granger causality of variable Y by a variable X means that we can predict Y better by knowing the past values of X than by only knowing the past values of Y (Granger1969). This procedure, also known as temporal causality, provides the closest causality test possible with non-experimental data (deleted for peer-review). We apply theDumitrescu and Hurlin(2012) panel causality test which is a test of Granger non-causality (Granger1969) accounting for heterogeneity across brands (Baltagi2013). As the causal relationships that exist for a brand can also exist for other brands, the use of cross-sectional information involves taking into account the heterogeneity across brands in the definition of the causal relationship. Accordingly,Dumitrescu and Hurlin(2012) statistic takes correctly into account brand heterogeneity when estimating the causal relationships between key endogenous variables and provides an overall Granger causality statistic for the whole sample averaged across brands. In order to avoid erroneous conclusions, we check whether a variable Granger causes another variable at any lag up to 20th lag and report the results with the lag that has the highest statistical significance (Trusov et al.2009) . We provide the results of Panel Granger Causality tests in Table4. We find support for our conjecture that owned and earned social media Granger cause CBBE ($p < 0.05$).

Table 4. Panel Granger Causality.

Response to	Owned Social Media	Earned Social Media Volume	Positive ESM Valence	Negative ESM Valence	Advertising Awareness	CBBE
Owned Social Media	–	0.000	0.000	0.000	0.000	0.043
Earned Social Media Volume	0.000	–	0.000	0.231	0.152	0.001
Positive ESM Valence	0.000	0.003	–	0.000	0.000	0.000
Negative ESM Valence	0.000	0.001	0.000	–	0.000	0.000
Advertising Awareness	0.000	0.435	0.000	0.000	–	0.000
CBBE	0.000	0.601	0.000	0.000	0.000	–

Minimum *p*-value across 20 lags. The null hypotheses assume that the variables shown in the left-most column do not Granger cause the variables shown in top-most row.

4.3 Panel Unit Root Tests

Recent literature suggests that panel-based unit root tests have higher power than unit root tests based on individual time series (Baltagi2013). While these tests are commonly termed "panel unit root" tests, theoretically, they are simply multiple-series unit root tests that have been applied to panel data structures (where the presence of cross-sections generates "multiple series" out of a single series). We begin by classifying our unit root tests on the basis of whether there are restrictions on the autoregressive process across cross-sections or series. First, one can assume that the persistence parameters are common across cross-sections. The Levin-Lin-Chu (LLC) (Levin et al.2002) and the Breitung (Breitung2000) tests employ this assumption. The null hypothesis is that of a unit root in both tests. Alternatively, one can allow the autoregressive coefficient to vary freely across cross-sections. The Fisher-ADF panel test is of this form (Maddala and Kim1998). We report the results in Table5 observing that all of the variables are stationary and thus enter the PVAR model in levels.

Table 5. Panel Unit Root Tests.

Panel Unit Root Tests	Levin, Lin and Chu (No Intercept, No Trend)	Breitung (Individual Intercept and Trend)	ADF-Fisher (No Intercept, No Trend)
Null Hypothesis	Common (Unit Root)	Common (Unit Root)	Individual (Unit Root)
Owned Social Media	0.000	0.000	0.000
Earned Social Media Volume	0.041	0.032	0.000
Positive ESM Valence	0.000	0.000	0.000
Negative ESM Valence	0.000	0.000	0.000
Advertising Awareness	0.000	0.000	0.000
Buzz	0.000	0.000	0.000
CBBE	0.000	0.000	0.000

4.4 Panel VAR Lag Selection

The optimal lag order ("n") is chosen using several criteria. Panel VAR analysis is predicated upon choosing the optimal lag order in both panel VAR specification and moment condition.Andrews and Lu(2001) proposed consistent moment and model selection criteria (MMSC) for GMM models which analogous to various commonly used maximum likelihood-based model selection criteria such as Akaike information criteria (AIC) (Akaike1969), Bayesian information criteria (BIC) (Schwarz1978) , and the Hannan–Quinn information criteria (HQIC) (Hannan and Quinn1979). Additionally, as an alternative criterion, we calculate the overall coefficient of determination (CD) that captures the proportion of variation explained by the panel VAR model with higher values preferable to lower ones. Such criteria should be used in conjunction with the Hansen's J statistic (Hansen1982) that checks whether the overidentification restriction is rejected at 5% significance level.

In Table6 we report the different criteria described above. First, we observe that although the model with 1 lag obtains the highest CD and Hansen's J and the lowest MBIC, MAIC, and MQIC, it does not reject Hansen's J statistic of overidentifying restriction at the 5% significance level. However, the models with lag 2, 3, 4 all reject the Hansen's J statistic. Within these 3 models, the lag 2 model obtains the highest CD and Hansen's J and the lowest MBIC, MAIC, and MQIC. Thus, we use the combination of different tests and criteria to select the second lag for the PVAR model.

Table 6. PVAR Lag-Selection Criteria.

Lag	Coefficient of Determination	Hansen's J	*Jp*-Value	MBIC	MAIC	MQIC
1	0.966	171.75	0.047	−1217.99	−116.24	−481.15
2	**0.935**	**95.66**	**0.796**	**−946.65**	**−120.33**	**−394.02**
3	0.930	56.33	0.912	−638.54	−87.66	−270.12
4	0.785	32.33	0.643	−315.10	−39.66	−130.89

Note: the bold figures indicate the lag order selected for the model.

4.5 *Model Specification*

We adopt a reduced form of the PVAR model in which each dependent variable is a linear function of its own past values, the past values of all other dependent variables, exogenous variables, and an error term. Based on Granger causality and unit root tests, we specify the PVAR model in Equation (1):

$$\begin{bmatrix} CBBE_t \\ Advert_t \\ PESMV_t \\ NESMV_t \\ ESMV_t \\ OSM_t \end{bmatrix} = \sum_{n=1}^{P} \begin{bmatrix} \gamma_{1,1}^n & \cdot & \gamma_{1,6}^n \\ \cdot & \cdot & \cdot \\ \gamma_{6,1}^n & \cdot & \gamma_{6,6}^n \end{bmatrix} \begin{bmatrix} CBBE_{t-n} \\ Advert_{t-n} \\ PESMV_{t-n} \\ NESMV_{t-n} \\ ESMV_{t-n} \\ OSM_{t-n} \end{bmatrix} + \begin{bmatrix} \varphi_{1,1} & \cdot & \varphi_{1,2} \\ \cdot & \cdot & \cdot \\ \varphi_{2,1} & \cdot & \varphi_{2,2} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} e_{CBBE,t} \\ e_{Advert,t} \\ e_{PESMV,t} \\ e_{NESMV,t} \\ e_{ESMV,t} \\ e_{OSM,t} \end{bmatrix} \quad (1)$$

where CBBE = customer-based brand equity, ESMV = earned social media volume, PESMV = positive ESM valence, NESMV = negative ESM valence, OSM = owned social media, and Advert = advertising awareness. The off-diagonal terms of the matrix capture the indirect effects among the endogenous variables and the diagonal terms capture the direct effects. The exogenous vector contains buzz and a deterministic trend to capture the impact of unobserved, gradually changing variables. We use heteroskedasticity-corrected standard errors.

4.6 *Impulse Response Functions (IRFs)*

We analyze dynamics of the system with impulse response functions (IRF) (Pesaran and Shin 1998). Based on the results of Granger causality tests, we use Cholesky ordering to impose a causal ordering on the variables. We continuously change the ordering to evaluate its robustness. We estimate standard errors using 1000 Monte Carlo simulations (deleted for peer-review) and sum the statistically significant IRFs to obtain final effects for each variable (Sims and Zha1999).

4.7 *Subsample-Level Analysis*

To assess the influence of product characteristics (utilitarian/hedonic and high/low involvement) and retailer characteristics (general, specialty, and restaurants), we separately estimate the models for each of the subgroups mentioned in the data section. The minimum number of observations being 2821 (pertaining to 7 brands in utilitarian-high involvement subsample) guaranteeing enough degrees of freedom for the model estimations.

5. RESULTS

5.1 *Main Results and Moderators*

In AppendixA, we present descriptive statistics and correlations for the sample variables. Table7shows PVAR results estimated on the full sample of 39 retailers along with four retail product categories: utilitarian-high involvement (UHI), utilitarian-low involvement (ULI), hedonic-high involvement, and hedonic-low involvement retailers.

Table 7. Impulse Responses of CBBE to Social Media for utilitarian-high involvement (UHI), utilitarian-low involvement (ULI), hedonic-high involvement (HHI), and hedonic-low involvement (HLI).

Impulse Variable	Sample of Brands	Response of CBBE
Earned Social Media Volume	Overall Sample	0.050***
	UHI	0.173***
	ULI	−0.031 ***
	HHI	0.102***
	HLI	0.030***
Negative ESM Valence	Overall Sample	−0.053 ***
	UHI	−0.153 ***
	ULI	−0.060 *
	HHI	−0.073 ***
	HLI	−0.014 *
Positive ESM Valence	Overall Sample	0.046 ***
	UHI	0.089 ns
	ULI	0.053***
	HHI	0.111***
	HLI	0.007 *
Owned Social Media	Overall Sample	0.106***
	UHI	0.128***
	ULI	0.210 *
	HHI	−0.293 ***
	HLI	0.015 *
Advertising	Overall Sample	0.332 ***
	UHI	0.293**
	ULI	0.541**
	HHI	0.380***
	HLI	0.262***

Notes: *** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$, ns = non-significant.

At the overall sample level, we find that Earned Social Media Volume (0.05, $p < 0.001$), Positive ESM Valence (0.046, $p < 0.001$), Owned Social Media (0.106, $p < 0.001$), and Advertising (0.332, $p < 0.001$) all positively affect CBBE. Thus, positive social media activity, as well as advertising increase retailers CBBE. Interestingly, advertising still has the highest effect on CBBE, confirming previous findings that advertising still constitutes an important way to affect customer perceptions of the firm (De Vries et al.2017) . In addition, we find that Negative ESM Valence (−0.053, $p < 0.001$) negatively affects CBBE, confirming previous research on the role of negative information in customer-based brand equity (Ho-Dacet al.2013). We thus find that valence and volume of ESM are equally important for CBBE.

At the subgroups level, we find a few sign changes and considerable heterogeneity in the effect sizes of IRFs. Earned Social Media Volume has the highest effect on both utilitarian-high involvement and hedonic-high involvement retailers (0.173, $p < 0.001$ and 0.102, $p < 0.001$ respectively). Thus, the volume of earned social media is effective in driving CBBE for these brands, implying that brand popularity metrics (e.g., likes) are very relevant for high-involvement products. Interestingly, we find that for utilitarian-low involvement brands (e.g., Kroger, Publix), the effect of earned social media volume on CBBE is negative and significant. Given that utilitarian and low involvement brands typically are not very exciting to talk about, their volume of conversation might not be effective, or even detrimental to CBBE. Next, we find that Positive ESM Valence benefits CBBE of hedonic-high involvement retailers the most (0.111, $p < 0.01$) and Negative ESM Valence harms CBBE of utilitarian-high involvement retailers the most (−0.153, $p < 0.01$). Thus, for high involvement brands (both utilitarian and hedonic), social media constitutes a double-edge sword. Consistent with our expectation, overall it appears that retailers of high involvement products are more sensitive to earned social media compared to retailers of low involvement products. On the positive side, they can rely on earned social media volume and positive ESM valence to increase CBBE, but on the negative side they are very sensitive to negative ESM valence. Thus, such brands must be able to avoid negative consumer reactions, as it might harm their CBBE. Although Owned Social Media affects CBBE positively at the overall sample level, it harms hedonic-high involvement retailers (−0.293, $p < 0.001$). This has important managerial implications which we discuss in the Discussion section. The impact of advertising awareness on CBBE is consistently large and positive across the 4 subgroups, underscoring the importance of traditional advertising to the retail sector.

Table8shows the IRFs for 3 retailer subcategories. The impacts of Owned and Earned Social Media are strong for general retail compared to specialty retail and restaurants. Interestingly, Owned Social Media's impact on CBBE is significantly positive for general retail (1.648, $p < 0.001$), non-significant for restaurants (0.004, p >

0.1), and significantly negative for specialty retail (−0.046, $p < 0.001$). On the other hand, restaurants and specialty retail benefit from advertising (0.196, $p < 0.001$ and 0.064, $p < 0.001$ respectively) while CBBE of general retail suffers (−0.548, $p < 0.001$). This suggests that Owned Social Media and advertising awareness work as substitutes in various retail categories. The negative impact of Owned Social Media on CBBE in specialty retail may imply that their consumers trust advertising much more than Owned Social Media. We expand more on this result in the discussion section.

Table 8. Impulse Responses of CBBE to Social Media for General, Restaurants, and Specialty.

Impulse Variable	Sample of Brands	Response of CBBE
Earned Social Media Volume	Overall Sample	0.050 ***
	General	0.917 **
	Restaurants	0.022 ***
	Specialty	0.026 ***
Negative ESM Valence	Overall Sample	−0.053 ***
	General	−2.225 ***
	Restaurants	0.010 ns
	Specialty	0.024 ***
Positive ESM Valence	Overall Sample	0.046 ***
	General	0.409 ***
	Restaurants	0.021 ***
	Specialty	0.077 ***
Owned Social Media	Overall Sample	0.106 ***
	General	1.648 ***
	Restaurants	0.004 ns
	Specialty	−0.046 ***
Advertising	Overall Sample	0.332 ***
	General	−0.548 ***
	Restaurants	0.196 ***
	Specialty	0.064 ***

Notes: *** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$, ns = non-significant.

Table 9. Robustness to alternative lag specification.

Impulse Variable	Sample of Brands	Response of CBBE		
		Lag 2 (main model)	Lag 3	Lag 4
Earned Social Media Volume	Overall Sample	0.050	0.061	0.093
	UHI	0.173	0.219	0.271
	ULI	−0.031	−0.086	−0.228
	HHI	0.102	0.156	0.151
	HLI	0.030	0.026	0.026
Negative ESM Valence	Overall Sample	−0.053	−0.059	−0.059
	UHI	−0.153	−0.161	−0.175
	ULI	−0.060	−0.132	−0.090
	HHI	−0.073	−0.101	−0.071
	HLI	−0.014	−0.013	0.001
Positive ESM Valence	Overall Sample	0.046	0.046	0.045
	UHI	0.000	0.000	0.000
	ULI	0.053	0.053	0.174
	HHI	0.111	0.111	0.096
	HLI	0.007	0.007	0.010
Owned Social Media	Overall Sample	0.106	0.106	0.145
	UHI	0.128	0.128	0.157
	ULI	0.210	0.210	0.371
	HHI	−0.293	−0.293	−2.437
	HLI	0.015	0.015	0.012
Advertising	Overall Sample	0.332	0.332	0.421
	UHI	0.293	0.293	0.340
	ULI	0.541	0.541	0.658
	HHI	0.380	0.380	0.080
	HLI	0.262	0.262	0.230

Notes: All estimates are significant at $p < 0.05$ level. 0s denote non-significant effects.

6. DISCUSSION

We have explored the effects of social media on CBBE in the retail sector. We make three contributions to the marketing theory and practice. First, we are among the first few to show that social media affects CBBE, which is an important market-based asset. This finding has long-term implications for brand management. Thus far, the extant literature has shown either correlational effects of social media on firm value (e.g.,Tirunillai and Tellis2012) or short-term effects through consumer mind-set metrics (e.g.,Colicev et al.2018). CBBE is both a short-term and long-term performance metric, given its immediate effect on brand sales (e.g., next quarter) (Seggie et al.2007) and more lasting effect on cash flows and long-term financial value (Rego et al.2009). Considering that some measures that form CBBE are connected to long-term measures of consumer perceptions towards the brand (e.g., satisfaction) it portrays brand’s longer-term orientation. Thus, CBBE being a key determinant of our research implies a potentially causal effect of social media on firm value. Although we don’t study the full chain of effects from social media to firm value, our research illuminates the underlying mechanism in this chain through CBBE.

Second, we highlight the importance of social media for retailers. In the fiercely competitive retail sector, creating and sustaining CBBE is a major challenge for retailers and likely to be a costly affair. For example, we find that an important determinant of CBBE in retail sector is advertising awareness. However, achieving and maintaining high levels of advertising awareness can be expensive. In contrast, owned social media is relatively inexpensive and earned social media is largely free. Thus, we urge retailers to emphasize social media much more than traditional advertising. Previous studies have urged for more research on the role of social media for retailers and B2B companies (Järvinen et al.2012) . Overall, we add to this stream of research as well as to the stream that shows that using marketing metrics (e.g., on social media) can lead to a better customer relationship management (CRM) (Li2011) and value for the firm (Hanssens and Pauwels2016).

Third, our subsample-level analysis provides important managerial insights to retailers. Social media emerges as an important driver of CBBE for the retailers of high involvement products. As retailing brands increasingly use social media to augment/replace their traditional marketing activities, high involvement brands (e.g., Amazon) can now be more confident of a positive return on such spending (Hoffman and Fodor2010). One interesting finding is that for high involvement retailers (both hedonic and utilitarian), social media can act as a double-edged sword. On one side, earned social media volume and positive ESM valence have a large positive effect on CBBE. On the other side, negative ESM valence harms these retailers the most. Thus, high involvement retailers have to carefully manage their consumer sentiment on social media. In addition, whereas owned social media plays a beneficial role for utilitarian high involvement products, it is harmful for hedonic high involvement products. We interpret this result to recommend retailers of utilitarian-high involvement products to emphasize owned social media and invest more efforts in connecting to consumers to share information and resolve their problems. Hedonic-high involvement retailers will perhaps benefit from analyzing the nature of their owned social media messaging, which some consumers may perceive as “pushy”, leading to lower CBBE. Finally, the impact of advertising on CBBE is consistently large and positive, underscoring the importance of traditional advertising to the retail sector.

When we split the sample into subgroups based on the type of retailing operations, we find surprising results. General retailers get the most bang for their buck as owned and earned social media have large impacts on CBBE. Advertising harms CBBE of these retailers, which indicates that general retailers may benefit from shifting part of their advertising budget to social media marketing. On the other hand, specialty retailers and restaurants experience a negative or no impact of owned social media on CBBE. They, however, experience a strong impact of advertising. As earned social media still affects CBBE positively for these retailers, we suggest moving budgets allocated to owned social media to improving earned social media. For example, hiring additional staff to address negativity on earned social media will result in lower negative earned social media valence, which in turn will increase CBBE.

Future Research Directions

Our study paves the way for future research. First, our study shows the effects of social media on CBBE but does not consider the financial performance metrics. Future research can empirically test the potentially mediating effects of CBBE in the social media-sales and firm value link. In addition, future studies might develop a theoretical approach of why owned social media and earned social media affect CBBE. Second, future studies might dig deeper into the reasons why social media has a very strong effect on general retailers and why specialty retailers and restaurants experience a negative or no impact of owned social media on CBBE. Third, future studies might consider other industries in which the link between social media and CBBE can be of interest. For example, airlines and banking might present an interesting context for such studies. Fourth, we use aggregate brand-level data, which we believe to be appropriate for our study. Future research might employ disaggregate individual consumer-level data that can enable more precise estimation of social media effects on CBBE. Fifth, although Facebook is the most commonly used social media platform by retailers, we expect future research to consider other rising platforms such as Twitter, YouTube, and Instagram. For example, Instagram enables brands to engage with consumers using images and videos and enjoys immense popularity among luxury brands. How such vivid content influences CBBE is an interesting unanswered question. It's possible that on Instagram, owned social media of hedonic-high involvement retailers has a positive impact on CBBE in contrast to the negative impact that we find. Finally, further research can analyze owned social media as well as traditional content more granularly to determine when owned social media complements traditional advertising.

Our study sheds light on the relationship between social media and CBBE in the retail industry context. Understanding this relationship should help us generate specific conditions under which owned and earned social media move the needle for our organizations.

Appendix A

Table A1. Descriptive Statistics.

Variable	Mean	SD	Min	Max
CBBE	0.000	1.000	−2.306	3.819
Earned Social Media Volume	0.000	1.000	−5.427	14.240
Owned Social Media	1.664	1.853	0.000	40.000
Negative ESM Valence	3.593	9.888	0.000	447.000
Positive ESM Valence	3.914	9.702	0.000	473.000
Advertising Awareness	28.940	16.610	0.000	84.510
Buzz	13.080	9.053	−32.520	50.420

Table A2. Correlations: Pooled across brands.

	Owned Social Media	Earned Social Media Volume	Positive ESM Valence	Negative ESM Valence	Advertising Awareness	Buzz	CBBE
Owned Social Media	1.00						
Earned Social Media Volume	0.08^{a}	1.00					
Positive ESM Valence	0.18^{a}	0.07^{a}	1.00				
Negative ESM Valence	0.15^{a}	0.06^{a}	0.83^{a}	1.00			
Advertising Awareness	0.13^{a}	0.01	0.23^{a}	0.18^{a}	1.00		
Buzz	-0.01^{c}	0.01	0.08^{a}	0.04^{a}	0.48^{a}	1.00	
CBBE	0.08^{a}	0.01	0.19^{a}	0.15^{a}	0.61^{a}	0.69^{a}	1.00

$^{c}\ p < 0.1$, $^{b}\ p < 0.05$, $^{a}\ p < 0.01$.

Table A3. Correlations: Averaged across brands.

	Owned Social Media	Earned Social Media Volume	Positive ESM Valence	Negative ESM Valence	Advertising Awareness	Buzz	CBBE
Owned Social Media	1.00						
Earned Social Media Volume	0.13^{a}	1.00					
Positive ESM Valence	0.06^{a}	0.09^{a}	1.00				
Negative ESM Valence	0.05^{a}	0.06^{a}	0.46^{a}	1.00			
Advertising Awareness	0.03^{a}	0.01	0.06^{a}	0.05^{a}	1.00		
Buzz	0.02^{c}	0.01	-0.01^{a}	0.01^{a}	0.37^{a}	1.00	
CBBE	-0.01^{a}	0.01	0.05^{a}	-0.01^{a}	0.29^{a}	0.43^{a}	1.00

$^{c}\ p < 0.1$, $^{b}\ p < 0.05$, $^{a}\ p < 0.01$.

Conflicts of Interest:

The authors declare no conflict of interest.

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