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Improving Consumer Mindset Metrics and Shareholder Value Through Social Media: The Different Roles of Owned and Earned Media

Although research has examined the social media–shareholder value link, the role of consumer mindset metrics in this relationship remains unexplored. To this end, drawing on the elaboration likelihood model and accessibility/diagnosticity perspective, the authors hypothesize varying effects of owned and earned social media (OSM and ESM) on brand awareness, purchase intent, and customer satisfaction and link these consumer mindset metrics to shareholder value (abnormal returns and idiosyncratic risk). Analyzing daily data for 45 brands in 21 sectors using vector autoregression models, they find that brand fan following improves all three mindset metrics. ESM engagement volume affects brand awareness and purchase intent but not customer satisfaction, while ESM positive and negative valence have the largest effects on customer satisfaction. OSM increases brand awareness and customer satisfaction but not purchase intent, highlighting a nonlinear effect of OSM. Interestingly, OSM is more likely to increase purchase intent for high involvement utilitarian brands and for brands with higher reputation, implying that running a socially responsible business lends more credibility to OSM. Finally, purchase intent and customer satisfaction positively affect shareholder value.

Keywords: marketing–finance interface, owned social media, earned social media, consumer decision journey, shareholder value

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American companies now spend on average 10% of their marketing budgets on social media (CMO Survey 2016). Among *Fortune* 500 companies, 73% have Twitter accounts, 66% have Facebook fan pages, and 62% have YouTube channels (Heggestuen and Danova 2013). These examples of brand-controlled social media are commonly termed "owned social media" (OSM). Companies also get social media exposure through voluntary, user-generated brand mentions, recommendations, and so on. Such social media activities that a company does not directly generate or control are commonly termed "earned social media" (ESM) (Stephen and Galak 2012). Recent studies show that 42% of Facebook users have mentioned a brand in their status updates (Mazin 2011) and that 19% of all tweets by Twitter users are brand-related (Jansen et al. 2009). The widespread prevalence of ESM and OSM is a testament to their increasing importance to consumers and brands. Yet, in the latest CMO Survey (2016), four out of five marketers report an inability to quantitatively measure the impact of social media on business performance. At the backdrop of increasing social media adoption, the disconnect between social media spending and its perceived impact on firm performance is glaring.

Over the last two decades, shareholder value has gained prominence in marketing academia as a marquee firm performance metric. Recent marketing literature finds a positive relationship between social media and shareholder value. For example, Luo, Zhang, and Duan (2013) and Tirunillai and Tellis (2012) show that ESM leads to improved stock market metrics. This stream of research posits that social media affects consumer mindset metrics such as brand awareness, purchase intent, or customer satisfaction, which subsequently lead to higher firm performance. Yet, no research has empirically tested the impact of social media on firm stock market performance via consumer mindset metrics (see Table 1).

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TABLE 1
Review of Relevant Studies

Study	Owned Social Media	Earned Social Media	Brand Fan Following	Consumer Mindset Metrics	Stock Market Effects	Coverage of Multiple Sectors
Stephen and Galak (2012)	Yes (blog)	Yes (user posts on blogs and forums)	Yes (number of forum members)	No	No	No: 1 firm in 1 sector (microloans)
Tirunillai and Tellis (2012)	No	Yes (rating, volume, and valence of reviews)	No	No	Yes	Yes: 15 brands from 6 sectors
Goh, Heng, and Lin (2013)	Yes (posts on Facebook)	Yes (user comments on Facebook)	No	No	No	No: 1 firm in 1 sector
Luo, Zhang, and Duan (2013)	No	Yes (Internet search)	No	No	Yes	No: 9 brands of computer and software sectors
Nam and Kannan (2014)	No	Yes (bookmarks, social tags)	No	No	Yes	Yes: 44 firms in 14 sectors
Schulze, Schöler, and Skiera (2014)	Yes	Yes	No	No	No	Yes: 759 Facebook apps in 22 sectors
Kumar et al. (2016)	Yes (posts)	No	No	No	No	No: 1 retailer in 1 sector (wine and spirits)
Srinivasan, Rutz, and Pauwels (2016)	No	Yes (Facebook likes)	No	No	No	No: 1 brand in 1 sector (fast-moving consumer goods)
Pauwels, Aksehirli, and Lackman (2016)	No	Yes (conversation topics)	No	No	No	No: 1 retailer in 1 sector
Pauwels et al. (2016)	Yes	Yes (website visits)	No	No	No	Yes: 4 firms in 4 sectors
This study	Yes (Facebook, Twitter, YouTube)	Yes (Facebook, Twitter, YouTube)	Yes (Facebook, Twitter, YouTube)	Yes (three stages of CDJ)	Yes	Yes: 45 brands in 21 sectors

Such research is of interest to both academics and managers. First, academics are keenly interested in exploring different ways by which social media can affect shareholder value. A direct impact of social media on the stock market is plausible because investors observe social media (Chen et al. 2014). For instance, if a high volume of social media activity generates enough investor attention, more investors will hold a firm's stock, resulting in easily diversifiable idiosyncratic risk and higher firm value (Merton 1987). More central to marketing, an indirect impact of social media on shareholder wealth is also plausible, through consumer mindset metrics such as brand awareness and purchase intent (Peters et al. 2013), but has not yet been empirically established. Second, different managers in the same firm are often rewarded based on different metrics, including financial performance for senior executives and consumer mindset metrics for brand managers (Hanssens and Pauwels 2016). Because such metrics are far from perfectly correlated (Katsikeas et al. 2016), a lack of knowledge of which social media metrics affect which specific consumer mindset metrics will likely lead to a suboptimal social media strategy (Lamberton and Stephen 2016). Thus, for marketers, knowledge of more intricate linkages between social media, consumer mindset, and shareholder value is more actionable.

To fill this research gap, we study the effects of ESM and OSM on three mindset metrics mapped to the consumer's decision journey (CDJ) (Batra and Keller 2016; Court et al. 2009) and their consequent impact on shareholder value. Specifically, we seek to address the following research questions: (1) How do ESM and OSM relate to the three consumer mindset metrics, namely, brand awareness, purchase intent, and customer satisfaction? and (2) Through which of these three consumer mindset metrics do specific social media metrics such as OSM and volume and valence of ESM affect stock market performance?

We make four contributions to the extant literature. First, we contribute to the emerging research on the value relevance of social media by linking different types of social media to brand awareness, purchase intent, and customer satisfaction—three consumer mindset metrics corresponding to three stages of the CDJ. Drawing on Petty and Cacioppo's (1986) elaboration likelihood model (ELM) we argue that consumers have varying levels of motivation to process information in each stage of CDJ. Furthermore, we posit that ESM and OSM have varying levels of accessibility and diagnosticity (Feldman and Lynch 1988). The extant literature on online word of mouth (WOM) mostly investigates why people spread WOM. In contrast, we study how social media adds value to the firm. Based on this framework, we offer a set of novel, testable propositions, which we test using high-frequency daily data on social media, consumer mindset metrics, and shareholder value.

Second, we empirically show that social media affects shareholder value via specific consumer mindset metrics. We find that brand fan following improves all three mindset metrics. We find that ESM engagement volume affects brand awareness and purchase intent but not customer satisfaction, whereas ESM positive and negative valence have the largest effects on customer satisfaction. We also find that OSM improves brand awareness and customer satisfaction, but not purchase intent. Finally, purchase intent and customer satisfaction have positive impacts on shareholder value. Thus, we show that the impact of social media on shareholder value is partially accounted for by the changes in consumer mindset metrics.

Our third contribution is to address the puzzling gap between increasing social media spending and its lack of perceived effectiveness. A substantial proportion of marketers perceive that social media contributes almost nothing to company performance (CMO Survey 2016). Our research suggests that it is critical to deploy the right social media strategy to affect specific mindset metrics. For example, we find that although OSM increases brand awareness and customer satisfaction, it can reduce purchase intent. However, marketers often appear to use OSM as another push channel similar to advertising that is directed at persuading customers to buy (e.g., Hoffman and Fodor 2010). The mismatch between marketers' apparent goals and the performance metrics where OSM is actually effective may drive the perception that social media contributes little to company performance. Further, while marketers may find ESM mostly uncontrollable, we find that they can use OSM to positively shape conversations on ESM and thus indirectly improve consumer mindset metrics and firm value. This result is complementary to Mochon et al.'s (2017) finding that Facebook "likes" impact consumers only if the firm is also active on OSM. Thus, our study assists marketers in crafting more effective social media strategy.

Finally, we study boundary conditions for the effects of OSM on purchase intent. OSM is more likely to increase purchase intent for high-involvement utilitarian brands and for firms with higher reputation (e.g., superior product quality, positive leadership, fair compensation). Our interpretation is that running a socially responsible business lends more credibility to one's controlled social media. Thus, our analysis demonstrates higher OSM effectiveness as an indirect benefit of reputation. Likewise, firms that have increased advertising may enjoy synergy or halo effects from OSM. In contrast, managers of firms with lower reputation must carefully evaluate the way they are using social media. For one, it pays to use OSM to address customer complaints, potentially increasing perceived quality and positive word of mouth. Indeed, we find that OSM leads to higher purchase intent for firms with negative perceptions about product quality.

Conceptual Framework

Figure 1 shows our conceptual framework. We draw on the literature in information processing to model the impact of ESM and OSM on the three stages of the CDJ: brand awareness, purchase intent, and customer satisfaction. We adopt Petty and Cacioppo's (1986) ELM and argue that consumers have varying levels of motivation to process information in different stages of the CDJ. Further, we use the Feldman and Lynch (1988) accessibility/diagnosticity perspective to argue for distinct impacts of ESM and OSM on each stage of the CDJ depending on their accessibility and diagnosticity. Finally, we link ESM, OSM, and CDJ to firm value.

Owned and Earned Social Media

Marketing literature typically categorizes social media into OSM and ESM (Srinivasan, Rutz, and Pauwels 2016; Stephen and Galak 2012). OSM refers to a brand's communication created and shared through its own online social network assets, such as a Facebook fan page and a YouTube channel. In contrast, ESM refers to the brand-related content that entities other than the brand—typically the consumers—create, consume, and disseminate through online social networks.

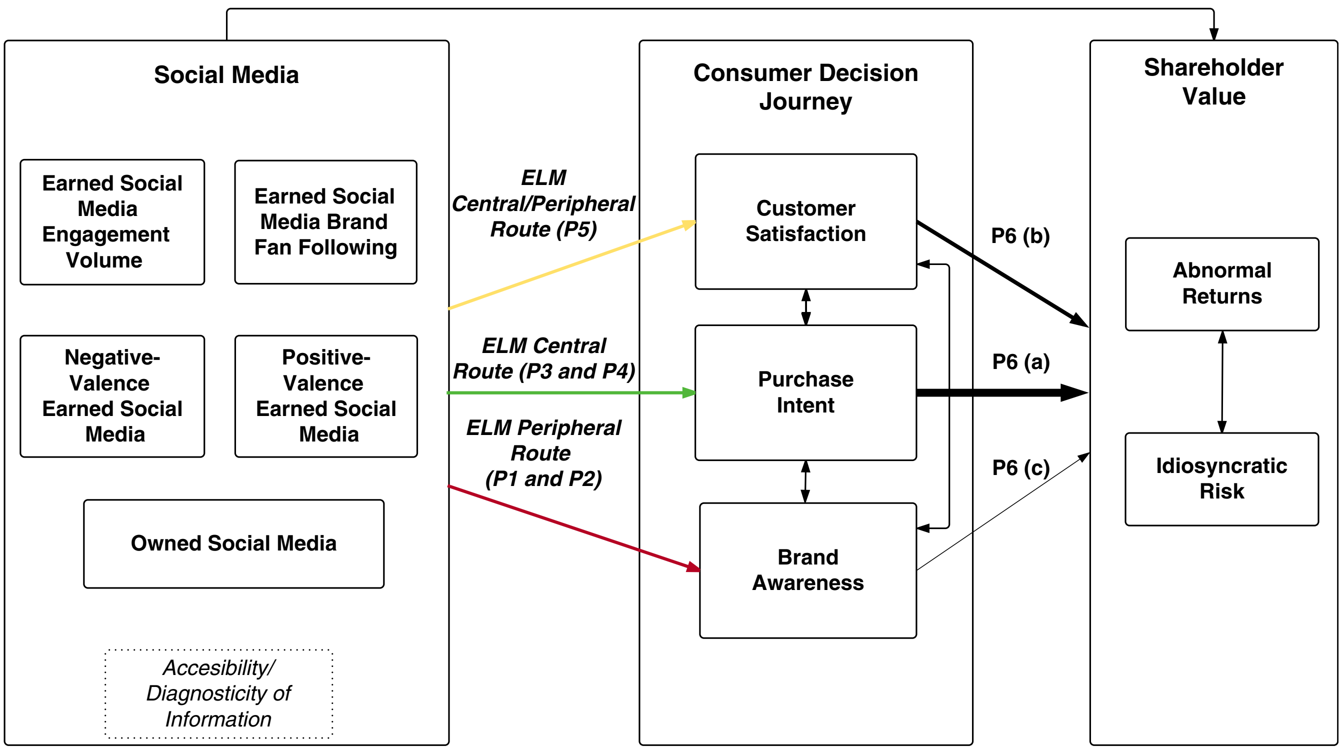
ESM is a multidimensional construct and often split into its volume and valence (e.g., Tirunillai and Tellis 2012). ESM engagement (ENG) volume refers to the earned media impressions that users voluntarily create for brands (e.g., retweeting a brand's tweets on Twitter). ESM valence captures the positive and negative sentiment of the ESM content. We add to ESM a third dimension of brand fan following (BFF) representing the total brand following[1] (e.g., Facebook "likes," Twitter followers). Brands can benefit from large fan following in multiple ways, including the passive exposure of consumers to profiles of brand fans who are similar to them ("mere virtual presence" in Naylor, Lamberton, and West 2012) and targeting brand fans with customized content (John et al. 2016). Because detailed metrics of such activities are not available to researchers across many brands and sectors, we propose BFF as an imperfect yet useful metric to capture the effects of a brand's social network beyond the available OSM and ESM metrics.

Stages of the CDJ and Consumer's Information Processing

The extant literature has modeled a CDJ in various ways (e.g., Batra and Keller 2016; Court et al. 2009). Although CDJ can have a granular representation, broadly, it consists of three key stages that map onto consumer mindset: brand awareness,

[1]We thank an anonymous reviewer for this labeling suggestion.

FIGURE 1
Conceptual Framework



Notes: The different colors of lines represent the route to persuasion: red = peripheral, green = central, and yellow = mix of peripheral/central. (In the print edition, black = peripheral, gray = central, and dashed = mix.) Thicker (thinner) lines represent higher (lower) effects of CDJ stages on shareholder value.

purchase intent, and customer satisfaction. We elaborate on these stages more in detail in the following sections.

To conceptualize how consumers process information in the CDJ, we adopt Petty and Cacioppo's (1986) ELM. This model proposes a continuum of routes, from peripheral to central, by which ESM and OSM persuade consumers in each stage of the CDJ. At one end of the continuum, termed the "peripheral route," persuasion occurs because of a simple cue in the persuasion context that induces change in the consumer mindset without necessitating scrutiny of the true merits of the information presented in the communication (Herr, Kardes, and Kim 1991). At the other end of the continuum, termed the "central route," persuasion results from a consumer's careful and thoughtful deliberation of the true merits of the information presented in the communication, in our case, OSM and ESM. Whether a consumer processes information using the central route, the peripheral route, or a combination of the two depends partly on the consumer's motivation to process information (Petty and Cacioppo 1986).

We further argue that the effects of OSM and ESM on CDJ depend on the interplay between the high consumer motivation to process information (Petty and Cacioppo 1986) and the level of diagnosticity of information contained in OSM and ESM (Feldman and Lynch 1988). Diagnosticity refers to the extent to which information content helps consumers categorize a brand in a unique group (e.g., a brand with high quality, a brand that satisfies the consumer's needs). Based on ELM, we argue that, depending on the route to persuasion and on the level of accessibility and diagnosticity of information, ESM and OSM will have different effects on the successive CDJ stages, as summarized in Table 2.

Brand Awareness (Propositions 1 and 2)

Consumers may become aware of brands through social media in various ways. For example, they may see brands mentioned in social media posts by their friends (ESM) or in brand-generated communication (OSM). In the awareness stage, consumers' motivation to process complex information is likely to be low, implying that they take the peripheral route to persuasion (Petty, Cacioppo, and Schumann 1983). Accordingly, consumers are more affected by the amount and virality—the ability to quickly spread far and wide—of brand-related information on social media compared with the actual content of such information.

We argue that frequent exposure to OSM, ENG volume, and BFF should lead to increased awareness of the brand (Keller 1993; Nedungadi and Hutchinson 1985) for the following reasons. First, previous research reports that advertising makes brands more accessible in the minds of consumers and leads to higher brand awareness (Mitra and Lynch 1995). We posit a similar effect of frequent OSM on consumers. Firms often disseminate information such as new product launches through videos, images, and positive stories about their brands on social media. For example, a recent study finds that 65% of the Interbrand 100 brands post on Facebook at least on average five times per week (Simply Measured 2014). Such frequent

TABLE 2
ELM and the Effects of Owned and Earned Social Media on the Stages of CDJ

	Brand Awareness	Purchase Intent	Customer Satisfaction
Consumer motivation to process information	Low	High	Medium
Route to persuasion	Peripheral	Central	Between peripheral and central
Factors that impact consumer persuasion	Accessibility of information	Accessibility and diagnosticity of information	Accessibility and diagnosticity of information
Proposed underlying mechanism of social media impact	Consumers are more affected by the amount and virality of brand-related information than by the actual content of such information.	Consumers are more affected by actual content of the information, which is more diagnostic and requires higher motivation.	Consumers are affected by both the amount of information to reduce cognitive dissonance and by the actual content of similar experiences by other consumers.
Supporting literature	Keller (1993); Nedungadi and Hutchinson (1985)	Cacioppo and Petty (1981); Herr, Kardes, and Kim (1991)	Adams (1961); Festinger (1957); Ma, Sun, and Kekre (2015)
Proposed main drivers within OSM and ESM	ENG volume, BFF, and OSM	Positive- and negative-valence ESM	Both OSM and ESM
Propositions supported	• P_{1a} ✓ • P_{1b} ✓ • P_{1c} ✓ • P_2 ✓	• P_{3a} × • P_{3b} × • P_{4a} ✓ • P_{4b} ✓ • P_{4c} ✓	• P_5 ✓

postings generate brand exposure and create top-of-mind brand recall (Universal McCann 2013). Thus, increased OSM volume should have a positive effect on brand awareness through the peripheral route to persuasion.

Second, brands can also achieve higher exposure through ESM. For example, viral content is spread quickly through Facebook shares or Twitter retweets. Such ESM volume tends to be more accessible in the minds of consumers, leading to higher brand awareness (e.g., Goh, Heng, and Lin 2013). Third, popular brands on social media may have higher exposures due to the algorithms used by social networking sites. For instance, Facebook's news feed algorithm displays a user "liking" a brand on the user's Facebook time line. This makes the brand salient to the user's online social network, thereby automatically improving the brand's visibility. The brands with larger BFF are likely to gain relatively more awareness from improved visibility. Consumers on other online social networks such as Twitter and YouTube will have a similar high exposure to brands with a large BFF. Recent research confirms this second-order beneficial effect on the online friends of a brand's fans (John et al. 2016; Naylor, Lamberton, and West 2012). Therefore, a larger BFF makes brands more accessible to consumers and should lead to increased brand awareness (Mochon et al. 2017). This leads us to our first proposition:

> P_1: The higher a brand's (a) ENG volume, (b) BFF, and (c) OSM, the higher its brand awareness.

Whereas ESM volume likely increases brand awareness, the effects of positive- and negative-valence ESM on brand awareness are less clear. Positive-valence ESM has more virality than negative-valence ESM (Berger and Milkman 2012; Heimbach and Hinz 2016), suggesting that positive-valence ESM is more accessible. For example, on the one hand, studies have shown that positive WOM is more common than negative WOM, with the average incidence ratio of 3:1 (East, Hammond, and Wright 2007). On the other hand, negative-valence ESM is comparatively more diagnostic (Herr, Kardes, and Kim 1991). In the awareness stage, consumers are affected more by the accessibility of the message than its diagnosticity. Therefore, due its higher accessibility, positive-valence ESM will have a higher impact on brand awareness than negative-valence ESM. This leads us to our second proposition:

> P_2: Positive-valence ESM has a higher impact on brand awareness than negative-valence ESM.

Purchase Intent (Propositions 3 and 4)

While forming purchase intent, consumers are motivated to process claims made on OSM and ESM and to scrutinize their merits. In this stage, consumers tend to make brand evaluations under high cognitive elaboration and adopt the central route to persuasion (Cacioppo and Petty 1981; Herr, Kardes, and Kim 1991). Therefore, arguments that contain ample diagnostic information are more relevant for purchase intention than messages that rely on simplistic associations (Feldman and Lynch 1988; Petty and Cacioppo 1986).

While larger ENG volume and BFF lead to repeated brand exposure, they are less diagnostic than ESM valence because they do not help consumers categorize brands as good or bad. For example, recent evidence suggests that having many “likes” does not necessarily translate into more positive brand attitudes (John et al. 2016) or purchases (Lake 2011). In addition, social impact theory (Latané 1981) advocates that having a large number of supporters (e.g., fans, followers) does not imply more positive brand attitudes and higher purchase intent. Nonetheless, a large brand fan following facilitates interactions between similar consumers who share information and influence each other (privately) in brand evaluations (Bruhn, Schoenmueller, and Schäfer 2012; Renfrow 2014; Turri, Smith, and Kemp 2013). Similarly, higher ENG volume may indicate a level of interest about the brand in the consumer’s social network, leading to higher purchase intent. Therefore, we expect BFF and ENG volume to have a moderately positive effect on purchase intent.

In contrast to ENG volume and BFF, ESM valence is highly diagnostic because it contains opinions about the pros and cons of a product (Goh, Heng, and Lin 2013). For example, whereas positive-valence ESM increases perceived quality and reduces perceived risk associated with a purchase (Dimoka, Hong, and Pavlou 2012), negative-valence ESM leads to the opposite effects (Dellarocas 2006). Thus, we expect a large positive impact of positive-valence ESM and a large negative impact of negative-valence ESM on purchase intent, followed by the positive impact of ENG volume and BFF.

> P_3: (a) Positive-valence ESM and (b) negative-valence ESM have higher impacts on purchase intent than do ENG volume and BFF.

Previous research is divided on the effects of OSM on purchase intent. On the one hand, the “truth effect” (Hasher, Goldstein, and Toppino 1977) suggests that message repetition on OSM will lead to increased belief in the message because familiarity to brand attributes builds credibility in consumer minds (Arkes, Boehm, and Xu 1991). Therefore, persuasive appeals on OSM might be attractive to consumers during brand evaluations, and OSM can encounter less resistance if it is not perceived as advertising.

On the other hand, consumers might perceive OSM as disguised advertising and look at such tactics with suspicion (Campbell and Kirmani 2008). Because the source of this information is the brand whose goal is to persuade consumers to purchase products, consumers often remain skeptical about claims made by brands (Grossman 1981; Milgrom and Roberts 1986). Accordingly, brands that make many claims in their communication may experience lowered brand attitude as consumer skepticism increases (Shu and Carlson 2014). Empirical studies involving sales revenues as a dependent measure also find mixed results. A few field studies report that OSM leads to higher sales (Hewett et al. 2016; Kumar et al. 2013, 2016), while others report a lack of evidence for such effects (Danaher and Dagger 2013; Goh, Heng, and Lin 2013; Stephen and Galak 2012). Due to the increasing role of social influences on purchase and decreasing control of brands over consumer sentiments expressed and viewed online (Batra and Keller 2016), it appears that brands have partially lost control in the purchase intent stage of the CDJ (Pauwels and Van Ewijk 2013).

In addition to low credibility, OSM also suffers from low diagnosticity. Because brands control OSM, presumably with professional help, OSM will be overwhelmingly positive about the brand irrespective of its real product quality. This makes OSM less diagnostic because it does not help consumers in ranking the brands on relevant performance metrics. As a result, we propose that OSM has the lowest impact on purchase intent due to its low diagnosticity and higher consumer skepticism about the claims made by brands.

> P4: OSM has a lower impact on purchase intent than do (a) ENG volume, (b) BFF, and (c) positive-valence ESM.

Customer Satisfaction (Proposition 5)

In the postpurchase phase, consumers compare the actual product experience with their prepurchase expectations, leading to customer satisfaction or dissatisfaction. In this stage, consumers might access information available through ESM to verify the degree of similarity between their own product experience and those of other consumers. Previous studies have shown that in this situation, consumers are more likely to look for consonant information (Adams 1961) to reduce postpurchase cognitive dissonance (Festinger 1957). However, as product novelty subsides, consumers also face declining arousal and interest and spend less time thinking about the product (Richins and Bloch 1986). Due to this lowered motivation to process information, we argue that consumers are likely to follow a mix of central and peripheral routes to persuasion in the postpurchase phase. In the central route, consumers will weight negative information more than positive information because negative information has higher diagnosticity than positive information (Herr, Kardes, and Kim 1991). However, compared with the purchase intent stage, consumers are less likely to use the central route to persuasion because more cognitive processing could lead to cognitive dissonance (e.g., realizing that a competing brand was better), which is an undesired consequence. Thus, customer satisfaction is an outcome of less intense elaboration than purchase decisions (Batra and Keller 2016), resulting in reduced importance of the diagnosticity of information. However, compared with the brand awareness stage, consumers must process more information to evaluate product performance and decide whether to repurchase the brand (Lemon and Verhoef 2016). This mix of central and peripheral routes, thus, means that all the ESM valence and volume metrics may impact customer satisfaction, but their relative impact remains an empirical question.

Postpurchase, OSM performs two important functions. First, OSM can improve customer satisfaction by providing consonant information. For example, consumers might downplay the negative aspects of product-related experience if brands provide enough consonant information (Chen and Lurie 2013). A second function of OSM is to address customer service issues. For example, airlines commonly use Twitter to resolve passenger queries in real time. In such cases, marketers have an opportunity to use OSM to handle customer service requests and establish better customer relationships (Ma, Sun, and Kekre 2015). Universal McCann (2013) reports that 65% of consumers who get a response to their complaints feel more valued as customers and become more likely to recommend the brand. Such OSM is likely to shape consumer attitudes favorably, improving customer experience and satisfaction (Stephen, Sciandra, and Inman 2015). However, the impact of OSM on customer satisfaction is likely to be limited due to the lower familiarity of consumers with OSM relative to ESM valence (Huang et al. 2017) and, in general, the higher trust consumers have in other consumers versus brand employees who are generating OSM (Salesforce 2016). Thus, we expect a moderately positive effect of OSM on customer satisfaction.

P_5: The higher the OSM, the higher the customer satisfaction.

CDJ and Shareholder Value (Proposition 6)

Stock market investors constantly seek value-relevant information about listed firms. For example, studies have shown that investors commonly purchase brand-attitude metrics that provide incremental information to accounting performance measures in order to gain the smallest informational advantage over competition (Mizik and Jacobson 2008). Such brand-attitude and customer metrics (e.g., customer lifetime value) have been shown to affect firm value (Bharadwaj, Tuli, and Bonfrer 2011; Ittner and Larcker 1998; Mizik and Jacobson 2008). Similarly, a 2011 Brunswick Group study of investors finds that around 43% of social media chatter has become an important determinant in their investment decisions (Tirunillai and Tellis 2012). Previous research identifies two reasons for such a direct impact of social media on firm value. First, investors may react immediately to ESM and OSM (Tirunillai and Tellis 2012), anticipating the delayed effects of brand activity on brand awareness, purchase intent, and satisfaction (Hanssens et al. 2014; Pauwels et al. 2004). Second, both ESM and OSM may increase stock price without an effect through the firm's future accounting performance. Such effect has been demonstrated for advertising by Joshi and Hanssens (2010). Along these lines, research demonstrates that the stock market reacts to the chatter beyond weekly sales and product launches (McAlister, Sonnier, and Shively 2012). Consistent with our research focus, we next explain why we also expect an indirect effect of social media on firm value through CDJ metrics.

Brand awareness, purchase intent, and customer satisfaction may have differing levels of value-relevant information for investors. Although brand awareness is the first step in the CDJ, it is unlikely to fully translate into purchase intent or (repeat) purchase. In contrast, higher purchase intent provides a good proxy for future sales (Mizik and Jacobson 2008) and should be incrementally valued by investors. Similarly, higher customer satisfaction should lead to brand loyalty, which results in lower marketing and sales costs, lower risk of cash flows, and higher value of growth options, consequently enhancing firm value (Malshe and Agarwal 2015). However, the effects of customer satisfaction may materialize in a relatively distant future compared with purchase intent. Thus, higher purchase intent is likely to have more value relevance to short-term investors than higher customer satisfaction.

Previous research has shown that favorable consumer mindset metrics translate to higher stock performance with lower risk (Fornell et al. 2006; Johansson, Dimofte, and Mazvancheryl 2012; Mizik and Jacobson 2008). Tuli and Bharadwaj (2009) report that firms with superior customer satisfaction have lower systematic risk. Recently, Bayer, Tuli, and Skiera (2017) find that disclosing forward-looking consumer metrics substantially reduced perceived risk about firms' future prospects among investors. For example, increased purchase intent signals higher future customer acquisition rates, which should decrease firms' idiosyncratic risk.

The persistence and value relevance of the three consumer mindset metrics may also differ due to the way they are attained. ELM posits that attitude changes resulting from the central route have greater temporal persistence and more accurately predict consumer behavior compared with attitude changes resulting from the peripheral route (Petty and Cacioppo 1986, p. 175). Thus, brand awareness, which results from the peripheral route, is likely to be less persistent and a weaker predictor of consumer behavior than customer satisfaction, which results from a mix of the peripheral and central routes and has been shown to increase firm value (Fornell et al. 2006). Because purchase intent involves processing information using the central route to persuasion, we expect that it is an even stronger predictor of consumer behavior and impacts firm value the most of the three metrics:

P_6: (a) Purchase intent has the highest positive impact on firm value, (b) followed by customer satisfaction and (c) brand awareness.

Data

Sample

To test our conceptual framework, we require a data set combining social media constructs (OSM, ENG volume, BFF, and positive- and negative-valence ESM) with consumer mindset metrics and shareholder value in the same time interval. Given the fast pace of online interactions and investor reactions, the time interval should be relatively short. Moreover, we need identical metrics on a large number of brands to make valid, reliable, and generalizable inferences. To assemble such a data set, we took the following steps. First, we obtained detailed OSM and ESM data on 184 brands from a third-party data provider. Second, we obtained data on consumer mindset metrics, which were available for 122 of the 184 brands. Third, we restricted the sample to the brands that follow a corporate branding strategy (84 brands) so that changes in shareholder value are more clearly attributable to the changes in consumer perceptions of only one brand. Fourth, brands must be listed on one of the two U.S. stock exchanges (NASDAQ/NYSE) because we use shareholder value as the dependent variable (45 brands).

TABLE 3
Measures and Data Sources

Variable	Description	Source
ABRET	Abnormal returns	CRSP
Risk	Idiosyncratic risk	CRSP
Brand awareness	Brand awareness. We apply factor analysis on the YouGov metrics and obtain a three-factor solution with awareness emerging as the first factor. The two variables that load on this factor are word-of-mouth exposure and awareness.	YouGov
Purchase intent	Brand purchase intent. We apply factor analysis on the YouGov metrics and obtain a three-factor solution with purchase intent emerging as the second factor. The three variables that load on this factor are consideration set inclusion, purchase intent, and whether the respondent is a current customer.	YouGov
Customer satisfaction	Customer satisfaction. We apply factor analysis on the YouGov metrics and obtain a three-factor solution with customer satisfaction emerging as the third factor. The three variables that load on this factor are perceived value, satisfaction, and recommendation.	YouGov
Brand awareness (competition)	Consumer mindset metric representing sector average brand awareness. We compute the average score for all the brands in the sector for awareness daily.	YouGov
Purchase (competition)	Consumer mindset metric representing sector average brand purchase intent. We compute the average score for all the brands in the sector for purchase intent daily.	YouGov
Customer satisfaction (competition)	Consumer mindset metric representing sector average brand customer satisfaction. We compute the average score for all the brands in the sector for customer satisfaction daily.	YouGov
ESM BFF	Earned social media brand fan following. A one-dimensional factor extracted from p on three metrics (number of likes on Facebook, number of followers on Twitter, and number of subscribers on YouTube).	Proprietary data source
ENG volume	Earned social media engagement. A one-dimensional factor extracted from PCA on three metrics (daily number of PTAT[a] on Facebook, retweets by users on Twitter, and video views on YouTube).	Proprietary data source
OSM	Owned social media. A one-dimensional factor extracted from PCA on four metrics (number of own posts on Facebook, number of own tweets, number of replies to users, number of brand own retweets on Twitter).	Proprietary data source
Negative-valence ESM	The number of negative user posts on a brand's Facebook page.	Proprietary data source
Positive-valence ESM	The number of positive user posts on a brand's Facebook page.	Proprietary data source
Paid media	The dollar amount spent on advertising (TV, radio, newspapers).	Kantar Media

TABLE 3
Continued

Variable	Description	Source
Dividend distributions	Corporate action on distributing dividends to their shareholders.	Factiva
Earning announcements	Corporate action on announcing the quarterly earnings to their shareholders.	Factiva
Mergers and acquisitions	Whether a firm has undergone identity changes.	Factiva
New product announcements	Announcements of new products.	Factiva
Mktcap	The market capitalization of the firm given by the number of shares outstanding times the price of the stock.	CRSP

[a]"People Talking About This" (PTAT) metric implies that users voluntarily engage in telling a story about a brand (Facebook Insights).
Notes: To be able to perform the analysis at the daily level, we attributed the constant previous months' advertising expenditure to each day of the current month. CRSP = Center for Research in Security Prices.

These four criteria lead to our selection of the following 45 brands in 21 industry sectors: apparel and shoes (Nike), appliances (General Electric), beverages (Coca-Cola), cable and satellite (Verizon Wireless), car makers (Ford, General Motors, Honda, Toyota), consumer electronics (Sony), clothing stores (Gap), communications (AT&T, Microsoft, Dish Network, HP, IBM, Dell), banking (Citibank, Wells Fargo), department stores (Target, Dillard's, Macy's, Home Depot, Sears, Lowe's, Nordstrom, Walmart), dining fast food (McDonald's, Burger King), dining specialty (Starbucks), financial services (American Express), grocery stores (Safeway), insurance (Progressive, MetLife), Internet sites (Amazon, Netflix), networks (Walt Disney, Time Warner), retail gasoline (BP America, Chevron, Shell), specialty retail (Best Buy, Walgreens), airlines (Delta, Southwest), and travel (Expedia).

Merging the key variables with advertising, firm size, and announcements on new products introductions, dividends, earnings, and mergers and acquisitions (M&A), we obtain a balanced panel of 45 brands covering 273 trading days (October 31, 2012, through November 29, 2013) resulting in 12, 285 brand-day observations. Table 3 shows the variable operationalization, which we detail next. Descriptive statistics are provided in Web Appendix A.

Social Media Measures

In contrast to consumer mindset metrics, social media measures are not designed to be representative of the entire population of current or prospective customers (Ruths and Pfeffer 2014). It is exactly because of their platform-specific dynamics and sample bias (e.g., Schweidel and Moe 2014) that we do not expect a full overlap with the survey-based consumer mindset metrics (see also Pauwels and Van Ewijk 2013). Because the social media space is vast and constantly changing (Smith, Fischer, and Yongjian 2012), it is infeasible to cover the entire spectrum of social media platforms. Still, to guard against platform-specific threats to generalizability, we obtain data from three diverse and popular social media platforms, namely, Facebook, Twitter, and YouTube. We sourced data from a third-party data provider that collects and archives social media data using a set of automated web-based tools.[2]

Owned social media (OSM). Facebook and Twitter are the two main social media platforms companies use to spread company news (e.g., new product announcements) and engage with consumers. Accordingly, we collect the daily cumulative number of "brand posts" on Facebook as well as "brand tweets," "brand replies to users," and "brand retweets of user tweets" on Twitter. All these metrics correspond to the activities brands perform on their OSM. Collecting data about OSM on YouTube was not possible at the time of the study.[3]

Earned social media (ESM). As discussed previously, we split ESM into three components: BFF, ENG volume, and positive- and negative-valence ESM.

ESM brand fan following (BFF). We rely on direct measures of overall brand following on Facebook, Twitter, and YouTube to get BFF. These respective measures are the daily cumulative numbers of Facebook "likes," Twitter "followers,"

[2]We ascertained the validity of the data by using the following two-step procedure. In the first step, over a period of ten days, we accessed a brand's Facebook page, Twitter account, and YouTube channel and manually collected the metrics displayed on the social media accounts (e.g., Facebook likes and PTAT; Twitter "followers"; YouTube subscribers and video views). We also counted brand's daily Facebook posts and Twitter tweets over the same period. We repeated this procedure for all the brands in our sample. In the second step, we compared our data on all these metrics with the data vendor's records on the same metrics. We found no discrepancies between the two sets of metrics, thereby suggesting that the data provider reliably collects and archives data from Facebook, Twitter, and YouTube.

[3]YouTube data could not be collected, either in an automated fashion as was done with the other social media activity variables or even manually. For example, the website Klout.com, which claims to measure the impact of an individual's social media activity and is commonly used as a performance or notoriety metric by online marketing professionals, has only managed to incorporate data from YouTube in late 2015.

and YouTube "subscribers," which we collect for each of the brands in our study as measures of BFF.

ESM engagement (ENG) volume. To collect the measures of ENG volume, we rely on the metrics of user engagement on each respective platform. We collect the daily cumulative number of "people talking about this" (PTAT) on Facebook, Twitter "user retweets," and YouTube "video views." PTAT is defined by Facebook Insights as the number of people who have created a story from a brand page post. This metric combines all the voluntary user engagement that is directed toward a brand (e.g., user comments/shares/likes on brand posts; hashtags; user posts on brand wall). The volume of retweets has been shown to impact brand fortunes (Kumar et al. 2013). Finally, YouTube video views capture engagement on a more visual level, often with brand-related content, such as product reviews, demonstrations, unboxing of products, and events (Smith, Fischer, and Yongjian 2012).

ESM valence. We measure valence as the numbers of positive- and negative-sentiment user posts on Facebook brand pages.[4] Consistent with the advice of Babić et al. (2015), this is a composite volume-valence metric, which captures the number as well as the polarity of the user posts. To derive the valence of the textual data, we use the naive Bayes algorithm, which is a popular linear classifer known for its simplicity and high efficiency. The probabilistic model of naive Bayes classifer is based on the Bayes' theorem, and it classifies posts into positive or negative valence categories based on the input training set of lexical words. Recently, Tirunillai and Tellis (2012) use a similar approach within the marketing literature.

After identifying the social media constructs of OSM, BFF, and ENG volume, we apply factor analysis with Varimax rotation on our metrics within each construct and obtain a one-factor solution for each of the constructs. We use the factor scores to obtain the final variables of OSM, BFF, and ENG volume. Each social media metric has a high loading on the respective factors for each construct, and each factor has adequate reliability, as measured by Cronbach's alpha (for detailed results, see Web Appendix B).

Consumer Mindset Metrics

We obtain consumer mindset metrics from YouGov, which uses online consumer panels to monitor brand perceptions. For the U.S. market, YouGov surveys 5,000 randomly selected consumers (from a panel of 5 million consumers) each day. To assure representativeness, YouGov weights the sample by age, race, gender, education, income, and region. In any one survey, an individual respondent is asked about only one measure for an industry, reducing common method bias and measurement error. YouGov is the most accurate metric of political predictions (Matthews 2012), has been previously used in the marketing literature (e.g., Hewett et al. 2016; Luo, Raithel, and Wiles 2013), and presents at least four advantages. First, YouGov administers the same set of questions for each brand, enabling across-brand comparisons. Second, YouGov uses a large panel of consumers, capturing the general opinion of the crowd. Third, the large panel size and random selection of respondents imply that YouGov data captures between-subject variance. Fourth, YouGov data are collected daily, thereby quickly incorporating changes in consumer perceptions.

We operationalize mindset metrics according to YouGov metrics that map well with brand awareness (advertising awareness, received WOM), purchase intent (consideration, purchase intent, current customers), and customer satisfaction (perceived value, satisfaction, recommendation).[5] Because we do not want to impose a priori assumptions that item loadings are the same across brands, we perform a brand-level factor analysis with Varimax rotation on these metrics. For each brand, we obtain the same three-factor solution (each of the three eigenvalues is greater than 1), with each factor representing one of the three key consumer mindset metrics: brand awareness, purchase intent, and customer satisfaction. Each mindset metric item loads higher on one single factor than on any other factors, indicating good discriminant validity of the factors (see Web Appendix B). We obtain the competitive score on each metric in a similar fashion, averaging across competing brands in the sector to which the brand belongs.

Shareholder Value: Abnormal Returns and Idiosyncratic Risk

We capture different aspects of shareholder value with abnormal returns and idiosyncratic risk. Abnormal returns are the stock returns that are above and beyond the expected stock returns based on market-wide common risk factors, whereas idiosyncratic risk captures the firm-specific risk that is uncorrelated with these common risk factors. We estimate abnormal returns from raw stock returns by controlling for the common risk factors documented in the finance literature (Carhart 1997; Fama and French 1993). We obtain stock returns from the University of Chicago's Center for Research in Security Prices (CRSP) database and the common risk factors from Wharton Research Data Service. We specify brand's returns as

$$(1)\qquad R_{i,t} - R_{f,t} = \beta_{0i} + \beta_{1i}\left(R_{m,t} - R_{f,t}\right) + \beta_{2i}SMB_t + \beta_{3i}HML_t + \beta_{4i}MOM_t + \varepsilon_{i,t},\ \ \varepsilon_{i,t} \sim N\left(0, \sigma_{i,t}\right),$$

where $R_{i,t}$ is the returns for firm i in time t, $R_{m,t}$ is average market returns, $R_{f,t}$ is the risk-free rate, SMB_t is size factor, HML_t is value factor, MOM_t is momentum factor, β_{0i} is the intercept, β_s are the factor coefficients, and ε_{it} is the model

[4]Because six brands (BP, Disney, IBM, McDonalds's, Starbucks, and Nike) prohibited user posts over our sample period, we collect the user posts for the remaining 39 out of 45 brands. Thus, six of our brand-specific models do not have the variables of "positive" and "negative" comments, and our reported average elasticities for these variables are based on the 39 remaining brands. The text corpus for sentiment analysis consists of 465,034 user posts for the 39 brands. Next, we run the naive Bayes classifier and extract sentiment from each post for a given brand on a given day. Because there could be more than one user post per day, we take the daily cumulative number of positive and negative posts as our two social media valence metrics.

[5]While alternative data providers of consumer mindset metrics are available (e.g., Young and Rubicam 5 Pillars; see http://www.yr.com/bav), their data are collected less frequently, at the quarterly or yearly level. The exact questions used in the YouGov survey are available upon request from the authors.

residual. The abnormal returns on time period t + 1 are calculated using the following formula, where $\hat{\beta}$ are estimated coefficients:

$$(2)\qquad AR_{t+1} = (R_{i,t+1} - R_{f,t+1}) - \Big[\hat{\beta}_{0i} + \hat{\beta}_{1i}(R_{m,t+1} - R_{f,t+1}) + \hat{\beta}_{2i}SMB_{t+1} + \hat{\beta}_{3i}HML_{t+1} + \hat{\beta}_{4i}MOM_{t+1}\Big].$$

We repeat this procedure for every brand for a rolling window of 250 trading days prior to the target day to get estimated daily abnormal returns. For our main model, we use the natural logarithm of $1 + AR_{t+1}$. The idiosyncratic risk is the estimated variance of the residuals, $\sigma_{i,t}$.[6]

Control Variables

Following the firm valuation models widely used in marketing (e.g., Tirunillai and Tellis 2012) we include following control variables: advertising expenditure, market capitalization (value of equity) (Mktcap), new product introductions, mergers and acquisitions (M&A), earnings announcements, and dividend distributions. We provide a detailed description of these control variables in Web Appendix C.

Methodology

We adopt the persistence-modeling framework (Dekimpe and Hanssens 1995), which adequately captures the modeling needs for this study. First, we aim to uncover how changes in online social media metrics can lead to changes in the assessment of firm value by investors. Vector autoregression (VAR) models forecast all endogenous variables and quantify the effects of model-unexpected changes through the generalized impulse response functions, which are robust to the assumptions of causal ordering of the variables (Pesaran and Shin 1998). In addition, because our endogenous variables[7] can have unexpected components, such components are captured through the error terms in the VAR model. Second, VAR models offer a unified treatment of immediate and dynamic effects, which can be expected for OSM and ESM on daily metrics of consumer mindset metrics and even shareholder value (see, e.g., Pauwels et al. 2004). Third, the VAR model allows for dynamic feedback loops (Figure 1) among endogenous variables. Finally, VAR enables controlling for nonstationarity, serial correlation, and reverse causality (Granger and Newbold 1986). Our analysis consists of several methodological steps (Web Appendix C).

Model Specification

Based on the unit root and cointegration tests, we specify the VAR model in Equation 3:

$$(3)\qquad \begin{bmatrix} Abret_t \\ Risk_t \\ Awareness_t \\ Purchase_t \\ Satisfaction_t \\ Awareness\_comp_t \\ Purchase\_comp_t \\ Satisfaction\_comp_t \\ Positive_t \\ Negative_t \\ ENG_t \\ BFF_t \\ OSM_t \end{bmatrix} = \sum_{n=1}^{p} \begin{pmatrix} \gamma^n_{1,1} \cdots \gamma^n_{1,13} \\ \vdots \qquad \vdots \\ \gamma^n_{13,1} \cdots \gamma^n_{13,13} \end{pmatrix} \begin{bmatrix} Abret_{t-n} \\ Risk_{t-n} \\ Awareness_{t-n} \\ Purchase_{t-n} \\ Satisfaction_{t-n} \\ Awareness\_comp_{t-n} \\ Purchase\_comp_{t-n} \\ Satisfaction\_comp_{t-n} \\ Positive_{t-n} \\ Negative_{t-n} \\ ENG_{t-n} \\ BFF_{t-n} \\ OSM_{t-n} \end{bmatrix} + \begin{pmatrix} \varphi_{1,1} \cdots \varphi_{1,7} \\ \vdots \qquad \vdots \\ \varphi_{7,1} \cdots \varphi_{7,7} \end{pmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \\ x_6 \\ x_7 \end{bmatrix} + \begin{bmatrix} e_{Abret,t} \\ e_{Risk,t} \\ e_{Awareness,t} \\ e_{Purchase,t} \\ e_{Satisfaction,t} \\ e_{Awareness\_comp,t} \\ e_{Purchase\_comp,t} \\ e_{Satisfaction\_comp,t} \\ e_{Positive,t} \\ e_{Negative,t} \\ e_{ENG,t} \\ e_{BFF,t} \\ e_{OSM,t} \end{bmatrix},$$

where Abret = abnormal returns, Risk = idiosyncratic risk, Awareness = brand awareness of the focal brand, Purchase = purchase intent of the focal brand, Satisfaction = customer satisfaction of the focal brand, Awareness_comp = brand awareness of the competitors, Purchase_comp = purchase intent of the competitors, Satisfaction_comp = customer satisfaction of the competitors, Positive = positive-valence ESM, Negative = negative-valence ESM, ENG = ESM ENG volume, BFF = brand fan following, and OSM = owned social media. All variables are included in logs, with the exception of positive and negative comments, which on some days take 0 values. The

[6]The correlations among social media metrics, consumer mindset metrics, and abnormal returns and risk are within the range [–.01, .41] reported by Katsikeas et al. (2016, p. 44) in the meta-analysis on performance metrics. This implies that we have a moderate correlation between key variables that indeed capture distinct concepts.

[7]While the model predicts the baseline for each endogenous variable (and thus the error shocks are unexpected by the model), that is not the case for the exogenous variables such as advertising and new product introductions. To the extent that changes to such variables are expected (by consumer or investors), our effect estimate will be conservative (i.e., closer to zero) and have more noise (i.e., higher standard error) than the effect of unexpected changes. Thus, our results represent a lower bound on the impact of these exogenous variables.

off-diagonal terms of the matrix $\Gamma - \gamma_{kl}^{n}$ estimate the indirect effects among the endogenous variables and the diagonal terms estimate the direct effects. The exogenous vector X contains seven control variables—advertising expenditure, new product announcements, mergers and acquisitions, dividend distributions announcements, earnings announcements, and market capitalization—and a deterministic trend t to capture the impact of omitted, gradually changing variables. We perform standard diagnostic tests for autocorrelation (see Web Appendix C), normality, and heteroskedasticity of VAR residuals and find no violations of these assumptions at the 5% level of significance.

Mizik and Jacobson (2009) discuss how serial autocorrelation may result in bias in estimates with a subsequent understatement of the true standard errors (also known as spurious regression). To address this issue, we first check whether the variables that enter our model are stationary, with the help of both individual and panel stationarity tests. The nonstationary variables enter the model in first differences. We report in Table WA8 the results of the Lagrange multiplier (LM) autocorrelation test that confirms that we have no serial autocorrelation in the model. Therefore, the optimal lag order is chosen using the Akaike information criterion (AIC) and taking into account the serial autocorrelation LM test in order to balance lag-selection criteria with autocorrelation bias. We also refer to Web Appendix C for details on the observation-to-parameter ratio, which on average exceeds the threshold value of 5 (Leeflang et al. 2015).

After estimating Equation 3, we also estimate a set of restricted models (RM_1–RM_4) and follow Srinivasan, Vanhuele, and Pauwels (2010) in calculating the forecast error variance decomposition (FEVD; i.e., dynamic R^2) of abnormal returns for each of these models.

Separate VAR models and aggregation over brands

We estimate the VAR model for each brand separately and provide detailed explanations in Web Appendix C. We aggregate our results across brands by means of the added Z method (Rosenthal 1991). The added Z method allows for the combination of *p*-values across different brands for each effect in the model. We take each brand-specific estimate and its standard error to obtain the Z score (standard-normal statistic). As we follow established practice in marketing and assess the statistical significance of each impulse response value by applying a one-standard-error band (Sims and Zha 1999; Slotegraaf and Pauwels 2008; Trusov, Bucklin, and Pauwels 2009), we take only the effects with absolute Z values larger than 1. Next, we sum the Zs and divide the sum by the square root of the number of included brands (45). Moreover, the overall effect size is the weighted average of the response parameters across the brands, where weighting is done by the inverse of the standard error.

Results

Model-Free Evidence

For Burger King (a main brand in a category with low seasonal sensitivity), Figure A1 in Web Appendix A displays the standardized scores of purchase intent, ENG volume, and negative-valence ESM over the period of analysis. Note that several of the changes to purchase intent are preceded by similar changes to ENG volume, reflecting the positive correlation of .183 between their time series. In contrast, negative-valence ESM sometimes moves with purchase intent and sometimes against it, as reflected in the low correlation of .032. Contrary to common wisdom, this would suggest that Burger King's performance is driven by ENG volume rather than negative-valence ESM. But, of course, such model-free evidence is only a preliminary indication. For a more rigorous analysis, we need to account for lags, feedback loops, and other drivers, which we do in our VAR model.

Granger Causality

The results of the Granger causality tests (see Web Appendix C) show support for the dynamic relationships in our conceptual framework (Figure 1). Consistent with Figure 1, ENG volume, BFF, and OSM Granger-cause brand awareness, purchase intent, and customer satisfaction ($p < .05$), while purchase intent and all social media metrics Granger-cause abnormal returns ($p < .05$) and customer satisfaction ($p < .05$), Granger-causes idiosyncratic risk. Moreover, we find feedback loops between our variables (see Web Appendix D), highlighting the need for a multiple-equation system such as that in Equation 3.

Stationarity, Unit Roots, and Cointegration

We check the nature of the time-series data by performing unit root tests for each variable (see Web Appendix C). OSM, ENG volume, consumer mindset metrics for focal brand and competitors, and abnormal returns are stationary for all brands, so they enter the system in levels. Idiosyncratic risk always enters first-differenced; the model variable thus represents the change in idiosyncratic risk. For some brands, BFF and valence metrics enter the VAR system-differenced.[8] Finally, we do not find any cointegrating equation among our variables (see Web Appendix C), eliminating the need for vector error correction models.

Relative Importance of Metrics: FEVD

From the VAR parameters, we derive FEVDs evaluated at 30 days to investigate whether, and to what extent, ENG volume, BFF, OSM, and ESM valence metrics explain consumer mindset metrics and firm value (see Web Appendix D). We find that social media variables (OSM and ESM) explain 7.3% of variance in abnormal returns and 7.5% of variance in risk, while mindset metrics of the focal brand and competitors explain 7.9% of variance in abnormal returns and 8.4% of variance in risk. In

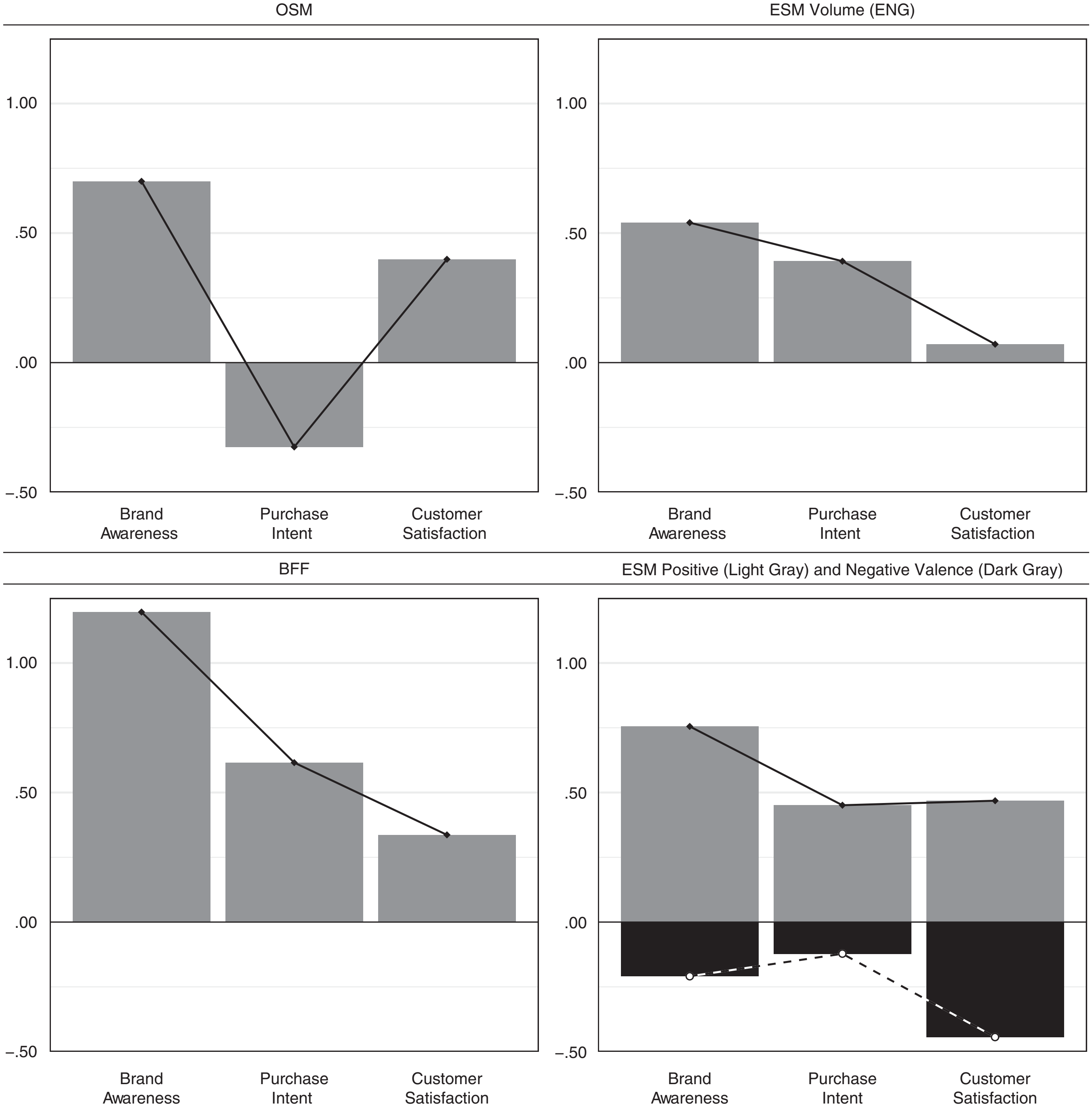
[8]To aggregate these results, we use the added Z method. This enables us to overcome the challenges related to aggregating the effects of differenced and nondifferenced (i.e., level) variables in our model. The added Z method weights each estimate by its standard error, making the results directly comparable and interpretable across brands. The added Z method involves calculating each brand's Z by dividing the respective impulse response function (e.g., OSM on brand awareness) by its standard error, which is equivalent to accumulating both impulse response function and standard error over any given period. Thus, this method is insensitive to the operationalization of the variable (differenced or in levels) and enables us to generate comparable Z values across differenced and level variables for different brands.

TABLE 4
Impulse Responses of Main Endogenous Variables in the Study

	Brand Awareness		Purchase Intent		Customer Satisfaction		Abnormal Returns		Idiosyncratic Risk	
	Impact	Significance (%)	Impact	Significance (%)	Impact	Significance (%)	Impact	Significance (%)	Impact	Significance (%)
OSM	.6998***	80	–.3255*	76	.3989**	74	.3053*	65	.0069n.s.	53
ESM BFF	1.1966***	78	.6154***	71	.3366*	69	.3349**	78	.0586n.s.	60
ENG volume	.5402***	76	.3914**	67	.0711n.s.	71	.4255**	52	.0690n.s.	53
Positive-valence ESM	.7551***	78	.4510**	60	.4684***	62	–.0458n.s.	65	–.3540*	65
Negative-valence ESM	–.2090n.s.	89	–.1224n.s.	81	–.4441**	73	–.4601**	81	.4039*	54
Brand awareness	—	—	–.0744n.s.	53	.3847*	66	.0220n.s.	62	.0937n.s.	84
Purchase intent	–.5836***	60	—	—	.5302***	56	.3538**	69	–.2938*	73
Customer satisfaction	.3806**	62	.6196***	64	—	—	.3303*	65	–.0380n.s.	78

*$p < .1$.
**$p < .05$.
***$p < .01$.
n.s.Not significant.
Notes: Estimates are from the VAR model and the impulse response functions. Effects across all brands can be evaluated by the added Z method (Rosenthal 1991).

FIGURE 2
Cumulative Impulse Response Functions of Owned and Earned Social Media on CDJ Stages



the restricted models (RM_1–RM_4), dropping mindset metrics from the model yields substantial drops in explanatory power (R^2) for both abnormal returns and idiosyncratic risk.

Cumulative Effects of Social Media on Consumer Mindset Metrics (P_1–P_5)

To assess P_1–P_5, we use the generalized impulse response function. We provide the cumulative elasticities of social media metrics on consumer mindset metrics in Table 4 and Figure 2.

Brand Awareness (P_1–P_2)

Overall, the cumulative elasticities indeed support $P_{1a–c}$ that ENG volume, BFF, and OSM each have positive effects on brand awareness. Apart from positive- and negative-valence ESM, our variables are operationalized in logs, and we interpret respective effects as elasticities. We find that a 1% change in ENG volume, BFF, and OSM is associated with a .54% ($p < .01$), 1.2% ($p < .01$), and .70% ($p < .01$) change in brand awareness, respectively. We also find supporting evidence for

P_2 that positive-valence ESM has a higher positive effect on brand awareness than negative-valence ESM ($t = 9.67$, $p < .01$). We find that a unit increase in positive-valence ESM is associated with .76% ($p < .01$) change in brand awareness while the effect of negative-valence ESM does not reach statistical significance (–.21%, $p > .1$).

Purchase Intent ($P_{3–4}$)

We do not find support for $P_{3a–b}$, which states that positive- and negative-valence ESM dominate the effects of ENG volume and BFF on purchase intent. We find that a unit increase in positive-valence ESM is associated with a .45% ($p < .05$) change in purchase intent, while a corresponding increase in negative-valence ESM does not reach statistical significance (–.12%, $p > .1$).

In addition, we find that a 1% change in BFF and ENG volume is associated with a .62% ($p < .1$) and a .39% ($p < .05$) change in purchase intent, respectively. Results of t-tests do not show any significant difference between the effects of positive-valence ESM and ENG volume ($t = 1.057$, $p > .1$), whereas they do show the difference between the effects of BFF and positive-valence ESM ($t = –2.980$, $p < .01$). We discuss these findings in the "Discussion" section. We find support for P_4 in that the positive impact of OSM is lower than the impacts of ENG volume ($t = 6.13$, $p < .01$), BFF ($t = 10.44$, $p < .01$) and positive-valence ESM ($t = 7.34$, $p < .01$) on purchase intent. We find that a 1% change in OSM is associated with a marginally significant –.33% ($p < .1$) change in purchase intent.

Customer Satisfaction (P_5)

Finally, we find support for P_5 that OSM is positively associated with customer satisfaction. We find that a 1% change in OSM is associated with a .4% ($p < .05$) change in customer satisfaction. We also we find that a unit increase in positive- and negative-valence ESM is associated with a .47% ($p < .05$) and a –.44 ($p < .05$) change in customer satisfaction, respectively.

Cumulative Effects of CDJ on Shareholder Value (P_6)

We find that a 1% change in purchase intent and customer satisfaction is associated with an increase in abnormal returns of .35% ($p < .05$) and a marginally significant increase of .33% ($p < .1$), respectively, whereas the smaller effect of a change in brand awareness does not reach statistical significance (.02, $p > .1$). Therefore, we find partial support for P_6 in that both purchase intent ($t = 7.264$, $p < .01$) and customer satisfaction ($t = 6.568$, $p < .01$) have larger effects on abnormal returns than does brand awareness. Given the average market capitalization of $3 billion in our sample, a 1% increase in purchase intent and customer satisfaction increases firm value by $10.6 million and $9.9 million, respectively. However, we do not find a significant difference between the effects of purchase intent and customer satisfaction on abnormal returns ($t = .46$, $p > .1$). In addition, we find that a 1% change in purchase intent is associated with only a marginally significant .29% ($p < .1$) lower idiosyncratic risk.

Social Media Effects on Shareholder Value

Table 4 also shows the average cumulative effects of each social media metric on abnormal returns. We find that a 1% change in OSM, BFF, and ENG volume and a unit increase in negative-valence ESM results in a .31% ($p < .1$), a .33% ($p < .05$), a .31% ($p < .1$), a .42% ($p < .05$), and a –.46% ($p < .05$) change in abnormal returns, respectively. Finally, we find that a unit increase in positive-valence ESM decreases idiosyncratic risk by .35% ($p < .1$) and a unit increase in negative-valence ESM increases idiosyncratic risk by .40% ($p < .1$). The effects of OSM, ENG volume, and BFF do not reach statistical significance.

Second-Stage Analysis

Beyond the reported average effects, we further investigate the brand-level OSM–CDJ link[9] because OSM is under full managerial control, and thus it would be beneficial for managers to understand the conditions under which OSM is most effective. Drawing on previous literature, we investigate firm-level, product category–level, and brand-level characteristics. Specifically, we focus on firm's corporate social performance (CSP), whether the brand is hedonic or utilitarian, and product purchase involvement (PPI). Much marketing literature attests to the positive effects of CSP on consumer behavior (Berens, Van Riel, and Van Bruggen 2005; Sen and Bhattacharya 2001). Our theoretical framework suggests that firms with higher CSP should have lower consumer concerns about OSM's limited credibility and higher OSM diagnosticity. Bart, Stephen, and Sarvary (2014) find that utilitarian brands with high PPI have a higher impact of mobile advertising on brand attitude. Along similar lines, we expect that more consumers will use the central processing route while evaluating a utilitarian brand with high PPI (vs. all other brands) and therefore may rely on OSM in evaluating the brand. Accordingly, we also include interaction of hedonic/utilitarian and PPI. Finally, we also include several other mindset metrics, such as brand impressions, perceived quality, and so on. In this analysis, we used L1 regularized logistic regression to model the probability that a given impulse response function was positive (vs. zero or negative) (for specifics, see Web Appendix D).

We find that higher perceived quality and existing positive impressions about the brand positively impact the OSM–brand awareness link. This is consistent with our conceptual framework because consumers who know a high-quality brand are more likely to share its OSM, bringing it to the attention of consumers who do not yet know the brand. In addition, the firms that pay fair compensation, indicating better treatment of employees, enjoy a higher likelihood of a positive OSM–brand awareness effect. While we found a negative impact of OSM on purchase intent on average, several brands show positive effects. The OSM–purchase intent link is more likely to be positive for firms with better leadership and fair compensation policies. Interestingly, firms with perceived negative product quality have a higher likelihood of a positive effect of OSM on purchase intent. This suggests that firms with poor quality

[9]We also perform a similar analysis on the overall effects of ESM (volume and valence); for a detailed discussion, see Web Appendix D.

perceptions in our sample are using OSM to address consumer concerns and enhance willingness to buy. Importantly, like Bart, Stephen, and Sarvary (2014), we find that the probability of OSM positively affecting purchase intent is higher for utilitarian brands with high PPI. This suggests that OSM helps consumers of such brands in forming their purchase intent. Finally, firms with better human rights records and reputations for managing resources efficiently, indicating higher environmental consciousness, enjoy a higher likelihood of a positive impact of OSM on customer satisfaction. Similarly, the firms that have increased advertising in the past month have a higher likelihood of a positive OSM–customer satisfaction link. This suggests that firms in our sample are using a combination of traditional advertising and OSM to influence positive WOM.

Robustness Checks

Panel VAR. As an alternative to brand-level VARs, we estimate a panel VAR model (PVAR) (Holtz-Eakin, Newey, and Rosen 1988) by industry. We continue to find results qualitatively similar to our main results (see Web Appendix D).

Models with fewer variables. We estimate a set of restricted models (e.g., without risk) and find that the full model obtains a better fit (see Web Appendix D). For the full model with risk, we obtain an AIC of 10.52 and a Bayesian information criterion (BIC) of 18.38, while for the model without risk, we obtain an AIC of 12.53 and a BIC of 20.35. Thus, both information criteria support the full model with risk.

Parameter-to-observation ratio. Although the average parameter-to-observation ratio in our sample is 6.57, which is above the recommended value of 5 (Leeflang et al. 2015), we also check the robustness of the results by removing the brands with a ratio below 5. We find no significant difference in the results (see Table WA23 in Web Appendix E).

Robustness to outliers. Given that our main effects reported in Table 4 are composed of the sum of Z values from each brand, we also check for outliers. Only the negative brand awareness–purchase intent link appears driven by an outlier; removing it renders the link insignificant.

Principal component analysis (PCA). Instead of factor analysis, we construct our social media and customer mindset variables with PCA, revealing that each of the social media constructs is unidimensional. We also sum the measured variables that load together under each construct. We find no significant difference in the model results.

Discussion

The wide adoption of social media by consumers and businesses should have far-reaching consequences (Lamberton and Stephen 2016). Recent studies have investigated a few such consequences by showing strong effects of social media on firm performance (e.g., Tirunillai and Tellis 2012). However, it is unclear why and how these effects occur. We propose that social media affects shareholder value by altering consumer mindset metrics (brand awareness, purchase intent, and customer satisfaction) mapped to CDJ (Batra and Keller 2016; Court et al. 2009), which contains value-relevant information for stock market participants. Using VAR models, we link the measures of ESM (ENG volume, BFF, and positive- and negative-valence ESM), as well as OSM, to stages of CDJ (brand awareness, purchase intent, and customer satisfaction) and to shareholder value, measured as abnormal returns and idiosyncratic risk. In this section, we highlight the research and managerial contributions of our research.

Research Contributions

We contribute to the emerging research on the value relevance of social media by studying the links between social media, CDJ, and shareholder value. We argue that in different stages of the CDJ, consumers will have different levels of motivations to process information. The extant literature on online WOM mostly investigates *why* people spread WOM. In contrast, we study *how* social media adds value to the firm. To that end, we quantify the specific CDJ consequences of this WOM. Our conceptual framework thus paves the way for studying more nuanced effects of social media on consumers. We argue that consumers process social media with varying degrees of rigor and thought to form brand awareness, purchase intent, and customer satisfaction. In the brand awareness stage, consumers use the peripheral route and pay attention to simple cues. In the purchase intent stage, consumers take the central route and process information in an elaborate way. Finally, in the customer satisfaction stage, consumers take a route between peripheral and central, which leads to a moderate likelihood of elaboration. Furthermore, we posit that ESM and OSM have varying levels of accessibility and diagnosticity (Feldman and Lynch 1988). By relying on the consumer motivation and accessibility and diagnosticity of social media, we offer a set of novel propositions, which we test using high-frequency daily data on social media, consumer mindset metrics, and shareholder value.

Our second contribution is to empirically show that social media impacts CDJ, which in turn affects shareholder value. This contributes to both the seminal work on offline advertising and WOM and to the current social media research. As to the former, our study shows to what extent previous work on offline advertising applies to today's connected world. Given our rationale of elaboration likelihood and accessibility/diagnosticity, offline advertising should and does increase brand awareness more than purchase intent and other related constructs (e.g., Srinivasan, Vanhuele, and Pauwels 2010). However, its effect on customer satisfaction is unclear (note that Grewal, Chandrashekaran, and Citrin [2010] and Malshe and Agarwal [2015] show a positive impact of *total* advertising) because offline advertising does not typically allow firms to address specific customer complaints (as OSM does), nor does it allow customers to interact with each other as ESM does, leaving lasting and efficiently measurable traces (in contrast to offline WOM). This is important because social media enables managers and consumers to redefine their relationship as a personalized, two-way interaction. The specific managerial levers to do this remain uncertain, however, as some actions may backfire (Hoffman and Fodor 2010). This study shows that OSM is associated with higher customer satisfaction; future research should delve deeper into the mechanisms and boundary conditions. As to social media research, no study analyzes all three CDJ metrics together. A few studies have established that social media has an impact on shareholder value. However, these studies do not include consumer mindset metrics in the empirical model, so it is impossible to know whether the shareholder value impact was via consumers or some other stakeholders, such as investors, employees, and so on. Our results show that social media impacts CDJ stages that in turn affect shareholder value. Thus, our research also contributes to the marketing–finance interface by answering the recent call for research on the return on investment (ROI) of social media marketing (Kumar 2015).

Managerial Implications

Our study has several implications for practitioners. First, we find that OSM on average increases brand awareness and customer satisfaction, but not purchase intent, which has the strongest impact on shareholder value. The implication of this finding is that marketers must start formulating social media strategies that are distinct from the strategies deployed in traditional media. Rather than spending marketing dollars on OSM to persuade customers to buy their products, marketers and social media managers should craft their OSM messages to target customers to improve brand awareness and customer satisfaction. In particular, due to value relevance of customer satisfaction, OSM that is targeted toward helping customers postpurchase—addressing their concerns, reinforcing their purchase decisions, and thereby reducing cognitive dissonance—is much more valuable than OSM crafted to persuade customers to buy the firm's products. Following this recommendation should increase the ROI of OSM.

Second, we offer specific metrics to evaluate the impact of OSM and ESM. In terms of Hanssens et al. (2014), our analysis demonstrates which CDJ metrics both are responsive to marketing actions and convert into firm value. Therefore, marketing managers should have an easier time demonstrating the firm value impact of their activities to more finance-oriented executives (Katsikeas et al. 2016) and thus to obtain sufficient marketing budgets.

Third, we find that OSM positively influences the ESM volume metrics of BFF, ENG, and positive-valence ESM (see Web Appendix E). This result is complementary to Mochon et al.'s (2017) finding that Facebook likes (BFF) impact consumers only if the firm is also active on OSM. OSM allows managers to improve ESM (which they typically cannot control) and thus indirectly improve consumer mindset metrics. Currently, this indirect impact of OSM is unlikely to be accounted for by marketers. We advise them to include these indirect paths in their analyses of social media marketing ROI. Without consideration of the indirect effects, social media ROI is likely to be underestimated.

Fourth, we study boundary conditions for the effects of OSM. Although OSM affects purchase intent negatively on average, it increases purchase intent for utilitarian products with high involvement. This implies that OSM is welcome for more rational, deliberate purchase behavior, and suggests the same may hold for B2B categories—a key area for future research.[10]

[10]We thank an anonymous reviewer for this insight.

Moreover, we find that OSM has substantially higher effects on consumer mindset metrics for firms with higher reputation (superior product quality, positive impressions, leadership, fair compensation, human rights, reputation for managing resources efficiently, and environmental consciousness). In other words, running a socially responsible business lends more credibility to one's OSM. Likewise, firms with increased advertising may enjoy synergy or halo effects from OSM. In contrast, managers of firms with lower credibility must carefully evaluate the way they are using social media. For example, companies with negative public perception of their product or service quality (e.g., airlines) can use OSM to tackle customer complaints, which may perceived quality and positive WOM. Indeed, we find that OSM leads to higher purchase intent for firms with negative perceptions about product quality.

Finally, we quantify the differential impacts of ESM metrics such as increasing BFF and improving ENG and ESM valence, and contrast them to impacts of OSM, thereby helping managers design more effective social media strategies. We find that BFF improves all three stages of the CDJ, emphasizing the role of overall brand following in impacting the consumer mindset. In addition, ENG volume affects both brand awareness and purchase intent, while positive- and negative-valence ESM have the largest effect on customer satisfaction. Furthermore, we offer boundary conditions for the contrasting effect of BFF, ENG, and ESM valence. We find that small firms should rely more on using BFF and ENG for improving purchase intent, whereas large firms should focus on the valence of ESM. For firms scoring high on corporate transparency and fair compensation to employees, we find that consumers pay more attention to ESM valence than to BFF and ENG.

Limitations and Future Research

Our research has a few limitations that pave the way for future research directions. First, because our data set is limited to relatively bigger, publicly traded firms, we encourage future research on how social media affects CDJ for smaller and non–publicly traded brands. We expect that the reputation effects will be stronger for smaller firms with no public stock trading. Future studies might investigate under which conditions OSM can be effective for smaller brands and how social media metrics drive their CDJ. Second, our focus on OSM and ESM effects leaves unanswered interesting questions on the mechanisms driving the stock market effects. If such effects do not show up in terms of changes in future cash flows or residual intangible asset values, are they evidence of mispricing? Or instead, do our offered metrics provide information that would reduce mispricing, and should they be different for risk versus returns aspects of stock performance? In addition, we do not investigate the *strength* (intensity) of ESM valence. For example, more intense positive-valence ESM may impact brand performance more than less intense negative-valence ESM, and vice versa. Future research should consider this interesting empirical question, which we are unable to answer due to data limitations. Fourth, although we have a large set of metrics, due to data limitations, we do not measure the extent to which consumers interact in a two-way dialogue with brands via social media platforms. For example, firms may use Twitter as an inbound communication channel for customers (e.g., airlines that use it as a mechanism for customers to ask real-time questions). Future studies may integrate such metrics in their framework. Fifth, our consumer mindset metrics are drawn from an online panel of consumers and therefore may be more susceptible to social media effects than measures drawn from an offline panel. More research is needed on this issue, building on recent studies that show a strong impact of online media on consumer mindset metrics measured in offline surveys (Hewett et al. 2016; Pauwels and van Ewijk 2013). Finally, the negative impact of negative-valence ESM on purchase intent is nonsignificant. For brevity, we do not explore this further in our second-stage analysis, but our conjecture is that brand characteristics such as brand loyalty and reputation, as well as social media user characteristics such as representativeness, may moderate this effect. Further research may explore these contingencies in depth.

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