The effect of emotional positivity of brand-generated social media messages on consumer attention and information sharing

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Abstract

The literature has overlooked whether emotional positivity in social media messages posted by brands has the same effect on different types of consumer engagement behaviors on social media. Furthermore, whether brands' emotional positivity plays a role in shaping the impact of message emotionality is unclear. To address these gaps, the authors develop and test a model of the impact of emotional positivity of social media messages posted by brands on consumers' personal engagement and interactive engagement behaviors. The authors also examine whether and how brand emotional positivity interacts with message emotional positivity in triggering these responses. Based on a sample of 62,255 Twitter messages posted by brands the authors find that, in general, emotional positivity has an opposite effect in terms of stimulating personal engagement (likes) versus interactive engagement (retweets). Brand emotional positivity negatively moderates the link between message positivity and both types of user responses.

Keywords: brands; social media; message positivity; brand emotions; Twitter; communication effectiveness

1. Introduction

The recent years have seen a dramatic increase in brands using social media for advertising, communicating, and engaging with customers. According to a survey of top USA marketers, firms now spend on average 12% of their marketing budgets on social media, and this figure is expected to surpass 20% in the next five years (CMO survey, 2018). Many firms view social media as cheaper, faster, and more effective, than traditional methods, in exploiting network effects and achieving customer and marketing outcomes (Stieglitz & Dang-Xuan, 2013). Indeed, research indicates that in addition to the brand-related activities of social media influencers and consumers, brands' direct activities on social media also positively impact business performance by stimulating brand adoption, enhancing consumer spending, and increasing consumer cross-buying (Akpinar & Berger, 2017; Beckers, van Doorn, & Verhoef, 2018; Berger et al., 2018; Liu, Shin, & Burns, 2021; Parker et al., 2018; Swani et al., 2017). A key issue for firms, therefore, is understanding how brand messages on social media can be best framed to gain consumers' attention, provoke positive interactions and stimulate actions such as message propagation (Gensler, Völckner, Liu-Thompkins, & Wiertz, 2013; Tellis et al., 2019; Yuki, 2015).

Drivers of consumer reactions to social media messages uncovered in previous research include content-related and structural features of messages, characteristics of information senders and receivers, and network size (Stieglitz & Dang-Xuan, 2013; Walker, Baines, Dimitriu & Macdonald, 2017). In recent years, researchers are increasingly turning to the textual properties of social media messages and assessing their impact on consumers' attention and information sharing behavior. One content-related driver that has generated significant interest among political marketing, information management and marketing scholars is the emotional content in social media messages (Araujo, Neijens, & Vliegenthart, 2015; Heimbach and Hinz, 2016; Moussa, 2019; Stieglitz & Dang-Xuan, 2013; Walker, Baines, Dimitriu &

Macdonald, 2017). This focus is understandable given the importance of emotions in driving consumer behavior.

The focus of our study is on the effect of emotionality in brand social media messages on consumer reactions in the same context. Two important gaps in the literature drive this focus. First, despite the prevalence of brands on social media, brand-focused studies that specifically focus on emotionality are rare (for exceptions see Tellis et al., 2019; Araujo, Neijens, & Vliegenthart, 2015; Yuki, 2015) and often provide conflicting results. Focusing specifically on commercial brands is important because findings in other contexts may not be applicable to a brand context. Indeed, a recent political marketing study cautions that consumers' "retweeting behavior may differ …when tweets are sent out by organizations" (Walker, Baines, Dimitriu & Macdonald, 2017: 290). However, conclusions about consumer reactions to emotionality in brand social messages are as deeply mixed as in other contexts. On the one hand, emotional cues do not directly affect consumer information sharing (Araujo et al., 2015), while on the other hand, the presence of affective content increases the likelihood that a message will be shared with others (Yuki, 2015). Such contradictions, aligned with the paucity of brand-focused studies, means that it is not clear why and how emotions in social media posts influence consumers' behaviors in a brand-related context.

Secondly, and more pertinent to this study, is the need to understand how emotionality drives different types of consumer behaviours on social media, i.e., personal engagement and interactive engagement behaviors (see Oh et al., 2017). Personal engagement involves the user's interaction with the content (e.g., likes and views) while interactive engagement involves socialization with the brand or sharing content with other consumers (e.g., retweets, shares and comments). Clearly message characteristics can affect different consumer reactions in different ways (Tellis et al., 2019). For instance, a recent study shows that Facebook messages with certain characteristics were more likely to be liked but less likely to be shared (Heiss, Schmuck

& Matthes, 2018). Given that these consumer behaviors might themselves have different impacts on important outcomes, such as sales (Oh et al., 2017), understanding whether emotionality in brand messages differentially impacts them, is crucial. From a practical perspective, this understanding can guide firms in crafting their social media content in ways that are more likely to generate the outcomes they seek (Swani et al., 2017). For example, if emotionality differentially impacts different consumer responses, a message designed to gain the attention of brand followers might be framed differently from a message where the objective is to encourage propagation by loyal followers to their own networks (e.g., Jalali & Papatla, 2019). Yet, with a few exceptions (e.g., De Vries et al., 2012), research on the distinct impacts of emotionality of brand-generated messages on both personal and interactive user engagement behavior is very limited. Thus, we contribute to the literature via examining the differential effects of emotionality in brands' social media messages on both personal and interactive engagement behavior. We differentiate our work from previous studies, which implicitly assume that emotionality in brand messages has uniform effects on different types of consumer responses, by providing theoretical reasons for why emotionality in brand messages might impact different types of behaviors differently and then demonstrating this empirically.

Furthermore, extant research has shown that consumer perceptions of a brand's characteristics can influence the effectiveness of the brand's messages (Davis et al., 2019; Du, Bhattacharya, & Sen, 2010; Luo, Baker, & Donthu, 2019). One brand characteristic which may be relevant to understanding the consumer consequences of emotions in brand messages is brand personality. To our knowledge, no previous study has addressed the question of whether and how emotionality in brand social media posts (a content-related driver) interacts with brand emotionality (a context-specific brand personality characteristic) to inform customer reactions. By tackling this question, i.e., whether the effect of message emotionality is contingent upon the personality of the brand, our research makes a key contribution to ongoing discussions on the importance of brand characteristics in predicting consumers' actions (De Vries, Gensler, & Leeflang, 2012; Pansari & Kumar, 2017).

Twitter is a suitable context to test our study as it is one of the most popular social media platforms for brand engagement with customers (e.g., Dessart, Veloutsou, & Morgan-Thomas, 2015; Godey et al., 2016; Simon & Tossan, 2018). In addition to this, messages posted on Twitter can often impact the global media ecosystem (Elayan et al., 2020). To test our model, we use a sample of 62,255 messages generated by the Twitter accounts of Interbrand's 100 best global brands. In testing our model, it is crucial to explain the context of the study and how we operationalise personal and interactive engagement. We focus on "likes" as a type of personal engagement and "retweets" as interactive engagement, i.e., sharing content with other users. Furthermore, to develop our hypotheses, we review the literature on motivations for information sharing to suggest how and why emotional content in brand tweets may differentially impact likes and retweets. We also theorize (and test empirically) how emotionality at the brand level moderates the impact of tweet emotionality on likes and retweets. We use the terms tweet emotional positivity, (hereafter TEP) and brand emotional positivity (hereafter BEP) to refer to emotionality in a tweet and emotionality of a brand's personality on Twitter, respectively. This is because, as revealed in previous studies (and confirmed in our sample), emotional cues or language in corporate social media messages are very rarely negative and are generally positive in nature (e.g., Lin & Peña, 2011). The conceptual framework is displayed in Figure 1.

[INSERT FIGURE 1 ABOUT HERE; 2-COLUMN FITTING IMAGE]

In the following section we present the theoretical background for our research and develop the study's hypotheses. Next, we offer a comprehensive description of the methodology used. We subsequently detail the specification and the estimation of the Tobit models used to test our hypotheses. Following this, we outline the results attained and the robustness tests performed. Lastly, we discuss the theoretical and managerial implications as well as the limitations of our study and present opportunities for future research.

2. Conceptual framework

Our conceptual framework is divided into the following parts: emotionality in tweets, customer engagement on Twitter and motivation for sharing information. In the customer engagement section, we explain how likes and retweets reflect consumer attention and information sharing. The motivation for sharing section explains the fundamental reasons why people share. Although we do not measure these motivations, we use these motivations to guide us in formulating our hypotheses on why and how emotionality in brand tweets influences consumer sharing.

2.1 The Expression and Perception of Emotions

Strictly speaking, an emotion is a feeling or a sensation that is a process within a human being (Roberts, 1988). However, a broader definition considers not just the process within individuals but the expression. This broader definition allows a more natural interpretation of emotions in texts. In the context of social media, research shows that individuals can convey and perceive emotion through cues such as emotion words and linguistic markers, as well as paralinguistic cues such as emoticons (Stieglitz & Dang-Xuan, 2013). It is important here to distinguish between explicit (more direct) and implied (more indirect and vaguer) affective cues, when assessing written content. While implied emotional language refers to vaguely positive or negative content elements (“This is good news”), explicit emotional language and what we refer to as emotionality relates to whether emotions are explicitly expressed in a message ("We are delighted with this").

Two of the most discussed characteristics of emotions in the literature are valence and intensity (Mauss & Robinson, 2009). This is based on the circumplex model of emotion, developed by Russell (1980), in which valence (i.e., pleasure) and arousal (i.e., activation) are represented on a plane within an emotional circumplex of affect. In this two-dimensional model (APA, 2020), valence is considered a core dimension of emotion, and since in our work we focus on higher (rather than middling) levels of valence we refer to this as emotional positivity. Discrete emotions, such as happiness, sadness, surprise, anger, fear, disgust, and confusion can thus be either positive or negative in terms of valence, high or low in terms of intensity. Theoretically, both positive and negative emotions can be expressed in a single message (Heimbach & Hinz, 2016) and individuals can feel both positive and negative emotions simultaneously (Miyamoto, Uchida & Ellsworth, 2010). However, the negative emotions conveyed (or felt) might be weaker (or stronger) in intensity compared with the positive emotions. In such a case, the overall valence of the emotions expressed or felt is positive (negative) (Miyamoto, Uchida & Ellsworth, 2010).

2.2 Likes and Retweets as Forms of Consumer Engagement on Twitter

Calder et al. (2009) suggest that engagement on social media shares some commonality with other concepts such as consumers' attention, involvement, interest, and interactivity. Drawing from previous research on customer engagement on social media (e.g., Oh et al., 2017), we suggest that in the context of Twitter, the number of "likes" indicates the extent to which customers have paid "conscious attention" to a tweet (Vivek, Beatty & Morgan, 2012) and the number of "retweets" measures the extent of information sharing by customers (e.g., Tellis et al., 2019).

2.3 Motivation for Sharing

To understand how tweet emotionality influences the sharing of brand tweets, we briefly address three broad categories of motivations that drive information sharing generally: (1) self-serving, (2) social, and (3) altruistic motivations (Tellis et al., 2019). Self-serving motivations include the enjoyment of the sharing act, the need for self-enhancement, to foster reciprocity from others, and to express uniqueness (Berger & Milkman 2012; Lovett, Peres, & Shachar 2013). Consumers may also share information in order to engage with and feel connected to a social community (Ho and Dempsey 2010). Finally, altruistic motivations may also drive sharing. Individuals share content to show concern and empathy for others and to help others (Lovett, Peres, & Shachar, 2013). We rely on these sharing motivations to develop our hypotheses about how tweet emotionality affects sharing.

3. Hypotheses development

3.1 Emotions, Consumer Attention, and Information Sharing

Attention is the first step in the sharing process, since consumers are more likely to share messages that have captured their attention. Visual, verbal and other characteristics of a message can trigger or arouse consumer attention. Previous research has established that emotional cues can attract consumer attention and affect consumer desire to share information (Heimbach and Hinz, 2016; Stieglitz & Dang-Xuan, 2013). The presence of emotional stimuli has an impact on what individuals notice, learn, remember and, ultimately, on their judgments and decisions (Forgas & Wyland, 2006). Therefore, the higher the positivity of emotions in a tweet, the more likely it is that it will be noticed by consumers. This, ideally, should manifest itself in a greater number of likes and potentially retweets. However, it is important to note that likes “need not induce sharing if they do not foster or activate sharing motives” (Tellis et al., 2019 p:18).

An important factor that differentiates brand tweets from non-marketer generated tweets is that they are commercial in nature and designed to involve or persuade consumers. When engaging with brands, consumers generally attribute strategic motivations to brand communications (Smith & Hunt, 1978) and, as such, are likely to resist being persuaded by them (Friestad & Wright, 1994). Although, brand owners often want to include message characteristics that can draw consumer attention to their messages, some of these characteristics may also activate persuasion knowledge i.e., sensitize consumers to the commercial motives behind the message and thus make them more likely to resist persuasion (Tellis et al., 2019). In other words, emotional cues in a tweet make it more likely that the tweet will be noticed (a positive effect) but also more likely that it will activate persuasion knowledge (a negative effect).

In a climate of limited trust, such as between consumers and firms (Marín, Cuestas, & Román, 2016), displays of emotions in brands’ tweets increase the likelihood of increased customer scrutiny leading to more complex assessments of brands’ motives (Smith & Hunt, 1978) and consequently activating resistance to persuasion. When consumers resist being persuaded by a message, the likelihood that they will share the message goes against both the self-serving motivation of self-enhancement as well as socializing motives. Furthermore, while there may be altruistic reasons to share some brand messages high in emotionality, we contend that the triggering of persuasion knowledge by emotionality in the message should dampen the altruistic motive for sharing. Consequently, we hypothesise the following:

H1a: TEP has a negative impact on retweets.

H1b: TEP has a positive impact on likes.

3.2 The Moderating Influence of Brand Emotional Positivity

The brand relationship theory perspective suggests that by acting as identity-expressing symbols, brands acquire stereotypical images and identities (personalities) and/or become entified in consumer minds, which helps position them as social relationship partners (Aaker, 1997). Thus, when brands communicate through tweets, they simultaneously build and communicate their context-specific personality (Nandan, 2005).

Geuens et al. (2009), in their reassessment of measures of brand personality, consider emotionality as a non-product related brand personality attribute. Since our focus is on brand behaviour on Twitter, it is relevant to consider the emotionality of the brand as displayed within the same context, i.e., Twitter. Our understanding of brand emotionality is, thus, similar to studies using Interaction Process Analysis (e.g., Lin & Peña, 2011) which categorize brand Twitter personalities around two broad styles of communication: task-oriented and socioemotional-oriented communication. In the context of this study, the emotionality-related personality of the brand (BEP) is formed through the brands' tweets over time and higher levels of BEP are associated with brands whose tweets are on average higher in emotional positivity. We argue that when BEP is high, TEP will have a detrimental influence on both retweets and likes by followers. This notion is consistent with findings in the cognition and psychology literatures which suggest that when individuals are repeatedly exposed to a stimulus, a process of habituation occurs whereby, although the physical intensity of the stimulus remains, the response intensity decreases (Galak & Redden, 2018). In essence, because brand followers have been repeatedly exposed to similar tweets from the brand over time, emotions in a tweet from a high BEP brand convey little additional information. As such, the potential for emotional positivity in an individual tweet to provoke a reaction from consumers is weaker when the tweet originates from a brand with a high BEP compared to one with a low BEP. Put more formally:

H2a: BEP strengthens the negative relationship between TEP and number of retweets.

H2b: BEP weakens the positive relationship between TEP and number of likes.

4. Methodology

4.1 Research Setting

We conducted text analysis of social media messages posted by Interbrand’s 100 best global brands on Twitter. Twitter currently ranks as one of the leading social networks worldwide with more than 320 million monthly active users. Furthermore, 86% of *Fortune 500 companies* have a Twitter account (Statista 2018). Therefore, Twitter constitutes a suitable setting for our research. We selected Interbrand’s 100 best global brands due to their economic importance, global reach, and increasing reliance on social media. Studying big companies is an established practice (e.g., Swani et al., 2014) and Interbrand's ranking of the most valuable brands in the world has often been used as the basis for selecting brands when exploring consumer engagement with brands on social media (e.g., Labrecque, Swani, & Stephen, 2019; Mandler et al., 2020). The brands examined cover a wide variety of industries. The use of a multi-industry sample enhances the generalizability of our findings. Table 1 provides an overview of the brands examined as well as the number of tweets collected per brand. All the brands included had at least one official verified Twitter account. Thirteen brands (namely Apple, Canon, DHL, Huawei, Ikea, Jack Daniels, Kellogg's, L'Oréal, Moët & Chandon, Panasonic, Santander, Smirnoff, and Sony) had more than one official Twitter account. For those brands, we selected the one with the greatest activity, as measured via the number of account followers. All the accounts included in the sample used the English language. The sample comprises brand-generated tweets between February 2009 to July 2017.

[INSERT TABLE 1 ABOUT HERE]

4.2 Data sources and Measurement

Tweet emotional positivity. We collected digital messages posted by the 100 brands from Twitter through the Application Programming Interface (API). The API enables authorized application developers to obtain relevant internal data about users and their messages (Tang, Fang, & Wang, 2014). The Twitter API stores historical information about each message, including the text of the message, when the message was created, the number of retweets generated by the message, and the number of likes generated by the message. For each of the 100 brands, we collected data on the maximum number of messages possible. Our license allowed us to retrieve data relating to a stated maximum of 3,200[1] most recent Twitter messages per brand, where a brand had that many tweets. Our initial sample comprised 307,404 tweets.

In line with established practice, we use sentiment analysis to assess the overall level of positivity of each tweet (Tang, Fang, & Wang, 2014). Given the large number of tweets to be analyzed we decided to use an automated sentiment analysis technique. Similar to what happens with messages posted in other social media channels (e.g., Facebook, Instagram), Twitter messages frequently contain slang, shorthand syntax, incorrect spellings and grammar, repeated letters and words, inconsistent punctuation, and overall a high proportion of out-of-vocabulary terms. Therefore, we narrowed our options to tools that have been shown to perform well in social media datasets (Ritter, Clark, & Etzioni, 2011). We based our final choice on the systematic comparison of techniques performed by Ribeiro et al. (2016). Ribeiro et al. (2016) find that the Valence Aware Dictionary for Sentiment Reasoning (VADER) method developed by Hutto and Gilbert (2014) consistently outperforms other techniques in terms of accuracy and coverage of sentiment expressions, as well as showing good performance across a variety of domains (e.g., travel industry in Alaei et al., 2019). VADER continues to be a popular tool for detecting emotional valence (Antonakaki et al., 2021: p.11), having been employed in a range of relevant analyses (e.g., Mitra & Jenamani, 2020; Borg & Boldt, 2020). Furthermore, VADER is free and openly available, which allows for maximum reproducibility by other researchers. Besides several limitations and concerns over accuracy of lexicon-based approaches (e.g., Kübler et al., 2020), more broadly Hartmann et al. (2019) point out the benefits of interpretability of a lexicon-based sentiment analysis approach, such as VADER. Kübler et al. (2020) provide a useful distinction between "bottom-up" (basically machine learning) and "top-down" (mostly lexicon based) sentiment extraction approaches (SET), arguing that under certain circumstances, such as weaker/stronger brands and experience/search goods, "top-down" approaches may be more suitable over "bottom-up" approaches and vice-versa. Given the varied mix of brands and the presence of brand-generated (rather than customer-/audience- generated) tweet content in our dataset, a "top-down" tool like VADER was deemed most appropriate for this study.

The VADER technique is based on a lexicon of over 7,500 expressions and on several refined grammatical and syntactic heuristics, such as negation (e.g., "this isn't really all that great"), contrastive conjunctions (e.g., "the experience here is great, but the service is absolutely horrible"), or capitalization/punctuation characteristics (e.g., "The food here is GOOD!!!" has stronger positivity as opposed to "The food here is good!"). Hence, the VADER approach allows to accurately distinguish the polarity of a sentiment displayed in a message (i.e., whether the sentiment is positive or negative), as well as its strength. In the present study, we are interested in analyzing the overall degree of positivity displayed in Twitter messages. Therefore, we use the normalized compound score produced by VADER. Such a score reflects the "net" level of positivity of a message after accounting for both the positive and negative elements of that message. The compound score varies between -1 and 1, which correspond, respectively, to the maximum level of overall negativity and to the maximum level of overall positivity. As mentioned previously, our focus is on overall message positivity. To focus on messages that are clearly positive we only considered for analysis messages with a compound score of at 0.7 or higher. As a result, our final sample of Twitter messages comprises 62,255 messages. The use of the 0.7 threshold is in line with established practice and considerably reduces the chances of erroneously classifying messages that do not have sufficient emotional language, as positive messages (Hung & Lin, 2013; Kim & Hovy, 2004). The threshold helps to ensure that tweets indeed contain fairly unambiguous, explicitly valenced, emotional content. The use of such a threshold also serves the purpose of ensuring, as much as possible, that the tweets do indeed capture emotional positivity, rather than tone or middling valence. Due to the nature of our data, we did not control for the 0.7 level of negativity. Despite our large dataset, the percentage (and thus number) of tweets with a negative score was extremely small. There was hardly any tweet with a 0.7 (or above) level of negativity. This is not uncommon in brand-generated tweets as brands generally try to convey positive emotions to their customers (e.g., Lin & Peña, 2011). Notwithstanding, in other domains, e.g., politics, it may be more likely to find a significant proportion of tweets with a negative emotionality score.

Two researchers with experience in discourse analysis manually examined a random sample of 110 tweets (the sampling choice of tweets being in line with Kim et al., 2018 and Le et al., 2019) to test agreement with VADER. This was conducted on a simple binary classification scale, to see whether a tweet indeed contains emotional positivity (i.e., the VADER score was equal and over 0.7) or not. This resulted in 100% agreement, where all sampled tweets were correctly labelled in terms of emotional positivity. The procedure just described, therefore, enhances our confidence regarding the appropriateness of using VADER in our study. We also did not find the use of sarcasm or irony to be prevalent in the sample. As per findings in Sykora et al. (2020), this indicates that such type of content is probably not likely to be prevalent in the dataset. Some example tweets to illustrate typical emotional language use are: *"Proud to win 10 new @user_name awards, recognizing our commitment to innovation <url>"*, *"@user_name You look wonderful no matter what, <anonymised-name>! We're thrilled you enjoyed your drink!"*, or *"The joy of getting lost in Venice? Stumbling across amazing photo opportunities <url>"*.

Brand emotional positivity. To measure degree of BEP we computed the average value of valence across all the tweets we collected for the brand. We did not exclude tweets with valence lower than 0.7 for computing degree of BEP. The reason is that BEP can be considered as a facet of the brand's online identity. In this context, researchers agree a brand's online identity is the result, among other aspects, of all the messages posted by the brand (Nandan, 2005). Accordingly, the degree of BEP is a consequence of every message the brand posts (not just of its positive messages).

User responses. We obtained measures for retweets and likes for brand tweets via the Twitter API.

Control variables. We controlled for message and brand related characteristics that can have an impact on user responses to enhance the exploratory power of our model and, thus, reduce the chances of endogeneity. In terms of message characteristics, we controlled for the number of hashtags and number of weblinks included in the message, and for the number of Twitter users mentioned in the message (Dang-Xuan et al., 2013; Swani et al., 2014). We obtained data for such controls via the Twitter API. At the brand level, we controlled for the average level of user responses, industry and number of Twitter followers. We used dummy variables for the brand's industry based on the categorization provided by Interbrand. We measured the brand's average level of user responses through the average number of retweets per Twitter message posted by the brand (across all the Twitter messages we collected for the brand) and via the average number of likes per Twitter message posted by the brand (also across all the Twitter messages collected for the brand). Such controls for post, brand and follower-related aspects (such as the industry and the number of followers/fans), are well-established within the literature regardless of the social media platform on focus (e.g., Schultz's (2017) Facebook-based study). We gathered the data to compute those averages and data on the brand's number of followers through the Twitter API. We report descriptive statistics in Table 2 and correlations among variables in Table 3.

[INSERT TABLES 2 AND 3 ABOUT HERE]

5. Analysis

5.1 Data Challenge

The objective of our analysis is to model the impact of TEP on the number of retweets and likes. One technical issue is that the two dependent variables (number of retweets and number of likes) are truncated below zero. Furthermore, the inspection of the data reveals that there is a disproportionately large frequency of zeros for both dependent variables. Approximately 55% of Twitter messages are retweeted zero times and 39% are liked zero times. Censoring the zeros results in a loss of information and biased estimates. The use of traditional ordinary least squares regression for the entire sample would also lead to biased estimates. Hence, we use the left-censored Tobit model (e.g., Kumar, Bhagwat, & Zhang, 2015).

5.2 Statistical Model

The general formulation of our model is given in terms of a structural equation, also called index function:[2]

$$Y_i^* = X_i^{'}\beta + \varepsilon_i \,, \tag{1}$$

where the errors (ε_i) are assumed to be independent and identically distributed with mean 0 and constant variance σ^2 ($\varepsilon_i \sim N(0, \sigma^2)$), and independent of the regressors X_i. The variables contained in the vector of regressors X_i are explained in the next section. The parameters vector (β) represents the set of coefficients to be estimated. The independent variables (X_i) are always observed, i.e., not truncated. The index or latent variable (Y_i^*) - in this case, the natural logarithm of number of retweets/likes - is observed for values above zero and censored for those equal to zero. The variable that is effectively observed is Y_i, which represents the effective number of retweets/likes. Y_i can be represented by the following equation:

$$Y_i = \begin{cases} Y_i^* = X_i^{'}\beta + \varepsilon_i & se \;\; Y_i^* > 0 \\ 0 & se \;\; Y_i^* \le 0. \end{cases} \tag{2}$$

The model in equation (2) combines:

(i) the $\text{Prob}(Y_i = 0) = 1 - \Phi\left(\frac{X_i^{'}\beta}{\sigma}\right)$, where σ is the standard deviation of the error term and $\Phi(.)$ represents the normal cumulative distribution function at $X_i^{'}\beta / \sigma$;

(ii) the truncated normal distribution with expected value given by $E(Y_i \mid Y_i > 0) = X_i^{'}\beta + \sigma \frac{\phi(X_i^{'}\beta/\sigma)}{\Phi(X_i^{'}\beta/\sigma)}$, where $\phi(.)$ corresponds to the normal density function at $X_i^{'}\beta / \sigma$.

Therefore, it is not appropriate to restrict the analysis only to the positive observations.

5.3 Variables

Equations 3 and 4 show the variables comprised in our model.

$$Y_{1ij}^{*} = \beta_0 + \beta_1 \mathrm{TEP_{ij}} + \beta_2 \mathrm{BEP_j} + \beta_3 \mathrm{TEP_{ij}} \times \mathrm{BEP_j} + \beta_4 \mathrm{TWHASH_{ij}}$$
$$+\beta_5 \mathrm{TWUSER_{ij}} + \beta_6 \mathrm{TWLINK_{ij}} + \beta_7 \mathrm{BIND1}_j + \beta_8 \mathrm{BIND2}_j + \beta_9 \mathrm{BIND3}_j$$
$$+\beta_{10} \mathrm{BIND4}_j + \beta_{11} \mathrm{BIND5}_j + \beta_{12} \mathrm{BIND6}_j + \beta_{13} \mathrm{BRETW}_j$$
$$+\beta_{14} \mathrm{BFOLLOW}_j + \varepsilon_{\mathrm{ij}} \quad (3)$$
$$Y_{2ij}^{*} = \beta_0 + \beta_1 \mathrm{TEP_{ij}} + \beta_2 \mathrm{BEP_j} + \beta_3 \mathrm{TEP_{ij}} \times \mathrm{BEP_j} + \beta_4 \mathrm{TWHASH_{ij}}$$
$$+\beta_5 \mathrm{TWUSER_{ij}} + \beta_6 \mathrm{TWLINK_{ij}} + \beta_7 \mathrm{BIND1}_j + \beta_8 \mathrm{BIND2}_j + \beta_9 \mathrm{BIND3}_j$$
$$+\beta_{10} \mathrm{BIND4}_j + \beta_{11} \mathrm{BIND5}_j + \beta_{12} \mathrm{BIND6}_j + \beta_{13} \mathrm{BLIKE}_j$$
$$+\beta_{14} \mathrm{BFOLLOW}_j + \varepsilon_{\mathrm{ij}} \quad (4)$$

Y^{*}_{1ij} and Y^{*}_{2j} are, respectively, the natural logarithm of number of retweets and the natural logarithm of number of likes corresponding to tweet *i* sent by brand *j*. We choose to use the logs of both the number of retweets and the number of likes rather than the raw values due to the magnitude of the raw values, which reaches hundreds of thousands. The use of logarithms compresses the scales, thereby reducing the variance of the error term and, hence, mitigating heteroscedasticity. It also makes the estimates less sensitive to outliers (see Wooldridge, 2009, p.191) and allows for the interpretation the coefficients in percentages.

The variable TEP is degree of emotional positivity of a tweet. BEP indicates the level of online positivity of a brand. To address collinearity problems linked to the simultaneous inclusion of TEP, BEP, and their interaction (i.e., TEP x BEP) in equations 3 and 4, we used residual centering (Little, Bovaird, & Widaman, 2006). Residual centering refers to regressing a product term onto the variables that compose such product term. The residuals of the regression are then used to represent the interaction effect. Residual centering guarantees full orthogonality between a product term and its first-order terms (Little, Bovaird, & Widaman 2006).

TWHASH is the number of hashtags included in a tweet. TWUSER corresponds to the number of Twitter users mentioned in the tweet. TWLINK is the number of weblinks included in the tweet. BIND1-BIND6 are dummy variables for the brand's industry. BRETW and BLIKE are, respectively, the average number of retweets and the average number of likes for the brand across the tweets sampled. The inclusion of BRETW and BLIKE in the models aims at accounting for, respectively, the overall level of 'conscious attention' customers pay to the brand and the extent of information sharing by customers with regard to the brand. BFOLLOW is the number of Twitter followers of the brand.

5.4 Estimation

To estimate equations 1-4, we need to define the log-likelihood function. We estimate them by maximum likelihood, for which contributes both the $\text{Prob}(Y_i = 0)$ and the conditional density of Y_i, given that Y_i is positive, i.e., $f(Y_i \mid Y_i > 0)$, times $\text{Prob}(Y_i > 0)$. The log-likelihood function is given by:

$$\log L(\beta, \sigma^2) = \sum_{Y_i=0} \log\left[1 - \Phi\left(\frac{X_i^{'}\beta}{\sigma}\right)\right] + \sum_{Y_i>0} \log\left[\frac{1}{\sqrt{2\pi\sigma^2}} \exp\left\{-\frac{1}{2}\left(\frac{(Y_i - X_i^{'}\beta)^2}{\sigma^2}\right)\right\}\right]. \quad (5)$$

Assuming that the model is correctly specified, we get consistent and asymptotically efficient estimators of β and σ^2. In the present research, we are interested in the marginal effect associated with a change in a given regressor k (X_{ik}) on the expected value of Y_i given X_i. The marginal effects are then computed as follows:

$$\frac{\partial E(Y_i \mid X_i)}{\partial X_{ik}} = \beta_k \Phi(X_i^{'}\beta / \sigma). \quad (6)$$

Therefore, the marginal effect associated with each regressor is the product of the respective estimated coefficient and the probability of a positive outcome. Although we could use robust standard errors to account for heteroscedasticity, our model would still remain highly sensitive to this problem. The best practice consists of accounting directly for heteroscedasticity via estimating a heteroscedastic Tobit assuming a pattern for the heteroscedasticity (Maddala & Nelson, 1975). We use the Tobit Multiplicative Heteroscedasticity Regression developed for Stata by Shehata (2011).

Maddala and Nelson (1975) show that, with this kind of model, ignoring heteroscedasticity leads to inconsistent estimators if the true model is heteroscedastic. Therefore, we rely on the results from a heteroscedastic Tobit where we assume a generic specification for the pattern of heteroscedasticity (for further details see Shehata (2011) and Greene (2012, pp. 858-859)). The specification is as follows:

$$\sigma_i^2 = \sigma^2 \left[\exp\left(Z_i' \delta\right)\right]^2, \tag{7}$$

where δ is the additional vector of parameters to estimate and Z_i is a vector of either some or all explanatory variables. We consider a fairly generic specification of equation 7 containing all explanatory variables, i.e., all X_i.[3] We then need to replace σ_i in the log-likelihood function and to estimate the parameter vectors β and δ, as well as the constant σ, by maximum likelihood.

6. Results

Findings are reported in Table 4. At the bottom of the table we report the number of observations, log-likelihood values obtained in each estimation and respective Schwarz Bayesian Information Criterion (SBIC) for model selection. The models with the lowest SBIC for each analysis are the preferred ones. We also assess the quality of our models via looking at the McFadden's Pseudo-R2 and at the likelihood ratio test for global significance of the estimated coefficients. The pseudo-R2 statistic is .206 for the model that has number of retweets as dependent variable (hereafter referred to as "retweets model") and .106 for the model that has number of likes as dependent variable (hereafter referred to as "likes model"). Furthermore, the likelihood ratio test for global significance of the estimated coefficients equals 33,147.6 ($p \approx 0$) for the "retweets" model and 20,318.4 ($p \approx 0$) for the "likes" model. These figures are very satisfactory when compared to typical non-linear models (Green, 2012), indicating good fit with the data and high level of predictive power.[4] The heteroscedasticity LR test always rejected the null hypothesis of homoscedasticity (see last row in Table 5), giving support to the heteroscedastic model. Hence, we report and analyze the respective estimated marginal effects in the next section. Moreover, we use the marginal effects of the coefficients which are statistically significant to plot graphical representations of the relationship between message positivity and user responses (see figures 2, 3, 4 and 5).

[INSERT TABLE 4 ABOUT HERE]

[INSERT FIGURES 2, 3, 4, AND 5 ABOUT HERE; 1.5-COLUMN FITTING IMAGES]

6.1 Information Sharing (Retweets)

H1a states that TEP has a negative impact on retweets. H1a is fully supported as the marginal effect corresponding to the "main" effect of TEP on number of retweets is negative and significant (marginal effect = -.167, $p < .05$).[5] Information on the effect of TEP on the number of retweets is also included in the interaction between TEP and BEP and the latter is also statistically significant. Hence, it is necessary to consider both coefficients to make inferences on the effect of TEP on number of retweets (Kam & Franzese, 2007). In this context, H2a anticipates that BEP negatively moderates the impact of message positivity on retweets (the impact becomes more negative as BEP rises). H2a is corroborated as findings show that the marginal effect corresponding to the interaction between TEP and BEP is negative and significant (marginal effect = -.2.502, p < .01). Figure 2 presents a three-dimensional illustration of the impact of TEP on number of retweets across the range of values of BEP in our sample. Figure 3 also shows the impact of TEP on number of retweets, although in a two-dimensional format (for low, average and high levels of BEP). As shown in Figures 2 and 3, TEP has a negative effect on number of retweets for low levels of BEP and such effect becomes more negative as BEP increases. Hence, Figures 2 and 3 show that the data support both H1a and H2a.

6.2 Likes (Attention)

H2a predicts that TEP has a positive impact on likes. H2a is only partially supported. Specifically, the coefficient that corresponds to the "main" effect of TEP on number of likes is positive and significant (marginal effect = .653, p < .01).[6] Yet, similarly to the "retweets" model, information on the impact of TEP on the number of "likes" is also included in the interaction between TEP and BEP and this interaction is also statistically significant. In this context, H2b posits that BEP weakens the positive impact of TEP on likes. H2b is supported as results show that the marginal effect associated with the interaction between TEP and BEP is negative and significant (marginal effect = -.933, p < .01). Figure 4 presents a three-dimensional illustration of the link between TEP and number of likes across the different values of BEP. Figure 5 shows the same relationship in a two-dimensional format (for low, average, and high levels of BEP). Figures 4 and 5 both show that TEP has a strong positive impact on number of likes for low levels of BEP. Yet, as BEP increases, such positive effect diminishes in magnitude. Eventually, under high levels of BEP, the impact of TEP on number of likes becomes negative. Therefore, Figures 4 and 5 show that H2b is corroborated but that support for H2a is only partial.

6.3 Robustness Checks

We tested the robustness of our models in two ways. First, we ran them using simple Tobit models in which we assumed the error terms to be homoscedastic. While the magnitude of the coefficients was different (as expected), their sign and level of significance are in line with the heteroscedastic Tobit specification that was used to test our models. Therefore, such results offer evidence that our results are robust. As the heteroscedasticity LR test supports its heteroscedastic version there is no need to report the homoscedastic version, however the respective results are available upon request. Second, given the large standard deviations of number of retweets and number of likes (see Table 3) it could be the case that a few outliers were driving our results. Therefore, to avoid those potential outliers or the user biases (i.e., that a small percentage of users create large amounts of tweets), we follow Tsou et al. (2017) and remove the top 1% of tweets and likes to center the analysis on the more common messages from the general users. This means that as a robustness check we ran the models excluding the top 1% of tweets with the most retweets/likes. The results of those models are reported in Table 6. Inspection of Table 6 reveals that our conclusions remain the same, thereby offering further evidence that our results are robust.

[INSERT TABLE 5 ABOUT HERE]

7. Discussion

7.1 Theoretical Implications

While social media content posted by brands has received a fair amount of research attention, research on the differential impact of emotional content on distinct user behaviors is limited. In addition, there is insufficient understanding of the effect of brand identity in shaping the effect of emotional content. Based on a large sample of messages posted by Interbrand's

100 best global brands on Twitter, we analyze the impact of emotionality in brand tweets on two key consumer reactions on Twitter: retweets and likes. We also examine the moderating role of brand emotionality on the relationship between TEP and these two outcomes.

The results offer two key theoretical implications. First, we extend knowledge on the effect of emotional cues in brand social media posts on consumer attention and information sharing. Current studies on the impact of emotions in brand social media messages on consumer reactions often do not consider different outcomes. Consequently, they implicitly assume that the effect of emotionality does not differ across types of consumer responses. In our study, we empirically demonstrate that this is not the case. Specifically, we find that TEP has a consistent negative impact on information sharing (retweets). This finding contradicts some earlier findings in the political marketing literature (e.g., Dang-Xuan et al., 2013) and echoes comments by Walker et al. (2017: 290) that retweeting behavior may differ when tweets are posted by organizations, since there may be different relationships between followers and message senders in different contexts. We also find that the impact of TEP on likes can be either positive or negative depending on the overall degree of the emotional positivity of the brand that posts the message. It can be concluded, therefore, that while emotional positivity in brand messages on social media may be less beneficial when a firm's goal is message propagation, it can be a useful tool for stimulating interest among the brand's own social media followers. This is a key distinction that, with few exceptions (e.g., De Vries et al., 2012), has not been addressed in the literature.

Second, we examine, for the first time, the role of brand identity in influencing social media users' responses to brand social media messages. By highlighting how BEP interacts with TEP in determining user responses we contribute to the literatures on social media communication and brand identity. The moderating effects found in this study suggest that the relationship between emotional positivity in brand messages and user responses is more complex than previously suggested. Specifically, greater levels of BEP aggravate the negative effect of TEP in triggering information sharing (retweets). Yet, in the case of likes, direction and strength of the impact of TEP depends on the degree of BEP: while the impact is strong and positive for low levels of BEP, it becomes increasingly less positive as BEP rises and is even negative for brands with high levels of emotional positivity.

7.2 Managerial Implications

Brands have devoted increasing attention to consumer responses to the social media content they generate due to the impact of those responses on various brand outcomes. In this context, we offer two key managerial recommendations. First, managers need to recognize that the use of emotional cues in social media posts is not equally effective for all consumer behavior outcomes. Because messages high in emotionality can capture the attention and interest of social media followers, brands can use emotional language as a means of increasing users' personal engagement with the brand. Yet, emotional positivity in brand messages has a negative impact on information sharing (retweets). Thus, managers may need to be cautious about using emotional language on Twitter if their objective or goal is to stimulate interactive engagement or active message dissemination.

We highlight instances where different types of content might prove more effective in pursuit of different communication goals. For instance, a firm might want to communicate a message (e.g., a deal) to its loyal followers or seek some form of personal engagement from its customers. The goal in this instance is not specifically to reach a wider audience through retweets but to gain the attention or engagement of its current followers. Our findings suggest that the use of emotional cues in brand posts should be beneficial here. However, if the primary aim is to encourage further dissemination of the message by its followers, the use of emotional language should be limited.

Second, managers need to be cognizant of the fact that the effectiveness of emotionality in social media messages in triggering user responses depends on the brand's level of emotional positivity. This has important implications for social media content over time. While high TEP leads to more likes, posting messages with high TEP over time increases BEP and leads to emotionality being less effective in generating consumer interest in brand messages. It is, thus, critical that emotional cues are used sparingly in order to keep BEP at a level where TEP remains effective for purposes of stimulating user interest. The clear implication is that firms may need to introduce some amount of variation in terms of emotionality into the messages they post on social media. Since in the case of stimulating information-sharing, as highlighted earlier, low TEP is always preferable, much of the variation needs to be focused on messages intended to gain attention (likes). One way to do this is to (when seeking for likes) make more (less) important messages more (less) emotionally charged. By doing so, they can reap the positive benefits of a high/low TEP on consumer attention/information sharing and ameliorate the negative effects of a high BEP.

7.3 Limitations and Further Research Directions

Our research is subject to several limitations. First, due to data limitations, we did not include the role of user characteristics (e.g., age, socioeconomic status) in our model. Those variables may have an impact on social media user responses, or they may affect the link between TEP and these consumer responses. While our post hoc analyses show that our models are robust, the addition of such user-related variables could contribute to further understanding the relationships between emotional positivity in brand messages and consumer reactions. Furthermore, while we are confident that by focusing on tweets with high TEP scores, we capture the *contribution of emotionality* to consumer responses to brand tweets, we were unable to control for some other message characteristics (e.g., type of message) that might influence consumers reactions. Future research on brand message emotionality might control for other message characteristics that have been shown to drive sharing and retweeting.

Additionally, in terms of detection of emotionality there are numerous other sentiment analysis techniques, including non-lexicon-based methods such as deep learning neural network techniques or ensemble and hybrid techniques (Antonakaki et al., 2021). Future work could, thus, use those techniques to further validate the findings of the present study. There are also noteworthy considerations of biases across text analysis methods that deserve further attention, such as biased negative sentiment scoring towards age and gender related language in sentiment analysis (e.g., Díaz et al., 2018).

Additionally, this study focused on tweets from Interbrand's 100 best global brands. This list consists of large brands, with a well-established Twitter and social media presence. Therefore, future research should examine smaller brands, that might demonstrate different levels of emotionality and emotional positivity and contrast them with larger brands in order to uncover differential effects on consumer engagement behaviors. Future research might also focus on corporate (instead of brand) message emotionality and on the corresponding user engagement implications. Furthermore, while we expect that our findings will be generalizable to other platforms, future research should test these effects on other social media sites to further validate our results. Also, we measured BEP as an average of TEP (for each brand). Yet, it would have been beneficial to have also used a survey-based approach to assess BEP, in order to validate the measure we adopted. It is, therefore, advisable that future studies adopt survey-based approaches for validating the measure of BEP. Finally, we did not examine whether and how brands' communication with consumers outside of social media (e.g., on TV, radio) within the same time period can leverage consumers' online/offline responses to brand social media messages. Thus, future research should investigate this.

8. Conclusion

In this study we examined the impact of emotionality in brand social media communication with its followers on different user responses, and how the personality of the brand shapes that impact. Emotional positivity has different impacts in terms of triggering personal engagement (likes) versus interactive engagement (retweets). Brand emotional positivity negatively moderates the impact of message positivity on both types of user responses. It is advisable that managers use emotional language and cues parsimoniously in order not to erode its effectiveness. Future studies should extend the present research via, for instance, examining the antecedents of emotionality in brand-generated social media messages, or analyzing if and how brands' communication with consumers outside of the social media arena can be useful in terms of boosting users' responses to brand-generated social media messages.

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Endnotes

[1] The Twitter GET statuses/user_timeline API endpoint (i.e., https://developer.twitter.com/en/docs/twitter-api/v1/tweets/timelines/api-reference/get-statuses-user_timeline) is documented as facilitating the retrieval of up to 3,200 most recent tweets per account; however, the API actually allowed us to retrieve additional messages for some brands (the maximum number of tweets retrieved was 3,249).

[2] For further details on this model see, among others, Greene (2012), Long (1997) and Maddala (1983).

[3] A simple test for heteroscedasticity is the Likelihood Ratio (LR) test where the null hypothesis is $\delta = 0$ for all coefficients.

[4] The pseudo-R2 assesses the model that better fits to data. While pseudo-R2 cannot be interpreted independently or compared across datasets like the usual OLS R2, they are valid and useful in evaluating multiple models predicting the same outcome on the same dataset. It only has meaning when compared to another pseudo-R2 of the same type, on the same data, predicting the same outcome. In this situation, the higher pseudo-R2 indicates which model better predicts the outcome. Hence, we selected the models that fits better to both the “retweets” type model and “likes” type model, but we cannot compare them across these two types by the reasons indicated above. For further details see Long (1997) and Freeze and Long (2006).

[5] In very simple and practical terms, this means that an increase of 0.1 in compound score index of message positivity will lead to a decrease of about 1.67% in the number of retweets, ceteris paribus. However, when combined with the effect of brand positivity, we observe a jump in the magnitude of this negative effect. A better picture of these combined effects is provided in Figures 2 and 3.

[6] This means that an increase of 0.1 in compound score index of message positivity will lead to an increase of about 6.53% in the number of likes, ceteris paribus. When combined with the effect of brand positivity, not only the magnitude but, most importantly, the sign of the effect change. A better picture of these combined effects is provided in Figures 4 and 5.

Table 1: Overview of brands examined

Brand	Number of Tweets	Sector	Brand	Number of Tweets	Sector	Brand	Number of Tweets	Sector	Brand	Number of Tweets	Sector
Apple	3,205	Technology	Ikea	3,249	Retail	Allianz	3,112	Financial Services	Mastercard	3,229	Financial Services
Google	3,225	Technology	Zara	3,240	Apparel	Siemens	3,233	Diversified	DHL	3,212	Logistics
Coca Cola	3,224	Beverages	Pampers	3,239	FMCG	Gucci	3,217	Luxury	Land Rover	3,230	Automotive
Microsoft	3,186	Technology	UPS	3,233	Logistics	Goldman Sachs	3,219	Financial Services	FedEx	3,220	Logistics
Toyota	3,239	Automotive	Budweiser	3,237	Alcohol	Danone	2,873	FMCG	Harley Davidson	3,247	Automotive
IBM	3,221	Business services	J.P. Morgan	3,212	Financial Services	Nestle	3,249	FMCG	Prada	1,426	Luxury
Samsung	2,600	Technology	eBay	3,225	Retail	Colgate	3,215	FMCG	Caterpillar	3,218	Diversified
Amazon	3,243	Retail	Ford	3,231	Automotive	Sony	3,208	Electronics	Burberry	3,227	Luxury
Mercedes-Benz	3,239	Automotive	Hermes	103	Luxury	3M	3,221	Diversified	Xerox	3,228	Business Services
General Electric	3,195	Diversified	Hyundai	3,203	Automotive	Adidas	3,223	Sporting Goods	Jack Daniel's	2,686	Alcohol
BMW	3,233	Automotive	Nescafe	3,226	Beverages	Visa	2,875	Financial Services	Sprite	3,246	Beverages
MacDonald’s	3,243	Restaurants	Accenture	3,211	Business Services	Cartier	1,390	Luxury	Heineken	3,216	Alcohol
Disney	3,240	Media	Audi	3,223	Automotive	Adobe	3,209	Technology	Mini	3,212	Automotive
Intel	3,245	Technology	Kellogg's	3,211	FMCG	Starbucks	3,206	Restaurants	Dior	2,264	Luxury
Facebook	3,241	Technology	Volkswagen	1,316	Automotive	Morgan Stanley	3,248	Financial Services	PayPal	3,230	Financial Services
Cisco	3,218	Technology	Philips	2,315	Electronics	Thomson Reuters	3,204	Media	John Deere	3,205	Diversified
Oracle	3,230	Technology	Canon	3,246	Electronics	Lego	3,218	FMCG	Shell	3,043	Energy
Nike	3,231	Sporting Goods	Nissan	3,221	Automotive	Panasonic	3,229	Electronics	Corona	3,199	Alcohol
Louis Vuitton	3,242	Luxury	Hewlett Packard	3,215	Technology	Kia	3,215	Automotive	MTV	3,246	Media
H&M	3,241	Apparel	L'Oréal	3,237	FMCG	Santander	3,216	Financial Services	Johnnie Walker	2,284	Alcohol
Honda	3,238	Automotive	AXA	3,241	Financial Services	Discovery Communications	3,238	Media	Smirnoff	3,228	Alcohol
SAP	3,225	Technology	HSBC	1,887	Financial Services	Huawei	3,235	Technology	Moët & Chandon	3,056	Alcohol
Pepsi	3,205	Beverages	HP	3,202	Technology	Johnson & Johnson	3,213	FMCG	Ralph Lauren	3,229	Apparel
Gillette	3,209	FMCG	Citi	3,233	Financial Services	Tiffany & Co	3,244	Luxury	Lenovo	3,245	Technology
American Express	3,212	Financial Services	Porsche	3,237	Automotive	KFC	3,224	Restaurants	Tesla	3,221	Automotive

Table 2: Descriptive statistics

Variable	M	SD
Tweet Level Predictors		
TEP	.818	.069
Number of hashtags included	.492	.779
Number of users mentioned	1.019	.655
Number of weblinks included	.493	.621
Brand Level Predictors		
BEP	.418	.157
Average number of retweets	37.323	116.690
Average number of likes	48.442	129.022
Total number of followers	1,663,939	3,347,855
Dependent variables (uncensored)		
Number of retweets for Tweet	31.468	869.437
Percentage left censored	54.6%	
Number of likes for Tweet	42.067	1314.296
Percentage left censored	38.9%	

Table 3: Correlations among variables included in the study

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. Number of retweets for Tweet (log)																
2. Number of likes for Tweet (log)	.76*															
3. TEP	-.16*	-.12*														
4. BEP	-.37*	-.28	.29*													
5. Number of hashtags included in Tweet	.35*	.28*	-.09*	-.25*												
6. Number of users mentioned in Tweet	-.20*	-.41*	.04*	.07*	-.11*											
7. Number of weblinks included in Tweet	.55*	.47*	-.12*	-.29*	.29*	-.27*										
8. Industry dummy 1	.04*	.08*	.02*	.08*	.09*	-.01*	-.02*									
9. Industry dummy 2	.07*	.01*	-.03*	-.09*	.03*	-.01*	.10*	-.08*								
10. Industry dummy 3	-.02*	-.05*	.06*	-.01*	.00	.03*	.05*	-.09*	-.04*							
11. Industry dummy 4	-.05*	-.08*	.14*	.06*	.09*	.03*	.00	-.16*	-.07*	-.07*						
12. Industry dummy 5	-.15*	-.14*	.00	.16*	-.07*	.02*	-.12*	-.14*	-.06*	-.06*	-.12*					
13. Industry dummy 6	.04*	.00	-.09*	-.07*	-.06*	-.01	.11*	-17*	-.07*	-.08*	-.15*	-.13*				
14. Brand's average number of retweets	.43*	.34*	-.06*	-.32*	.03*	.01*	.12*	-.04*	-.04*	.11*	-.12*	-.11*	.05*			
15. Brand's average number of likes	.49*	.45*	-.07*	-.29*	.06*	-.05*	.16*	.03*	-.06*	-.07*	-.12*	-.12*	-.01*	.88*		
16. Brand's number of followers	.17*	.17*	-.07*	-.14*	-.10*	.03*	-.00	-.14*	-.08*	-.04*	-.16*	-.16*	.27*	.43*	.37*	

Note: **p* < .05. Industry dummy 1 = Automotive; Industry dummy 2 = Business services; Industry dummy 3 = Electronics; Industry dummy 4 = Financial Services; Industry dummy 5 = FMCG; Industry dummy 6 = Technology; Hence, the base-category in our model comprises a miscellaneous of other residual industries/sectors like: alcohol, apparel, beverages, diversified, energy, logistics, luxury, media, restaurants, retail, and sports.

Table 4: Marginal effect estimates of heteroscedastic Tobit models

	Estimates	
Variables	**Number of retweets**	**Number of likes**
TEP	-.167*	.653**
BEP	-.225	.666**
TEP x BEP	-2.502**	-.933*
Control variables		
Number of hashtags included in Tweet	.238**	.150**
Number of users mentioned in Tweet	-.098**	-1.217**
Number of weblinks included in Tweet	.716**	.430**
Industry dummy 1	-.229**	-.164**
Industry dummy 2	.070**	-.176**
Industry dummy 3	-.196**	.194**
Industry dummy 4	.065**	-.167**
Industry dummy 5	.013	.074**
Industry dummy 6	-.062**	-.073**
Brand's average number of retweets	.347**	N.A.
Brand's average number of likes	N.A.	.225**
Brand's number of followers	.005	.104**
# Observations	62,255	62,255
$LogL_{model}$	-72074.0	-85347.1
Goodness-of-Fit Statistics		
SBIC [a]	144479.2	171025.3
Pseudo-R2 [b]	.206	.106
Likelihood ratio test [c]	$\chi^2_{(14)} = 33{,}147.6$, p <.001	$\chi^2_{(14)} = 20{,}318.4$, p < .001
Heteroscedasticity LR test	$\chi^2_{(14)} = 1{,}155.5$, p <.001	$\chi^2_{(14)} = 8{,}751.1$, p < .001

*p < .05 (two-tailed test).

**p < .01 (two-tailed test).

[a] Computed as $-2*LogL_{model}+K*LogN$, where K is the number of parameters in the estimated model and N is the number of observations

[b] Computed as $1-(logL_{model}/logL_{null})$

[c] Computed as $-2(logL_{model}-logL_{null})$

Notes: N.A. = not applicable; number of observations = 62,255; number of brands = 100.

Table 5: Robustness check: excluding the top 1% observations for retweets and likes

	Estimates	
Variables	**Number of retweets**	**Number of likes**
TEP	-.206**	.659**
BEP	-.110	.752**
TEP x BEP	-2.803**	-1.149**
Control variables		
Number of hashtags included in Tweet	.235**	.149**
Number of users mentioned in Tweet	-.093**	-1.201**
Number of weblinks included in Tweet	.701**	.407**
Industry dummy 1	-.201**	-.128**
Industry dummy 2	.074**	-.155**
Industry dummy 3	-.211**	.184**
Industry dummy 4	.074**	-.162**
Industry dummy 5	.013	.071**
Industry dummy 6	-.049**	-.047**
Brand's average number of retweets	.319**	N.A.
Brand's average number of likes	N.A.	.201**
Brand's number of followers	.003	.100**
# Observations	61,632	61,632
$LogL_{model}$	-69621.0	-87081.8
Goodness-of-Fit Statistics		
SBIC [a]	139572.9	174340.1
Pseudo-R2 [b]	.184	.135
Likelihood ratio test [c]	$\chi^2_{(14)} = 36{,}772.4$, p <.001	$\chi^2_{(14)} = 22{,}215.1$, p < .001
Heteroscedasticity LR test	$\chi^2_{(14)} = 1{,}232.4$, p <.001	$\chi^2_{(14)} = 9{,}214.7$, p < .001

*p < .05 (two-tailed test).

**p < .01 (two-tailed test).

[a] Computed as $-2*LogL_{model}+K*LogN$, where K is the number of parameters in the estimated model and N is the number of observations

[b] Computed as $1-(logL_{model}/logL_{null})$

[c] Computed as $-2(logL_{model}-logL_{null})$

Notes: N.A. = not applicable; number of observations = 61,632; number of brands = 100.

Figure 1: Conceptual framework [2-COLUMN FITTING IMAGE]

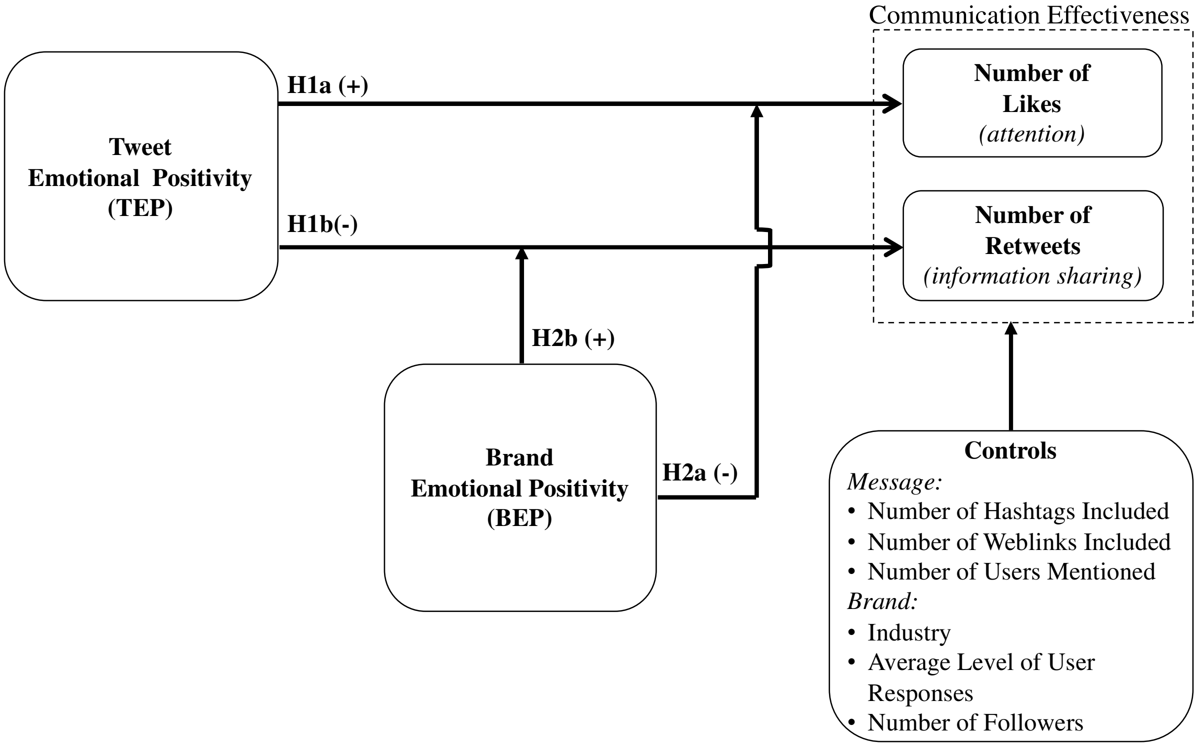


Figure 2: Three-dimensional view of the link between TEP and number of retweets under different levels of BEP [1.5-COLUMN FITTING IMAGE]

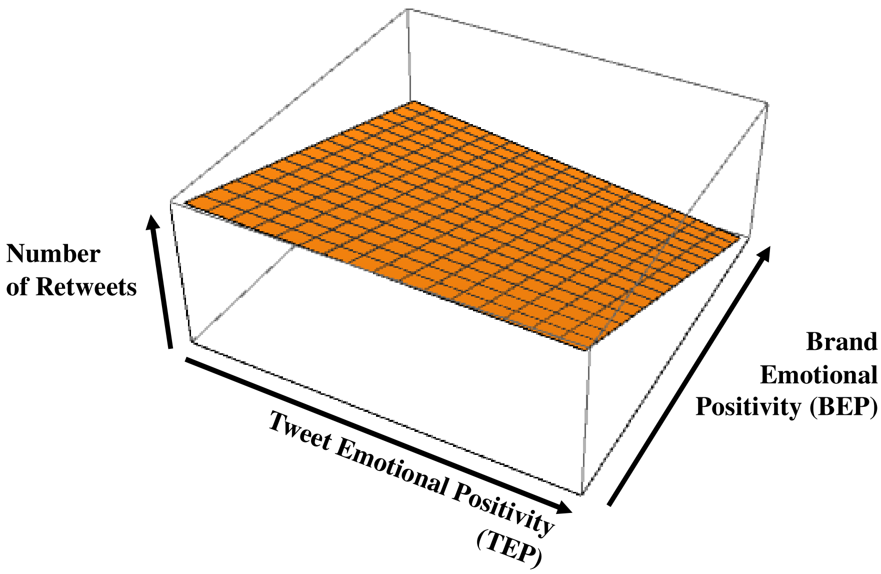
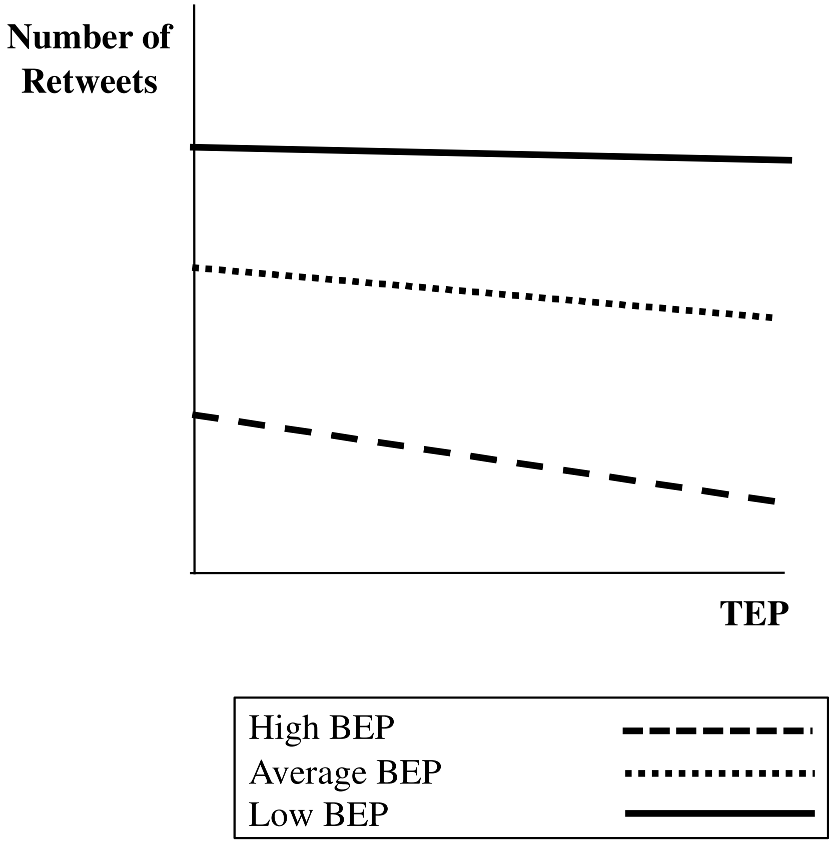


Figure 3: Two-dimensional view of the link between TEP and number of retweets under different levels of BEP [1.5-COLUMN FITTING IMAGE]



Note: The figure shows the slope of TEP at the mean and at ± 2.5 standard deviations from the mean of BEP.

Figure 4: Three-dimensional view of the link between TEP and number of likes under different levels of BEP [1.5-COLUMN FITTING IMAGE]

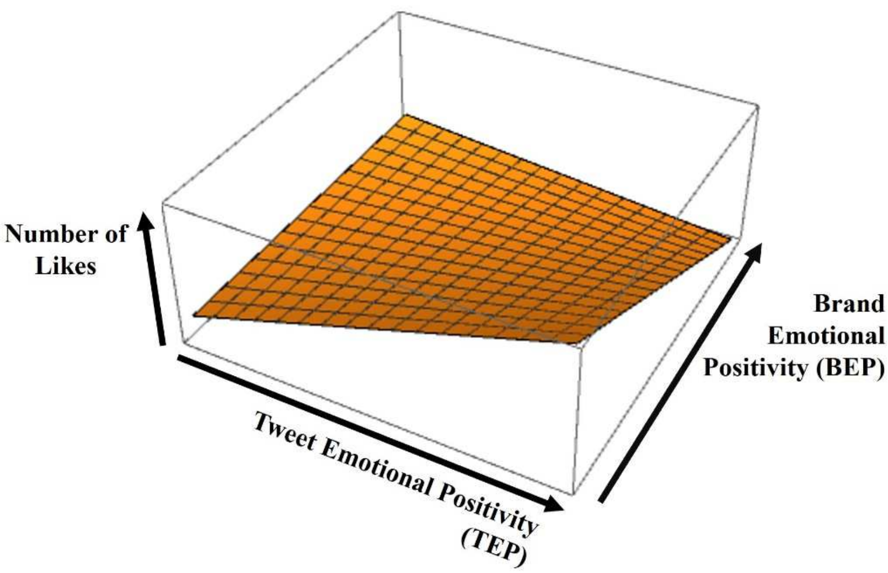
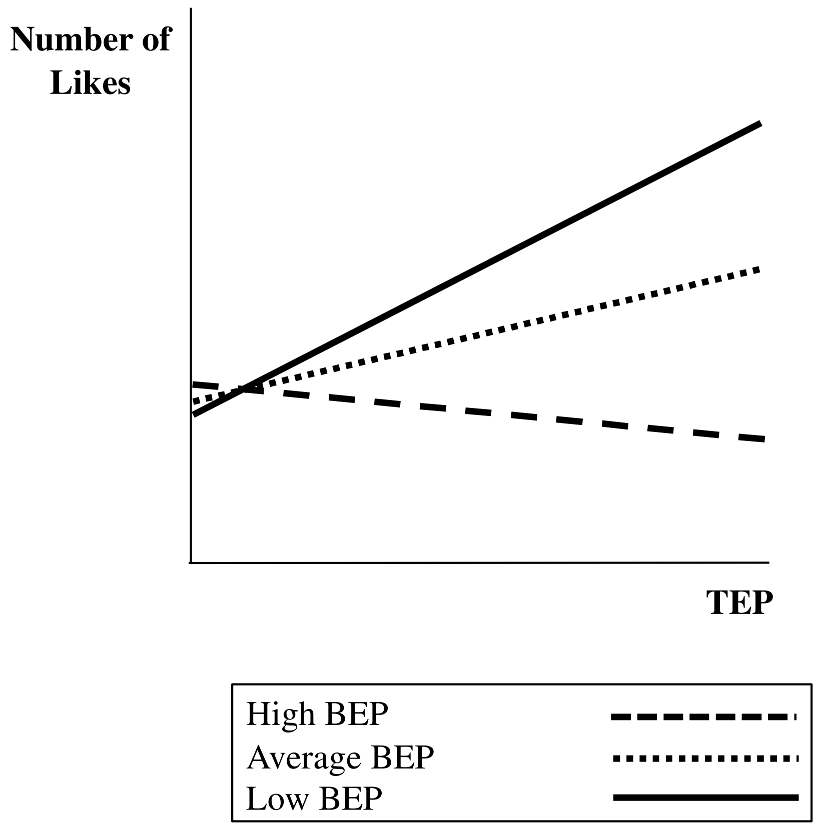


Figure 5: Two-dimensional view of the link between TEP and number of likes under different levels of BEP [1.5-COLUMN FITTING IMAGE]



Note: The figure shows the slope of TEP at the mean and at ± 2.5 standard deviations from the mean of BEP.